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Intergenerational Mobility in Slums: Evidence from a Field Survey in Jakarta

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Slums are central to the global debate on inequality, serving as entry points for people moving to cities in search of economic opportunity. Yet we know little about the extent of intergenerational mobility in slums due to a lack of data tracking families across generations (including family members who no longer live together), as well as a lack of data covering slums. This paper addresses these empirical challenges using a field survey of four slums in Jakarta, tracking educational mobility spanning three generations: grandparents, parents, and children. Among grandparents who have less than primary education, only 24% of their children achieve junior secondary schooling or more. By contrast, among parents with less than primary education, 69% of their children attain junior secondary schooling or more. Overall, the patterns suggest improvements in educational mobility across generations. Moreover, there is suggestive evidence that groups with high educational mobility also exhibit high occupational mobility.

Keywords: intergenerational mobility, slums, urbanization
JEL codes: O18, R20

I. Introduction

The United Nations estimates that 1 billion people, close to one-third of the world's urban population, live in slums. Slums are at the heart of the global debate over income inequality. They serve as entry points for many people moving to cities in search of economic opportunity. Slums are also often characterized by poor living conditions, raising concerns that they represent poverty traps that impede upward mobility.

Yet we know surprisingly little about the extent of intergenerational economic mobility in slums (see Marx, Stoker, and Suri 2013 for a review of literature on slums). There are three major data constraints. First, most datasets do not have indicators to identify slum locations, and the ones that do often have geographic

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units that are too coarse. As a result, these datasets may not include enough slum residents. A second constraint is a lack of data spanning multiple generations. Third, there is limited information about family members who no longer reside together, because most surveys ask only about demographic information for people living in the same residence.

This paper addresses these empirical challenges using a field survey of four slums in Jakarta to study intergenerational educational mobility. The survey includes 160 households (664 individuals) and was conducted in 2016 in four centrally located slums in Jakarta. The survey includes information about education and occupation spanning three generations: grandparents, parents, and children. Importantly, the sample includes information about grandparents and children who do not reside with the household head.

I use several methods to characterize intergenerational educational mobility in these four slums. The primary metrics rely on transition matrices and conditional transition probabilities (Bhattacharya and Mazumder 2011). I focus on transitions from less than primary schooling to junior secondary schooling and beyond, conditioning on different subgroups (such as earlier versus later cohorts, migrants versus natives, and males versus females). While comparisons across subgroups are descriptive and not meant to be causal, they highlight where the potential barriers to mobility might be.

Next, I estimate intergenerational elasticities in years of schooling. The elasticities are not easily comparable across subgroups because they capture the rate of regression to the subgroup means. I report the means for different subgroups. A faster convergence toward a higher subgroup mean suggests greater mobility. Following Hertz et al. (2007), I also report intergenerational correlations, which capture "standardized persistence." These correlations standardize schooling outcomes by the standard deviation of schooling for each generation. Standardizing can be important for developing countries that experienced dramatic secular improvements in education outcomes.

Overall, I find large improvements in educational mobility across generations. The conditional transition probabilities are easiest to compare across subgroups. For example, among grandparents who have less than primary education, only 24% of their children achieve junior secondary schooling or higher. By contrast, among parents who have less than primary education, 69% of their children have junior secondary schooling or more. When comparing natives born in Jakarta and migrants born elsewhere, I find that natives have slightly greater mobility (transition probabilities of 47% for natives versus 38% for migrants).

Turning to estimates of intergenerational elasticities, the overall elasticity for years of schooling is 0.27, implying that educational disparities are smaller among children of more versus less educated parents. Interestingly, the intergenerational elasticity for younger generations (0.17 for parents and children) is around half of the elasticity for older generations (0.4 for grandparents and parents), implying greater educational mobility for the younger cohort. In addition, average schooling is higher for the younger generations (11 years) than for the older generations (8 years). Together, these findings point to greater mobility toward a higher mean in the younger cohorts relative to the older cohorts. Looking across subgroups, I find larger elasticities for migrants relative to natives who were born in Jakarta, with both groups having similar means.

The improvements in educational mobility in these slums echo broader improvements in schooling attainment in Indonesia, mitigating concerns that slum residents are trapped in a low human capital equilibrium. According to the World Bank, primary school completion rates exceeded 95% by 1985 and junior secondary school completion rates increased from 69% in 2002 to 81% in 2013. These patterns are consistent with schooling policies that have expanded access to education, including a nationwide program to build schools in the 1970s (Duflo 2001), a large-scale slum upgrading program in Jakarta in the 1970s and 1980s (Harari and Wong 2018), as well as compulsory schooling policies.

Next, I investigate labor market outcomes to examine whether the robust patterns for educational mobility readily translate to occupational mobility. I measure the likelihood of transitioning from low-income occupations (farmers, cleaners, and laborers) to high-income occupations (retail, administrative, teachers, and police officers). There is less variation across the subgroups with respect to occupational mobility. Interestingly, cohort pairs (household heads and their children or household heads and their parents) exhibiting above-median educational mobility have a 48% chance of transitioning from low- to high-income occupations, relative to a 36% chance for cohort pairs with below-median educational mobility. When respondents were asked why they do not have a formal sector job, 21% reported that they did not have adequate schooling and 11% reported they lacked necessary skills or experience, pointing to the importance of education in the mobility process.

Finally, I explore the extent to which these four centrally located slums provide access to occupations with high incomes. Interestingly, 34% of males (63% of females) work at home or in the neighborhood, while 47% of males (35% of females) work in the town center. Incomes of workers in the town center are 49% greater than incomes of residents working in slums, even after controlling for gender, education, experience, and occupation. The concentration of work in slums in spite of the large disparities in income across places of work is suggestive of barriers to labor market access for slum residents.

While the survey data addresses concerns related to the lack of coverage of slum residents and bias due to coresidency, one important caveat is its generalizability beyond the sample. Ideally, it would be useful to have a nationally representative sample that identifies slum residents and tracks them across generations, regardless of residency. In addition, it would be important to track mobility over time to assess bias from endogenous sorting.

This paper is related to a small but growing literature on economic well-being in slums, which has its roots in seminal work by Lewis (1954) and Harris and Todaro (1970). Field (2007) studies a large titling program in Peru; Cavalcanti, Da Mata, and Santos (2017) model the formation of slums; Cattaneo et al. (2009) examine the impact of improving housing conditions in Mexico on child health and adult happiness; Feler and Henderson (2011) study the provision of local services in Brazil; and Barnhardt, Field, and Pande (2017) investigate a slum relocation program in India. Moreover, a related line of research examines urban development and slums. For example, Marx, Stoker, and Suri (2015) focus on ethnic patronage and private investments in slums in Kenya; Henderson, Venables, and Regan (2016) model the dynamic development process of slums in Kenya; Harari and Wong (2018) examine slum upgrading in Indonesia; and Michaels et al. (2018) study sites and service programs in slums in Tanzania.

There is limited work on intergenerational mobility in low-income countries, especially for slums. Krishna (2013) investigates economic mobility in slums in Bangalore but does not examine educational mobility. Hertz et al. (2007) report intergenerational elasticities in schooling for 42 countries, including low- and high-income countries, such as the United States (0.46), Norway (0.4), Switzerland (0.49), Bangladesh (0.58), Chile (0.64), South Africa (0.69), Ghana (0.71), and Colombia (0.80). Using survey data from 2000, they estimate an intergenerational elasticity of 0.78 for Indonesia. This estimate is not directly comparable given the different population means. In particular, the lower elasticity for slums in this paper (0.27) does not indicate more mobility in these four slums.

The rest of the paper proceeds as follows. Section II provides a background on Indonesia and the four slums. Section III describes the data. Section IV presents the empirical framework. Section V presents the results. Section VI concludes.

II. Background

Indonesia is the fourth most populous country in the world with around 250 million people and a gross domestic product per capita of $3,500 in 2016. The city of Jakarta has a population of 10 million and is part of a larger metropolitan region with more than 30 million people. The poverty rate was 12% in 2012 (World Bank 2014).

By many measures, Indonesians have achieved significant improvements in educational attainment in the past few decades, as discussed in the introduction. The government introduced compulsory schooling in primary education (6 years) in 1950, which it later extended to junior secondary school (9 years) in 1994, and to high school (12 years) in 2013. Historically, the government has tended to prioritize education, with more than 20% of the government's budget committed to education. Besides compulsory schooling policies, the government also embarked on a large school construction program in the 1970s. In Jakarta, slum upgrading programs have also expanded access to schools.

The urban sector is rapidly growing in importance in Indonesia. According to the World Bank, Indonesian cities are growing faster than other Asian countries. Slightly more than half of the population live in cities, with more than two-thirds expected by 2025. Of the 21 million jobs created between 2001 and 2011, 18 million were in urban areas and 17 million were in the service sector (Lewis 2014).

The slums in the field survey are centrally located. On average, workers spend 27 minutes commuting to work, which is remarkably short given traffic congestion in Jakarta. Their jobs are an average of 7 kilometers from their homes. The high concentration of residents working in slums is consistent with Field (2007), who finds that providing property titles substantially shifts labor supply away from work at home. In the sample, only 15% of households reported having a title and more than 60% reported being anxious that they may be evicted by their landlord and the government.

In addition, these slums have relatively good access to local services. As many as 94% of households reported having access to electricity and 79% reported having their own latrines. Households also reported being satisfied with access to health services, education, electricity, and water.

While the slums are centrally located, not all of the residents are able to access formal sector jobs in the town center. Around one-third of males (63% of females) work at home or in the neighborhood, 47% of males (35% of females) work in the town center, and 9% of males work in factories in industrial centers. The rest do not have permanent locations (many are food vendors or work in the service sector). Those who work in the neighborhood are mostly sellers, laborers, or providers of transportation services. Those who work in the town center are part of retail establishments or restaurants, or have administrative jobs. About 22% of the slum residents are self-employed without employees and 13% have employees.

III. Data

The main data source is a field survey of four slums in Jakarta. I conducted the field survey in 2016, as part of a broader project with Mariaflavia (Nina) Harari on urban development patterns in Jakarta. The sample comprises 160 households (664 individuals). While there are several administrative surveys in Indonesia, the main difficulty is identifying slum residents. For example, the Indonesian Family Life Survey (IFLS) includes rich individual information, but asks only whether the *kelurahan* (urban village) has a slum, which would make the information on these urban villages too coarse to identify slums in Jakarta.[1]

[1]There are around 260 administrative localities in Jakarta. A locality is an important administrative unit where land transactions are recorded and public services are provided. Localities are akin to urban villages, with the

Table 1. **Demographics for Household Heads**

	Jakarta	Slums (Field Survey)				
Variable	**Mean**	**Mean**	**SD**	**P25**	**P50**	**P75**
Age	45	49	13	40	49	58
Male	0.85	0.81	0.40	1	1	1
Born in Jakarta	0.58	0.48	0.50	0	0	1
Household size	4.10	5.00	2.30	4	5	6
Years of schooling	10.00	7.20	3.90	3	6	9
Completed high school	0.51	0.24	0.43	0	0	0
Completed college	0.10	0.04	0.19	0	0	0

P = percentile, SD = standard deviation.
Notes: Summary statistics for household heads in two different samples. Column 1 corresponds to statistics for Jakarta computed from the 2008 Susenas households survey. The subsequent columns report data for 160 household heads in the field survey. The statistic for whether the household head was born in Jakarta was obtained from the 2010 population census (this variable was not available in the 2008 Susenas).
Sources: Author's calculations and 2008 Susenas survey.

The sampling strategy was as follows. The enumerators were told to visit four localities in Jakarta. Within each locality, the team identified *rukun warga* (hamlets, an administrative unit smaller than localities) that have slums, according to local officials. They then selected one hamlet randomly. Next, they identified the *rukun tetangga* (subhamlets) that have slums and randomly selected two subhamlets. Finally, they randomly selected 20 households from each subhamlet. In total, the sample has 160 households.

Table 1 reports summary statistics for 160 household heads in the survey, compared to all of Jakarta.[2] The average age of a household head is 49 years, slightly above the average for Jakarta (45 years). Males comprise 81% of the household heads in the survey, and 48% were born in Jakarta (compared to 85% and 58%, respectively, for the Jakarta sample). The average household size is 5, compared to 4.1 for Jakarta. The average years of schooling is 7.2 years, relative to 10 years for Jakarta. Moreover, only 24% completed high school and 4% completed tertiary education, compared to 51% and 10%, respectively, for Jakarta. The average annual household income is $3,500 in the slum sample, relative to a gross regional product per capita of $14,000 for Jakarta (Badan Pusat Statistik 2016).

To track educational mobility, the survey includes information on schooling attainment for all members residing in that household. Crucially, the survey also asks about the education and occupation of the oldest child, the second oldest child, and the parents of the household head, regardless of their residencies. For

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average locality having an area of 2.5 square kilometers and 10 hamlets. Since not all hamlets in a locality are slums, data at the locality level would be too coarse to identify slums.

[2]The statistics for Jakarta were largely calculated from the 2008 Susenas (a nationally representative household survey), except for the indicator on whether a household head was born in Jakarta, which was obtained from the 2010 population census. I do not use the Indonesian Family Life Survey (IFLS) because it covers only 13 out of 27 provinces in Indonesia.

Table 2. **Schooling Attainment across Generations** (%)

Education:	<Primary	Primary	Junior Secondary	High School	College+	Total
Grandparents	47	37	9	6	1	100
Parents	25	30	21	20	4	100
Children	5	15	17	53	10	100

Source: Author's calculations.

intergenerational linkages, I primarily consider two cohort pairs (household heads and their children plus household heads and their parents).[3] I drop individuals who have not completed schooling, keeping those 18 years old and above.[4] The primary estimation sample for educational mobility includes 333 cohort pairs.

Table 2 presents average schooling attainment for three generations: grandparents, parents, and children. For the grandparents, 47% have less than primary education and 37% have primary education only. For the parents, 45% have junior secondary schooling and beyond. For the youngest cohort (children), 53% have a high school education and 10% have a college education and beyond. On average, the grandparents have 5 years of education, the parents have 8 years, and the children have 11 years of schooling.

Aside from education, the survey also includes information on labor market outcomes for the top two earners in the household, including information on occupation, place of work, and monthly income. Traditional occupation categories in some administrative surveys have tended to focus on agricultural occupations, and may miss many occupations that are common in slums (these tend to be related to service or retail sectors, with many being self-employed). For the field survey, respondents were asked to describe their occupations and I categorized their descriptions. The three most common occupations (comprising slightly more than half of the occupations) are sellers, drivers, and construction workers or contractors. To examine intergenerational mobility in occupations, the survey also inquired about occupations for children and grandparents who were not residing with the respondents. The sample for occupational mobility includes 292 cohort pairs with nonmissing occupation information (section V.B.1). Finally, I also examine labor market access for 248 working individuals (section V.B.2).

IV. Empirical Framework

The empirical analysis focuses on intergenerational mobility in education. Relative to estimating mobility in permanent income, there are fewer empirical challenges for educational mobility. First, measurement error is less of a concern

[3]The results are similar if I include spouses of household heads and their children, but I do not have information for parents of spouses.

[4]The results are similar if I restrict the minimum age to 25 years.

for schooling whereas measurement error in earnings could lead to attenuation bias for income mobility estimates. Also, individuals tend to complete their education early in their lifetime so there is less of a life-cycle bias, unlike earnings, which can change significantly throughout the life cycle. Finally, there is less of a selection concern with schooling in Indonesia because educational attainment rates are high, unlike unemployment rates.

I present three measures of educational mobility. The main measure of mobility will comprise transitional probabilities, which are easy to interpret and compare across subgroups. I present transition matrices across discrete categories of educational attainment. In particular, for subgroups, I report conditional transition probabilities (Bhattacharya and Mazumder 2011), focusing on the transition from below primary education (for the older cohort) to junior secondary schooling and beyond (for the children). As Indonesia has had near universal primary completion rates since the 1980s, there is relatively less variation in primary education attainment rates. I report 95% confidence intervals for the estimates, obtained from bootstrapping over 100 iterations.

Second, I present estimates of intergenerational elasticities:

$$\ln(s_c) = \alpha + \beta \ln\left(s_p\right) + \varepsilon \tag{1}$$

where s_c is the child's years of schooling, s_p is the parent's years of schooling, and ε is an idiosyncratic error term. The unit of analysis is a pair of cohorts (grandparents–parents or parents–children). The estimation sample has 333 parent–child pairs. Standard errors are clustered at the household level.

The parameter of interest is β, the intergenerational elasticity for schooling. It measures differences in outcomes between children of more versus less educated parents, with $1 - \beta$ corresponding to educational mobility. β also captures the rate of regression to the population mean, which is different across the subgroups. The estimating equation implies that the data generation process for s_c is characterized by the rate of convergence and the mean. For example, finding greater mobility toward a lower mean may not necessarily indicate an improvement.

For the third metric, following Hertz et al. (2007), I present estimates of intergenerational correlations for education. As shown below, the correlation (ρ) is obtained by multiplying the elasticity by the ratio of the standard deviations for parents (σ_p) and for children (σ_c).

$$\rho = \frac{\sigma_p}{\sigma_c}\beta \tag{2}$$

This metric effectively standardizes educational attainment by the standard deviation for each generation to account for secular changes in education across generations. For example, an overall expansion in schooling over time (such as what Indonesia has experienced) could increase the variance in schooling for younger cohorts. In this case, the intergenerational correlation would be lower than the elasticity, indicating weaker (standardized) persistence. For example, Hertz et al. (2007) estimate that the intergenerational elasticity in education is 0.58 for Viet Nam, but the correlation is only 0.4. Moreover, they find that intergenerational elasticities declined steadily over time for Asia, but correlations remained stable. This indicates that much of the educational mobility improvements captured by the decline in intergenerational elasticities was driven by differences in the overall dispersion in educational attainment.

There are several empirical threats to estimating intergenerational mobility in education. First, most surveys only collect information for households whose members reside together. In the data, I find more mobility when including cohort pairs that are living together. This is consistent with the more upwardly mobile child living with and supporting the parents. Moreover, only 15% of the household heads are living with their parents, so conditioning on coresidence excludes many grandparents.

Another important concern is entry and exit of slum residents. To the extent that upwardly mobile residents are more likely to leave the slums and less mobile residents are more likely to stay in the slums, the estimated effect will tend to underestimate intergenerational mobility. By contrast, if less successful migrants leave the slums, I would be overestimating mobility. Residents in the survey are not very mobile. The 5-year mobility rate is less than 6% and the average length of stay is 24 years. Finally, an important concern is external validity, as the four slums in the sample are centrally located and have higher-quality amenities.

V. Results

A. Educational Mobility

I begin by presenting the overall transition matrix of educational mobility. Table 3 represents a transition matrix across five categories of educational attainment, including less than primary, primary, junior secondary, high school, and tertiary education. The rows represent children's schooling and the columns correspond to parent's education. Each column sums to 100%.

The mass is clearly concentrated below the diagonal, consistent with educational mobility. For example, while 44% of parents have not completed primary education (column 1), 32% of their children completed primary education, 14% completed junior secondary school, and 28% completed high school and beyond. Column 2 shows that among the older cohort who have completed primary schooling (35% of the sample), 69% of their children completed education beyond primary schools.

Next, panel A of Table 4 presents conditional transition probabilities across subgroups. I focus on the transition from below primary to junior secondary schooling and above. The brackets present 95% confidence intervals from

Table 3: **Transition Matrix for Educational Attainment** (%)

	Parent's Education				
Child's Education	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
1	26	8	4	0	17
2	32	23	15	11	0
3	14	25	17	11	0
4	25	35	56	67	33
5	3	9	8	11	50
Total	100	100	100	100	100

Notes: The five categories of educational attainment are less than primary (1), primary (2), junior secondary (3), high school (4), and tertiary (5). Each cell reports the percentage of children with educational attainment (row), conditional on parent's educational attainment (column).
Source: Author's calculations.

bootstrapping. Column 1 shows that for parents who have not completed primary education, 42% of their children completed at least junior secondary school (this corresponds to the last three rows in column 1 in Table 3). Notably, this transition probability is higher (78%) if we condition on cohort pairs that coreside in slums. The coresiding sample excludes working children, who have their own households and tend to exhibit lower mobility, as well as grandparents, who also tend to be associated with lower mobility. Indeed, columns 2 and 3 show strong improvements in upward mobility from the earlier cohorts (grandparents–parents) to the later cohorts (parents–children). If the grandparents have less than primary education, then only 24% of the parents have junior secondary education and beyond. However, if the parents have below primary schooling, then 69% of their children have junior secondary schooling.

All these parents were born in the slums. It would be a concern if a large fraction of the parents sorted into these centrally located slums in search of mobility for their children. Since the parents did not choose to locate in the slums, it is reassuring that the 69% estimate is unlikely to be driven by endogenous sorting (of course, endogenous exits remain potentially concerning). This upward educational mobility pattern is consistent with the expansion of compulsory schooling through junior secondary school in 1994. Columns 4 and 5 show slightly greater mobility for natives born in Jakarta (47%) compared to migrants born outside Jakarta (38%), although their confidence intervals overlap. Finally, the last two columns show a greater probability of upward mobility for females than males.

Panel B of Table 4 presents intergenerational elasticities with respect to educational achievement. Panel C presents intergenerational correlations (with p-values in brackets). Column 1 reports an intergenerational elasticity of 0.27 and a correlation of 0.28, suggesting that educational disparities are smaller in the younger cohort, even after accounting for differences in dispersion across generations.

Table 4. **Intergenerational Educational Mobility in Slums**

Dependent Variable	**Ln(child's education)**						
Sample:	**All (1)**	**Grandparents (2)**	**Parents (3)**	**Migrants (4)**	**Jakarta Natives (5)**	**Male (6)**	**Female (7)**
Panel A: Conditional Transition Probability							
Ln(parent's education)	0.42	0.24	0.69	0.38	0.47	0.31	0.54
	[0.28,0.56]	[0.08,0.40]	[0.46,0.93]	[0.18,0.58]	[0.26,0.68]	[0.13,0.49]	[0.22,0.85]
Panel B: Intergenerational Elasticity							
Ln(parent's education)	0.27^{***}	0.40^{***}	0.17^{**}	0.37^{***}	0.15	0.37^{***}	0.08
	(0.06)	(0.10)	(0.06)	(0.08)	(0.09)	(0.08)	(0.09)
No. of observations	333	170	163	175	158	229	104
R-squared	0.08	0.13	0.06	0.13	0.03	0.14	0.01
Mean	9.6	8.3	10.8	9.5	9.6	9.5	9.6
Panel C: Intergenerational Correlation							
Ln(parent's education)	0.28	0.36	0.24	0.36	0.16	0.41	
	[0.00]	[0.00]	[0.002]	[0.00]	[0.04]	[0.00]	

Notes: The unit of analysis is a pair of generations (grandparents–parents and parents–children). The dependent variable is the logarithm of years of schooling for children and the regressor is the logarithm of years of schooling for parents. Column 1 includes 333 pairs with nonmissing information on educational attainment. Column 2 includes grandparents–parents pairs only and column 3 includes parents–children pairs only. Column 4 includes migrants and column 5 includes Jakarta natives. Columns 6 and 7 split the sample by gender. Panel A reports conditional transition probabilities (less than primary to junior secondary education and beyond), with 95% confidence intervals in brackets, obtained from bootstrapping. Panel B reports intergenerational elasticities with standard errors clustered by household. Panel C reports intergenerational correlations with p-values in brackets.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Source: Author's calculations.

To probe the extent to which intergenerational persistence is driven by family versus environmental contexts, I follow the framework developed by Solon (1999), who relates sibling correlations with intergenerational elasticities. In this model of human capital formation, schooling depends on intergenerational transmissions within the family and neighborhood effects. Under some assumptions, the sibling correlation depends on the square of the intergenerational elasticity, where $\rho_{siblings} = \beta^2 + \mu$, and μ corresponds to nonparental determinants of education (such as neighborhood effects). In the survey, the sibling correlation is 0.5. Using the elasticity estimate of 0.27 implies that up to 15% of the sibling correlation is driven by parental effects, with a large share left to be explained by other factors.

Next, I explore heterogeneity in intergenerational elasticities across subgroups. These subsample estimates measure mobility and regression to subsample means. While they are not readily comparable to the estimate in column 1, it is nonetheless instructive to assess the degree of heterogeneity across subgroups. I report the subsample means of the dependent variable (years of schooling of the younger cohort) at the bottom row of panel B.

Overall, the patterns are similar to those of the conditional transition matrix. Column 2 is restricted to the older generations (grandparents–parents) and column 3 examines only the younger generations (parents–children). The elasticity is more than twice as large for older generations (0.4) relative to younger generations (0.17). While elasticities are not directly comparable across subgroups in general, in this case, the mean is *higher* for younger generations (11 years of schooling, versus 8 years for older generations). A faster regression to a higher mean for younger generations suggests an improvement in educational mobility. Panel C shows that the differences between the two cohort pairs are smaller using correlations (0.36 for the older cohort versus 0.24 for the younger cohort). While these results are not necessarily a causal estimate of the effect of slums on upward mobility, they are consistent with compulsory and universal education as well as slum upgrading programs in Jakarta improving educational access for younger cohorts. The changes in estimates across subgroups are large and consistent with trends estimated by Hertz et al. (2007). They estimate that the elasticity fell by 0.04 units every 5 years for Indonesia (about 0.2 every 25 years).

The remaining columns in panel B show greater persistence for migrants (0.37) than for natives (0.15), and for males (0.37) than females (0.08 and insignificant). The means are similar for different subgroups, suggesting greater mobility for natives and females.

Next, Table 5 presents educational mobility estimates using Indonesia's national socioeconomic survey (Survei Sosial Ekonomi Nasional, widely known as Susenas) in 2008. The benefit of using Susenas is that it is nationally representative, but the limitation is that it collects schooling data only for

Table 5. **Intergenerational Educational Mobility, 2008 National Sample**

Dependent Variable	**Child's Education**		
Sample:	**All (1)**	**Urban (2)**	**Rural (3)**
Panel A: Conditional Transition Probability			
Ln(parent's education)	0.57	0.69	0.54
	[0.53,0.62]	[0.63,0.75]	[0.49,0.58]
Panel B: Intergenerational Elasticity			
Ln(parent's education)	0.33***	0.28***	0.27***
	(0.003)	(0.004)	(0.004)
No. of observations	665,332	250,949	414,383
R-squared	0.17	0.17	0.09
Mean	8.0	9.3	6.9

Notes: Educational mobility using data from a 2008 national household survey. Panel A reports conditional transition probabilities with 95% confidence intervals in brackets, obtained from bootstrapping. Panel B presents intergenerational elasticities with standard errors clustered at the household level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Source: Author's calculations.

individuals who live together.[5] Nonetheless, it is instructive to examine educational mobility in the national sample. Panel A reports the conditional transition probabilities for all households (column 1), urban households (column 2), and rural households (column 3). The overall transition probability is 57%, greater than that for the slum survey (42%). Individuals reported greater mobility in urban settings (69%), compared to rural areas (54%) and the slums. Panel B shows similar elasticities in the urban and rural samples, but the urban sample has a higher mean (9 years, compared to 7 years for rural).

As discussed above, conditioning on coresidence in the slum sample increases the transitional probability to 78%, which is much greater than in the rural sample. In addition, the subgroup mean is also greater for coresidents in slums (11 years) than in the rural sample (7 years). These patterns suggest greater mobility among slum residents relative to the rural sector, albeit using the slum survey's limited sample size (93 cohort pairs that are coresiding).

B. Labor Market Access

Overall, the findings above are consistent with improvements in educational mobility across generations, mitigating concerns about slums representing poverty

[5]For example, Susenas surveys may be undercounting grandparents–parents cohort pairs that are not coresiding and these pairs tend to exhibit lower mobility (as discussed above). Thus, this coresidency bias would overestimate transition probabilities.

traps with low human capital formation. Next, I examine labor market outcomes for slum residents.

1. Occupational Mobility

I first explore occupational mobility by ranking occupations by income (see, for example, Abramitzky, Boustan, and Eriksson 2014). For the top two primary income earners for each household, I have information on their occupations and monthly income, which I used to rank occupations by income. I classified their occupations into aggregate categories based on the respondents' descriptions of the jobs. The highest incomes are associated with jobs in the public sector and independent sellers (around Rp3 million or $222 per month); followed closely by jobs in the formal retail sector (around Rp2.9 million); and administrative and managerial jobs, including jobs in banks and financial services (Rp2.6 million). The lowest incomes are associated with jobs in factories and security officers (around Rp2 million); construction jobs (Rp1.7 million); and service sector jobs, including cleaners (Rp1 million). The most common jobs are in retail, with 27% working as independent sellers (at food stands or kiosks), and 13% working in the formal retail sector (such as shopping centers). I classified the first four types of jobs—public sector, independent seller, formal retail, and administrative—as high-income occupations (the average income is above Rp2 million, the median in the sample). The rest are classified as low-income occupations. The conclusions are similar using other cutoffs to define high-income versus low-income occupations.

Table 6 presents conditional probabilities of transitioning from low-income to high-income occupations. In contrast to educational mobility, the patterns for occupational mobility are less robust. As discussed earlier, the occupational mobility estimates are less sharp and tend to be subjected to greater measurement error, life-cycle bias, and selection concerns due to unemployment. Nevertheless, education appears to be important. When I split the sample by educational mobility (bottom panel), I find that cohort pairs with high educational mobility (children with above-median education and parents with below-median education) have greater transition probability (48%) relative to those with low educational mobility (36%).

2. Slums and Labor Market Access

There is a large literature examining the role of workplaces in shaping labor market opportunities (Cutler and Glaeser 1997; Kling, Liebman, and Katz 2007; Chetty, Hendren, and Katz 2015). The centralized locations of slums may provide access to jobs and employment networks for workers. For example, Barnhardt, Field, and Pande (2017) examine a housing lottery in India that resettled slum dwellers to the city's periphery, and find that winners reported improved housing but no change in family income or human capital. This is consistent with the notion that

Table 6. **Intergenerational Occupational Mobility**

Sample:	**All (1)**	**Grandparents (2)**	**Parents (3)**	**Migrants (4)**	**Jakarta Natives (5)**
High-occupation jobs	0.40	0.40	0.43	0.41	0.40
	[0.19,0.62]	[0.16,0.63]	[0.05,0.81]	[0.11,0.71]	[0.09,0.70]
No. of observations	292	203	89	149	143
Sample:		**Low Educational Mobility**	**High Educational Mobility**	**Males**	**Females**
High-occupation jobs		0.36	0.48	0.38	0.48
		[0.10,0.62]	[0.16,0.81]	[0.15,0.62]	[0.17,0.78]
No. of observations		185	107	218	74

Notes: The unit of analysis is a pair of generations (grandparents–parents and parents–children). Similar to conditional transition probabilities reported in panel A of Table 4, the table above presents 95% confidence intervals in brackets, obtained from bootstrapping. The sample includes only cohort pairs with nonmissing occupation information. High-income occupations (average monthly income of more than Rp2 million) include jobs in the formal retail sector; administrative or office jobs (bankers, managers); jobs in the public sector (teachers, police officers); and sellers. Low-income occupations include service sector jobs, drivers, security officers, factory jobs, construction workers and laborers, cleaners, farmers, and homemakers. The transition probabilities present the likelihood of transitioning from low- to high-income occupations. The first two columns in the bottom panel split the sample by high educational mobility households (households where the older cohort's education level was below the median and the younger cohort's education level was above the median) and low educational mobility households. The last two columns split the sample by the gender of the child. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Source: Author's calculations.

slums in centralized locations can provide access to jobs and employment networks. In the data, less than 30% of workers reported finding a job by themselves, using ads, or through an employment agency. A majority of workers relied on friends and family to help them find a job. The data also show that 34% of employers required a reference or recommendation, and 24% required a background check.

Table 7 explores the relationship between slum residents' income and place of work. The dependent variable is the logarithm of monthly income (mean of Rp2.5 million or \$193). Column 1 includes four dummies for place of work. Column 2 adds demographic controls, including gender, years of schooling, experience, and experience squared. Column 3 adds occupation dummies and two self-employment dummies (self-employed with and without employees). Standard errors are clustered at the household level.

Column 1 indicates that income is 65% higher in the town center and 55% higher in industrial centers, relative to the omitted group (working at home or in the neighborhood). These significant differences remain after controlling for demographics and occupation fixed effects. The coefficients in column 2 are smaller but still substantial and significant, reflecting the notion that those who work in the town center and industrial center tend to be male and more educated. Controlling for gender reduces both coefficients by around 10 percentage points, and further controlling for years of schooling reduces both coefficients by an additional 10

Table 7. **Income and Place of Work**

Dependent variable	**Ln(income)**		
	(1)	**(2)**	**(3)**
Industrial	0.55**	0.32*	0.51**
	(0.18)	(0.15)	(0.17)
Town	0.65***	0.43***	0.49***
	(0.13)	(0.12)	(0.12)
Not permanent	0.31	−0.03	0.06
	(0.18)	(0.19)	(0.24)
Other	0.72*	0.48	−0.02
	(0.30)	(0.35)	(0.34)
No. of observations	248	248	248
R-squared	0.11	0.24	0.46
Demographics	N	Y	Y
Occupation	N	N	Y
Self-employed	N	N	Y

Notes: The dependent variable is the logarithm of income for the two primary income earners in each household, winsorized at the top 1%. The four key regressors are dummies for place of work, relative to working at home or in the neighborhood. Column 2 adds demographic controls (gender, years of schooling, experience, and experience squared). Column 3 controls for occupation fixed effects and two indicators for self-employed (with and without employees). Standard errors clustered by household are reported in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Source: Author's calculations.

percentage points. Column 3 shows that the results are robust to adding occupation controls. These large disparities in income by place of work, coupled with the high concentration of work in slums (particularly for women), point to potential barriers to labor market access for some slum residents.

Table 8 investigates compositional differences by comparing demographic characteristics by place of work. Column 1 shows that workers in the industrial sector and in the town center are 38% and 23%, respectively, more likely to be male. Column 2 shows that those working in the industrial sector have 2 more years of schooling, while those in the town center have 2.6 more years, compared to those working at home or in the neighborhood. Column 3 shows that high school completion appears to be more important for accessing jobs in the town center. Column 4 shows that the Javanese (the major ethnic group in Jakarta) are more likely to work in the industrial sector.

These demographic patterns characterize who works where and which subgroups face larger barriers to accessing high-income jobs in town centers and industrial centers. The large gender disparities suggest relatively larger potential gains from improving access for women. For example, Attanasio, Kugler, and Meghir (2011) and Attanasio et al. (2017) find that a vocational training program in Colombia helped women gain access to formal sector jobs. The probability of paid

Table 8. **Demographics and Place of Work**

	Male (1)	Years of Schooling (2)	High School (3)	Javanese (4)
Industrial	0.38*	1.99	0.13	0.32*
	(0.16)	(1.11)	(0.16)	(0.14)
Town	0.23***	2.60***	0.35***	−0.04
	(0.07)	(0.52)	(0.06)	(0.06)
Not permanent	0.57***	0.47	0.00	0.14
	(0.04)	(0.78)	(0.12)	(0.14)
Other	0.57***	0.43	−0.03	0.08
	(0.04)	(1.13)	(0.18)	(0.22)
No. of observations	248	248	248	248
R-squared	0.11	0.11	0.12	0.03
Mean	0.60	8.60	0.38	0.32

Notes: The table repeats column 1 of Table 7 but with demographics as the dependent variable instead of income. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Source: Author's calculations.

employment increased by close to 7%, hours worked per week increased by almost 3 hours, and wages rose by nearly 20%.

VI. Conclusion

This paper provides novel estimates of intergenerational educational mobility using a field survey of four slums in Jakarta, shedding new light on the potential for upward mobility in slums. I find significant improvements in educational mobility across cohorts and relatively greater mobility for natives than for migrants. Turning to occupational mobility, the patterns are less robust, but the estimates suggest that groups with high educational mobility also exhibit high occupational mobility.

While the results for educational and occupational mobility are encouraging, the improvements in educational attainment do not seem to readily translate to occupational gains for everyone. To probe the issue of labor market access further, I document where slum residents work and which jobs provide greater incomes. I find that many residents reported working in slums (especially women) in spite of potentially large income gains from working in nearby town centers. These findings suggest potential barriers to labor market access for certain groups of slum residents.

There are several caveats and directions for future research. One important limitation of the field survey is potential generalizability. Therefore, it would be interesting to explore a larger sample with a wider geographic scope, including other slums and nonslum areas. Another direction for future research is to explore other notions of social mobility, including income and relative mobility in economic ranks. Finally, it would be interesting to study the role of policies in accelerating economic mobility, including compulsory schooling laws, school construction programs, and slum upgrading programs that expand access to schooling.

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Dissecting Thailand's International Trade: Evidence from 88 Million Export and Import Entries

Tosapol Apaitan, Piti Disyatat, and Krislert Samphantharak*

This paper uses transaction-level data from Thailand to study concentration, specialization, and fragility of export activities. The paper shows that although exports have been an integral part of the development strategy of the country for several decades, direct engagement in international trade through exports is a rare activity. Export firms are different from their nonexport counterparts. Export activities are also extremely concentrated. There is a great deal of churning in Thai exports and exporting relationships are highly fragile. The findings highlight some cautions from a micro perspective about an export-oriented development strategy, particularly regarding concentration and vulnerability.

Keywords: export firms, export-oriented industrialization, international trade, Thailand
JEL codes: F10, F14, F40

I. Introduction

International trade is an important activity of an economy and is inseparable from economic development. Trade policies have been used to promote industrialization, and exports have been one of the key ingredients behind the growth of many economies over the past several decades, especially Asia's miracle economies.[1] However, there are some concerns with an export-oriented industrialization strategy. For example, this strategy makes the economy dependent on its importing counterparts and the global economy, the reason why we have repeatedly witnessed drops in gross domestic product (GDP) growth of

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[1]The literature on export-oriented industrialization and economic development, especially in Asia, is extensive. See, for example, Johnson (1982) for Japan, Amsden (1989) for the Republic of Korea, and Suehiro (2008) for Southeast Asia.

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export-oriented economies during global economic slowdowns. There is also a limit to this development strategy as growth becomes increasingly more difficult when more countries adopt similar export-led growth policies under a given set of global demand conditions.

These concerns, however, focus mainly on macroeconomic arguments. The objective of this paper is to point out additional cautious considerations based on evidence from micro data. In particular, this paper attempts to answer three questions. First, are exporting activities concentrated among few exporters or do they involve the majority of firms in the economy? Second, are exporters specialized or diversified across products and markets? Third, how fragile are exporting activities, i.e., how likely will those entering international markets survive over time? Analyzing granular international trade data from Thailand, one of the most open emerging economies in the world, this paper shows that Thai exports are extremely concentrated among a few large exporters, that there is limited diversification across destinations and products, and that exporting activities are highly fragile. These findings raise cautions for economies currently pursuing or aspiring to adopt a development strategy focusing on exports.

This paper joins others in the literature on heterogeneous firms in international trade.[2] This literature focuses on the firm level, where decisions and actions that actually drive trade flows are taken, allowing researchers to measure both the extensive and the intensive margins of trade which are central to understanding the evolution of aggregate trade flows. Focusing on the extensive margins—the number of firms that trade, the number of products they trade, and the number of countries they trade with—offers a complementary dimension to the more traditional focus on intensive margins—the value traded per firm, per product, or per country. Disaggregated data help identify potential winners and losers from trade-related developments and hence can shed light on their distributional implications.

However, most empirical studies on heterogeneity and international trade have relied on data from advanced economies. The use of granular-level census of firms from a developing economy is rare.[3] Exceptions include a study by Eaton et al. (2007), who use transaction-level customs data from Colombia to study firm-specific export patterns. They find that, in a typical year, nearly half of all Colombian exporters were new and tend to be extremely small in terms of their

[2]The literature on heterogeneous firms in international trade is extensive. Seminal work includes Eaton and Kortum (2002), Bernard et al. (2003), and Melitz (2003). These studies provide a theoretical model that incorporates a firm's decision making in an open market economy. For a survey on this literature, see Bernard et al. (2007a) and Melitz and Redding (2014).

[3]There are papers that use a sample of firms in developing countries to examine international trade and economic development. For example, Berman and Hericourt (2010) use a firm-level database containing 5,000 firms in nine economies to study how financial factors affect firms' export decisions and the amount exported by firms. Hallward-Driemeier, Iarossi, and Sokoloff (2002) use firm-level data from five East Asian countries to explore the patterns of manufacturing productivity across the region and the sources of export firms' greater productivity.

overall contribution to export revenues. Most of these firms also do not continue exporting in the following year, although those who survived continued to grow and expanded into new markets. Overall, export sales are dominated by a small number of very large and stable exporters.

Another exception is a study by Manova and Zhang (2009), who use data on Chinese trade flows and show that the bulk of exports and imports are captured by a few multiproduct firms that transact with a large number of countries. Firms also frequently exit and reenter into trade and regularly change their product mix and trade partners. The authors also find that most of the growth in Chinese exports was driven by deepening and broadening of trade relationships by surviving firms, while reallocations across firms contributed relatively less.

In another study, Arkolakis and Muendler (2010) use panel data from Brazil and show that few top-selling products account for the bulk of a firm's exports in a market and that firms systematically export their highest-sales products across multiple destinations. Finally, Lederman, Rodríguez-Claire, and Xu (2011) use customs data from Costa Rica to study the role of new exporting entrepreneurs in determining export growth. They also show that the rate of firm turnover into and out of exporting is high, but exit rates decline rapidly with the number of years the firm has been exporting. The exiting and entering firms tend to be significantly smaller than incumbent firms. Surviving new exporters actively adopted new products and abandoned weaker existing products they had started with.

Our paper adds to the literature by documenting international trade in Thailand using the universe of transaction-level customs data, supplemented by information from financial statements of all registered firms. To better understand internationally engaged firms, we examine the various dimensions of firm activities, including how many products they trade, how many countries they transact with, the concentration of trade across firms, and whether firms import as well as export. We also trace the evolution of these variables, as well as firm survival over time.[4]

Examining Thailand's international trade structure at a granular level makes an interesting case for a number of reasons. The country has adopted an export-oriented industrialization strategy since the late 1970s.[5] This strategy has led to rapid growth in exports: while exports grew at only 6% per year in the 1960s, the growth rate increased to 11% in the 1970s, 16% in the 1980s, and continued to grow

[4]In this paper, we focus mainly on exports, given its important role in the Thai economy. We note results for imports when they are of particular interest. The full set of results for imports is presented in the working paper version of this paper (Apaitan, Disyatat, and Samphantharak 2017).

[5]The reason for this policy was to respond to several events that adversely affected Thailand's balance of payments: the appreciation of the Thai baht, which was fixed to the United States (US) dollar; the decrease in prices of agricultural products; and the withdrawal of US military operations after the Viet Nam War. These events reduced foreign exchange and put pressure on the country's balance of payments. Coincidently, Thailand's shift to an export-oriented strategy took place at the time when there was a massive relocation of manufacturing firms from Japan and the newly industrializing economies (NIEs) to countries with lower labor costs in response to the Plaza Accord and the appreciation of the Japanese yen in 1985. See Samphantharak (2017) for a summary of Thailand's development strategy since the end of the Second World War.

rapidly into the early 1990s. Meanwhile, in the early 1990s manufacturing exports accounted for 75% of total exports, up from only 1% in the 1960s. Export-led industrialization, in turn, resulted in GDP growth of over 8% per year during 1980–1996. Even today, the country remains very open and highly integrated with the global economy. It participates in various free trade agreements and is an integral part of the global production chain in certain key industries, especially in auto and computer parts. The country's trade-to-GDP ratio is high, over 130% in 2016.[6] As an emerging economy whose impressive economic growth was fueled by the export sector, Thailand (among other East Asian economies) epitomizes a growth strategy emulated by many other developing countries. Understanding Thailand's trading activities will shed light on the distributional aspects of an export-oriented industrialized economy.

Our study presents several findings. First, although exports have been an integral part of Thailand's development strategy, direct engagement in international trade is a rare activity: only 5.7% of registered Thai firms exported to other countries in 2013. Second, trade is extremely concentrated. The top 5% of firms accounted for 88% of total Thai exports in 2015. At the same time, the top 5% of products and markets made up 77% and 67%, respectively, of all exports. We also find that most exporters tend to trade relatively few products and engage in trade with a relatively small number of countries. However, the small number of firms with the greatest product and trading-partner intensity account for the bulk of exports. Third, trading firms are special. They differ substantially from purely domestic firms and tend to be larger, more capital intensive, more productive, and utilize more external finance. Among exporters, those that also import stand out from the rest along similar margins. Fourth, there is a great deal of churning in Thai exports. In any given year, roughly one-third of exporters are new, and an equal number exit the market. Finally, exporting relationships are extremely fragile. The likelihood that an exporter or a given product–market–trader bundle remains in the market for more than 1 year is roughly 30%, although those that survive generally blossom and account for a disproportionate share of total export value.

The findings from this paper highlight some concerns over an export-oriented development strategy and have important policy implications. First, exporting activities are rare and exporting firms are different from nonexporting firms. Policies promoting exports should therefore pay attention to firm-specific attributes and identify factors that can reduce barriers to enter foreign markets. Second, given that exporting activities are fragile, with low survival rates, policies promoting exports must incorporate longer-term considerations. Reducing barriers for new firms to enter is not sufficient; making sure that they survive is also necessary. Finally, high levels of concentration have important implications for risk and

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[6] Unless stated otherwise, statistics are from the World Bank's World Development Indicators.

shock transmission. High concentration in exports implies that idiosyncratic shocks specific to particular traders, markets, or products can generate large repercussions on aggregate trade value. This implication raises a concern on the vulnerability of an export-dependent economy from a micro perspective, in addition to the traditional macro external-dependency argument.

The rest of the paper is structured as follows. Section II describes the data. Section III highlights the role of export firms and their characteristics, while section IV provides a comprehensive account of Thai exports at the extensive and intensive margins. Section V describes the dynamic evolution of Thai exports, by decomposing export growth along intensive and extensive margins and performing survival analyses.

II. Data

The main data source of our analysis is a database of all trade transactions collected by the Thai Customs Department at the Ministry of Finance. These data cover all shipments of goods that crossed into or out of Thailand between 2001 and 2015. The key variables include firm identification, destination and origin, commodity, value, currency, shipping method, point of entry and exit, tariffs and duties, as well as trade sanctions and preferential measures. To export or import goods, traders submit entry forms to the customs department. Individual entry forms may contain many items to be shipped. We will use the term *trader* to designate the party engaged in the trade transaction. Traders can be registered firms or ordinary individuals.

Table 1 presents summary statistics of the data. The upper panel reports the number of entry forms, items per entry, and number of traders in each year of the sample. While the number of entries has increased steadily, the number of items per entry has increased even more rapidly, with an average entry containing around nine items in 2015 compared to just under two in 2001. The total value of exports increased by roughly 260% during this time, from B2.79 trillion to B7.24 trillion.[7] A similar picture obtains for imports. All in all, we have information on over 546 million items exported or imported from around 88 million entries over a span of 15 years.

The second panel of Table 1 shows the number of traders categorized according to whether they export, import, or both export and import. For the latter we will use the term *hybrids*. Under our definition, *exporters* equals *pure exporters* plus *hybrids*. The same applies for importers. Between 2001 and 2009, the number of exporters rose from 21,289 to 38,114. Since then, however, the

[7]The exchange rate was approximately B35.72 per US dollar on December 31, 2015. The numbers presented in this article are in nominal terms. However, in 2001–2015 inflation in Thailand was low, ranging from the lowest rate of 0.2% (2003) to the highest rate of 2.4% (2008 and 2011). Cumulative inflation during this 15-year period was 16%.

Table 1. **Overview of Customs Data**

Number of Entries, Number of Items, and Total Value by Year

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Export															
Number of entries (million)	2.0	2.3	2.5	2.8	3.0	3.2	3.3	3.4	3.3	3.5	3.7	3.7	3.8	4.0	4.0
Number of items (million)	3.9	4.5	5.3	5.8	6.4	6.9	12.6	19.7	19.6	23.4	26.5	27.1	29.5	32.0	33.6
Average number of items per entry	1.9	2.0	2.1	2.1	2.1	2.2	3.8	5.9	6.0	6.8	7.2	7.4	7.8	8.1	8.5
Total value (trillion baht)	2.8	2.9	3.3	3.8	4.3	4.9	5.3	5.8	5.2	5.8	6.7	7.1	6.9	7.3	7.2
Import															
Number of entries (million)	1.7	1.8	2.1	2.3	2.4	2.6	2.6	2.7	2.5	3.0	3.1	3.3	3.4	3.4	3.5
Number of items (million)	3.9	4.2	5.0	5.4	5.9	6.3	7.4	21.4	22.1	28.0	29.8	34.2	36.8	38.0	40.7
Average number of items per entry	2.3	2.3	2.4	2.4	2.5	2.5	2.8	7.9	8.8	9.4	9.6	10.3	10.9	11.0	11.7
Total value (trillion baht)	2.7	2.5	3.1	3.8	4.6	4.8	4.9	5.9	4.6	5.9	7.0	7.9	7.6	7.4	6.9

Number of Traders by Year

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Total number of traders	44,251	48,352	54,101	57,644	60,716	61,945	66,505	81,212	87,026	87,834	92,674	97,404	98,647	93,221	95,320
Exporters	21,289	23,117	24,290	26,047	27,742	29,130	31,522	37,947	38,114	36,345	38,086	38,928	37,909	36,017	36,686
Pure exporters	8,325	9,460	10,021	10,871	11,912	8,162	14,551	19,443	19,361	17,661	18,595	19,219	18,001	16,313	17,017
Importers	35,926	38,892	44,080	46,773	48,804	53,783	51,954	61,769	67,665	70,173	74,079	78,185	80,646	76,908	78,303
Pure importers	22,962	25,235	29,811	31,597	32,974	32,815	34,983	43,265	48,912	51,489	54,588	58,476	60,738	57,204	58,634
Hybrids	12,964	13,657	14,269	15,176	15,830	20,968	16,971	18,504	18,753	18,684	19,491	19,709	19,908	19,704	19,669

Number of Products (6-digit)

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Export	4,384	4,429	4,461	4,487	4,555	4,551	4,633	4,555	4,576	4,586	4,725	4,917	4,825	4,768	4,769
Import	4,848	4,948	4,941	4,977	4,976	5,007	5,113	4,883	4,853	4,865	4,936	5,015	5,001	4,998	5,011

Sources: Thai Customs Department and authors' calculations.

Table 2. **Overview of Trading Firms, 2013**

	Registered Firms	Nonregistered Traders	Total
Pure exporters	7,408	10,593	18,001
	(7.5%)	(10.7%)	(18.2%)
Pure importers	28,282	32,456	60,738
	(28.7%)	(32.9%)	(61.6%)
Hybrids	17,562	2,346	19,908
	(17.8%)	(2.4%)	(20.2%)
Total	53,252	45,395	98,647
	(54.0%)	(46.0%)	(100.0%)

Sources: Thai Customs Department, Ministry of Commerce, and authors' calculations.

number of exporters actually declined to 36,686 in 2015. By contrast, the number of importers rose steadily from 35,926 in 2001 to 78,303 in 2015, the bulk of this increase coming from pure importers.

The last panel of Table 1 provides the number of products based on various Harmonized System (HS) classifications. We adopt the 6-digit classification scheme as it provides sufficiently fine product delineation while avoiding problems related to product reclassifications that would arise with a finer level of disaggregation. This classification yields 4,769 export products and 5,011 import products in 2015, both representing only modest growth over the sample.

III. Firms in Thai Exports

We first examine the characteristics of trading firms by supplementing the customs data with the Corporate Profile and Financial Statement (CPFS) data from Thailand's Department of Business Development at the Ministry of Commerce. The CPFS database consists of annual financial statements submitted to the department by all registered firms in Thailand. Key available variables include firm identification; balance sheet items (total and subitems of assets, liabilities, and equities); and income statement items (revenues, expenses, and net income). The data also include information on the type of business and industry in which each firm operates, as well as a registration year that allows us to calculate a firm's age. Merged with trade data, CPFS data provide additional information on major characteristics of traders who are registered firms.

Table 2 provides a snapshot of the overlap between the Thai Customs Department dataset and the CPFS. In 2013, there were a total of 98,647 traders.[8] Of these, just over half were registered firms. Thus, a large portion of trading activity in Thailand is conducted by nonregistered entities (individuals and firms). This, in part, reflects the large informal sector of the Thai economy. While the majority of

[8]Given a lag in collection and compilation of the CPFS data, the sample analyzed in this section covers data up to 2013.

Table 3. **Overview of Thai Exporters, Registered Firms Only, 2013**

	All Sectors	**Manufacturing**	**Retail and Wholesale**
Trading firms	53,252	16,350	29,843
	(12.2%)	(26.4%)	(20.5%)
Exporting firms	24,970	10,361	12,253
	(5.7%)	(16.7%)	(8.4%)
Pure exporters	7,408	2,129	4,456
	(1.7%)	(3.4%)	(3.1%)
Hybrids	17,562	8,232	7,797
	(4.0%)	(13.3%)	(5.4%)
Pure importers	28,282	5,989	17,590
	(6.5%)	(9.7%)	(12.1%)
Domestic firms	381,869	45,555	115,788
	(87.8%)	(73.6%)	(79.5%)
Total	435,121	61,905	145,631
	(100.0%)	(100.0%)	(100.0%)

Sources: Thai Customs Department, Ministry of Commerce, and authors' calculations.

pure exporters and importers are not registered, most hybrids are registered. In what follows in this section, we focus only on registered firms.

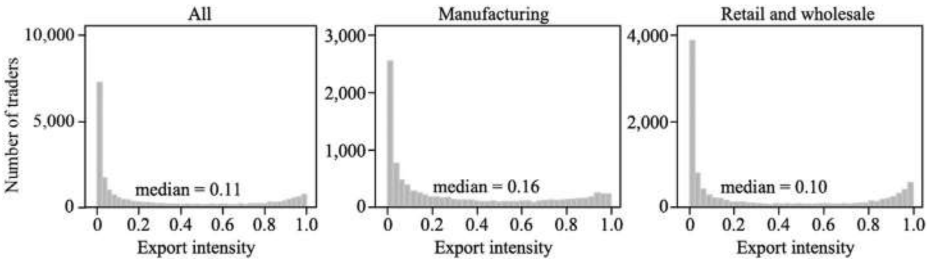
A. Exporters

Taking the universe of all registered firms as a starting point (435,121 firms), Table 3 shows that exporters are rare. Only 5.7% of all registered firms in Thailand engaged in exporting. Importing is also atypical with only 10.5% of firms importing (hybrids plus pure importers). Overall, an astounding 87.8% of Thai firms do not engage in *any* direct international trade. We also look at exporters in the manufacturing sector and the retail and wholesale sector separately, given the difference in the nature of their underlying economic activity: manufacturing firms mainly produce physical commodities that are sent abroad, while retailing and wholesaling firms are intermediaries that provide trading services. Exporting is less rare for manufacturing, with 16.7% of firms engaged in exports.

Figure 1 shows that export intensity, measured as the ratio of exports to total sales, takes a median value of 0.11. That is, export sales of the median firm account for just 11% of its total revenue. Moreover, there is concentration near zero and one, indicating a bipolar characteristic of Thai export firms: either firms specialize in export or they just dabble in it. Many do just the latter. Export intensity for exporters in manufacturing and retail and wholesale sectors broadly display a similar pattern (middle and right panels).

Figure 2 depicts the distribution of export compared to nonexport firms along a number of dimensions (first and last columns). Looking at median values, it is apparent that exporters tend to be more capital intensive (higher ratio of fixed assets to total assets), larger (higher revenue), more profitable (higher return on asset), and

Figure 1. **Export Intensity of Export Firms, 2013**



Sources: Thai Customs Department, Ministry of Commerce, and authors' calculations.

more efficient (higher turnover ratio measured as the ratio of revenues to asset), and have greater access to external finance (higher leverage ratios). Not surprisingly, manufacturing exporters tend to be larger and more capital intensive relative to retailing and wholesaling exporters, though the latter tend to have higher return on assets.

In light of our observation above that hybrid exporters play a very important role in Thai exports, we also present a comparison for hybrid versus pure exporters in Figure 3. With the exception of return on assets, the same pattern emerges. Hybrids are distinguished from other exporters in terms of size, capital intensity, efficiency, and leverage.

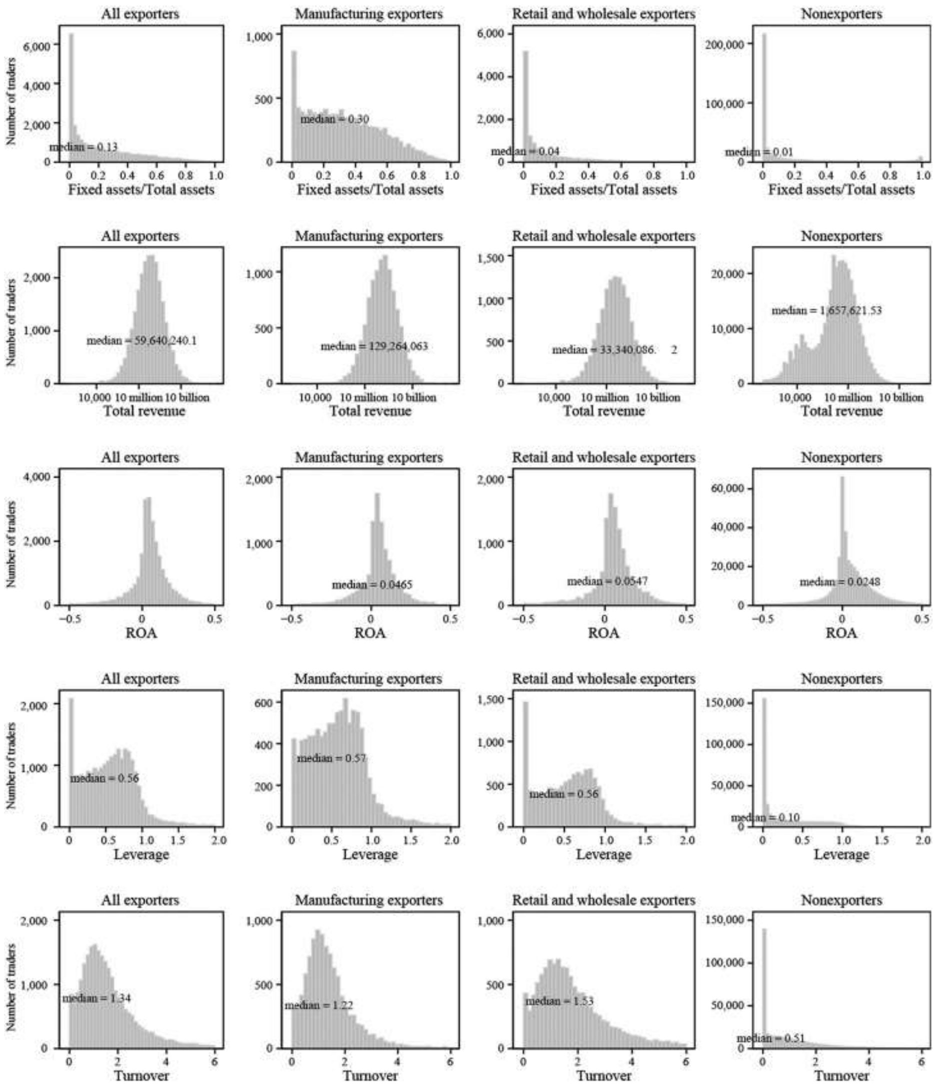
B. Implications

In summary, the observations documented in this section indicate that, despite having pursued an export-oriented development strategy for several decades, exporters constitute a very small fraction of all registered Thai firms. This low participation is consistent with data for other countries and points to the importance of entry costs to trade. Bernard et al. (2007a), for example, find that of the 5.5 million firms operating in the United States (US) in 2000 only 4% export. Similarly, Manova and Zhang (2009) show that the bulk of exports and imports of the People's Republic of China (PRC) are captured by just a few firms.[9]

Export firms are also special. They are different from domestic firms in terms of size, capital intensity, profitability, and efficiency. This is largely in line with previous findings in the literature (Eaton, Kortum, and Kramarz 2004; Bernard, Jensen, and Schott 2009; and references listed in these two papers) and raises a natural question of whether the differences already existed even before

[9]A caveat is that we have adopted a strict definition of international trade. A firm is deemed an exporter if it sells goods overseas. But many more firms may be supplying intermediate inputs that go into those final exports even though they themselves do not export directly. Thus, the importance of trade and the involvement of domestic firms in international trade will be understated by looking only at direct exporters.

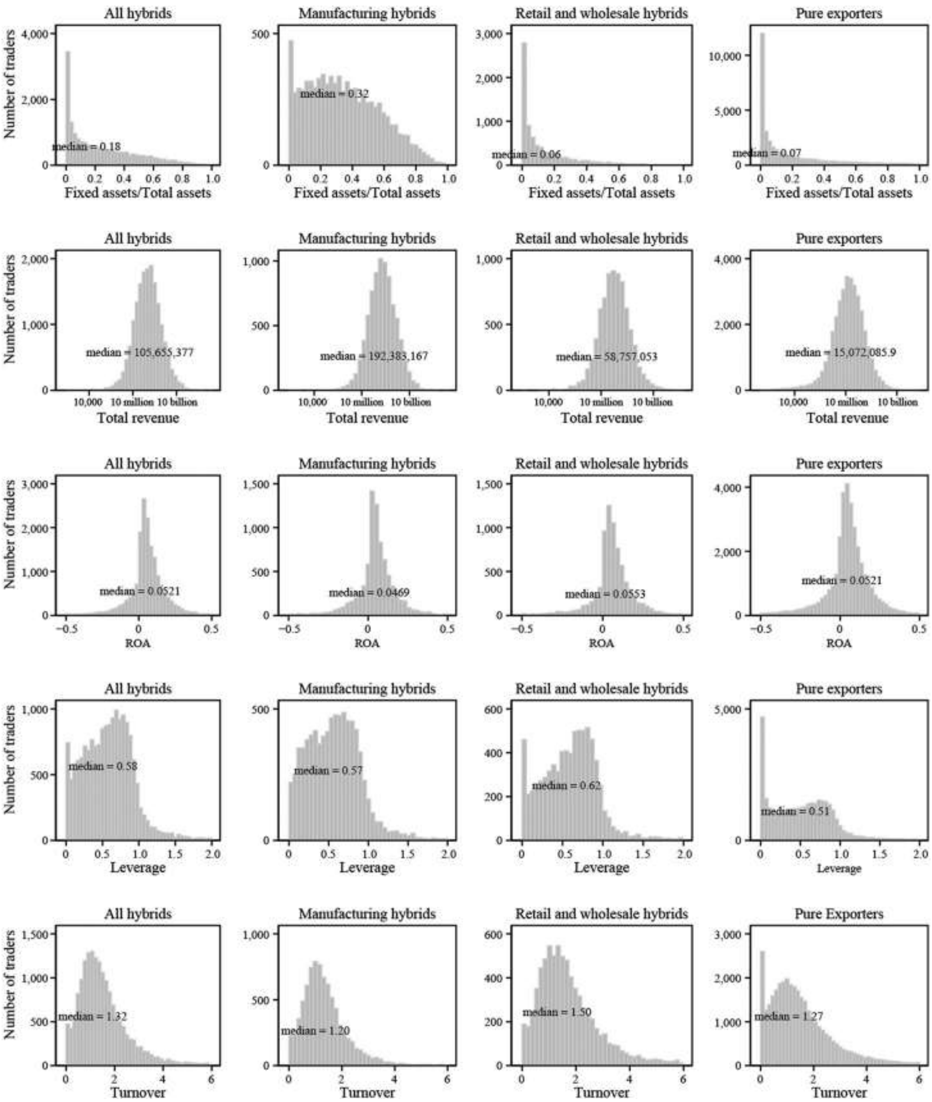
Figure 2. **Firm Characteristics—Exporters versus Nonexporters, 2013**



ROA = return on assets.
Sources: Thai Customs Department, Ministry of Commerce, and authors' calculations.

export firms began to trade. That is, do better and larger firms self-select into international trade, or does engagement in international trade over time make firms more efficient and grow? The overwhelming evidence in the literature is that these differences exist before entry (Bernard et al. 2007a). The heterogeneity among firms is systematically related to trade participation, with exporters being larger and more productive than nonexporters even prior to entering export markets. Most studies

Figure 3. **Firm Characteristics—Hybrids versus Pure Exporters, 2013**



ROA = return on assets.
Sources: Thai Customs Department, Ministry of Commerce, and authors' calculations.

also find little or no evidence of improved productivity as a result of becoming an exporter, though an abundance of evidence indicates that firms entering export markets grow substantially faster in employment and output than nonexporters. Thus, exporters are more productive, not as a result of exporting, but because only the most productive firms are able to overcome the costs of entering export markets.

Once they export, conditional on surviving, they scale up faster than domestic firms. This has both positive and normative implications.

On the positive side, such microeconomic heterogeneity helps to explain macroeconomic outcomes. When entry costs fall, high-productivity trading firms survive and grow, while lower-productivity domestic firms are more likely to fail. This reallocation of resource across firms raises aggregate productivity, both within sectors as well as for the economy as a whole, and is an important source of welfare gains from trade. On the normative side, entry costs appear to be the key barrier to trade. Rather than focusing policy on helping exporters improve, the emphasis should be ensuring that good firms are able to export. Entry barriers come in a myriad of forms, including tariffs, transport costs, distribution channels, marketing, unfamiliar regulation, and other informational asymmetries. On the one hand, these barriers could be firm specific and need policies targeting particular firms or industries. On the other hand, overcoming these barriers individually is costly, and the government should explore whether there is a potential role for governments to play in exploiting economies of scale and overcoming coordination failures in these areas.

IV. What, Where, and Who? A Granular Perspective of Thai Exports

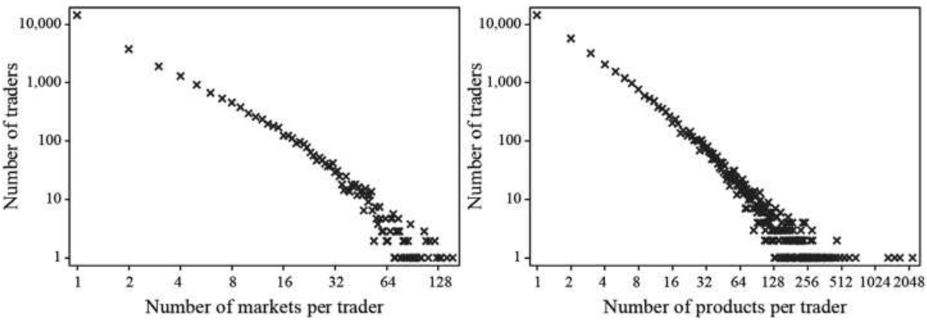
A unique feature of the customs data is that it provides information about the nexus between product, market, and trader. We call this product–market–trader (PMT) combination, where product x is exported to market n by firm i. This feature allows us to analyze trading activities beyond the firm-level data. We take advantage of this granularity of the data to examine the extensive and the intensive margins of Thai exports.

A. Extensive Margins

We examine three extensive margins of Thai exports: traders (exporters), markets (destinations), and products. First, from the perspective of traders, Figure 4 plots the distribution of exporters based on the number of markets they serve (left panel) and the number of products they sell (right panel). The frequency with which more markets and products are served declines smoothly and monotonically. Exporters generally sell few products to very few markets and most export just a single product to a single destination. This suggests that the fixed cost of expanding products and markets is high.

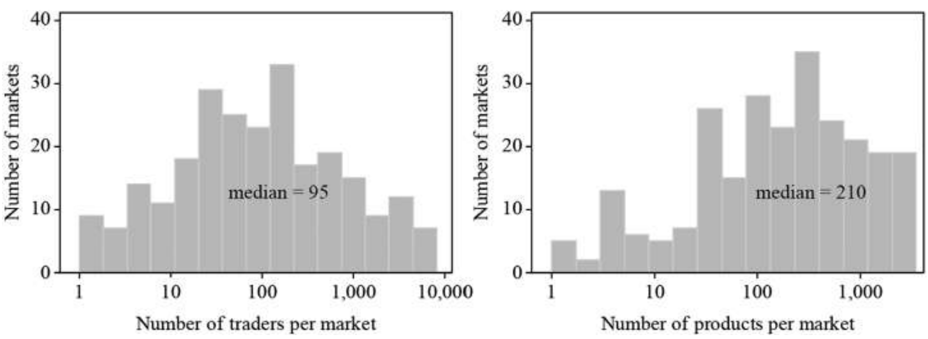
Second, turning to markets, Figure 5 shows the distribution of markets according to the number of traders per market and the number of products per market. While the number of traders per market is relatively small (median of 95 exporters per market), the number of products within a given market is relatively high (median of 210 products per market). This implies that traders are specialized

Figure 4. **Distribution of Number of Export Markets and Products per Trader, 2015**



Sources: Thai Customs Department and authors' calculations.

Figure 5. **Distribution of Number of Export Traders and Products per Market, 2015**



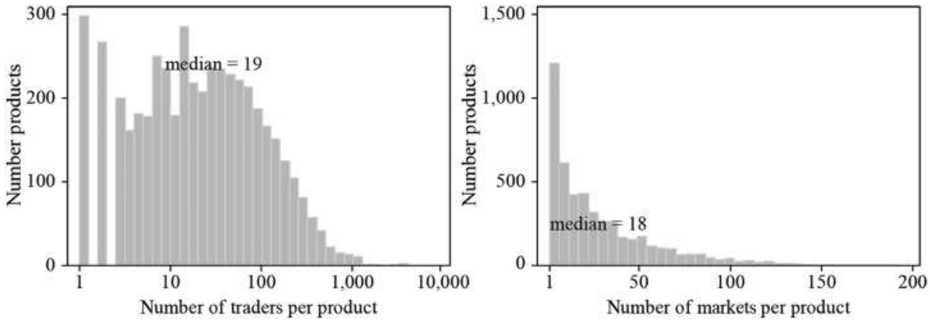
Sources: Thai Customs Department and authors' calculations.

in markets but diversified in products, and also suggests that entry barriers are high—most export markets are dominated by a few firms that sell many things.

Finally, at the product level, Figure 6 plots the distribution of products relative to the number of traders per product and the number of markets per product. The number of traders per product (left panel) is relatively small (median of 19 traders per product). At the same time, the right panel shows that most products are sold to a few markets (median of 18 markets per product, with bunching at one). In other words, Thailand exports few "global" products.

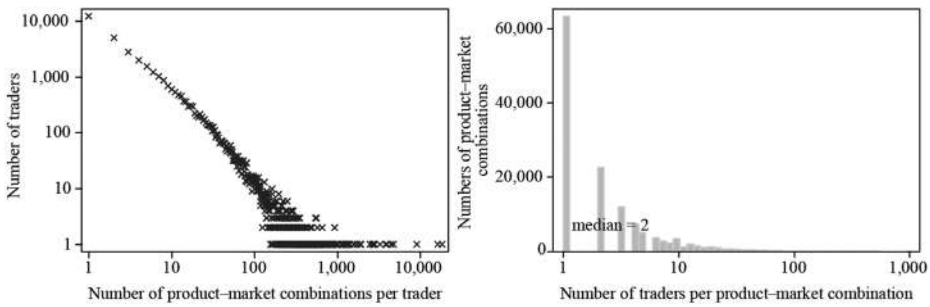
We can also examine exports through the lens of product–market (PM) combinations. The left-hand panel of Figure 7 shows the distribution of traders based on the number of PM combinations that each one trades. There is a very large variation in the number of PM combinations per trader, ranging from one to over 10,000 combinations. Most traders export just one PM bundle while a handful export over 1,000 bundles. The right-hand panel flips things around and shows the

Figure 6. **Distribution of Number of Export Traders and Markets per Product, 2015**



Sources: Thai Customs Department and authors' calculations.

Figure 7. **Distribution of Export Product–Market Combinations, 2015**



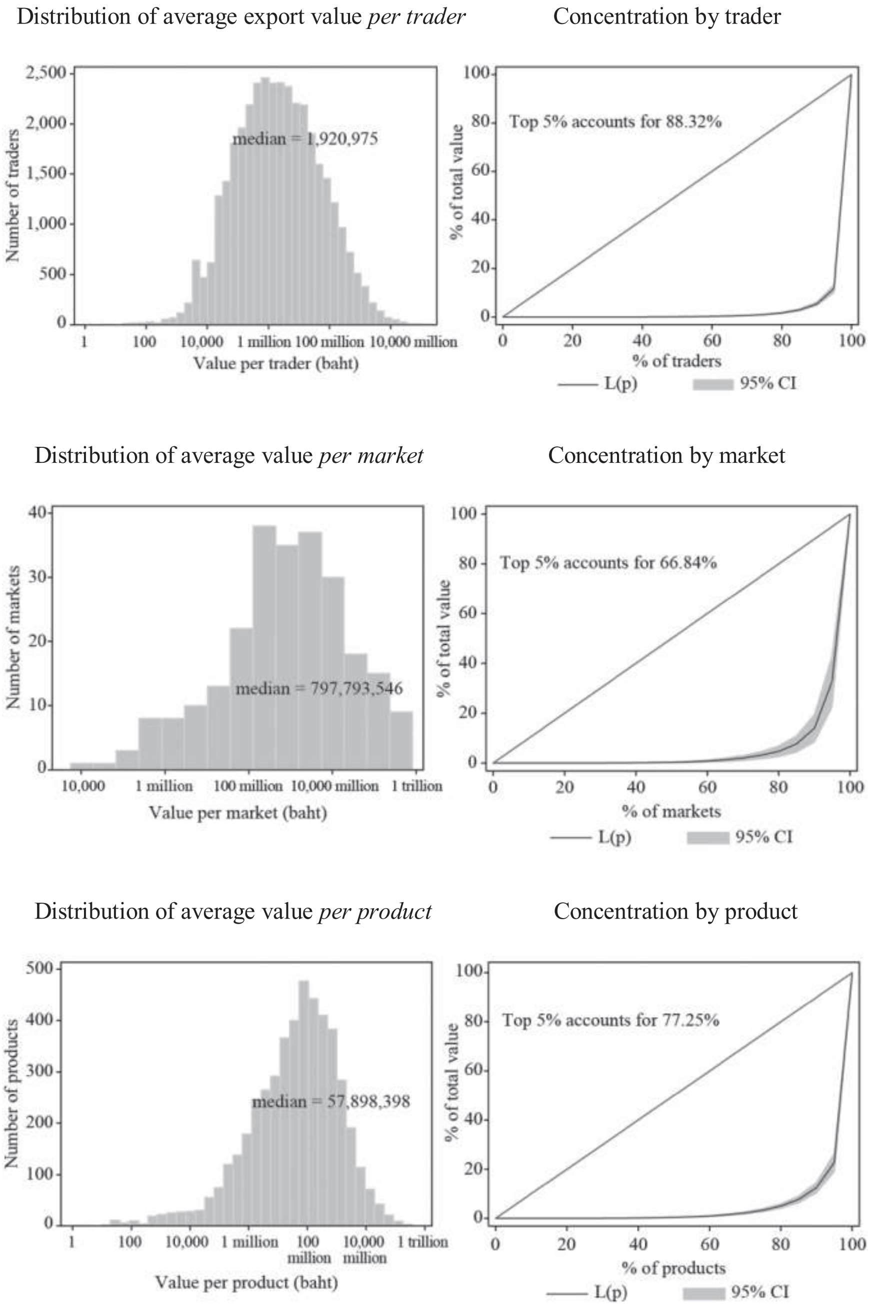
Sources: Thai Customs Department and authors' calculations.

distribution of PMs based on the number of traders per PM. A striking finding is that for most PM bundles, there is just one trader. This finding implies that Thai exporters evidently do not compete with one another by exporting the same product to the same country, resulting in a high degree of trader segmentation by PM bundle.

B. Intensive Margins

We next examine the value of exports at the PMT level. The left-hand column of Figure 8 shows the distribution of traders, markets, and products in terms of their average values. For example, the median value exported per trader in 2015 is rather small at around B1.9 million. More striking is the information presented in the right-hand column of Figure 8. Here we show the degree of export concentration from the PMT perspective. No matter how you look at it, Thai exports are highly concentrated. The top 5% of traders, markets, and products account for 88%, 67%,

Figure 8. **Intensive Margins, 2015**

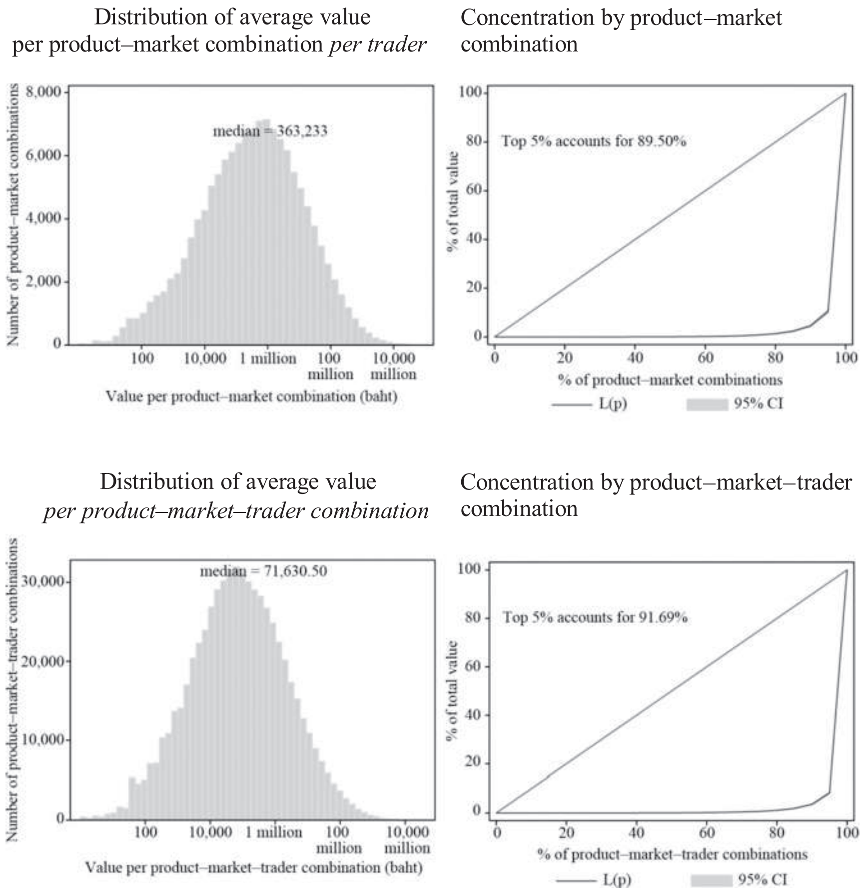


CI = confidence interval.

Note: The right column shows Lorenz curves for exports. If every trader, market, and product accounted for the same share of exports, the plot would lie on the diagonal equality line.

Sources: Thai Customs Department and authors' calculations.

Figure 9. **Intensive Margins by Product–Market and Product–Market–Trader Bundles, 2015**



CI = confidence interval.
Note: The right column shows Lorenz curves for exports. If every trader, market, and product accounted for the same share of exports, the plot would lie on the diagonal equality line.
Sources: Thai Customs Department and authors' calculations.

and 77%, respectively, of total export value. A handful of traders, markets, and products make up most of aggregate export value.

At a more granular level, we can also look at the distribution based on PM and PMT bundles. The top panel of Figure 9 shows that the typical value traded per PM bundle is quite small, around B300,000. More importantly, PM-level concentration is very high with the top 5% of PM bundles accounting for 90% of total exports. At the PMT level, the concentration is even higher with around 92% of total exports accounted for by the top 5% of PMT bundles. Thus, not only are exports concentrated across exporters, but within each firm, activity is also very

Table 4. **Distribution of Exporters and Export Value, 2015**

Share of Traders (%)

	Number of Countries						
Number of Products	**1**	**2**	**3**	**4**	**5–29**	**30+**	**All**
1	33.3	3.2	1.0	0.6	1.2	0.0	39.2
2	8.0	3.9	1.3	0.7	1.5	0.0	15.4
3	3.3	2.0	1.2	0.6	1.6	0.0	8.7
4	1.9	1.0	0.7	0.5	1.4	0.0	5.6
5–29	7.4	3.1	2.5	2.0	9.8	0.7	25.4
30+	1.4	0.4	0.2	0.2	2.7	0.8	5.7
All	55.3	13.6	6.8	4.6	18.1	1.6	100.0

Share of Value (%)

	Number of Countries						
Number of Products	**1**	**2**	**3**	**4**	**5–29**	**30+**	**All**
1	1.9	0.9	0.4	0.2	1.5	0.1	4.9
2	0.4	0.5	0.3	0.3	1.7	0.1	3.2
3	0.2	0.3	0.3	0.2	1.9	0.5	3.4
4	0.2	0.1	0.1	0.1	2.0	0.5	3.0
5–29	0.8	0.6	0.7	0.5	18.0	9.9	30.5
30+	0.6	0.2	0.1	0.2	15.2	38.7	55.0
All	4.0	2.5	1.9	1.5	40.2	49.9	100.0

Sources: Thai Customs Department and authors' calculations.

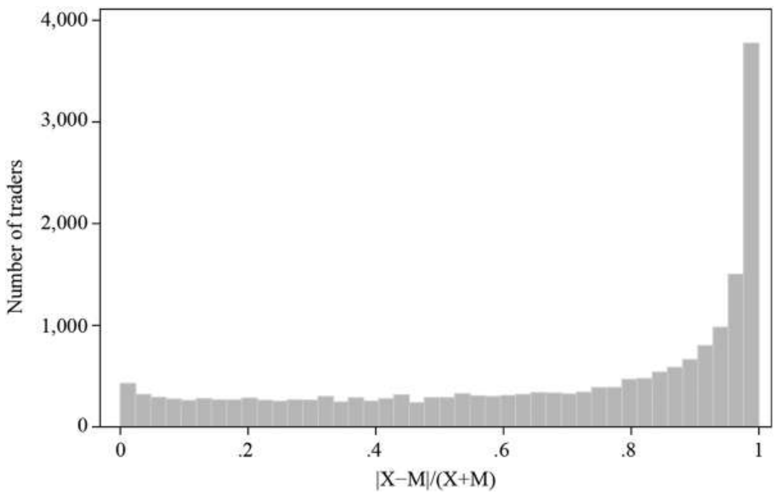
highly concentrated in a few PM bundles that account for much of each firm's exports.

C. The Product–Market–Trader Nexus

Combining the information on both the extensive and intensive margins, the top panel of Table 4 shows the distribution of traders based on the number of products exported and the number of destination markets, while the bottom panel presents a similar breakdown based on the share of export value. The table reveals a number of striking observations. The number of destination countries served by the average exporter is small: 55.3% of Thai traders exported to a single market in 2015, though these exports represented just 4% of total export value. By contrast, traders exporting to five or more destinations accounted for around 20% of exporters but 90.1% of export value. A similar picture emerges with respect to the number of products exported. In 2015, 39.2% of exporters exported a single product abroad, though these accounted for a mere 4.9% of aggregate export value. Exporters of 30 or more products accounted for just 5.7% of all exporters but as much as 55% of total export value.

Moreover, 33.3% of all exporters exported a single product to a single market but made up just 1.9% of export value. At the other extreme, the 0.8% of exporters

Figure 10. **Simultaneous Exporting and Importing—Natural Hedge Index**



M = imports, X = exports.
Sources: Thai Customs Department and authors' calculations.

exporting 30 or more products to 30 or more countries accounted for almost 40% of aggregate exports. These observations reflect the importance of multiproduct and multimarket exporters in overall Thai exports. The small share of firms that dominate Thai exports are large in size and are relatively diversified across products and markets. Our findings are consistent with what Manova and Zhang (2009) find in the PRC, where a large share of exports and imports are captured by a few multiproduct firms that transact with a large number of countries.

D. Hybrid: Exporter–Importer Firms

The literature finds that firms that simultaneously export and import typically exhibit the highest levels of performance (for example, Bernard et al. 2007a and 2007b). To get a sense of the extent to which traders engage in both exports and imports, Figure 10 shows the distribution of traders in our sample based on their "natural hedge" ratios. This is calculated, for each trader, as the ratio of the absolute value of exports minus imports divided by the total trade undertaken, or |exports – imports| / (exports + imports). A ratio of zero indicates that exports and imports are exactly equal, hence a perfect natural hedge. On the other hand, a ratio of 1 indicates that the trader engages exclusively in only one activity. Evidently, the bulk of Thai traders have no natural hedge, exporting or importing only. Of those that do both, many are skewed to the higher end of the index (low natural hedge).

Table 5 documents the overall role of hybrids. In 2015, 53.6% of exporters also imported while only 25.1% of importers also exported. Strikingly,

Table 5. **Exporter–Importer Firms**

	2001	2007	2011	2015
Number of hybrids				
Total	12,964	16,971	19,491	19,669
Share of exporters (%)	60.9	53.8	51.2	53.6
Share of importers (%)	36.1	32.7	26.3	25.1
Number of downstream production-chain exporters (DPE)				
Total	3,295	3,801	3,901	3,532
Share of exporters (%)	15.5	12.1	10.2	9.6
Share of importers (%)	9.2	7.3	5.3	4.5
Value traded by hybrids				
Share of total exports (%)	92.4	93.4	92.5	93.3
Share of total imports (%)	90.4	92.1	91.9	89.7
Value traded by downstream production-chain exporters (DPE)				
Share of total exports (%)	27.6	31.1	30.2	32.6
Share of total imports (%)	21.6	31.3	30.5	26.7

Sources: Thai Customs Department and authors' calculations.

hybrid traders account for 93.3% of total export value and 89.7% of aggregate imports. Thus, Thai international trade is overwhelmingly dominated by firms that simultaneously export and import. This is consistent with previous findings in the literature. Bernard, Jensen, and Schott (2009) document that over 50% of firms in the US that import also export, and these firms account for close to 90% of the country's trade.

Thai customs data allow hybrids to be further decomposed into traders that import intermediate products and export final goods, or what we call "downstream production-chain exporters" (DPE). These traders are of interest because they are likely to be part of global production networks, hence engaged in high value-added activity while at the same time more exposed to fluctuations in the global economy. We define DPEs as traders whose majority of exports are final goods and majority of imports are intermediate goods. Table 5 reveals that DPEs made up just 9.6% of all exporters in 2015 but accounted for 32.6% of total exports.

We next present the distribution of hybrid and DPE exporters along combined extensive and intensive margins as we did for overall exporters. Table 6A shows that most hybrids export five or more products to five or more destinations. This is in contrast to overall exporters, many of whom export just a single product to a single market as shown above. In terms of value, it is striking that the 3.2% of hybrids that export 30 or more products to 30 or more markets account for just under half of all exports by hybrid traders. Hybrid trade is dominated by a few large and well-diversified traders. The same message carries over to DPEs. As shown in Table 6B, the 5.2% of all DPEs that export 30 or more products to 30 or more markets account for 64.3% of total exports by DPEs.

Table 6A. **Distribution of Hybrid Exporters and Export Value, 2015**

Share of Traders (%)

	Number of Countries						
Number of Products	**1**	**2**	**3**	**4**	**5–29**	**30+**	**All**
1	1.3	1.0	0.3	0.2	0.3	0.0	3.2
2	1.4	2.8	0.9	0.5	0.9	0.0	6.5
3	1.0	1.9	1.4	0.7	1.2	0.0	6.2
4	0.7	1.3	1.1	0.7	1.3	0.0	5.0
5–29	3.5	6.3	6.4	5.9	25.3	0.6	48.1
30+	0.8	1.3	1.5	1.5	22.8	3.2	31.0
All	8.7	14.6	11.6	9.5	51.7	3.9	100.0

Share of Value (%)

	Number of Countries						
Number of Products	**1**	**2**	**3**	**4**	**5–29**	**30+**	**All**
1	0.0	0.0	0.1	0.0	0.4	0.0	0.6
2	0.0	0.1	0.2	0.0	0.2	0.0	0.6
3	0.1	0.1	0.1	0.1	0.4	0.0	0.7
4	0.0	0.0	0.0	0.1	0.4	0.1	0.7
5–29	0.2	0.3	0.5	0.5	9.0	2.9	13.3
30+	0.1	0.2	0.4	0.6	35.7	47.4	84.5
All	0.4	0.8	1.2	1.4	46.0	50.4	100.0

Sources: Thai Customs Department and authors' calculations.

Table 6B. **Distribution of Downstream Production-Chain Exporters and Export Value, 2015**

Share of Traders (%)

	Number of Countries						
Number of Products	**1**	**2**	**3**	**4**	**5–29**	**30+**	**All**
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.9	3.1	0.7	0.4	0.6	0.0	5.6
3	0.8	2.2	1.2	0.8	0.9	0.1	6.0
4	0.5	1.4	1.2	0.9	1.6	0.0	5.6
5–29	3.0	6.1	6.2	6.1	29.3	1.2	51.9
30+	0.6	0.9	0.9	1.0	22.2	5.2	30.8
All	5.7	13.7	10.2	9.3	54.6	6.5	100.0

Share of Value (%)

	Number of Countries						
Number of Products	**1**	**2**	**3**	**4**	**5–29**	**30+**	**All**
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.1
3	0.0	0.0	0.0	0.2	0.1	0.0	0.3
4	0.0	0.0	0.0	0.0	0.2	0.0	0.3
5–29	0.1	0.1	0.3	0.3	4.0	1.5	6.2
30+	0.0	0.1	0.1	0.1	28.6	64.3	93.1
All	0.1	0.3	0.4	0.6	32.9	65.7	100.0

Sources: Thai Customs Department and authors' calculations.

Table 7. **Distribution of Exporters and Their Balance Sheet Attributes, 2013**

Median Return on Assets (%)

	Number of Countries						
Number of Products	**1**	**2**	**3**	**4**	**5–29**	**30+**	**All**
1	4.6	4.1	4.3	4.2	4.3	3.2	4.5
2	4.2	4.8	4.4	4.9	3.8	2.2	4.4
3	4.8	5.3	5.0	4.3	4.1	4.7	4.7
4	5.8	5.7	5.5	5.7	5.0	5.7	5.5
5–29	5.6	5.0	6.0	6.4	5.4	5.4	5.5
30+	9.5	8.1	6.9	7.1	6.7	7.9	7.5
All	4.8	4.9	5.1	5.5	5.2	6.1	5.0

Median Turnover Ratio

	Number of Countries						
Number of Products	**1**	**2**	**3**	**4**	**5–29**	**30+**	**All**
1	1.4	1.4	1.4	1.6	1.4	1.9	1.4
2	1.3	1.4	1.4	1.6	1.4	0.9	1.4
3	1.5	1.4	1.4	1.2	1.4	1.3	1.4
4	1.3	1.4	1.5	1.5	1.4	1.7	1.4
5–29	1.6	1.4	1.4	1.4	1.3	1.3	1.4
30+	3.8	2.2	1.6	2.0	1.5	1.6	1.8
All	1.4	1.4	1.4	1.5	1.4	1.4	1.4

Sources: Thai Customs Department and authors' calculations.

E. Firm Attributes, Export Products, and Export Destinations

Finally, Table 7 presents median return on assets and median turnover ratio of registered firms tabulated jointly by the number of destinations and the number of products. It shows that exporters that serve a greater number of products and markets generally have higher return on assets and higher turnover ratios. Thus, not only are firms that dominate exports bigger and more diversified, they also tend to be more efficient as their scale grows.

F. Implications

In summary, the overall message of this section is that Thai international trade is extremely concentrated. A handful of the largest traders, the largest markets, and the most intensively exported products account for much of Thai exports. From a trader's perspective, most exports are undertaken by a small number of well-diversified traders exporting a large number of products to a large number of countries. These traders invariably also import. The finding on high concentration of Thai exports is consistent with studies in other countries. Using French export data by firm and destination market, for example, Eaton, Kortum, and Kramarz (2004) find that more than 60% of the variation in exports across markets of different sizes is explained by the extensive margin of the number of exporting firms. For developing countries, Arkolakis and Muendler (2010) use data from Brazil and find that few top-selling products account for the bulk of a firm's exports in a market.

There are many possible explanations for export concentration. The unequal distribution of trade could reflect large differences in productivity across firms. These differences could be exacerbated by a high degree of substitutability between goods varieties, so that even small productivity differences across firms, which translate into small differences in prices, lead to higher-priced varieties exiting the market. Alternatively, there could be economies of scale in distribution and marketing, or market-specific and product-specific sunk costs that favor high-productivity firms when it comes to expanding across markets and products. For example, Arkolakis and Muendler (2010) argue that productive firms choose to reach a large number of consumers in a market and incur large market penetration costs, while less productive firms choose to reach smaller markets.

Such high levels of concentration have important implications for risk and shock transmission. In particular, idiosyncratic shocks specific to particular traders, markets, or products can have big repercussions on aggregate trade value. Indeed, Di Giovanni, Levchenko, and Mejean (2014) show that for French exports, firm-specific shocks explain a substantial share of aggregate export fluctuations. This comes not just from the direct impact of large firms, but also through indirect linkages across firms. High concentration at the PM and PMT levels are particularly worrisome because idiosyncratic shocks at this level that seem isolated (e.g., a problem with exports of a particular machine component to one market by a single producer) can have widespread repercussions on total exports. A corollary is that aggregate tools, such as monetary policy, may not be well-suited to dealing with export fluctuations driven by idiosyncratic shocks to firms or unique PM and PMT bundles.

V. The Dynamics of Thai Exports

This section examines the dynamic evolution of Thai exports focusing on the extensive margin and longevity survival of export relationships, both at the trader and PMT levels. We begin by defining export relationships at two levels. At the trader level, a relationship is the occurrence of export activity by a particular trader in a given year. At the PMT level, a relationship is the occurrence of export activity in a particular PMT bundle, i.e., export of product x to market n by trader i in a given year. We define a relationship as "new" if it is less than 1 year old.

Table 8 provides an overview of the dynamics of Thai exports from various dimensions. Of note is the steady decline in the growth of traders, with the number of traders actually declining on average during 2011–2015. Similarly, growth in

Table 8. **Overview of Thai Export Dynamics**

Annual Average (%)	**2001–2007**	**2007–2011**	**2011–2015**	**2001–2015**
Growth in value	14.9	7.0	1.9	11.4
Growth in number of products	0.9	0.5	0.2	0.6
Growth in number of markets	0.0	0.4	1.6	0.6
Growth in number of traders	8.0	5.2	−0.9	5.2
Growth in number of PMT relationships	8.0	4.8	0.5	5.7
Fraction of new traders	33.3	42.2	37.2	37.0
Fraction of lost traders	26.6	37.0	38.1	32.8
Value-weighted fraction of new traders	1.9	1.5	1.8	1.7
Value-weighted fraction of lost traders	0.8	0.8	0.9	0.8
Fraction of new PMT relationships	61.5	58.3	52.4	58.0
Fraction of lost PMT relationships	54.7	53.6	51.9	53.6
Value-weighted fraction of new relationships	14.6	8.4	9.1	11.3
Value-weighted fraction of lost relationships	10.0	7.3	6.9	8.4

PMT = product–market–trader.
Sources: Thai Customs Department and authors' calculations.

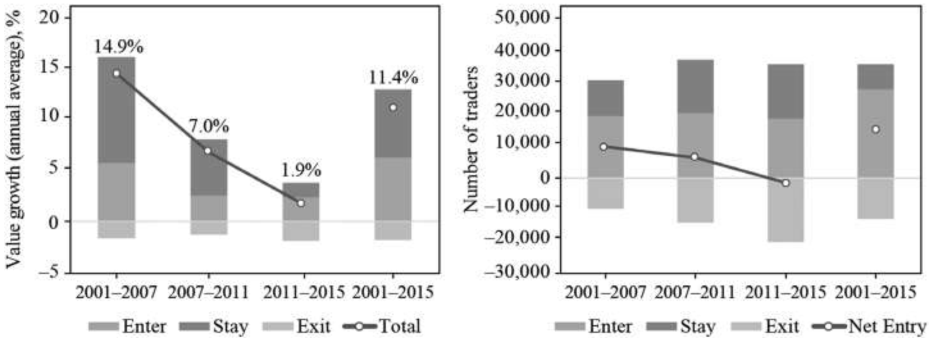
the number of PMT relationships has declined substantially. Both of these suggest that the degree of dynamism in Thai exports has fallen. The middle panel of the table provides a glimpse of the "churn"—traders entering and exiting the market—underlying Thai exporters. On average, around 40% of traders enter and exit a market each year, though their contribution to total exports is very small: from 2011 to 2015 new traders accounted for roughly 1.8% of exports each year, while those that exited made up just 0.9%. Looking at a more granular level, the bottom section of Table 8 shows that between 2011 and 2015, just over half of all PMT relationships were new and lost on average per year. These made up around 7%–9% of total exports.

A. Growth Decomposition

The decomposition of export growth can be carried out on a number of dimensions. Over a given period, the change in export value is driven by (i) *existing* products, markets, or traders—those that were present in the base year as well as the last year; (ii) *new* products, markets, or traders—those that entered during the period and remained until the end; and (iii) *lost* products, markets, or traders—those that were present in the base year but exited during the period. Of course, there may be products, markets, or traders that enter and exit during the period, but these are awash when comparing end-to-end growth rates. More precisely, we adopt the following definitions for $k =$ *product, market, or trader*:

Entry $\equiv$ new k that are present at the end date but not at the start date (e.g., entry for 2011–2015 equals new k that were present in 2015 but not at the end of 2010, representing new entrants);

Figure 11. **Export Growth Decomposition at Trader Level**



Sources: Thai Customs Department and authors' calculations.

Exit ≡ *k* that exit after the start date (e.g., exit for 2011–2015 equals all *k* that were present in 2010 but not at the end of 2015, representing lost incumbents); and

Stayers ≡ *k* that are present at the beginning and end of the period (e.g., stayers for 2011–2015 are those *k* that were present at the end of 2010 and 2015, representing survivors).

Given these definitions, we can proceed to decompose export growth. Note that the sum of entry and exit represents change on the net extensive margin, while stayers reflect the intensive margin. Focusing at the trader level, Figure 11 shows that over time, the relative contribution of incumbent traders to export growth has steadily declined with new traders becoming more important. Exiting traders have also weighed more heavily. During the 2011–2015 period, exports grew by 1.9% per year on average. This was underpinned by a growth of 2.4% from entrants, 1.5% from stayers, and –2% from exits. The right panel of Figure 11 shows the absolute number of traders entering, exiting, and staying. Of note is that during 2011–2015, the absolute number of traders fell as indicated by a negative net entry (the sum of entry and exit).

Table 9 takes a closer look at the characteristics of exporters who enter, exit, and stay in the market over time. Since we are looking across ranges of years, we list for stayers both the characteristics at the beginning and the end of the range. Compared to stayers, traders who enter and exit the export market tend to be much smaller—both in terms of export value and size of fixed assets—and tend to export few products to fewer markets and have lower return on assets. This is consistent with a Darwinian process of selection. It would be interesting to explore how these performance gaps increase when one conditions only on entrants that survive. It could be the case, for example, that conditional on survival, new entrants are even more productive than incumbents. We leave this for future work.

Table 9. **Characteristics of Traders**

Year	Exits	Stayers Beginning	Stayers End	Entrants	All Types Beginning	All Types End
Median value of exports (million baht)						
2003–2007	0.5	9.2	11.9	0.4	2.7	1.8
2007–2011	0.3	8.7	9.7	0.2	1.8	1.1
2011–2015	0.1	11.1	11.5	0.4	1.1	1.9
Median number of products						
2003–2007	2	4	4	2	3	3
2007–2011	1	4	4	2	3	2
2011–2015	2	4	4	1	2	2
Median number of markets						
2003–2007	1	3	3	1	2	1
2007–2011	1	3	3	1	1	1
2011–2015	1	3	3	1	1	1
Median size of fixed assets (million baht)						
2005–2007	1.8	6.1	6.9	1.3	4.8	4.1
2007–2011	1.2	7.6	8.7	1.2	4.1	4.0
2011–2013	1.1	6.5	7.6	1.4	4.0	4.5
Median return on assets (%)						
2005–2007	2.9	4.2	4.8	3.8	4.0	4.6
2007–2011	3.1	5.1	4.9	4.5	4.6	4.8
2011–2013	4.0	5.0	5.1	4.6	4.8	5.0

Sources: Thai Customs Department, Ministry of Commerce, and authors' calculations.

The number of entries and exits into exports, what we call churning, is important in its own right. The empirical trade literature has shown that within-industry reallocations of resources are an important source of average industry productivity growth as low-productivity firms exit and high-productivity firms expand to enter export markets (Melitz and Redding 2014). This process of resource reallocation is part and parcel of "creative destruction" that is at the core of Schumpeterian growth theory (Aghion, Akcigit, and Howitt 2014). That said, excessive churning may also be a source of concern if it reflects wasteful resources spent by unproductive entrants or exits of productive producers that are no longer able to operate due to financial frictions or other barriers. Thus, while we want to highlight the degree of churning, we present it as a stylized fact and, without further analysis, abstain from making judgments on whether the high degree of churning observed in certain periods, sectors, and regions is healthy or not.

Table 10 presents trader churning by broad sectors and regions. The churning rate for any given year is defined as the gross sum of new entrants and exits divided by the total number of traders at the end of the previous year. During the entire sample, the average churning rate per year is 69.8%. That is, in a typical year,

Table 10. **Trader Churning Rate** (%)

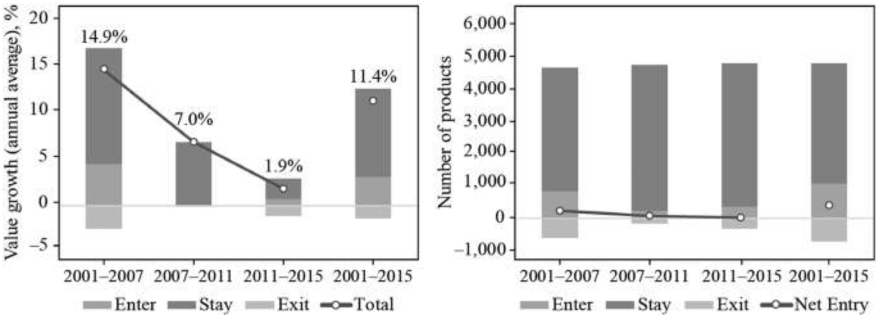
	2001–2007	2007–2011	2011–2015	2001–2015
Aggregate	59.9	79.2	75.3	69.8
By sector				
Agricultural products	72.2	69.3	72.3	71.4
Food	66.5	64.5	65.3	65.6
Mineral products	97.6	88.1	82.8	90.7
Chemicals and rubbers	71.1	68.7	66.6	69.2
Wood and leather products	81.2	105.9	90.4	90.8
Textiles and wearing apparels	78.3	134.7	117.9	105.7
Metals and other materials	71.2	86.1	75.4	76.7
Machinery	84.2	95.2	84.6	87.5
Transportation	105.9	101.2	97.1	102.1
Miscellaneous	89.7	113.0	103.4	100.3
By region				
ASEAN	69.9	67.1	68.2	68.6
Australia	64.0	67.0	60.1	63.7
People's Republic of China	84.4	77.3	70.1	78.3
East Asia	71.3	69.5	67.6	69.8
European Union	59.2	64.7	63.9	62.1
Hong Kong, China	67.7	63.1	59.5	64.1
India	80.9	76.2	65.8	75.3
Japan	51.8	86.6	75.5	68.5
United States	55.0	59.0	60.2	57.6
Rest of the world	57.8	74.7	66.3	65.1

ASEAN = Association of Southeast Asian Nations.
Sources: Thai Customs Department and authors' calculations.

entering and exiting traders amount to almost 70% of all traders. The sectors with the highest churn rate are textiles and wearing apparels and transportation, the former showing a significant increase since 2007. Looking across regions, traders exporting to the PRC have the largest churn rate over the entire sample, though the rate has declined over time. The opposite applies in the case of Japan.

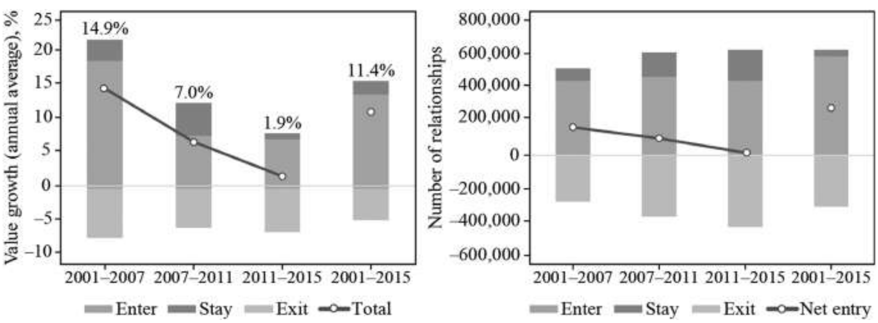
Turning to product dimension, Figure 12A shows export growth decomposition at the product level. Given that the number of products change slowly, it is not surprising to see that the bulk of export growth is driven by growth in exports of existing products. That said, during the trade boom between 2001 and 2007, the entry of new products did play a significant part in driving export growth. Finally, decomposing growth at the most granular PMT level reveals a starkly different picture, as shown in Figure 12B. The formation and disappearance of PMT relationships—the extensive margin—plays a big part in export growth. During 2011–2015, for example, new PMT bundles contributed on average 7.3% of export growth per year, while exiting relationships reduced exports by around 6.5% every year. Existing PMT relationships, by contrast, grew by 1.1% per year on average. Thus, the 1.9% average yearly growth belies the large amount of expansion and contraction at the extensive margin.

Figure 12A. **Export Growth Decomposition at Product Level, 2011–2015**



Sources: Thai Customs Department and authors' calculations.

Figure 12B. **Export Growth Decomposition at Product–Market–Trader Level, 2011–2015**



Sources: Thai Customs Department and authors' calculations.

Table 11. **Export Growth Decomposition at Firm Level**

	Enter				
	New PMs (percentage points)	**Old PMs** (percentage points)	**Stay** (percentage points)	**Exit** (percentage points)	**Total** (%)
2001–2007	1.3	4.5	10.7	−1.7	14.9
2007–2011	0.3	2.3	5.6	−1.3	7.0
2011–2015	0.2	2.2	1.5	−2.0	1.9
2001–2015	2.0	4.5	6.8	−1.9	11.4

PM = product–market.
Sources: Thai Customs Department and authors' calculations.

Digging deeper into this granular PMT-level decomposition reveals further insights about the PM bundles that new traders engage in. We are interested in exploring whether new entrants extend the universe of Thailand's PM export bundles—exporting an existing product to a new market, exporting a new product to an existing market, or both—or simply compete in an existing PM space. Focusing on the trader level, Table 11 takes the export growth decomposition shown on the left panel of Figure 11 and splits the contribution of new entrants into those that export existing PM bundles and those that export new ones. We find that the majority of the contribution to export growth from new traders has been from existing PMs, particularly in the recent period. During 2011–2015, for example, new entrants with new PMs contributed only 0.2 percentage points to total export growth, much lower than the contribution of 2.2 percentage points from new entrants with existing PMs. This suggests that new entrants tend to choose to compete with incumbents rather than going to untapped markets. Possible explanations include positive externalities from the incumbents that help save entry costs for new entrants or a lack of demand in the markets not currently served by existing traders. Alternatively, the low growth rate of new entrants with new PMs raises a concern over the inability of Thai firms to initiate new products into new markets.[10]

B. Survival Analysis

In light of the high degree of churning observed, with many traders entering and exiting the export market each year, we take a closer look at the frailty of exporting by estimating survival probabilities of export relationships. Besedes and Prusa (2007) show that the frailty of export relationships, defined as unique PM bundles, is an important factor underlying the differences in long-run export growth across countries. Exploiting the more granular nature of our data, we examine the frailty of export relationships both at the trader level as well as the PMT level.

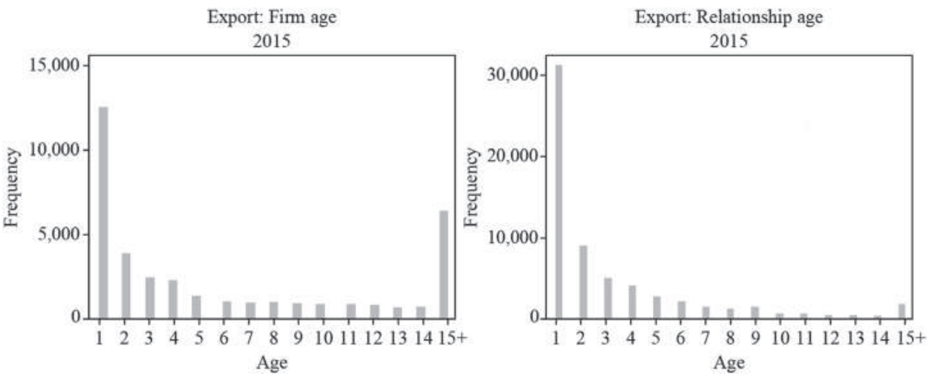
To analyze survival, we construct "relationship spells" from our data focusing only on new entrants in our sample (i.e., we drop incumbent traders or PMT bundles in 2001). If a given export relationship appears in two or more distinct nonoverlapping spells, for example, trader *i* exports during 2003–2005 and then again in 2008–2009, we treat these as two independent spells. With this criterion, we have 592,648 export spells at the trader level, and 12,819,202 spells at the PMT level.

We are particularly interested in the difference between new and long-term relationships. Figure 13 shows the distribution of export relationships by age at the end of 2015. The left panel shows the distribution at the trader level. Clearly, most exporters are new and the number of traders who enter during our sample and survive generally falls with the number of years. The spike in the category of traders 15 years and older reflect traders who have been present since the start of our sample in 2001. At the PMT level, the general message is the same except that the number of PMT bundles that have been present since 2001 is very small.

[10]This finding is different from the overall global pattern presented by Kehoe and Ruhl (2013), who analyze a panel of 1,900 country pairs and find that this product extensive margin accounts for 10% of the growth in trade for North American Free Trade Agreement country pairs, and 26% of the trade growth between the US and Chile, the People's Republic of China, and the Republic of Korea.

Figure 13. **Distribution of Export Relationships by Age, 2015**

Distribution of durations at firm level | Distribution of durations at PMT level



PMT = product–market–trader.
Sources: Thai Customs Department and authors' calculations.

Table 12. **Long-Term Relationships, 2015**

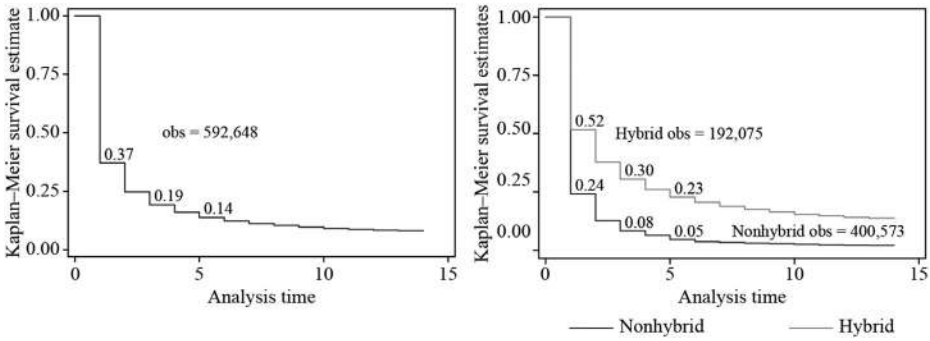
Fraction of value traded by long-term relationships (%)	
Trader level	64
PMT level	19
Average growth of value traded by long-term relationships (%, 2001−2015)	
Trader level	6
PMT level	5
Fraction of long-term relationships (%)	
Trader level	17
PMT level	3

PMT = product–market–trader.
Sources: Thai Customs Department and authors' calculations.

In Table 12 we report that as of 2015, the fraction of relationships that are long term (i.e., present in all years of the sample since 2001) amount to 17% at the firm level and only 3% at the PMT level. Yet these relationships account for a sizable amount of total exports. Long-term firms made up 64% of total exports in 2015 while long-term PMT amounted to 19%. The average annual deepening of long-term relationships is also shown in the table.

These results contrast with the situation for new relationships presented in Table 8. Between 2001 and 2015, new relationships at the PMT level made up on average 58% of all relationships in a given year and these accounted for around 11% of total export value. At the trader level, new relations made up around 37% of all relationships and accounted for just 1.7% of total exports. The fact that new relationships account, in value terms, for a considerably smaller portion than those of established relationships reinforces the view that new relationships only have a meaningful impact on aggregate export growth if they survive and

Figure 14. **Survival Probability at Trader Level**



Note: A trader that exports and imports at least once, even if not in the same year, is classified as a hybrid for its entire life. The probability is estimated from the Kaplan–Meier survival function.
Sources: Thai Customs Department and authors' calculations.

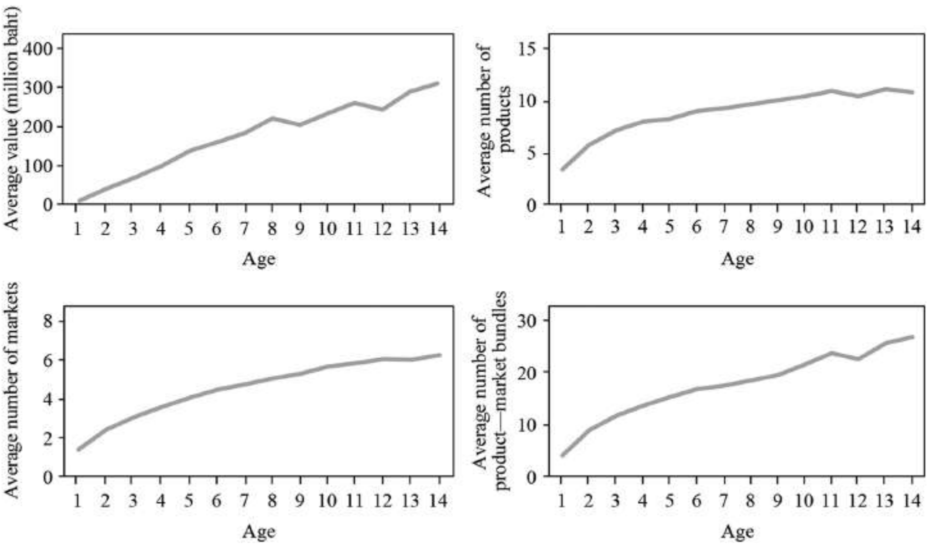
deepen—they are too small in their early years to have any appreciable effect on export growth.

Following Besedes and Prusa (2007), we proceed to estimate the Kaplan–Meier survival function, both at the trader and PMT levels based on new relationships during 2001–2015. This function describes the survival probabilities of relationships as the number of years in service increases. There are a couple of striking results. First and foremost, export duration is remarkably brief. As shown in the left-hand panel of Figure 14, 63% of trader-level relationships fail after the first year, and by the end of the fifth year around 86% of exporters have left the market. Breaking up new entrants into pure exporters and hybrids reveals a sizable difference between the two, as shown in the right panel of Figure 14. Pure exporters are twice as likely to fail after the first year compared to hybrids, with the gap widening into later years.

The second notable observation is that new relationships are much more likely to fail than existing ones. This can be seen in Figure 14 by the steep slope of the survival function over the first 3 or so years, before markedly flattening out after that. That is, in the first 3 years, the risk of failure is very high (i.e., the probability of survival drops substantially year by year). Thereafter, the change in survival probability is very small as we progress through the years, reflecting a fairly small risk of failure.

Given the frailty of new exporters, a natural question is whether those that survive have special attributes. Figure 15 provides some evidence by showing that survivors are indeed different. The longer traders remain in the export business, the more they export in value terms, the greater the number of products they export, and the greater the number of markets they export to. The overall combination of PM

Figure 15. **Characteristics of Surviving Exporters**



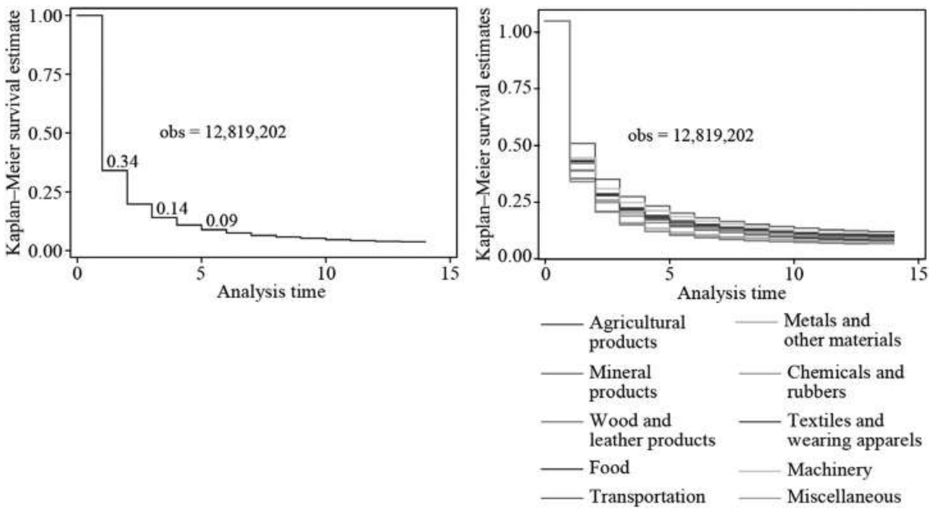
Sources: Thai Customs Department and authors' calculations.

bundles exported also increases with age. This finding is consistent with Schmeiser (2012), who finds evidence that the geographic expansion of firm exports occurs over time. Using firm-level data on the Russian Federation, she finds that learning plays a significant role in explaining the observed entry patterns.

Moving on to the PMT level, Figure 16 shows that survival probabilities are even more precarious compared to traders. The probability that a particular PMT bundle survives beyond the first year is just 34% (left panel). This trails off significantly as the number of years increases, and by the fifth year the survival probability is a mere 9%. There are significant sectoral differences in this regard, with survival probability highest for minerals and lowest for wood and leather products (right panel).

Overall, our findings contribute to the study of entrepreneurs in international trade and the role of the extensive margin. Evidence from Thai firms is similar to what Lederman, Rodríguez-Clare, and Xu (2011) find in Costa Rica, where the rate of firm turnover into and out of exporting is high, but exit rates decline rapidly with age. The exiting and entering firms tend to be significantly smaller than incumbents. They argue that the surviving new exporters actively took on new products (for the firm, but not necessarily new for the country) and gave up weaker existing products they had started with, and their export growth rates were very high during a period when those of incumbent exporting firms were actually negative.

Figure 16. **Survival Probability at Product–Market–Trader Level**



Note: A trader that exports and imports at least once, even if not in the same year, is classified as a hybrid for its entire life. The probability is estimated from the Kaplan–Meier survival function.
Sources: Thai Customs Department and authors' calculations.

C. Implications

In summary, this section shows that there is a great deal of churning among Thai exporters. In any given year, roughly one-third of exporters are new and an equal share exits the market. Looking at unique PMT bundles, the proportions of new entrants and exits jump to over half. While this dynamism is consistent with efficiency-improving resource reallocation, it could also be indicative of wasteful entrants and exits as many new exporters cannot overcome barriers to successful exporting. We find that exporters who enter and leave the market tend to be smaller, less diversified, and less profitable than incumbents.

Evidently, export growth is also increasingly being driven by the extensive margin. Over the past decade, changes on the extensive margin have become increasingly important in driving aggregate export growth. Existing exporters and PMT bundles account for a decreasing share of exports. Exporting is a dynamic undertaking and promoting export growth requires greater attention to new firms as well as a new configuration of products and markets.

Finally, this section also shows that export relationships are very fragile. The likelihood that an exporter or a given PMT bundle remains in the market for more than 1 year is very low. But those that survive generally blossom and account for a disproportionate share of aggregate exports. The challenge of exporting, therefore, is not simply one of overcoming fixed costs of entry, but also one of remaining in the market in subsequent years. The fact that most relationships end quickly suggests that many exporters will not be able to recover the sunk cost required to enter an export market. This may partly explain why exporters are relatively rare. It also suggests that the assumption of a constant probability of exiting in the standard Melitz (2003) model may be inappropriate.

VI. Conclusion

This paper has documented the tremendous skewness in Thai international trade: despite decades-long implementation of an export-led development strategy, only a small minority of firms import and export, and they are big. The implication is clear. When it comes to thinking about Thai trade, one must think about big traders. Many of these are likely to be multinationals. Trading firms also stand out from domestic firms both in terms of scale and efficiency. These findings reinforce the importance of resource allocation among traded and nontraded sectors in Thailand's overall productivity. The high degree of churning and the overall frailty of export relationships also suggest that exporting is difficult and successful firms are those that have overcome productivity hurdles before entering the market. The findings from this paper highlight some concerns about an export-oriented development strategy, particularly regarding concentration and fragility of an export-dependent economy from a micro perspective, in addition to the traditional macro external-dependency argument.

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Foreign Direct Investment and Productivity: A Cross-Country, Multisector Analysis

Rodolphe Desbordes and Loe Franssen*

This paper adopts a cross-country, multisector approach to investigate the intra- and inter-industry effects of foreign direct investment (FDI) on the productivity of 15 emerging market economies in 2000 and 2008. Our main finding is that intra-industry FDI has a large positive effect on total and "exported" labor productivity. The effects of FDI on total factor productivity are much more elusive, both in statistical and economic terms. This result suggests that foreign firms raise the performance of their host economies through a direct compositional effect. Foreign firms tend to be larger and more input intensive and have greater access to foreign markets than domestic firms. Their greater prevalence mechanically increases average labor productivity and export performance.

Keywords: foreign direct investment, productivity, sector level, services
JEL codes: F23, O16

I. Introduction

Many emerging market economies actively seek to attract foreign direct investment (FDI) because they believe that multinational enterprises will contribute to economic growth by creating new job opportunities, enhancing capital accumulation, and increasing total factor productivity (TFP).[1] In practice, these growth-enhancing effects have been difficult to detect. Recent cross-country studies, using a wide range of econometric techniques, do not generally find evidence that FDI affects gross domestic product (GDP) per capita (Carkovic and Levine 2005; Herzer, Klasen, and Nowak-Lehmann 2008; Iamsiraroj and Ulubasoglu 2015). Likewise, single-country, firm-level evidence on the inter- and intra-industry effects of foreign firms on the TFP of domestic firms is

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[1]Excellent surveys of the expected effects of FDI on host economies can be found in Navaretti and Venables (2005), Caves (2007), and Dunning and Lundan (2008).

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ambiguous (Havránek and Iršová 2011).[2] Both these strands of the literature have shortcomings. On the one hand, considering a country as the unit of analysis is likely to lead to a significant aggregation bias. On the other hand, firm-level studies are often country specific and tend to focus on the manufacturing sector.[3] In their quest for the indirect effects on the TFP of domestic firms, the latter studies also neglect the direct contribution that foreign firms can make to sector-specific labor productivity.[4] There is therefore a need for a cross-country, multisector investigation of the effects of FDI on various measures of host countries' productivity.

This paper attempts to address this need. We use a sector-level database, covering the years 2000 and 2008, of the FDI presence in 24 manufacturing and service sectors of 15 emerging market economies. Our FDI proxy is the share of the labor force employed by foreign firms. This is a direct and tangible indicator of the prevalence of foreign firms. Our database includes detailed and high-quality information for all sectors on output, inputs, inter-industry linkages, and export indicators. Such a richness allows us to investigate the potentially heterogeneous effects of intra- and inter-industry FDI on the TFP and labor productivity of the manufacturing and service sectors. Lastly, our data are time varying. We can control for a large number of unobserved effects at the country-sector level. Hence, while we do not carry out the type of granular analysis found in firm-specific studies, our empirical analysis offers more external validity than country-specific studies, more internal validity than cross-country studies, greater coverage of sector-specific FDI presence than many studies, an encompassing assessment of the potential effects of FDI on productivity, and relatively high robustness against an omitted variable bias.

We find that a larger foreign presence tends to have a positive and statistically significant impact on TFP through manufacturing backward FDI linkages and within-industry presence. The latter result only holds for service sectors and the economic effects are modest. In the short run, doubling manufacturing backward FDI linkages (intra-industry FDI in services) would increase TFP by about 2% (5%). When we examine the determinants of labor productivity, a different picture emerges. We no longer find consistent inter-industry FDI effects. On the other hand, the effect of intra-industry FDI is large, positive, and statistically significant,

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[2] In line with the rest of the literature, we use "industry" as a synonym for "sector." Occasionally, we refer to "broad industries," which are the secondary and tertiary sectors.

[3] Fernandes and Paunov (2012) is one of the few exceptions. See their literature review for a list of studies on FDI in services and manufacturing TFP.

[4] Lipsey (2004) and Navaretti and Venables (2005) report that foreign firms are usually found to be much more productive than domestic firms, largely because they make much more intensive use (per worker) of physical capital, human capital, and intermediates. They are also likely to be more export oriented. Criscuolo (2006) shows that foreign affiliates, thanks to their higher labor productivity and growing share in total employment, accounted for 40% or more of labor productivity growth in the manufacturing and service sectors of Organisation for Economic Co-operation and Development (OECD) countries in the late 1990s.

and holds across broad industries. Doubling intra-industry FDI in either the manufacturing or service sectors would increase value added per worker by about 20% in the short run. Part of this increase in labor productivity appears to be the outcome of improved FDI-induced export performance. Overall, our results suggest that the presence of foreign firms improves host countries' average performance simply because these firms are larger, unconditionally more productive, and more integrated in the world economy than domestic firms.

The rest of this paper proceeds as follows. In section II, we describe the effects that FDI can be expected to have on host economies' development. In section III, we present our empirical methodology. In section IV, we describe our key variables and the data used. In section V, we provide our results. In section VI, we investigate whether our results apply to the Asian countries of our sample. Finally, in section VII, we conclude and discuss the findings and limitations of our study.

II. Conceptual Framework

Assume that the labor productivity q of a domestic firm in a given country can be summarized as $q^N = \beta z(x)$, where β is an efficiency parameter and x is a set of characteristics that determines its productivity.[5] For a foreign firm, we have $q^F = \alpha z(x)$. Firms are heterogeneous as they do not share the same set of characteristics. The distribution of domestic firms' employment across domestic firms with different characteristics x is $n(x)$. The average productivity of domestic firms is therefore $\overline{q^N} = \int \beta z(x)n(x)dx$, $1 = \int n(x)dx$. The distribution of foreign firms' employment across foreign firms with different characteristics x is $m(x)$. The average productivity of foreign firms is therefore $\overline{q^F} = \int \alpha z(x)m(x)dx$, $1 = \int n(x)dx$. The overall average productivity is then $\bar{q} = (1 - \mu)\overline{q^N} + \mu\overline{q^F}$, where μ is the share of the total labor force employed by foreign firms.

Foreign firms may have characteristics that differ, on average, from those of domestic firms and that allow the former to be generally more productive, i.e., $x^F > x^n$. It is also possible that foreign firms are technically more efficient than domestic firms, i.e., $\alpha > \beta$. Finally, greater intra-industry or inter-industry FDI may also influence β through externalities, i.e., $\beta = \beta(\mu)$.

This conceptual framework suggests two lines of enquiries within the constraints of the data we have at hand. First, we can investigate whether the TFP of an economy is higher when the share of the labor force employed by foreign firms increases. Second, we can look for more general effects by exploring whether a greater foreign presence is associated with higher labor productivity.

[5]This section heavily draws on Navaretti and Venables (2005).

III. Empirical Methodology

A. Total Factor Productivity Estimation

To investigate the impacts of intra- and inter-industry FDI presence on TFP, we adopt the following econometric model:

$$\begin{aligned}\ln(GO_{sit}) = {} & \beta_1^B \ln(K_{sit}) + \beta_2^B \ln(L_{sit}) + \beta_3^B \ln(I_{sit}) + \beta_4 \ln(HFDI_{sit}) \\ & + \beta_5 \ln(BWFDIM_{sit}) + \beta_6 \ln(FWFDIM_{sit}) + \beta_7 \ln(BWFDIS_{sit}) \\ & + \beta_8 \ln(FWFDIS_{sit}) + \rho \ln(TFP_{sit-5}) + \alpha_{si} + \alpha_{st} + \varepsilon_{sit} \end{aligned} \quad (1)$$

where GO_{sit} is gross output of sector s in country i at period t, K_{sit} is capital services, L_{sit} is labor services, I_{sit} is intermediate inputs, $HFDI_{sit}$ is intra-industry FDI, $BWFDIM_{sit}$ is backward linkages from FDI in downstream manufacturing sectors, $FWFDIM_{sit}$ is forward linkages from FDI in upstream manufacturing sectors, $BWFDIS_{sit}$ is backward linkages from FDI in downstream service sectors, $FWFDIS_{sit}$ is forward linkages from FDI in upstream service sectors, TFP_{sit-5} is 5-year lagged TFP, α_{si} is a country-sector-specific effect, α_{st} is a sector-time-specific effect, and ε_{sit} is the error term. We allow $\beta_1 - \beta_3$ to differ across broad industries B (manufacturing and services).

Equation (1) is estimated in two distinct ways. We initially use a random effects (RE) estimator, replacing α_{si} by α_s and α_i. This allows us to exploit both the cross-sectional and time dimensions of our data to identify parameters of interest. More information can crucially matter in the context of explanatory variables measured with error. However, the consistency of the RE estimator is partly based on the assumption that the explanatory variables are not correlated with an unobserved time-invariant, country-specific factor that is part of the composite error term. This assumption could be too strong; for example, foreign investors may choose to locate in more structurally productive sectors. Hence, we also use a fixed effects (FE) estimator. By identifying our parameters solely on the basis of the time series variation in our data, we control for the influence of an unobserved time-invariant, country-sector-specific effect. On the other hand, we no longer exploit the information provided by the cross-sectional variation.

The input factors may also be correlated with unobserved time-invariant, country-sector-specific factors. They may also be simultaneously determined with output; in that case, an FE estimator would not help us to deal with this issue (Van Beveren 2012). For this reason, we also generate indirect estimates of TFP based on the use of an instrumental variables estimation. Exploiting all the years available in our database, omitting the FDI variables, and applying a system generalized methods-of-moments estimator (Blundell and Bond 1998), we estimate equation (1) separately for the secondary and tertiary sectors. Our indirect estimates of $\ln(TFP)$ are then $\ln(\widehat{TFP}_{sit}) = \ln(GO_{sit}) - \widehat{\beta_1^B}\ln(K_{sit}) - \widehat{\beta_2^B}\ln(L_{sit}) - \widehat{\beta_3^B}\ln(I_{sit})$. One drawback of this method is that estimates can be sensible to the choice of the internal instruments.[6]

We also include in our econometric models a 5-year lagged TFP term.[7] We do so for two reasons. First, we know from the literature on economic growth that the evolution of TFP toward its equilibrium value may follow a partial adjustment or convergence process (Solow 1956, Swan 1956). As such, emerging economies are expected to grow faster than developed economies. One reason for this is that the former are able to imitate new technology rather than having to innovate themselves, which would be costlier (Gerschenkron 1962, Barro and Sala-i-Martin 1997). Second, this lagged TFP term can capture unobserved country-sector factors.[8]

Overall, each estimation method has its pros and cons. To eliminate any concern about cherry-picking our favorite estimates, we report all results. Standard errors are clustered at the country-sector level.

B. Labor Productivity Estimation

The estimation of equation (1) reduces the impact of FDI to an effect on TFP. However, as stressed in section II, foreign firms may also have broad positive direct compositional effects on their host economies, leading to a rise in labor productivity (higher real value added per worker). We estimate therefore, in a second stage, the following model:

$$\begin{aligned}\ln(VA_{sit}) = {} & \gamma_1 \ln(VA_{sit-5}) + \gamma_2 \ln(HFDI_{sit}) + \gamma_3 \ln(BWFDIM_{sit}) \\ & + \gamma_4 \ln(FWFDIM_{sit}) + \gamma_5 \ln(BWFDIS_{sit}) + \gamma_6 \ln(FWFDIS_{sit}) \\ & + \alpha_{si} + \alpha_{st} + \varepsilon_{sit} \qquad (2)\end{aligned}$$

where VA_{sit} is value added per worker in sector s in country i at period t. We estimate equation (2) using either an RE estimator or an FE estimator.

Finally, we explore whether the influence of FDI on labor productivity partly occurs through the impact of FDI on export performance. Our outcome variables in this third and final stage are real gross exports per worker (X), real direct domestic value added embodied in gross exports per worker (VAX), and the ratio

[6]We use the second to fourth lags of the potentially endogenous variables and we collapse the set of instruments. For details, see Roodman (2009).

[7]Following Griffith (1999), when we estimate equation (1), the 5-year lagged term is proxied by the 5-year lagged input and output terms.

[8]It is well known that the dynamic RE and FE estimators are biased. However, whereas the bias of the estimator of the autoregressive parameter is large (and negative), the Monte Carlo simulations of Judson and Owen (1999) show that this is not the case for the bias of the estimators of the coefficients on the explanatory variables (1%–3% of the true value). Hence, we focus on short-run effects. Unlike long-run effects, their calculations do not involve the use of the estimated value of ρ.

of the two preceding variables (*VAX/X*). We adopt an econometric model similar to equation (2).

IV. Key Variables and Data

Our sector-level data on gross output, capital services, labor services (proxied by labor compensation per Fox and Smeets [2011]), employment, intermediate inputs, and input–output tables come from the World Input–Output Database.[9] Data on value added, gross exports, and domestic value added embodied in gross exports come from the Trade in Value Added Database created by the Organisation for Economic Co-operation and Development (OECD).[10] All values are deflated using country-sector-specific gross output and value added deflators.

We define intra-industry FDI ($HFDI_{sit}$) as the share of workers employed by foreign firms. Our data on the number of foreign workers come from the Investment Map database provided by the International Trade Centre.[11] Based on data originally collected by Dun & Bradstreet, this website provides sector-specific data on the latest number of foreign affiliates, the number of foreign affiliates established since 2000, and the total number of workers for a sample of the existing foreign affiliates.

We make the following assumptions to calculate $HFDI_{sit}$: (i) we assume that the latest year is 2008, (ii) we calculate the number of foreign affiliates in 2000 as the latest number minus the number of foreign affiliates established since 2000, (iii) we calculate the average number of workers in the foreign affiliates for which we have the data and consider that this average is reasonably close to the population average, and (iv) we multiply the average number of workers by the number of foreign affiliates in 2000 and 2008. As such, we find that industries employ foreign employees at an average rate of 19%, with industries such as electrical and optical equipment; coke, refined petroleum, and nuclear fuel; and financial intermediation employing significantly more than that (see Tables A2 and A3 in the Appendix).

Our assumptions are unlikely to fully hold in practice. Nevertheless, given that we have a large range of sectors and countries, as well as a large gap between our 2 years, we expect $HFDI_{sit}$ to have a reasonably high signal-to-noise ratio between and within country–partner pairs. Furthermore, the correlation coefficient between our intra-industry FDI variable and the share of financial FDI stocks in value added (for which we have very unbalanced data) is 0.5, which is significant at the 1% level.[12] Lastly, to reduce the influence of extremely high observations,

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[9] See http://www.wiod.org/home.

[10] See https://stats.oecd.org/index.aspx?queryid=66237.

[11] See http://www.investmentmap.org/.

[12] In addition, the correlation coefficient between our intra-industry FDI variable and the share of workers employed by foreign firms reported in the OECD Activity of Multinational Enterprises database for five countries from our sample in 2008 is 0.7, which is significant at the 1% level.

we cap $HFDI_{sit}$ to 1 and transform it as $HFDI_{sit} * 100 + 1$. We adopt the same transformation for the other FDI variables that we now describe.

To take into account the productivity effects of FDI in downstream sectors, we construct the following backward FDI linkage variables:

$$BWFDIM_{sit} = \sum_{k=1}^{M} \gamma_{skit} * HFDI_{kit} \tag{3}$$

$$BWFDIS_{sit} = \sum_{k=1}^{S} \gamma_{skit} * HFDI_{kit} \tag{4}$$

where γ_{skit} is the share of sector *s*' gross output that is supplied to downstream manufacturing (*M*) or service *(S*) sector *k* in country *i* at time *t*. As can be seen in Table A3 in the Appendix, firms supply on average 31% of their output to domestic downstream industries, with 11% going to downstream manufacturing industries and 18% to service industries.

Likewise, to take into account the productivity effects of FDI in upstream sectors, we construct the following forward FDI linkage variables:

$$FWFDIM_{sit} = \sum_{k=1}^{M} \delta_{skit} * HFDI_{kit} \tag{5}$$

$$FWFDIS_{sit} = \sum_{k=1}^{S} \delta_{skit} * HFDI_{kit} \tag{6}$$

where δ_{skit} is the share of sector *s*' total inputs supplied by upstream manufacturing (*M*) or service *(S*) sector *k* in country *i* at time *t*.[13] As can be seen in Table A3, firms source on average 61% of their inputs from domestic upstream industries other than their own. Furthermore, 18% of the inputs come from manufacturing industries and 36% from service industries.

Overall, matching the data that we have and focusing on emerging economies, we end up with a sample of 15 countries, 13 manufacturing sectors, 11 service sectors, and the years 2000 and 2008.[14] From a development perspective, this is an interesting sample since none of the countries were classified as high income in 2000. It includes large countries such as Brazil, India, the People's Republic of China (PRC), and the Russian Federation, as well as a group of Central and Eastern European economies that were going through a period of transitioning from a state-led to a market economy.[15] During 2000–2008, these

[13] Javorcik (2004) has pioneered the use of these linkage measures in the FDI literature.
[14] For data availability reasons, the latest year in section V is 2010.
[15] See https://en.wikipedia.org/wiki/World_Bank_high-income_economy.

Table 1. **Total Factor Productivity and Intra-Industry Foreign Direct Investment**

	ln(GO) RE [1]	ln(GO) FE [2]	ln(TFPe) RE [3]	ln(TFPe) FE [4]
ln(HFDI)	0.014**	0.029***	0.014**	0.023**
	(0.006)	(0.010)	(0.006)	(0.009)
Number of observations	702	702	702	702

FE = fixed effects estimator, GO = gross output, HFDI = intra-industry foreign direct investment, RE = random effects estimator, TFPe = total factor productivity estimates.

Notes: ***p-value < 0.01, **p-value < 0.05, and *p-value < 0.10. Cluster-robust standard errors are in parentheses. All regressions include 5-year lagged total factor productivity terms and sector-specific time effects. The GO columns include the log values of capital services, labor services, and intermediates, as well as their interactions with a dummy variable indicating whether the sector belongs to the broad services industry. The RE columns include country and sector fixed effects. The FE columns include country-sector fixed effects.

Sources: International Trade Centre. Investment Map. http://www.investmentmap.org/; Organisation for Economic Co-operation and Development. 2015. Trade in Value Added Database. https://stats.oecd.org/index.aspx?queryid=66237; and World Bank. 2000–2014. World Input–Output Tables. http://www.wiod.org/home.

countries experienced annual GDP growth rates of 5.6%, with the average for Asian countries reaching 7.4%. At the same time, these countries received significant sums of FDI inflows that comprised 5.2% of GDP annually.[16] As such, we believe this sample serves as an interesting case to examine the effects of FDI on productivity. The Appendix shows additional summary statistics.

V. Results

A. Total Factor Productivity

We report four sets of estimates, reflecting the use of two different methodologies to estimate TFP (direct and indirect) and two different panel data estimators (RE estimator and FE estimator). We consider a finding to be relevant if the magnitude, sign, and statistical significance of the coefficient on a given variable are highly consistent across estimation methods.

1. Intra-Industry Foreign Direct Investment

In Table 1, we only look at the impact of intra-industry FDI presence on TFP. In column 1, using direct TFP estimates and an RE estimator, a greater foreign presence in a given sector appears to be associated in a statistically significant

[16]See https://data.worldbank.org/data-catalog/world-development-indicators.

Table 2. **Total Factor Productivity, Intra- and Inter-Industry Foreign Direct Investment**

	ln(GO) RE [1]	ln(GO) FE [2]	ln(TFPe) RE [3]	ln(TFPe) FE [4]
ln(HFDI)	0.012**	0.024**	0.010*	0.024**
	(0.006)	(0.010)	(0.006)	(0.011)
ln(BWFDIM)	0.031***	0.028*	0.031**	0.028*
	(0.011)	(0.016)	(0.012)	(0.015)
ln(FWFDIM)	0.025**	0.011	0.015	0.005
	(0.012)	(0.014)	(0.012)	(0.014)
ln(BWFDIS)	−0.015	−0.046**	−0.022	−0.054**
	(0.018)	(0.023)	(0.019)	(0.024)
ln(FWFDIS)	0.023	0.033*	0.019	0.019
	(0.017)	(0.019)	(0.017)	(0.021)
Number of observations	702	702	702	702

BWFDIM = manufacturing backward foreign direct investment linkages, BWFDIS = services backward foreign direct investment linkages, FE = fixed effects estimator, FWFDIM = manufacturing forward foreign direct investment linkages, FWFDIS = services forward foreign direct investment linkages, GO = gross output, HFDI = intra-industry foreign direct investment, RE = random effects estimator, TFPe = total factor productivity estimates.

Notes: ***p-value < 0.01, **p-value < 0.05, and *p-value < 0.10. Cluster-robust standard errors are in parentheses. All regressions include 5-year lagged total factor productivity terms and sector-specific time effects. The GO columns include the log values of capital services, labor services, and intermediates, as well as their interaction with a dummy variable indicating whether the sector belongs to the broad services industry. The RE columns include country and sector fixed effects. The FE columns include country-sector fixed effects.

Sources: International Trade Centre. Investment Map. http://www.investmentmap.org/; Organisation for Economic Co-operation and Development. 2015. Trade in Value Added Database. https://stats.oecd.org/index.aspx?queryid=66237; and World Bank. 2000–2014. World Input–Output Tables. http://www.wiod.org/home.

manner with higher TFP in the same sector. This result holds when we use the indirect TFP estimates (column 3) and when we apply an FE estimator (columns 2 and 4). Given the lack of evidence supporting the existence of intra-industry externalities (Iršová and Havránek 2013), the effect of intra-industry FDI is likely to be related to the greater TFP of foreign versus domestic firms.

2. Intra-Industry and Inter-Industry FDI

In Table 2, we introduce in our initial model proxies for FDI linkages with manufacturing and services. We still find that intra-industry FDI raises TFP. Furthermore, in line with the microeconomic FDI literature, we find statistical evidence for a positive effect on TFP of an FDI presence in downstream manufacturing sectors. The economic effects are modest. In the short run, on the basis of the estimates reported in column 4, doubling intra-industry FDI from the

Table 3. **Total Factor Productivity and Broad-Industry-Specific Estimates for Intra-Industry Foreign Direct Investment**

	ln(GO) RE [1]	ln(GO) FE [2]	ln(TFPe) RE [3]	ln(TFPe) FE [4]
ln(HFDI)*MAN	0.012**	0.010	0.009	0.011
	(0.006)	(0.011)	(0.006)	(0.012)
ln(HFDI)*SERV	0.000	0.055**	0.004	0.050**
	(0.009)	(0.023)	(0.009)	(0.021)
ln(BWFDIM)	0.031***	0.029*	0.032***	0.032**
	(0.011)	(0.017)	(0.012)	(0.015)
ln(FWFDIM)	0.025**	0.013	0.015	0.006
	(0.012)	(0.015)	(0.012)	(0.014)
ln(BWFDIS)	−0.015	−0.056**	−0.023	−0.063**
	(0.018)	(0.023)	(0.019)	(0.025)
ln(FWFDIS)	0.023	0.029	0.019	0.012
	(0.017)	(0.019)	(0.017)	(0.021)
Number of observations	702	702	702	702

BWFDIM = manufacturing backward foreign direct investment linkages, BWFDIS = services backward foreign direct investment linkages, FE = fixed effects estimator, FWFDIM = manufacturing forward foreign direct investment linkages, FWFDIS = services forward foreign direct investment linkages, GO = gross output, HFDI = intra-industry foreign direct investment, MAN or SERV = dummy variable indicating either manufacturing or services, RE = random effects estimator, TFPe = total factor productivity estimates.

Notes: ***p-value < 0.01, **p-value < 0.05, and *p-value < 0.10. Cluster-robust standard errors are in parentheses. All regressions include 5-year lagged total factor productivity terms and sector-specific time effects. The GO columns include the log values of capital services, labor services, and intermediates, as well as their interaction with a dummy variable indicating whether the sector belongs to the broad services industry. The RE columns include country and sector fixed effects. The FE columns include country-sector fixed effects.

Sources: International Trade Centre. Investment Map. http://www.investmentmap.org/; Organisation for Economic Co-operation and Development. 2015. Trade in Value Added Database. https://stats.oecd.org/index.aspx?queryid=66237; and World Bank. 2000–2014. World Input–Output Tables. http://www.wiod.org/home.

current 19% to 38% would increase TFP in a given sector by $([2^{0.024}] - 1) * 100\% = 1.7\%$. Similarly, doubling backward linkages from FDI in manufacturing sectors, by either doubling the supply coefficient from the current 11% (Table A3) or doubling the current share of foreign employees in downstream manufacturing industries (27%), would increase TFP by $([2^{0.028}] - 1) * 100\% = 1.96\%$. At the average sample values, the corresponding semielasticity terms are 0.10 and 0.66, the latter being in range of those reported in Havránek and Iršová (2011).

In Table 3, we investigate whether our estimates for intra-industry FDI diverge across broad industries (manufacturing and services). The FE estimates suggest that the impact of intra-industry FDI may be much stronger in service sectors, as indicated by $\ln(HFDI) * SERV$. In the short run, on the basis of the estimates reported in column 4, doubling intra-industry FDI linkages would increase TFP in service (manufacturing) sectors by 3.5% (0.8%).

Table 4. **Specific Services-Forward Foreign Direct Investment Linkages**

	ln(GO) RE [1]	**ln(GO) FE [2]**	**ln(TFPe) RE [3]**	**ln(TFPe) FE [4]**
ln(HFDI)	0.012**	0.025**	0.011*	0.025**
	(0.006)	(0.010)	(0.006)	(0.010)
ln(BWFDIM)	0.031***	0.027*	0.031***	0.028*
	(0.011)	(0.016)	(0.012)	(0.015)
ln(FWFDIM)	0.026**	0.012	0.016	0.006
	(0.012)	(0.015)	(0.012)	(0.014)
ln(BWFDIS)	−0.015	−0.043*	−0.023	−0.053**
	(0.018)	(0.024)	(0.019)	(0.024)
ln(FWFDISS)	0.022	0.030	0.022	0.019
	(0.018)	(0.019)	(0.018)	(0.021)
Number of observations	702	702	702	702

BWFDIM = manufacturing backward foreign direct investment linkages; BWFDIS = services backward foreign direct investment linkages; FE = fixed effects estimator; FWFDIM = manufacturing forward foreign direct investment linkages; FWFDISS = services-forward foreign direct investment linkages related to the following upstream sectors: (i) electricity, gas and water supply; (ii) transport and communications; (iii) financial intermediation; and (iv) real estate and business services; GO = gross output; HFDI = intra-industry foreign direct investment; RE = random effects estimator; TFPe = total factor productivity estimates.

Notes: ***p-value $<$ 0.01, **p-value $<$ 0.05, and *p-value $<$ 0.10. Cluster-robust standard errors are in parentheses. All regressions include 5-year lagged total factor productivity terms and sector-specific time effects. The GO columns include the log values of capital services, labor services, and intermediates, as well as their interaction with a dummy variable indicating whether the sector belongs to the broad services industry. The RE columns include country and sector fixed effects. The FE columns include country-sector fixed effects.

Sources: International Trade Centre. Investment Map. http://www.investmentmap.org/; Organisation for Economic Co-operation and Development. 2015. Trade in Value Added Database. https://stats.oecd.org/index.aspx?queryid=66237; and World Bank. 2000–2014. World Input–Output Tables. http://www.wiod.org/home.

In Table 4, we examine the distinct influence of specific forward linkages from FDI in service sectors. Following Fernandes and Paunov (2012), we focus on linkages with the following upstream service sectors: (i) electricity, gas, and water supply; (ii) transport and communications; (iii) financial intermediation; and (iv) real estate and business services. As indicated by Fernandes and Paunov, these sectors are characterized by the facilitating and intermediating role they play for downstream firms. In addition, Table A2 shows that these are the service sectors that exhibit the highest foreign employment shares. However, we still fail to find an impact of forward linkages from FDI in service sectors on TFP.

B. Labor Productivity

In Table 5, we examine whether intra- and inter-industry FDI influences labor productivity (real value added per worker). This single factor productivity indicator is of great interest to policy makers and is frequently employed to make

Table 5. **Labor Productivity and Multisector Foreign Direct Investment**

	ln(VA) RE [1]	**ln(VA) FE [2]**	**ln(X) RE [3]**	**ln(X) FE [4]**	**ln(VAX) RE [5]**	**ln(VAX) FE [6]**	**VAX/X RE [7]**	**VAX/X FE [8]**
ln(HFDI)	0.174***	0.258***	0.217***	0.421***	0.217***	0.348***	−0.005	−0.018
	(0.030)	(0.085)	(0.037)	(0.136)	(0.039)	(0.114)	(0.004)	(0.012)
ln(BWFDIM)	0.024	0.166	−0.066	−0.047	−0.070	−0.082	0.004	−0.022
	(0.054)	(0.120)	(0.071)	(0.156)	(0.074)	(0.154)	(0.006)	(0.017)
ln(FWFDIM)	0.017	−0.018	0.044	−0.086	0.002	−0.146	−0.021***	−0.020*
	(0.053)	(0.077)	(0.078)	(0.121)	(0.078)	(0.117)	(0.006)	(0.011)
ln(BWFDIS)	−0.008	−0.678***	−0.121	−0.720***	−0.089	−0.621***	0.008	0.031
	(0.068)	(0.185)	(0.105)	(0.233)	(0.108)	(0.226)	(0.009)	(0.028)
ln(FWFDIS)	0.154**	0.147	0.325***	0.171	0.396***	0.143	0.000	−0.011
	(0.071)	(0.135)	(0.111)	(0.202)	(0.110)	(0.194)	(0.008)	(0.024)
Number of observations	696	696	696	696	696	696	696	696

BWFDIM = manufacturing backward foreign direct investment linkages, BWFDIS = services backward foreign direct investment linkages, FE = fixed effects estimator, FWFDIM = manufacturing forward foreign direct investment linkages, FWFDIS = services forward foreign direct investment linkages, HFDI = intra-industry foreign direct investment, RE = random effects estimator, SERV = dummy variable indicating whether the sector belongs to the broad services industry, VA = value added per worker, VAX = direct domestic value added embodied in exports per worker, VAX/X = share of direct domestic value added in gross exports, X = gross exports per worker.

Notes: ***p-value < 0.01, **p-value < 0.05, and *p-value < 0.10. Cluster-robust standard errors are in parentheses. All regressions include 5-year lagged total factor productivity terms and sector-specific time effects. The RE columns include country and sector fixed effects. The FE columns include country-sector fixed effects.

Sources: International Trade Centre. Investment Map. http://www.investmentmap.org/; Organisation for Economic Co-operation and Development. 2015. Trade in Value Added Database. https://stats.oecd.org/index.aspx?queryid=66237; and World Bank. 2000–2014. World Input–Output Tables. http://www.wiod.org/home.

international performance comparisons. It is also less sensitive to assumptions than TFP. Another advantage is that it allows us to account for the effects of FDI on domestic activity that are not mediated via TFP changes, e.g., different usage of factors of production.

In columns 1 and 2, we find that intra-industry FDI is strongly associated with higher labor productivity. In contrast with our previous findings, the economic effects are much larger. Using the estimates reported in column 2, in the short run, doubling intra-industry FDI would increase labor productivity by about 20%. Columns 3 through 6 show that part of this effect appears to be driven by FDI-induced integration via global value-added chains. Intra-industry FDI is consistently associated with improved export performance, measured either as exports per worker (*X*) or direct domestic value added embodied in exports per worker (*VAX*). In columns 7 and 8, we look at whether multisectoral FDI can induce value-added upgrading in the sense of increasing the share of domestic value-added content in gross exports (*VAX/X*). This does not appear to be the case, including for intra-industry FDI. On the other hand, greater manufacturing forward FDI linkages tend to induce value-added downgrading, possibly because firms make greater use of inter-industry intermediates that are produced by foreign firms.

In Table 6, we investigate whether these results hold when we allow for a differential effect of intra-industry FDI across broad industry sectors by interacting $\ln(HFDI)$ with an industry dummy variable that indicates whether the host industry is a manufacturing sector ($\ln(HFDI) * MAN$) or a service sector ($\ln(HFDI) * SERV$). We still observe a strong effect of intra-industry FDI, particularly in the manufacturing sector. On the other hand, the effect is insignificant in the service sectors. In section VI, we will come back to this difference between broad industry classifications.

Lastly, focusing on inter-industry FDI variables, as in the previous section, results are ambiguous as the sign, magnitude, and statistical significance of the coefficients on these variables vary widely across columns. For example, it is not clear how FDI in service sectors influences labor productivity or export performance, although our results suggest a positive role for forward linkages from FDI in service sectors. In addition, we do not find a statistically significant effect for backward linkages from FDI in manufacturing sectors anymore. To the extent that these externalities truly exist at the TFP level, they do not appear to be translated into greater labor productivity.

VI. Regional Comparisons

Table A1 shows that countries located in Central and Eastern Europe are predominant in our sample. In this last section, we explore how our results compare across the three regions mentioned in Table A1. To do so, we interact the FDI variables with three dummy variables, *CEEU*, *LAC,* and *Asia*, which take the value

Table 6. **Labor Productivity and Broad-Industry-Specific Estimates for Intra-Industry Foreign Direct Investment**

	ln(VA) RE [1]	**ln(VA) FE [2]**	**ln(X) RE [3]**	**ln(X) FE [4]**	**ln(VAX) RE [5]**	**ln(VAX) FE [6]**	**VAX/X RE [7]**	**VAX/X FE [8]**
ln(HFDI)*MAN	0.194***	0.247**	0.234***	0.472***	0.233***	0.382***	−0.004	−0.016
	(0.035)	(0.099)	(0.040)	(0.164)	(0.043)	(0.139)	(0.005)	(0.013)
ln(HFDI)*SERV	−0.069	0.045	−0.057	−0.202	−0.057	−0.131	−0.001	−0.005
	(0.050)	(0.130)	(0.059)	(0.188)	(0.062)	(0.178)	(0.006)	(0.021)
ln(BWFDIM)	0.010	0.170	−0.077	−0.067	−0.081	−0.095	0.004	−0.023
	(0.054)	(0.121)	(0.071)	(0.157)	(0.074)	(0.155)	(0.006)	(0.017)
ln(FWFDIM)	0.020	−0.017	0.047	−0.093	0.004	−0.150	−0.021***	−0.020*
	(0.054)	(0.077)	(0.078)	(0.124)	(0.078)	(0.119)	(0.006)	(0.011)
ln(BWFDIS)	0.004	−0.686***	−0.112	−0.681***	−0.080	−0.595**	0.008	0.032
	(0.068)	(0.186)	(0.106)	(0.236)	(0.108)	(0.231)	(0.009)	(0.028)
ln(FWFDIS)	0.159**	0.142	0.330***	0.192	0.400***	0.157	0.000	−0.011
	(0.071)	(0.134)	(0.112)	(0.198)	(0.111)	(0.193)	(0.009)	(0.024)
Number of observations	696	696	696	696	696	696	696	696

BWFDIM = manufacturing backward foreign direct investment linkages, BWFDIS = services backward foreign direct investment linkages, FE = fixed effects estimator, FWFDIM = manufacturing forward foreign direct investment linkages, FWFDIS = services forward foreign direct investment linkages, MAN or SERV = dummy variable indicating either manufacturing or services, RE = random effects estimator, VA = value added per worker, VAX = direct domestic value added embodied in exports per worker, VAX/X = share of direct domestic value added in gross exports, X = gross exports per worker.

Notes: ***p-value < 0.01, **p-value < 0.05, and *p-value < 0.10. Cluster-robust standard errors are in parentheses. All regressions include 5-year lagged total factor productivity terms and sector-specific time effects. The RE columns include country and sector fixed effects. The FE columns include country-sector fixed effects.

Sources: International Trade Centre. Investment Map. http://www.investmentmap.org/; Organisation for Economic Co-operation and Development. 2015. Trade in Value Added Database. https://stats.oecd.org/index.aspx?queryid=66237; and World Bank. 2000–2014. World Input–Output Tables. http://www.wiod.org/home.

of 1 when a country is located in Central and Eastern Europe, Latin America, or Asia, respectively.

In Table 7, the variable $\ln(HFDI) * SERV * CEEU$ indicates that the effects of intra-industry FDI on TFP are especially present in the service sectors of the Central and Eastern European countries in our sample. On the other hand, Table 8 indicates that the impact of intra-industry FDI on total and exported labor productivity is much higher in the Asian manufacturing sectors than in the other region–sector combinations, especially when we only exploit the time series dimension of our data (the FE estimates). This finding is in line with the more general findings of Tables 3 and 6, which indicated that FDI is associated with higher TFP in services (Table 3) and higher labor productivity in manufacturing sectors (Table 6). In addition, there is some limited evidence that value-added upgrading took place (Table 8, columns 7 and 8).

The fact that intra-industry FDI seems to particularly benefit both European services as well as Asian manufacturing is surprising since they do not share many commonalities. In terms of skill endowments, for example, Table A4 shows that the median of average years of schooling in Europe during 2000–2010 is 10.8, while it is only 6.4 in Asia. In addition, European service sectors in Europe comprise significantly more skilled workers (78%) than Asian manufacturing sectors (44%). Therefore, finding a single factor that can explain why horizontal FDI benefits these region–sectors specifically seems unlikely.

Instead, the explanation is more likely to be related to the underlying differences between our two measures of productivity: TFP and labor productivity. Since value added per worker is also affected by other factors of production, labor productivity can be considered only a partial measure of productivity. TFP, on the other hand, as a residual productivity measure, controls for such input factors that are captured by x in our conceptual framework. Then, an FDI-induced TFP premium suggests that foreign firms are better able to transform the same inputs into output, meaning that foreign firms' technical efficiency exceeds that of domestic firms ($\alpha > \beta$). On the other hand, evidence of a (significantly higher) FDI-induced labor productivity premium means that foreign firms tend to inhibit more productive characteristics ($x^F > x^N$), such as capital intensity, size, or skilled employees. These more productive foreign firms will then mechanically increase the overall productivity of a host economy, as per the equation $\bar{q} = (1 - \mu)\overline{q^N} + \overline{\mu q^F}$, a process known as the compositional effect of FDI (Navaretti and Venables 2005).

In line with that framework, we expect the TFP premium to depend on host economies' absorptive capacity such as the level of human capital. We therefore interact our FDI variables with the years of schooling, as a proxy for human capital, in Table 9. Here, we would expect a positive interaction term, as the TFP spillover from FDI should be higher for more levels of human capital.

Table 7. **Total Factor Productivity and Region-Specific Estimates**

	ln(GO) RE (1)	**ln(GO) FE (2)**	**ln(TFPe) RE (3)**	**ln(TFPe) FE (4)**
ln(HFDI)*MAN*CEEU	0.012*	0.004	0.010	0.010
	(0.006)	(0.011)	(0.006)	(0.013)
ln(HFDI)*SERV*CEEU	0.003	0.066***	0.007	0.062***
	(0.009)	(0.025)	(0.009)	(0.022)
ln(BWFDIM)*CEEU	0.022*	0.028	0.019	0.036*
	(0.013)	(0.020)	(0.013)	(0.021)
ln(FWFDIM)*CEEU	0.040***	0.008	0.024*	−0.009
	(0.015)	(0.017)	(0.014)	(0.016)
ln(BWFDIS)*CEEU	−0.016	−0.092***	−0.025	−0.087***
	(0.016)	(0.028)	(0.017)	(0.030)
ln(FWFDIS)*CEEU	0.016	0.029	0.003	0.035
	(0.020)	(0.029)	(0.019)	(0.029)
ln(HFDI)*MAN*Asia	0.004	0.004	0.009	0.009
	(0.007)	(0.029)	(0.007)	(0.029)
ln(HFDI)*SERV*Asia	0.004	0.046	0.009	0.053
	(0.018)	(0.068)	(0.019)	(0.086)
ln(BWFDIM)*Asia	0.019*	0.018	0.012	0.018
	(0.011)	(0.019)	(0.012)	(0.021)
ln(FWFDIM)*Asia	−0.007	0.017	−0.007	0.031
	(0.015)	(0.028)	(0.016)	(0.032)
ln(BWFDIS)*Asia	−0.031	−0.022	−0.015	0.013
	(0.030)	(0.046)	(0.032)	(0.054)
ln(FWFDIS)*Asia	0.023	0.028	0.039*	0.012
	(0.018)	(0.029)	(0.021)	(0.031)
ln(HFDI)*MAN*LAC	0.020	0.074	0.017	0.170*
	(0.019)	(0.108)	(0.020)	(0.100)
ln(HFDI)*SERV*LAC	−0.009	−0.069	−0.003	−0.300**
	(0.015)	(0.192)	(0.016)	(0.142)
ln(BWFDIM)*LAC	0.042**	0.019	0.047**	0.031
	(0.019)	(0.043)	(0.022)	(0.046)
ln(FWFDIM*LAC	0.037	0.171	0.045	0.254
	(0.034)	(0.168)	(0.035)	(0.159)
ln(BWFDIS)*LAC	−0.004	0.189	−0.004	0.119
	(0.046)	(0.146)	(0.048)	(0.157)
ln(FWFDIS)*LAC	0.071	0.150	0.074	−0.095
	(0.058)	(0.154)	(0.059)	(0.143)
Number of observations	702	702	702	702

Asia = dummy variable indicating whether the country is in Asia, BWFDIM = manufacturing backward foreign direct investment linkages, BWFDIS = services backward foreign direct investment linkages, CEEU = dummy variable indicating whether the country is in Central and Eastern Europe, FE = fixed effects estimator, FWFDIM = manufacturing forward foreign direct investment linkages, FWFDIS = services forward foreign direct investment linkages, GO = gross output, HFDI = intra-industry foreign direct investment, LAC = dummy variable indicating whether the country is in Latin America, MAN or SERV = dummy variable indicating either manufacturing or services, RE = random effects estimator, TFPe = total factor productivity estimates, VA = value added per worker, VAX = direct domestic value added embodied in exports per worker, VAX/X = share of direct domestic value added in gross exports, X = gross exports per worker.

Continued.

Table 7. *Continued.*

Notes: ***p-value < 0.01, **p-value < 0.05, and *p-value < 0.10. Cluster-robust standard errors are in parentheses. All regressions include 5-year lagged total factor productivity terms and sector-specific time effects. The RE columns include country and sector fixed effects. The FE columns include country-sector fixed effects.
Sources: International Trade Centre. Investment Map. http://www.investmentmap.org/; Organisation for Economic Co-operation and Development. 2015. Trade in Value Added Database. https://stats.oecd.org/index.aspx?queryid=66237; and World Bank. 2000–2014. World Input–Output Tables. http://www.wiod.org/home.

On the other hand, the compositional effect depends on the difference between domestic ($\overline{q^N}$) and foreign firms' productivity ($\overline{q^F}$). We therefore want to interact our FDI variables with a measure of domestic firms' productivity. As a proxy, we take the host economies' log labor productivity in the year 2000, $\ln(VA)_{2000}$, which is our earliest year of observation. The rationale is that, due to growing FDI over time, q is least affected by $\overline{q^F}$. Here, we expect a negative interaction term since the lower the initial labor productivity in the year 2000, the greater the gap between $\overline{q^F}$ and $\overline{q^N}$ and thus the larger the composition effect of FDI. Table A5 provides the descriptive statistics: the average labor productivity per region in the year 2000. As it shows, Latin America has significantly higher value added per worker (\$11,653) than both Central and Eastern Europe (\$5,145) and Asia (\$4,007).

Tables 9 and 10 show evidence in line with our hypotheses. Table 9 shows a significantly positive interaction coefficient between intra-service-industry FDI and our proxy for human capital, $\ln(HFDI) * SERV * \ln(HC)$, when using country-sector fixed effects (columns 2 and 4). Apparently, the relatively large amount of years of schooling in Europe (Table A4) can partly explain why the European service sector has been able to achieve higher TFP spillovers from intra-industry FDI. The highly significant interaction coefficient $\ln(HFDI) * \ln(VA)_{2000}$ in Table 10, on the other hand, can explain why Asian manufacturing labor productivity benefited disproportionally from intra-industry FDI. Namely, while horizontal FDI, $\ln(HFDI)$, is associated with significantly higher labor productivity, this effect is significantly larger for host economies that have lower initial labor productivity, as noted by $\ln(HFDI) * \ln(VA)_{2000}$. As we know from Table A5, Asia had the lowest labor productivity of all regions, partly providing an explanation for the findings of Table 8.

All in all, these results contribute to the finding that developing economies in our sample benefited from FDI largely through a compositional effect caused by the influx of more productive foreign firms, rather than direct spillovers among foreign and domestic firms. In addition, our results suggest that the three large Asian countries in our sample—India, Indonesia, and the PRC—have disproportionately benefited from the entry of foreign firms and the associated deployment of global value chains.

Table 8. **Labor Productivity and Region-Specific Estimates**

	ln(VA) RE (1)	**ln(VA) FE (2)**	**ln(X) RE (3)**	**ln(X) FE (4)**	**ln(VAX) RE (5)**	**ln(VAX) FE (6)**	**VAX/X RE (7)**	**VAX/X FE (8)**
ln(HFDI)*MAN*CEEU	0.185***	0.182**	0.244***	0.333**	0.235***	0.242**	−0.007	−0.009
	(0.036)	(0.091)	(0.044)	(0.154)	(0.048)	(0.115)	(0.005)	(0.015)
ln(HFDI)*SERV*CEEU	−0.143**	0.040	−0.096	−0.249	−0.108	−0.151	−0.003	−0.003
	(0.057)	(0.126)	(0.070)	(0.195)	(0.074)	(0.183)	(0.007)	(0.023)
ln(BWFDIM)*CEEU	0.018	0.082	−0.123	−0.303	−0.123	−0.326*	0.007	−0.029
	(0.066)	(0.147)	(0.093)	(0.227)	(0.098)	(0.187)	(0.009)	(0.035)
ln(FWFDIM)*CEEU	0.114*	0.076	0.106	0.039	0.073	−0.001	−0.021***	−0.020
	(0.068)	(0.104)	(0.090)	(0.194)	(0.093)	(0.170)	(0.007)	(0.021)
ln(BWFDIS)*CEEU	−0.061	−0.883***	−0.163	−0.570**	−0.168	−0.548**	0.002	0.022
	(0.087)	(0.258)	(0.119)	(0.265)	(0.127)	(0.254)	(0.012)	(0.041)
ln(FWFDIS)*CEEU	0.144	−0.024	0.298**	−0.104	0.383***	−0.162	−0.003	−0.013
	(0.096)	(0.225)	(0.125)	(0.293)	(0.133)	(0.268)	(0.011)	(0.042)
ln(HFDI)*MAN*Asia	0.308***	0.886***	0.299***	1.112***	0.325***	1.096***	0.010	−0.004
	(0.058)	(0.196)	(0.070)	(0.290)	(0.074)	(0.330)	(0.006)	(0.025)
ln(HFDI)*SERV*Asia	−0.052	−0.158	−0.049	0.119	−0.059	−0.113	−0.010	−0.055
	(0.079)	(0.297)	(0.107)	(0.459)	(0.113)	(0.488)	(0.012)	(0.058)
ln(BWFDIM)*Asia	−0.085	−0.061	−0.098	−0.177	−0.130	−0.278	−0.003	−0.042**
	(0.087)	(0.143)	(0.113)	(0.281)	(0.113)	(0.276)	(0.010)	(0.021)
ln(FWFDIM)*Asia	−0.022	−0.087	0.074	−0.192	0.033	−0.301	−0.013	−0.000
	(0.090)	(0.149)	(0.152)	(0.236)	(0.156)	(0.233)	(0.011)	(0.023)
ln(BWFDIS)*Asia	0.025	−0.439	−0.321	−1.284**	−0.222	−0.876	0.033	0.117***
	(0.177)	(0.289)	(0.249)	(0.577)	(0.236)	(0.533)	(0.023)	(0.042)
ln(FWFDIS)*Asia	−0.012	0.260	0.388**	0.371	0.414**	0.382	0.011	0.026
	(0.128)	(0.207)	(0.190)	(0.347)	(0.187)	(0.331)	(0.018)	(0.028)

Continued.

Table 8. *Continued.*

	ln(VA) RE (1)	ln(VA) FE (2)	ln(X) RE (3)	ln(X) FE (4)	ln(VAX) RE (5)	ln(VAX) FE (6)	VAX/X RE (7)	VAX/X FE (8)
ln(HFDI)*MAN*LAC	0.143**	−0.595	0.190**	0.100	0.205**	0.049	−0.009	−0.070
	(0.056)	(1.022)	(0.084)	(1.368)	(0.090)	(1.664)	(0.006)	(0.043)
ln(HFDI)*SERV*LAC	−0.065	1.737	−0.084	1.621	−0.088	1.991	−0.001	0.166**
	(0.059)	(1.784)	(0.076)	(1.949)	(0.078)	(2.232)	(0.006)	(0.083)
ln(BWFDIM)*LAC	0.006	−0.562*	−0.077	−0.888**	−0.095	−0.829*	0.001	0.037*
	(0.068)	(0.295)	(0.084)	(0.441)	(0.085)	(0.478)	(0.006)	(0.019)
ln(FWFDIM*LAC	−0.077	−1.214*	−0.046	−0.260	−0.086	−0.286	−0.022***	−0.110*
	(0.066)	(0.660)	(0.104)	(1.207)	(0.097)	(1.194)	(0.007)	(0.060)
ln(BWFDIS)*LAC	0.011	3.106***	0.013	3.668**	0.086	3.554**	0.012	−0.153**
	(0.098)	(1.087)	(0.144)	(1.704)	(0.143)	(1.803)	(0.011)	(0.071)
ln(FWFDIS)*LAC	0.191	2.531***	0.386	2.560	0.507**	3.064*	−0.008	0.145
	(0.145)	(0.968)	(0.262)	(1.766)	(0.252)	(1.770)	(0.013)	(0.089)
Number of observations	696	696	696	696	696	696	696	696

Asia = dummy variable indicating whether the country is in Asia, BWFDIM = manufacturing backward foreign direct investment linkages, BWFDIS = services backward foreign direct investment linkages, CEEU = dummy variable indicating whether the country is in Central and Eastern Europe, FE = fixed effects estimator, FWFDIM = manufacturing forward foreign direct investment linkages, FWFDIS = services forward foreign direct investment linkages, GO = gross output, HFDI = intra-industry foreign direct investment, LAC = dummy variable indicating whether the country is in Latin America, MAN or SERV = dummy variable indicating either manufacturing or services, RE = random effects estimator, VA = value added per worker, VAX = direct domestic value added embodied in exports per worker, VAX/X = share of direct domestic value added in gross exports, X = gross exports per worker.

Notes: ***p-value < 0.01, **p-value < 0.05, and *p-value < 0.10. Cluster-robust standard errors are in parentheses. All regressions include 5-year lagged total factor productivity terms and sector-specific time effects. The RE columns include country and sector fixed effects. The FE columns include country-sector fixed effects.

Sources: International Trade Centre. Investment Map. http://www.investmentmap.org/; Organisation for Economic Co-operation and Development. 2015. Trade in Value Added Database. https://stats.oecd.org/index.aspx?queryid=66237; and World Bank. 2000–2014. World Input–Output Tables. http://www.wiod.org/home.

Table 9. **Total Factor Productivity and Human Capital**

	ln(GO) RE (1)	**ln(GO) FE (2)**	**ln(TFPe) RE (3)**	**ln(TFPe) FE (4)**
ln(HC)*MAN	0.294***		0.339***	
	(0.110)		(0.091)	
ln(HC)*SERV	0.002		−0.033	
	(0.058)		(0.055)	
ln(HFDI)*MAN	0.033	0.118	0.057*	0.173*
	(0.029)	(0.104)	(0.030)	(0.103)
ln(HFDI)*SERV	0.014	−0.275*	−0.003	−0.278*
	(0.058)	(0.147)	(0.060)	(0.167)
ln(HFDI)*MAN*ln(HC)	−0.010	−0.047	−0.022	−0.071
	(0.013)	(0.043)	(0.013)	(0.044)
ln(HFDI)*SERV*ln(HC)	−0.006	0.146**	0.003	0.146*
	(0.026)	(0.064)	(0.026)	(0.075)
ln(BWFDIM)	0.012	−0.033	0.017	−0.024
	(0.050)	(0.135)	(0.055)	(0.131)
ln(BWFDIM)*ln(HC)	0.007	0.031	0.005	0.027
	(0.023)	(0.062)	(0.025)	(0.060)
ln(FWFDIM)	−0.037	0.150	0.009	0.241**
	(0.064)	(0.114)	(0.070)	(0.114)
ln(FWFDIM)*ln(HC)	0.029	−0.060	0.004	−0.103**
	(0.029)	(0.052)	(0.031)	(0.051)
ln(BWFDIS)	0.061	0.541***	0.122	0.484**
	(0.094)	(0.181)	(0.102)	(0.198)
ln(BWFDIS)*ln(HC)	−0.034	−0.279***	−0.066	−0.252***
	(0.041)	(0.085)	(0.044)	(0.091)
ln(FWFDIS)	0.168*	−0.150	0.160	−0.062
	(0.093)	(0.146)	(0.098)	(0.147)
ln(FWFDIS)*ln(HC)	−0.068	0.087	−0.066	0.038
	(0.043)	(0.070)	(0.045)	(0.071)
Number of observations	702	702	702	702

BWFDIM = manufacturing backward foreign direct investment linkages, BWFDIS = services backward foreign direct investment linkages, FWFDIM = manufacturing forward foreign direct investment linkages, FWFDIS = services forward foreign direct investment linkages, GO = gross output, HC = log of years of schooling to proxy human capital, HFDI = intra-industry foreign direct investment, MAN or SERV = dummy variable indicating either manufacturing or services, RE = random effects estimator, TFPe = total factor productivity estimates, VA = value added per worker, VAX = direct domestic value added embodied in exports per worker, VAX/X = share of direct domestic value added in gross exports, X = gross exports per worker.

Notes: ***p-value < 0.01, **p-value < 0.05, and *p-value < 0.10. Cluster-robust standard errors are in parentheses. All regressions include a 5-year lagged total factor productivity term, sector-specific time effects, and a dummy indicating broad industry classifications. The GO columns include the log values of capital services, labor services, and intermediates, as well as their interaction with a dummy variable indicating whether the sector belongs to the broad service industry The RE columns include country and sector fixed effects. The FE columns include country-sector fixed effects.

Sources: International Trade Centre. Investment Map. http://www.investmentmap.org/; Organisation for Economic Co-operation and Development. 2015. Trade in Value Added Database. https://stats.oecd.org/index.aspx?queryid=66237; Wittgenstein Centre for Demography and Global Human Capital. 2015. Wittgenstein Centre Data Explorer Version 1.2. http://witt.null2.net/shiny/wic/; and World Bank. 2000–2014. World Input–Output Tables. http://www.wiod.org/home.

Table 10. **Labor Productivity and Initial Labor Productivity**

	ln(VA) RE (1)	**ln(VA) FE (2)**	**ln(X) RE (3)**	**Ln(X) FE (4)**	**ln(VAX) RE (5)**	**ln(VAX) FE (6)**	**VAX/X RE (7)**	**VAX/X FE (8)**
$\ln(VA)_{2000}$	0.573^{***}		0.664^{**}		0.766^{***}		0.030	
	(0.203)		(0.259)		(0.267)		(0.021)	
ln(HFDI)	0.431^{***}	1.351^{***}	0.685^{***}	2.595^{***}	0.735^{***}	1.853^{***}	0.018	-0.128^{**}
	(0.151)	(0.352)	(0.226)	(0.453)	(0.223)	(0.448)	(0.017)	(0.064)
$\ln(HFDI)*\ln(VA)_{2000}$	-0.034^{*}	-0.144^{***}	-0.059^{**}	-0.281^{***}	-0.065^{**}	-0.194^{***}	−0.003	0.014^{*}
	(0.019)	(0.045)	(0.027)	(0.057)	(0.027)	(0.055)	(0.002)	(0.008)
ln(BWFDIM)	0.073	−0.033	0.667^{*}	−0.319	0.664	−0.307	0.003	−0.105
	(0.281)	(1.011)	(0.398)	(1.174)	(0.408)	(1.212)	(0.036)	(0.152)
$\ln(BWFDIM)*\ln(VA)_{2000}$	−0.001	0.019	-0.083^{*}	0.023	-0.081^{*}	0.018	0.001	0.010
	(0.033)	(0.129)	(0.046)	(0.150)	(0.047)	(0.154)	(0.004)	(0.019)
ln(FWFDIM)	0.731^{**}	2.813^{***}	0.583	0.243	0.591	0.773	−0.036	0.095
	(0.355)	(0.799)	(0.462)	(1.106)	(0.477)	(1.107)	(0.036)	(0.113)
$\ln(FWFDIM)*\ln(VA)_{2000}$	-0.088^{**}	-0.368^{***}	−0.069	−0.046	−0.073	−0.119	0.002	−0.014
	(0.043)	(0.104)	(0.055)	(0.142)	(0.056)	(0.142)	(0.004)	(0.014)
ln(BWFDIS)	0.345	−0.738	−0.785	−2.710	−0.754	−2.185	−0.027	−0.014
	(0.423)	(1.260)	(0.583)	(1.749)	(0.605)	(1.723)	(0.063)	(0.261)
$\ln(BWFDIS)*\ln(VA)_{2000}$	−0.048	0.032	0.070	0.281	0.070	0.229	0.004	0.007
	(0.052)	(0.166)	(0.069)	(0.234)	(0.072)	(0.228)	(0.007)	(0.033)
ln(FWFDIS)	−0.337	-4.157^{***}	0.825	−1.653	0.152	−2.329	-0.137^{**}	0.031
	(0.491)	(1.176)	(0.582)	(1.573)	(0.608)	(1.559)	(0.064)	(0.229)
$\ln(FWFDIS)*\ln(VA)_{2000}$	0.057	0.568^{***}	−0.070	0.249	0.025	0.335	0.018^{**}	−0.005
	(0.062)	(0.153)	(0.074)	(0.209)	(0.077)	(0.205)	(0.008)	(0.031)
Number of observations	696	696	696	696	696	696	696	696

BWFDIM = manufacturing backward foreign direct investment linkages, BWFDIS = services backward foreign direct investment linkages, FE = fixed effects estimator, FWFDIM = manufacturing forward foreign direct investment linkages, FWFDIS = services forward foreign direct investment linkages, HFDI = intra-industry foreign direct investment, $\ln(VA)_{2000}$ = log of value added per worker in the year 2000, RE = random effects estimator, TFPe = total factor productivity estimates, VA = value added per worker, VAX = direct domestic value added embodied in exports per worker, VAX/X = share of direct domestic value added in gross exports, X = gross exports per worker.

Notes: ***p-value < 0.01, **p-value < 0.05, and *p-value < 0.10. Cluster-robust standard errors are in parentheses. All regressions include a 5-year lagged dependent variable term and sector-specific time effects. The RE columns include country and sector fixed effects. The FE columns include country-sector fixed effects.

Sources: International Trade Centre. Investment Map. http://www.investmentmap.org/; Organisation for Economic Co-operation and Development. 2015. Trade in Value Added Database. https://stats.oecd.org/index.aspx?queryid=66237; and World Bank. 2000–2014. World Input–Output Tables. http://www.wiod.org/home.

VII. Conclusions

In this paper, we have investigated how intra- and inter-industry FDI influences the average productivity of a sample of emerging market economies. Overall, we find a large positive effect of intra-industry FDI on total and export-related labor productivity. The fact that this effect is much harder to detect, in economic and statistical terms, when we examine the determinants of TFP suggests that foreign firms raise the performance of their host economies through a compositional effect. Foreign firms tend to be larger than domestic firms; they make more intensive use of (possibly better) physical capital, human capital, and intermediates; and they have greater access to foreign markets. Hence, their greater prevalence in a given sector mechanically increases average labor productivity and export performance.

As stressed by Lipsey (2004) and Navaretti and Venables (2005), this FDI-induced composition effect can be crucial for host countries' economic development. It should not be discounted in favor of potential foreign externalities for which we have not found robust evidence and whose existence is often conditional on domestic absorptive capacities.

In addition to improving their FDI attractiveness, governments should also ensure that they adopt policies that increase the quantity, quality, and technological level of local producers. This will leverage the benefits of FDI and sustain long-run economic development. These considerations led the Government of the PRC to introduce in 2006 and 2015, respectively, the Indigenous Innovation and Made in China 2025 policy packages to upgrade domestic manufacturing.

Finally, it should be acknowledged that our results need to be interpreted with caution. Our estimates are likely to be affected by an endogeneity bias that is related, at the very least, to measurement error. We nevertheless believe that our findings complement those based either on cross-country evidence or single-country, firm-level studies.

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Appendix. Descriptive Summary Statistics

Table A1. **List of Emerging Market Economies in the Database**

Central and Eastern Europe	Latin America	Asia
Bulgaria	Brazil	India
Czech Republic	Mexico	Indonesia
Hungary		People's Republic of China
Latvia		
Lithuania		
Poland		
Romania		
Russian Federation		
Slovakia		
Turkey		

Source: Authors' compilation.

Table A2. **Manufacturing and Service Sectors in the Database**

Broad Industry	ISIC rev 3.1	Sector Name	Median HFDI 2000 (%)	Median HFDI 2008 (%)
M	D15t16	Food, beverages, and tobacco	8	8
M	D17t19	Textiles, leather, and footwear	6	10
M	D20	Wood, of wood, and cork	5	12
M	D21t22	Pulp, paper, printing, and publishing	6	8
M	D23	Coke, refined petroleum, and nuclear fuel	25	46
M	D24	Chemicals and chemical products	14	29
M	D25	Rubber and plastics	15	14
M	D26	Other nonmetallic minerals	8	13
M	D27t28	Basic metals and fabricated metals	9	21
M	D29	Machinery, nec	20	42
M	D30t33	Electrical and optical equipment	41	57
M	D34t35	Transport equipment	30	42
M	D36t37	Manufacturing nec; recycling	18	17
S	E	Electricity, gas, and water supply	1	4
S	F	Construction	1	2
S	G	Wholesale and retail trade; repair of goods	6	7
S	H	Hotels and restaurants	4	6
S	I	Transport, storage and communications	5	5
S	J	Financial intermediation	28	42
S	K	Real estate, renting, and business activities	11	10
S	L	Public administration and defense	0	0
S	M	Education	0	0
S	N	Health and social work	0	0
S	O	Other community, social, and personal service activities	4	6

HFDI = intra-industry foreign direct investment, ISIC = International Standard Industrial Classification, M = manufacturing, nec = not elsewhere classified, S = services.
Source: Authors' compilation.

Table A3. **Summary Statistics**

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Value added ($) per worker (VA)	8,980.15	14,377.95	12.5	183,240.38	702
Real gross exports ($) per worker (X)	10,062.6	35,841.95	0	547,825.31	686
Real direct domestic VA ($) in gross exports (VAX)	2,542.46	6,247.34	0	72,482.41	684
Domestic use coefficient (δ)	0.61	0.17	0.17	0.97	702
Domestic supply coefficient (γ)	0.31	0.2	0	0.92	702
Domestic use coefficient from manufacturing sectors	0.18	0.13	0	0.71	702
Domestic supply coefficient to manufacturing sectors	0.11	0.1	0	0.51	698
Domestic use coefficient from service sectors	0.36	0.16	0.06	0.83	702
Domestic supply coefficient to service sectors	0.18	0.14	0	0.78	701
Share of foreign persons employed (HFDI)	19.89	25.29	1	101	702
HFDI in manufacturing sectors	27.78	18.01	2.8	67.23	702
HFDI in service sectors	10.28	6.15	2.24	22.56	702
Backward FDI linkages (BWFDI)	5.45	5.33	1	37.97	702
BWFDI from manufacturing sectors (BWFDIM)	4.09	4.54	1	35.29	702
BWFDI from service sectors (BWFDIS)	2.25	1.52	1	11.7	702
Forward FDI linkages (FWFDI)	9.75	7.72	1.38	56.23	702
FWFDI to manufacturing sectors (FWFDIM)	5.83	5.75	1.05	47.84	702
FWFDI to service sectors (FWFDIS)	4.56	3.54	1.15	35.43	702

Notes: Use (supply) coefficients are calculated as the share of inputs supplied by upstream (to downstream) industries. Foreign direct investment (FDI) variables have been transformed using $FDI * 100 + 1$. BWFDI (FWFDI) variables are the product of the supply coefficient γ (use coefficient δ) and HFDI in the downstream (upstream) sector.
Sources: Authors' calculations and International Trade Centre. Investment Map. http://www.investmentmap.org/; Organisation for Economic Co-operation and Development. 2015. Trade in Value Added Database. https://stats.oecd.org/index.aspx?queryid=66237; and World Bank. 2000–2014. World Input–Output Tables. http://www.wiod.org/home.

Table A4. **Skill Proxies**

Region	Schooling (Years)	Broad Industry	Share of Skilled Workers
Latin America	7.2	Manufacturing	0.57
		Services	0.65
Asia	6.4	Manufacturing	0.44
		Services	0.63
Central and Eastern Europe	10.8	Manufacturing	0.68
		Services	0.78

Notes: The share of skilled workers equals the share in total hours worked by high- and medium-skilled workers. Schooling represents the median of average years of schooling per country over the period 2000–2010.
Sources: International Trade Centre. Investment Map. http://www.investmentmap.org/; Organisation for Economic Co-operation and Development. 2015. Trade in Value Added Database. https://stats.oecd.org/index.aspx?queryid=66237; Wittgenstein Centre for Demography and Global Human Capital. 2015. Wittgenstein Centre Data Explorer Version 1.2. http://witt.null2.net/shiny/wic/; and World Bank. 2000–2014. World Input–Output Tables. http://www.wiod.org/home.

Table A5. **Region-Specific Labor Productivity, 2000**

Region	Value Added per Worker (\$, VA_{2000})
Latin America	11,652.87
Asia	4,007.16
Central and Eastern Europe	5,144.67

Source: International Trade Centre. Investment Map. http://www.investmentmap.org/.

Labor Market Returns to Education and English Language Skills in the People's Republic of China: An Update

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We reexamine the economic returns to education in the People's Republic of China (PRC) using data from the Chinese General Social Survey 2010. We find that the conventional ordinary least squares estimate of wage returns to schooling is 7.8%, while the instrumental variable estimate is 20.9%. The gains from schooling rise sharply with higher levels of education. The estimated returns are 12.2% in urban provinces and 10.7% in coastal provinces, higher than in rural and inland areas. In addition, the wage premium for workers with good English skills (speaking and listening) is 30%. These results are robust to controls for height, body mass index, and English language skills, and to corrections for sample selection bias. Our findings, together with a critical review of existing studies, confirm the growing significance of human capital as a determinant of labor market performance in postreform PRC.

Keywords: endogeneity bias, health, language skills, schooling
JEL codes: I26, J30

I. Introduction

The People's Republic of China (PRC) saw a four-fold increase in the level of consumption per capita and unprecedented economic growth during 1980–2010. The country's transition to a market economy saw the dissolution of social safety net programs and the end of full employment. Substantial physical capital investment during this transition led to greater demand for high-skilled labor, thereby increasing the importance of education as a determinant of labor market earnings (Heckman and Yi 2012). In prereform years, wages were administratively

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set, which suppressed the true returns to cognitive skills and schooling (Fleisher and Chen 1997, Chen and Feng 2000, Démurger 2001, Fleisher and Wang 2004). Returns to schooling were low in the early years after the beginning of economic reform in 1978 but increased in the 1990s (Zhao and Zhou 2002).[1] Therefore, an updated analysis of how education is paying off in the labor market is important for understanding the evolution of income distribution in transition economies.

The PRC's rapid economic growth was accompanied by a considerable increase in earnings inequality.[2] Moreover, the country's postreform "open door" policy attracted foreign direct investment and multinational companies, leading to strong demand for skilled workers along the rapidly expanding industrial coast.[3] Therefore, it is important to understand how skills and education are rewarded across rural and urban locations, and across coastal and inland cities.[4]

Understanding the determinants of rising returns to education—a labor market phenomenon in transition economies—can also help us understand the difference between the PRC and other transition countries in terms of labor market characteristics. Unsurprisingly, following the shift from an administratively determined wage system to a market-oriented one in the early 1990s, there has been a significant increase in research on the economic profitability of human capital investment in the PRC.

Most estimates of labor market returns correspond to the early years of reform and hence are unlikely to be a good guide given the unprecedented transformation of the PRC economy during the 1990s. Spatial differences in infrastructure growth and physical investment are also likely to have caused important variations in the way schooling impacts labor market earnings (Fleisher and Chen 1997). Therefore, we add to the existing literature by using the Chinese General Social Survey (CGSS) 2010 dataset and provide an up-to-date account of the labor market returns to education in the PRC.

Our empirical model accounts for two important determinants of earnings: health capital, which includes height, body mass index (BMI), and self-reported health status; and English language proficiency that were both ignored by most of the recent studies on the PRC. Moreover, our empirical analysis addresses concerns over endogeneity and sample selection biases. We use information on parental death during the respondent's childhood and parental schooling as excluded instruments to estimate the instrumental variable (IV) model. Nonrandom selection into waged work is modeled using data on various measures of nonlabor income. Lastly, we

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[1]This pattern of rising returns to education is similar to the experience of other economies in Central and Eastern Europe that went through the transition from a planned economy to a market economy (Hung 2008).

[2]According to one account, the average real earnings of Chinese urban male workers increased by 350% during 1988–2009, increasing the variance in log earnings by 94% (Meng, Shen, and Xue 2013).

[3]For the interplay between human capital and foreign direct investment in the PRC, see Liu, Xu, and Liu (2004); Su and Liu (2016); and Salike (2016).

[4]According to Hung (2008), the returns to education in Central and Eastern Europe were about 2%–4% in the pretransition period, while those in the PRC were even lower at less than 2%.

report estimates for various subgroups—men versus women, rural versus urban, and coastal versus inland provinces—to document the heterogeneous nature of returns to schooling and skills in postreform PRC.

The rest of the paper is organized as follows. Section II briefly reviews the literature. Section III and section IV describe the data and empirical framework used in our study, respectively. Section V presents our econometric results. We conclude in section VI.

II. Literature Review: What Do We Know about Returns to Education in the People's Republic of China?

Existing studies on the PRC have estimated a Mincer-type earnings function using a variety of micro datasets. Our review of the published literature on returns to education for the period 1987–2016 identified a total of 68 studies (Table 1).[5]

Of these studies, 52 included residents in urban areas, 8 included residents in rural areas, and 10 were rural–urban migrants, while only 6 covered both urban and rural areas. Most studies (59) used household survey datasets. These include the Chinese Household Income Project (CHIP, 27 studies); China Health and Nutrition Survey (CHNS, 5); Chinese Twins Survey (4); China Urban Labor Survey (CULS, 3); Panel Data of Urban Residents from 20 cities in six provinces (3); China Urban Household Income and Expenditure Survey (CUHIES, 2); and Urban Household Survey (UHS, 2). A total of 13 studies used data from other well-established household surveys, such as the Chinese Labor Market Research Project (CLMRP) and Rural Urban Migration in China (RUMiC), among others. The remaining 8 studies used data from several firm-based surveys, while only 1 study (Mishra and Smyth 2015) used data from both a household survey (China Household Finance Survey) and a firm-level survey (Shanghai matched worker-firm survey 2007). In this section, we discuss only those studies that used household survey datasets.

A stylized fact from the literature is that returns to education in the PRC labor market in the 1980s and early 1990s were extremely low compared with the average returns in other Asian countries (9.6%), low- and middle-income countries (11.2%–11.7%), and the world (10.1%) (Psacharopoulos 1994). The rate of return in studies using data from the 1986, 1988, and 1993 CHIP surveys ranged from 1.5% to 4.5% for urban areas (Knight and Song 1991, 1995; Xie and Hannum 1996; Johnson and Chow 1997; Liu 1998; Maurer-Fazio 1999) and 0%–4% for rural areas (Knight and Song 1993; Parish, Zhe, and Li 1995; Johnson and Chow 1997). Apart from the findings using CHIP dataset, researchers who employed data from other household surveys during this period found comparatively low rates of return to

[5]For existing meta-analyses of studies on returns to education in the PRC, see Liu and Zhang (2013) and Awaworyi and Mishra (2014). Moreover, for a review of developing country estimates, see Psacharopoulos and Patrinos (2004).

Table 1. **Summary of Existing Studies on Returns to Education in the People's Republic of China**

Data Source	Sample	Author	Study Period	Method	Returns Estimate (%)
Chinese Household Income Project (CHIP)	Urban and rural	Johnson and Chow (1997)	1988	OLS	3.3–4.0
	Urban	Knight and Song (1991)	1986	OLS	2.4–3.0
		Knight and Song (1995)	1988	OLS	2.3
		Xie and Hannum (1996)	1988	OLS	2.2–4.5
		Liu (1998)	1988	OLS	2.9–3.6
		Maurer-Fazio (1999)	1988	OLS	4.5 (female), 2.9 (male)
		Li (2003)	1995	OLS	5.4
		Bishop and Chiou (2004)	1988–1995	OLS	2.8 (1988)–5.6 (1995)
		Li and Luo (2004)	1995	OLS; IV; GMM	7.5–8.9; 15.3–15.6; 15.0
		Appleton, Song, and Xia (2005)	1988–2002	OLS	3.6 (1988)–7.5 (2002)
		Bishop, Luo, and Wang (2005)	1988–1995	OLS	1.5 (1988)–4.4 (1995)
		Hauser and Xie (2005)	1988–1995	OLS	2.0 (1988)–7.4 (1995)
		Knight and Song (2005)	1995–1999	OLS	3.2 (1995)–4.1 (1999)
		Yang (2005)	1988–1995	OLS	3.3–3.9 (1988) to 5.9–7.3 (1995)
		Démurger et al. (2009)	2002	OLS	4.2–7.4
		Zhong (2011)	2002	OLS; IV	6.0–6.8; 4.2–6.5
		Wang (2013)	1995–2002	OLS; IV	5.6 (1995, female)–8.1 (2002, female), 3.6–6.6 (male); 7.3–11.8 (female), 4.4–8.8 (male)
		Qu and Zhao (2017)	2002–2007	OLS	6.0–9.6 (2002) to 2.1–4.0 (2007)
	Rural	Knight and Song (1993)	1988	OLS	Not statistically different from 0
		Parish, Zhe, and Li (1995)	1993	OLS	3.1
	Migrants	Démurger et al. (2009)	2002	OLS	3.6–7.3
		Zhu (2015)	2002–2007	OLS; NP	3.8 (2002)–4.9 (2007); 4.8–5.5
		Qu and Zhao (2017)	2002–2007	OLS	2.3–2.9 (2002) to 3.3–3.8 (2007)

Continued.

Table 1. *Continued.*

Data Source	Sample	Author	Study Period	Method	Returns Estimate (%)
China Health and Nutrition Survey (CHNS)	Urban and rural	Fang et al. (2012)	1997–2006	OLS; IV	9; 20
	Urban	Chen and Hamori (2009)	2004–2006	OLS; IV	7.7 (female), 8.1 (male), 7.9 (married women), 8.0 (married men); 14.5 (married women), 12.6 (married men)
		Qiu and Hudson (2010)	1989–2000	OLS	5.1–6.9
		Kang and Peng (2012)	1989–2009	OLS; IV	2.2 (1989, female)–10.3 (2009, female), 2.6–7.0 (male); 5.7–8.9 (female), 5.6–11.0 (male)
		Ren and Miller (2012)	1993–2006	OLS	2.0 (1993, female)–5.2 (2006, female), 0.8–5.6 (male)
Chinese Twins Survey	Urban	Li, Liu, Ma, and Zhang (2005)	2002	OLS; FE; GLS	8.2–8.4; 2.5–2.7; 2.5–2.7
		Li et al. (2007)	2002	OLS; FE; GLS	6.3–7.0; 3.2; 3.3
		Zhang, Liu, and Yung (2007)	2002	OLS; IV	8.8–9.8; 9.1–10.5
		Li, Liu, and Zhang (2012)	2002	OLS; FE	8.4; 2.7–3.8
China Urban Labor Survey (CULS)	Urban	Giles, Park, and Wang (2008)	2001	OLS; IV	8.3–9.6; 8.0–8.3
		Cai and Du (2011)	2001–2010	OLS	10.2 (2001)–11 (2010)
		Gao and Smyth (2015)	2001–2010	OLS; IV; Lewbel IV	6.8 (2001)–8.6 (2010); 8.2–9.1; 5.2–4.8
Panel Data of Urban Residents in 20 cities	Urban	Zhao and Zhou (2002)	1978–1993	OLS	1.8–3.5
		Fleisher and Wang (2005)	1975–1991	OLS; IV	1.4 (1975)–5.9 (1991); -0.1–15.8
Urban Household Survey (UHS)	Urban	Zhang et al. (2005)	1988–2001	OLS; Heckman	5.2 (1988, female)–13.2 (2001, female), 2.9–8.4 (male); 5.2–12.5 (female), 2.8–7.5 (male)
		Ge and Yang (2011)	1988–2007	OLS	3.6 (1988)–11.4 (2007)
Rural Urban Migration in China (RUMiC)	Urban	Sakellariou and Fang (2016)	2009	IV	6–9
	Migrants	Sakellariou and Fang (2016)	2009	IV	7–8
China Household Finance Survey (CHFS)	Urban	Mishra and Smyth (2015)	2011	OLS; IV; Lewbel IV	8.6–8.7; 17.5–18.9; 12.9–13.5

Continued.

Table 1. *Continued.*

Data Source	Sample	Author	Study Period	Method	Returns Estimate (%)
Others	Urban	Jamison and Van Der Gaag (1987)	1985	OLS	5.5 (female), 4.5 (male)
		Byron and Manaloto (1990)	1986	OLS; WLS	3.7; 3.9
		Maurer-Fazio (1999)	1992	OLS	4.9 (female), 3.7 (male)
		Qian and Smyth (2008b)	2005	OLS	12.1 (full sample), 9.3 (female), 13.6 (male)
		Deng and Li (2010)	2008	OLS	5.6–6.8
		Mishra and Smyth (2013)	2009–2010	OLS; IV	10.8–11.9; 21.4–22.9
		Jamison and Van Der Gaag (1987)	1985	OLS	5.5 (female), 4.5 (male)
	Rural	Yang (1997)	1990	OLS	2.3
		Wei et al. (1999)	1991	OLS	4.8
		De Brauw and Rozelle (2008)	2000	Heckman	4.3
	Migrants	Meng and Zhang (2001)	1996	OLS	4.8
		De Brauw and Rozelle (2008)	2000	Heckman	7.8
		Deng and Li (2010)	2008	OLS	6.8
		Frijters, Lee, and Meng (2010)	2008	OLS	3.0–4.0

FE = fixed effects, IV = instrumental variable, GLS = generalized least squares, GMM = generalized method of moments, NP = nonparametric kernel regression (nonparametric estimation), OLS = ordinary least squares, WLS = weighted least squares.

Notes: Only studies that used household survey data are presented in the table. Eleven studies that estimated only returns to higher education (college education) were excluded from the table (Gustafsson and Li 2000; Zhou 2000; Knight and Song 2003; Heckman and Li 2004; Fleisher et al. 2005; Wang et al. 2007; Li et al. 2012; Wang 2012; Carnoy et al. 2013; Meng, Shen, and Xue 2013; Messinis 2013). Eight studies that used only firm survey data were excluded from the table (Peng 1992; Gregory and Meng 1995; Fleisher, Dong, and Liu 1996; Meng and Kidd 1997; Fleisher and Wang 2001, 2004; Ho et al. 2002; Maurer-Fazio and Dinh 2004). One study (Mishra and Smyth 2015) used both household survey data (CHFS) and firm survey data (2007 Shanghai-matched worker–firm survey), but only the results based on household survey data are listed in the table.

Source: Authors' review of the literature.

schooling, around 3.7%–5.9% for urban areas, compared with 2.3%–4.8% for rural areas (Jamison and Van Der Gaag 1987, Byron and Manaloto 1990, Yang 1997, Wei et al. 1999, Maurer-Fazio 1999, Zhou 2000, Zhao and Zhou 2002, Fleisher and Wang 2005).

Another stylized fact is that returns to education have increased since the mid-1990s, along with improvements in wages and workers' contractual rights (Chan and Nadvi 2014). Studies that employed CHIP datasets found that the economic returns to each additional year of schooling increased to around 4.4%–8.9% in 1995 (Li 2003; Bishop and Chiou 2004; Li and Luo 2004; Bishop, Luo, and Wang 2005; Hauser and Xie 2005; Yang 2005), 4.1% in 1999 (Knight and Song 2005), 7.5%–8.1% in 2002 among urban residents (Appleton, Song, and Xia 2005; Wang 2013), and 3.6%–7.3% in 2002 among migrants (Démurger et al. 2009).

Findings from studies using non-CHIP datasets also indicate an increased rate of return after 1995. For example, research using another widely used dataset, CHNS, found that the rate of return rose sharply to 6.9% in 2000 (Qiu and Hudson 2010), 8.1% in 2004 (Chen and Hamori 2009), and around 9% in 2006 (Fang et al. 2012) in urban areas. Again, based on the CHNS dataset, Ren and Miller (2012) found that the returns to women increased from 2% in 1993 to 7% in 2004, while the returns to men increased from 0.8% to 3.1%. Similarly, Kang and Peng (2012) documented a larger increase in returns to education for Chinese women than men using the expanded CHNS dataset from 1989 to 2009. More precisely, the rate increased from 2.2% in 1989 to 10.3% in 2009 for women, but only from 2.6% to 7% for men. Additionally, these increased returns to schooling since the mid-1990s have been recorded in a large number of studies that used non-CHIP or non-CHNS survey datasets, including studies on rural workers (De Brauw and Rozelle 2008); migrant workers (Meng and Zhang 2001; Maurer-Fazio and Dinh 2004; De Brauw and Rozelle 2008; Deng and Li 2010; Frijters, Lee, and Meng 2010; Sakellariou and Fang 2016); and urban workers using the Chinese Twins Survey dataset (Li, Liu, Ma, and Zhang 2005; Zhang, Liu, and Yung 2007; Li et al. 2007; Li et al. 2012); CULS (Giles, Park, and Wang 2008; Cai and Du 2011; Gao and Smyth 2015); and CUHIES (Meng, Shen, and Xue 2013).

Apart from the overall returns to education, earlier studies looked into returns to specific education levels. Studies based on data from the period after higher education reform documented a sharp increase in returns to college education (Heckman and Li 2004; Fleisher et al. 2005; Giles, Park, and Wang 2008; Qian and Smyth 2008b; Zhong 2011; Li et al. 2012; Wang 2012; Carnoy et al. 2013; Meng, Shen, and Xue 2013), compared with those from before the reform period (Gustafsson and Li 2000, Knight and Song 2003, Li 2003, Bishop and Chiou 2004). Moreover, research on the postreform period argued that graduates from elite colleges earned a premium over other college graduates even after controlling for cognitive ability, academic major, college location, and students' individual characteristics and family backgrounds (Zhong 2011, Li et al. 2012). Existing literature also found that women benefited more from a university education than men, and similarly, urban residents earned more than rural residents with the same college degree (Qian and Smyth 2008, Wang 2012).

The pattern of returns to education in different regions has also changed since the mid-1990s. In contrast to the finding of Liu (1998), Li (2003) observed that the rate of return was higher in less developed provinces, such as Gansu, than in high-income provinces, such as Guangdong.

There are additional stylized facts relating to methodological issues. First, recent research has employed an instrumental variable (IV) approach to solve the endogeneity bias in educational attainment.[6] For the PRC, the IV estimates were higher than the corresponding ordinary least squares (OLS) estimates (Fleisher and Wang 2004; Heckman and Li 2004; Li and Luo 2004; Fleisher et al. 2005; Fleisher and Wang 2005; Zhang, Liu, and Yung 2007; Giles, Park, and Wang 2008; Chen and Hamori 2009; Zhong 2011; Fang et al. 2012; Kang and Peng 2012; Wang 2012; Mishra and Smyth 2013; Wang 2013; Gao and Smyth 2015; Mishra and Smyth 2015; Sakellariou and Fang 2016). Most of these studies used family-background variables to estimate the IV model. For instance, Heckman and Li (2004) used the 2000 CUHIES, and parental education and year of birth as instruments for an individual's education. Similarly, based on the 1995 CHIP data, Li and Luo (2004) estimated returns to schooling for young workers in urban areas using parental education and variables related to siblings as instruments. Moreover, using the 1988–2002 CHIP data, Fleisher et al. (2005) explored the private returns to schooling at the university level. They found that the IV and semiparametric estimates on the rate of return for college graduates were higher when parental schooling was the proxy for ability.[7]

In summary, while findings from existing research vary in terms of data sources, methods, and study periods, they generally confirm that gains from schooling have increased significantly. The estimated returns to schooling are higher in urban areas than in rural locations, and higher for female workers than for male workers. Moreover, the IV estimates that used parental education as instruments for an individual's schooling yielded higher returns than the OLS estimates. For the prereform period, the OLS estimates of the rate of return are around 1.4%–1.9% in urban areas, compared with 0%–2.6% in rural areas. For the postreform period, the OLS estimates show an increase of 3.3%–9% for the full sample, compared with the IV estimates of up to 20%. The OLS estimates also show an increase of

[6]For relevant international studies, see Arabsheibani and Lau (1999); Trostel, Walker, and Woolley (2002).

[7]Recently, some researchers have used the Lewbel (2012) IV method rather than the traditional IV approach to study the returns to schooling in the PRC, especially in urban areas (Gao and Smyth 2015, Mishra and Smyth 2015). Findings from either the conventional IV approach or the Lewbel IV method suggest that measurement errors exert a downward bias on OLS estimates.

0%–4.8% for the rural sample, and OLS estimates of 1.5%–12.1% for the urban sample, compared with the IV estimates of 4.2%–22.9%.

III. Data

In this paper, we use data from the CGSS 2010. The main advantage of CGSS over existing datasets (such as CHNS, CHIP, CLMRP, and RUMiC) is that, in addition to being representative of rural and urban areas of the PRC, it offers information on both language skills and health of the respondents. The CGSS 2010 sampled a total of 11,783 individuals, where 38.7% were from rural areas and 51.8% were women. Table A1 provides a breakdown of the sample observations across different groups and work status: (i) agricultural waged work, (ii) nonagricultural waged work, (iii) self-employed, (iv) in the labor force but unemployed, and (v) not in the labor force. Most studies relied on the second age group, females age 16–55 years and males age 16–60 years (16 is the youngest legal working age in the PRC, while 55 and 60 are the official retirement age). In this study, we follow Schultz (2002) and restrict the analysis to women age 25–55 years and men age 25–60 years. Our main analysis is restricted to individuals in waged work, both in agricultural and nonagricultural sectors. After ignoring cases with missing data, our working sample contains 4,223 waged workers. Table A2 summarizes all variables used in the regression analysis.

IV. Empirical Framework

As explained in section II, past studies on the PRC rarely controlled for cognitive skills despite the fact that market reforms of the 1990s were likely to have increased demand for such language and numeracy skills. Although schooling is expected to capture returns to cognitive skills, recent research documents a systematic economic return to cognitive skills around the world independent of schooling completed (Hanushek et al. 2015). Therefore, it is useful to know, in the context of the PRC, the pathways through which schooling is rewarded in the labor market.

Similarly, individuals with more schooling may have higher wages because they have better health and healthier behaviors.[8] At the same time, school attendance may ignore skills acquired through social channels and in the workplace. Existing studies on the PRC have not fully considered the interaction between schooling, skills, and health capital in determining labor market success. Recent studies have instead focused on the possibility that schooling is endogenous, owing to omitted health components, or that return to schooling is understated,

[8]The positive relationship between schooling and health is well established in the literature (see, for example, Grossman 2008; Silles 2009; Conti, Heckman, and Urzua 2010; and Heckman et al. 2014).

because it does not capture the quality of human capital. Consequently, researchers have modeled schooling attainment as an endogenous determinant of earnings by employing instrumental variable techniques (Li and Luo 2004, Heckman and Li 2004, Mishra and Smyth 2013, Chen and Hamori 2009, Mishra and Smyth 2015, Gao and Smyth 2015, Sakellariou and Fang 2016). In addition, some researchers have accounted for nonrandom selection into waged work by employing Heckman's (1979) two-step procedure (Zhang et al. 2005, Chen and Hamori 2009).

Keeping the above issues in mind, we specify a Mincerian earnings function where the log of monthly employment income (measured in renminbi) is regressed on years of schooling; work experience; work experience squared; gender; marital status; and a series of additional control variables including ethnicity; *hukou* type; marital status; health factors (height, self-reported health status, and BMI); proficiency in English; and location dummies.[9] In addition, we account for the endogeneity of years of schooling in the earnings function.

Existing studies on developed and developing countries such as the PRC have attempted to address the issue in an IV framework in two settings: experimental and nonexperimental. Experimental studies rely on various institutional reforms, such as changes in the minimum age of leaving school (Harmon and Walker 1995), which result in exogenous variation in educational attainment. Nonexperimental studies, on the other hand, use family background (Li and Luo 2004); parents' education (Heckman and Li 2004, Mishra and Smyth 2013); and spouse's education (Chen and Hamori 2009, Mishra and Smyth 2013, Gao and Smyth 2015) as instruments for education in the PRC and other countries (Trostel, Walker, and Woolley 2002). In this paper, we follow the second approach.

Therefore, in addition to OLS estimates, we present IV estimates where we instrument schooling completed using the following as excluded instruments: whether a parent died when the respondent was 14 years old, father's education, and mother's education. Following Case, Paxson, and Ableidinger (2004) and Gertler, Levine, and Ames (2004), we assume that timing of parental death is exogenous and serves as a negative shock to the respondent's schooling. On the other hand, the father's and mother's education are not correlated to their children's inherent abilities but have influence on their children's education when we use them as excluded instruments. It should be noted that studies that used parental education as an instrument to estimate returns to education in the PRC have often done so only for a subsample. This is because of how the survey is designed, where the instruments are available only for the respondents whose parents are present in the

[9]Since CGSS does not have data on work experience or tenure, we use information on age and school completion to define postschool experience. We assume the legal age for starting work is 16 years old. For those who completed secondary schooling, we calculate experience as current age minus years of schooling minus 6, but for those who didn't complete secondary schooling, experience is current age minus 16. This definition is consistent with existing studies on the PRC (Qian and Smyth 2008b, Gao and Smyth 2015, Mishra and Smyth 2015).

same household (Wang 2013). Our dataset doesn't suffer from this problem as all respondents are asked about parental background in a retrospective manner.

Apart from the endogeneity problem, another common methodological concern is the sample selection problem. If individuals select into the labor force on the basis of some unobserved attributes that also affect their wages, OLS estimates would yield biased estimates of the correlation between education and wages. In this paper, we follow Heckman (1979) to correct for nonrandom selection into waged work. First, we estimate a probit function for labor force participation where a sample selection correction term, lambda, is computed. Then the earnings function is estimated with the selection correction term as an extra variable. For the purpose of identifying the lambda term, at least one variable needs to be excluded from the wage equation, which is otherwise included in the probit equation. In our model, we follow Duraisamy (2002) and Asadullah (2006) who used data on nonlabor income (i.e., income received from bequest) as an excluded variable, leaving it out of the wage equation.[10]

V. Results

A. Ordinary Least Squares Estimates of Returns to Education

In this section, we estimate returns to education by adding additional controls for factors that are correlated with both wages and schooling. Moreover, we formally include a measure of English language skills alongside schooling.[11] Table 2 reports OLS estimates of the Mincerian earnings function for the full sample. To understand the true returns to education, we pursue a stepwise approach, sequentially adding controls for language proficiency and three measures of health—height, self-reported health status, and BMI—in the regression function. Four patterns follow from our analysis.

First, education has a significant and positive impact on earnings in the PRC even after we control for English language proficiency and health capital (specification 3). The rate of return to an additional year of schooling ranges from 7.8% to 8.8% in the full sample. Our OLS estimate is similar to the estimated average rate reported in existing literature on the PRC, which ranges between 7% and 10% (Chen and Hamori 2009, Mishra and Smyth 2015). The biggest decline in estimated returns to education (from 8.8% to 8%) occurs when we control for language proficiency (specification 1 versus 2). The decline in the rate of return to education after controlling for language skills may simply be because English is part of the institutional education received in school. Therefore, when such components

[10]We also considered income from land leasing and sale of property as additional identifying variables, but these were not significant in the first stage.

[11]English language skills are measured as a binary indicator and refers to proficiency at or above the standard level.

Table 2. **Ordinary Least Squares Estimates of the Determinants of Earnings with and without Controls for Language Skills and Health Endowments (full sample)**

	(1)	(2)	(3)	(4)	(5)
Personal characteristics					
Experience	0.004	0.005	0.006	0.008	0.008
	(0.59)	(0.75)	(1.03)	(1.30)	(1.20)
Experience squared	−0.001	−0.001**	−0.001**	−0.001**	−0.001**
	(1.01)	(2.22)	(2.32)	(2.27)	(2.19)
Female	−0.376***	−0.393***	−0.246***	−0.237***	−0.235***
	(14.64)	(15.32)	(7.05)	(6.83)	(6.75)
Minority	−0.002	0.003	0.007	−0.012	−0.011
	(0.04)	(0.06)	(0.17)	(0.27)	(0.27)
Nonagricultural *hukou*	0.205***	0.196***	0.175***	0.174***	0.173***
	(5.59)	(5.36)	(4.79)	(4.79)	(4.76)
Currently married	0.055	0.074	0.071	0.048	0.048
	(1.29)	(1.76)	(1.69)	(1.16)	(1.15)
Schooling and cognitive skills					
Years of education	0.088***	0.080***	0.079***	0.078***	0.078***
	(20.98)	(18.51)	(18.39)	(18.24)	(18.16)
Good English skills		0.317***	0.306***	0.306***	0.307***
		(7.10)	(6.88)	(6.92)	(6.94)
Health capital					
Height (centimeters)			0.014***	0.013***	0.014***
			(6.14)	(5.79)	(5.84)
Self-reported health status:					
Bad				−0.178***	−0.179***
				(3.94)	(3.95)
Good				0.116***	0.112***
				(3.75)	(3.60)
Body mass index (BMI):					
BMI < 18.5, underweight					−0.061
					(1.24)
25 ≤ BMI < 30, overweight					0.002
					(0.07)
BMI≥30, obese					−0.147*
					(1.68)
Geographic location					
Rural	−0.420***	−0.423***	−0.423***	−0.413***	−0.413***
	(11.54)	(11.68)	(11.73)	(11.52)	(11.50)
Eastern (coastal) region	0.404***	0.388***	0.376***	0.370***	0.371***
	(12.90)	(12.43)	(12.10)	(11.97)	(12.00)
Western region	−0.052	−0.057	−0.039	−0.022	−0.021
	(1.60)	(1.77)	(1.21)	(0.68)	(0.66)
Constant	6.238***	6.164***	3.712***	3.770***	3.773***
	(60.03)	(59.35)	(9.01)	(9.19)	(9.19)
Number of observations	4,223	4,223	4,223	4,223	4,223
Adjusted R-squared	0.49	0.49	0.50	0.51	0.51

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. "Good English skills" is a dummy variable which indicates whether a respondent's English skills (including speaking and listening) are at or above the standard proficiency level (=1) or not (=0). For self-reported health status, the reference category is "in normal health condition." For body mass index (BMI), the reference category is "normal, 18.5 ≤ BMI < 25." For regional dummies, the reference group is "central region."
Sources: Chinese General Social Survey (CGSS) and authors' calculations.

of education are included in the regression, they underestimate the true returns to education.

Second, in contrast to Mishra and Smyth (2015) where language proficiency has no statistically significant relationship with wages in the PRC, our results indicate a clear correlation—individuals with good English speaking and listening abilities earn wages that are 30% higher than those who do not have these skills (column 5). This positive earnings premium from foreign language skills is consistent with existing studies focusing on both developed countries (Leslie and Lindley 2001, Dustmann and Fabbri 2003 on the United Kingdom, Bleakley and Chin 2004 on the United States) and other developing countries (Azam, Chin, and Prakash 2013 on India; Di Paolo and Tansel 2015 on Turkey). Moreover, compared with returns to other skills, the returns to a foreign language (i.e., English skills) are extremely high (Fasih, Patrinos, and Sakellariou 2013).[12]

Third, consistent with the literature for both developed countries (Case and Paxson 2008, 2009; Heineck 2008; Hübler 2006) and developing countries (Schultz 2002, 2003; Dinda et al. 2006), health capital matters for earnings in the PRC. The OLS estimates suggest an additional centimeter of adult height is associated with a 1.4% higher wage in the full sample. This result is very close to some of the recent studies on returns to health capital in the PRC, including Gao and Smyth (2010) who were the first to confirm the height–wage premium in the PRC using the CULS 2005 data. They found that the wage return to height in urban areas is 1.1% and 0.9% for men and women, respectively. A later study by Elu and Price (2013) documented a similar rate of return to height (1.1%) based on urban and rural sample data from the CHNS 2006. Besides the height–wage premium, the returns to self-reported health status in our paper are also close to the results found by Zhang (2011) and Fang et al. (2012).

Fourth, work experience is not rewarded in terms of higher wages in the full sample. Subsample estimates of the earnings function presented in Table 3 show that this is also true for rural areas of the PRC.[13] However, we find a significant and inverse U-shaped relationship between experience and earnings in urban areas of the PRC. This is consistent with previous studies on urban areas of the PRC (Bishop and Chiou 2004; Appleton, Song, and Xia 2005; Gao and Smyth 2015). The return to work experience is low, only 2.7% in urban areas of the PRC using the CGSS 2010 dataset. This is in line with Appleton, Song, and Xia (2005), who document an increase in returns to education but a decrease in the returns to work experience in postreform PRC. Bishop and Chiou (2004) also report evidence of declining returns to experience in urban areas of the PRC between 1988 and 1995. One

[12]This is also true for the PRC. For example, Giles et al. (2003), using data from the China Adult Literacy Survey (CALS), find that the estimated return to adult literacy (capturing knowledge of the vernacular) for residents in urban areas of the PRC is 9.3%–11.4%.

[13]For rural areas of the PRC, Li, De Brauw, Rozelle, and Zhang (2005) also find experience to be insignificant, based on Heckman estimates of the earnings function.

Table 3. **Ordinary Least Squares Estimates of the Determinants of Earnings with and without Controls for Language Skills and Health Endowments (urban versus rural)**

	Urban					Rural				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Personal characteristics										
Experience	0.021***	0.027***	0.028***	0.028***	0.027***	0.009	0.006	0.004	0.001	0.001
	(2.57)	(3.28)	(3.42)	(3.42)	(3.35)	(0.83)	(0.57)	(0.35)	(0.07)	(0.01)
Experience squared	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001	−0.001	−0.001	−0.001	−0.001
	(2.87)	(3.46)	(3.52)	(3.36)	(3.33)	(0.94)	(1.17)	(1.27)	(1.45)	(1.38)
Female	−0.369***	−0.377***	−0.278***	−0.278***	−0.278***	−0.503***	−0.511***	−0.336***	−0.321***	−0.319***
	(12.16)	(12.49)	(6.29)	(6.30)	(6.28)	(11.71)	(11.85)	(6.19)	(5.94)	
Minority	−0.102	−0.091	−0.093	−0.101	−0.099	0.041	0.041	0.053	0.029	0.030
	(1.63)	(1.47)	(1.50)	(1.64)	(1.61)	(0.68)	(0.69)	(0.90)	(0.51)	(0.51)
Nonagricultural *hukou*	0.045	0.045	0.034	0.031	0.031	0.634***	0.611***	0.595***	0.586***	0.584***
	(1.25)	(1.28)	(0.95)	(0.88)	(0.88)	(6.12)	(5.86)	(5.75)	(5.72)	(5.69)
Currently married	−0.032	−0.017	−0.013	−0.024	−0.025	0.265***	0.266***	0.241***	0.197**	0.197**
	(0.69)	(0.37)	(0.29)	(0.53)	(0.54)	(3.32)	(3.34)	(3.04)	(2.50)	(2.50)
Schooling and cognitive skills										
Years of education	0.132***	0.124***	0.123***	0.122***	0.122***	0.026***	0.024***	0.024***	0.023***	0.022***
	(26.64)	(23.89)	(23.68)	(23.59)	(23.51)	(3.75)	(3.42)	(3.35)	(3.29)	(3.22)
Good English skills		0.215***	0.210***	0.209***	0.208***		0.298**	0.289**	0.282**	0.285**
		(5.08)	(4.96)	(4.96)	(4.92)		(1.91)	(1.86)	(1.83)	(1.86)
Health capital										
Height (centimeters)			0.009***	0.009***	0.009***			0.018***	0.016***	0.016***
			(3.08)	(3.01)	(3.08)			(5.19)	(4.61)	(4.64)
Self-reported health status:										
Bad				−0.192***	−0.194***				−0.109*	−0.108*
				(2.91)	(2.95)				(1.71)	(1.70)
Good				0.042	0.035				0.214***	0.211***
				(1.13)	(0.96)				(4.24)	(4.16)

Continued.

Table 3. *Continued.*

	Urban					Rural				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Body mass index (BMI):										
BMI < 18.5, underweight					−0.052					−0.046
					(0.81)					(0.64)
25 ≤ BMI < 30, overweight					−0.012					0.044
					(0.33)					(0.79)
BMI ≥ 30, obese					−0.240**					−0.023
					(2.38)					(0.16)
Geographic location										
Eastern (coastal) region	0.475***	0.465***	0.458***	0.452***	0.453***	0.244***	0.244***	0.233***	0.216***	0.216***
	(13.00)	(12.74)	(12.55)	(12.40)	(12.45)	(4.41)	(4.41)	(4.25)	(3.98)	(3.97)
Western region	0.084	0.085*	0.098**	0.102**	0.102**	−0.198***	−0.200***	−0.178***	−0.152***	−0.149***
	(1.87)	(1.89)	(2.19)	(2.28)	(2.27)	(4.35)	(4.40)	(3.94)	(3.38)	(3.29)
Constant	5.449***	5.418***	3.878***	3.906***	3.898***	6.395***	6.366***	3.192***	3.361***	3.354***
	(45.35)	(45.28)	(7.54)	(7.60)	(7.58)	(35.68)	(35.42)	(5.01)	(5.32)	(5.30)
Number of observations	2,288	2,288	2,288	2,288	2,288	1,935	1,935	1,935	1,935	1,935
Adjusted R-squared	0.43	0.44	0.44	0.44	0.45	0.19	0.19	0.21	0.22	0.23

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. "Good English skills" is a dummy variable which indicates whether a respondent's English skills (including speaking and listening) are at or above the standard proficiency level (=1) or not (=0). For self-reported health status, the reference category is "in normal health condition." For body mass index (BMI), the reference category is "normal, 18.5 ≤ BMI < 25." For regional dummies, the reference group is "central region."

Sources: Chinese General Social Survey (CGSS) and authors' calculations.

possible explanation for this declining return is that, unlike education, experience was overrewarded prior to the reform. Payments for seniority were a central feature of the prereform wage structure.[14] The other possibility is that skills acquired in a socialist economy by older workers have declined in value following the PRC's labor market transition to one more market oriented.

B. Ordinary Least Squares Estimates versus Instrumental Variable and Heckman Two-Step Estimates

We check the reliability of OLS estimates on the causal relationship between education capital and wages by comparing them with estimates using the IV and Heckman two-step models. Table 4 presents the returns to schooling based on OLS, IV, and Heckman sample selection correction estimation models for the full sample. Subsample specific results (female versus male, urban versus rural, and coastal versus inland regions) are also presented in the bottom panels of Table 4. All regressions control for personal characteristics, location dummies, and height, which is a predetermined health endowment (height). IV estimates are based on early parental death and parental education as excluded instruments. This serves as a way to address potential endogeneity bias in the estimated returns to education. On the other hand, excluding nonlabor income from bequest in the Heckman model identifies the selectivity term (lambda). Comparing OLS and selectivity-corrected Heckman estimates can help us understand the extent of sample selection bias in the OLS estimates.

In the OLS model, the estimated return is 7.8%. Furthermore, the result of the endogeneity test in column 2 rejects the null hypothesis that the OLS estimates are consistent. Using father's and mother's education and whether a parent died when the respondent was 14 years old as instruments, the IV rate of return yields 20.9%, which is 13.1 percentage points higher than the OLS return. Moreover, consistent with the international literature (Mendolicchio and Rhein 2014), we find that returns to education for female workers (OLS: 9%; IV: 23.7%) are higher than for male workers (OLS: 7.1%; IV: 17.9%) in both methods. The gender difference in returns to schooling increases by approximately 3% after correcting for endogeneity bias.

Table 4 also reports returns to schooling for urban versus rural residents, and coastal versus inland provinces. Returns to schooling are higher for urban workers (OLS: 12.2%) than their rural counterparts (OLS: 2.2%), which is consistent with earlier studies that report a clear gap in returns to education between urban and

[14]Moreover, Appleton et al. (2002) document an inverse U-shaped relationship between general work experience and the probability of retrenchment in the PRC in 1999. If experience was overrewarded in the prereform period, then experienced workers would be at greater risk of retrenchment and their wage premiums would subsequently decline. Other studies employing a similar measure of "postschool experience" in the context of urban areas of the PRC are Qian and Smyth (2008b) and Mishra and Smyth (2015). While Qian and Smyth (2008b), using 2005 survey data from the PRC's Institute of Labor Studies (ILS), do not find any significant relationship between experience and wages, Mishra and Smyth (2015) confirm a convex relationship between experience and earnings.

Table 4. **Ordinary Least Squares, Instrumental Variable, and Heckman Estimates of the Returns to Education**

	OLS	IV	Heckman Two-Step
Full sample (N = 4,223)	0.078*** (18.16)	0.209*** (10.42)	0.082*** (16.19)
F-test on excluded IVs		171.19	
Sargan overid test (p-value)		0.56	
Lambda			−0.045 (0.25)
Female sample (N = 1,797)	0.090*** (13.80)	0.237*** (8.39)	0.097*** (5.72)
F-test on excluded IVs		99.05	
Sargan overid test (p-value)		0.48	
Lambda			−1.974 (2.20)
Male sample (N = 2,426)	0.071*** (12.00)	0.179*** (6.47)	0.074*** (12.00)
F-test on excluded IVs		78.76	
Sargan overid test (p-value)		0.68	
Lambda			0.085 (0.36)
Urban sample (N = 2,288)	0.122*** (23.51)	0.219*** (11.77)	0.134*** (18.08)
F-test on excluded IVs		161.69	
Sargan overid test (p-value)		0.77	
Lambda			0.165 (0.90)
Rural sample (N = 1,935)	0.022*** (3.22)	0.088*** (1.52)	0.021*** (2.72)
F-test on excluded IVs		41.39	
Sargan overid test (p-value)		0.72	
Lambda			0.054 (0.14)
Eastern (coastal) region (N = 1,586)	0.107*** (15.41)	0.248*** (10.55)	0.123*** (13.84)
F-test on excluded IVs		107.54	
Sargan overid test (p-value)		0.52	
Lambda			0.596 (2.51)
Central region (N = 1,435)	0.056*** (7.69)	0.249*** (3.05)	0.063*** (6.39)
F-test on excluded IVs		22.87	
Sargan overid test (p-value)		0.24	
Lambda			−0.458 (1.48)
Western region (N = 1,202)	0.054*** (6.77)	0.101*** (2.89)	0.057*** (6.73)
F-test on excluded IVs		44.48	
Sargan overid test (p-value)		0.23	
Lambda			−0.075 (0.20)

IV = instrumental variable, OLS = ordinary least squares.
Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Early parental death along with father's and mother's education are used as excluded instruments in the IV model. Nonlabor income received from bequest is used as an excluded identifying variable in the Heckman model. For regional dummies, the reference group is "central region." All regressions were controlled for covariates included in model 5 of Table 2.
Sources: Chinese General Social Survey (CGSS) and authors' calculations.

rural areas (Zhang 2011). Once again, the OLS estimates are smaller than the IV estimates in all of these subsamples. In addition, the true rate of return is underestimated by 9.7 percentage points for urban workers and by 14.1 percentage points for workers in the coastal region, compared with only 6.6 percentage points for rural workers and 4.7 percentage points for workers in the western area.

One explanation for the relatively larger size of the IV estimates is that the instruments are weak or nearly invalid, or both (Murray 2006, Wooldridge 2002). The first stage regression results of the IV model along with the diagnostic test results are presented in Table A3. The F-test statistic corresponding to the estimated coefficients of early parental death and parental education are both significant and large (19 and 151, respectively), implying that the instruments are strong and significant determinants of years of schooling completed. Results also show that if a parent died when the child was 14 years old, then his years of schooling are reduced dramatically.

Turning to Heckman estimates, we do not find significant evidence of sample selection bias in our analysis. The identifying variable in the probit model has the expected sign (see Table A3). Higher unearned income from bequest is found to significantly decrease labor market participation. Nonetheless, the lambda term is not significant.

Overall, results from Table 4 confirm that for CGSS data, we can rely on OLS estimates to examine the causal relationship between schooling and earnings. OLS, if anything, only leads to more conservative estimates of the true returns to years of education completed in the PRC.[15] Therefore, the next section exclusively discusses estimates obtained from the OLS regression of wages to understand how returns to education and language skills vary in the PRC.

C. Heterogeneous Returns to Education and Language Skills

Next, we explore two particular channels through which returns to skills and schooling may have changed in postreform years. First, we reestimate returns to education and language skills for all subsamples. Second, we reestimate the returns to different levels of education vis-à-vis language skills for the full sample and all subsamples. Because the OLS method is shown to consistently produce a conservative estimate in the previous section, we use this to understand the heterogeneous nature of the returns in our data.[16]

Table 5 repeats the analysis presented in Table 2 for various subsamples, but only results specific to education and language skills are reported. The subsamples are female, male, urban, rural, eastern region, central region, and western region. First, we find that returns to education for female workers (9%) are still higher than

[15]Another reason to treat OLS estimates as conservative is because the larger value of the IV estimates may be capturing treatment effects only for the subgroup of observations that comply with the instrument, i.e., the causal effect is identified for the observations affected by the instrument (“compliers”) so that the estimates are of a “local average treatment effect” (LATE), averaged across these compliers (Imbens and Rubin 1997, Wooldridge 2002, Murray 2006). In our case, the IV estimation arguably captures the returns to education only for those individuals whose schooling are very sensitive to their parents’ support. If so, the effect size cannot be generalized to the whole population.

[16]This approach to using OLS to understand heterogeneous returns assumes that across subsamples studied, the direction and extent of downward bias in OLS estimates remain the same.

Table 5. **Ordinary Least Squares Estimates of the Returns to Education versus Language Skills, by Gender and Location**

		(1)	(2)	(3)	(4)	(5)
Female sample	Years of education	0.103***	0.093***	0.091***	0.090***	0.090***
(N = 1,797)		(16.13)	(14.17)	(13.98)	(13.90)	(13.80)
	Good English skills		0.379***	0.372***	0.369***	0.362***
			(5.88)	(5.79)	(5.80)	(5.67)
	Adjusted R-squared	0.51	0.52	0.52	0.53	0.53
Male sample	Years of education	0.079***	0.072***	0.071***	0.071***	0.071***
(N = 2,426)		(13.67)	(12.21)	(12.04)	(12.08)	(12.00)
	Good English skills		0.243***	0.232***	0.232***	0.232***
			(3.95)	(3.78)	(3.80)	(3.80)
	Adjusted R-squared	0.45	0.46	0.46	0.47	0.47
Urban sample	Years of education	0.132***	0.124***	0.123***	0.122***	0.122***
(N = 2,288)		(26.64)	(23.89)	(23.68)	(23.59)	(23.51)
	Good English skills		0.215***	0.210***	0.209***	0.208***
			(5.08)	(4.96)	(4.96)	(4.92)
	Adjusted R-squared	0.43	0.44	0.44	0.44	0.45
Rural sample	Years of education	0.026***	0.024***	0.024***	0.023***	0.022***
(N = 1,935)		(3.75)	(3.42)	(3.35)	(3.29)	(3.22)
	Good English skills		0.298**	0.289**	0.282**	0.285**
			(1.91)	(1.86)	(1.83)	(1.86)
	Adjusted R-squared	0.19	0.19	0.21	0.22	0.23
Eastern (coastal) region	Years of education	0.122***	0.109***	0.108***	0.108***	0.107***
		(18.32)	(15.50)	(15.33)	(15.39)	(15.41)
(N = 1,586)	Good English skills		0.319***	0.312***	0.309***	0.304***
			(5.70)	(5.56)	(5.55)	(5.46)
	Adjusted R-squared	0.44	0.45	0.45	0.45	0.46
Central region	Years of education	0.063***	0.059***	0.058***	0.056***	0.056***
(N = 1,435)		(8.76)	(8.04)	(7.95)	(7.72)	(7.69)
	Good English skills		0.209**	0.214**	0.194**	0.196**
			(2.29)	(2.34)	(2.16)	(2.19)
	Adjusted R-squared	0.34	0.35	0.35	0.37	0.37
Western region	Years of education	0.060***	0.057***	0.056***	0.056***	0.054***
(N = 1,202)		(7.44)	(7.00)	(6.99)	(6.93)	(6.77)
	Good English skills		0.221**	0.214*	0.212*	0.230**
			(1.88)	(1.83)	(1.82)	(1.98)
	Adjusted R-squared	0.42	0.43	0.44	0.44	0.45

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. "Good English skills" is a dummy variable which indicates whether a respondent's English skills (including speaking and listening) are at or above the standard proficiency level (=1) or not (=0). Full specifications for models 1–5 are shown in Table 2.
Sources: Chinese General Social Survey (CGSS) and authors' calculations.

for male workers (7.1%), even after controlling for personal characteristics; health indicators (height, self-reported health status, and BMI); and geographic locations, which is consistent with findings from previous studies (Kang and Peng 2012, Mishra and Smyth 2013, Wang 2013). The returns to women with good English skills (36%) are also higher than the returns to men (23%, see column 5). Second, in addition to this gender gap in returns to schooling, we observe a clear rural–urban gap in the returns. Our finding is consistent with Meng, Shen, and Xue (2013) who find that the rates of return to each additional year of schooling increased from 8% to 9.3% during 1988–2009. This increase is even larger in urban areas (about 3 percentage points higher), which is similar to the finding of Gao and Smyth (2015) for the period 2001–2010.

Turning to region-specific estimates, our analysis shows clear regional differences in the returns to education. The bottom three panels of Table 5 report estimates by region. We find that the eastern region of the PRC (i.e., coastal provinces) has a comparatively higher rate of return to schooling (10.7%) than the central (5.6%) and western regions (5.4%).

One explanation for this regional difference in returns to education might be the observed widening gap in the production of cognitive skills, assessed in terms of differences in per student recurrent expenditure, teacher quality, and physical conditions of schools between coastal and inland areas (Qian and Smyth 2008a; Cheng 2009; Bickenbach and Liu 2013; Yang, Huang, and Liu 2014; Whalley and Xing 2014). Zhong (2011) examined the relationship between college quality and returns to higher education in the PRC and confirmed that the returns vary significantly depending on school quality. Moreover, he found that the maximum earnings gap between recipients of high- and low-quality higher education is 28%, and the gap for annual returns reached 1.4% after controlling for ability. Thus, better education quality at both basic education level (Cheng 2009) and higher education level (Bickenbach and Liu 2013) has resulted in higher returns to education in coastal areas of the PRC.

Table 6 shows the returns to different levels of education for the full sample and seven subsamples. We find that the returns to schooling increase with higher levels of education, which are consistent with results found in studies of developing countries (Kuepié and Nordman 2016). We calculate the average rate of return r_i specific to each level using the estimated OLS coefficients in the following way:

$$r_i = (\beta_i - \beta_{i-1}) / (Y_i - Y_{i-1})$$

where i is the level of education, Y_i is the year of schooling at education level i, and β_i is the estimate of the coefficient on the corresponding education level dummy in the wage regression. Thus, the rate of return to higher education, a bachelor's degree and above, is 31.9%, which is higher than the returns found in some studies that focused on the prehigher education expansion period. For example, based on 1981–1987 data from the Chinese Academy of Social Sciences, Meng and Kidd (1997) found that the rate of return to a bachelor's degree or higher relative to primary education is 29.1% in 1981 and 31.3% in 1987.[17] Moreover, we also find

[17] Studies based on data from the posthigher education reform period documented a sharp increase in returns to college education (Heckman and Li 2004, Fleisher et al. 2005, Qian and Smyth 2008b).

Table 6. **Ordinary Least Squares Estimates of the Returns to Schooling by Levels of Education (full sample and subsamples)**

	Full Sample	**Female**	**Male**	**Urban**	**Rural**	**Eastern (Coastal) Region**	**Central Region**	**Western Region**
Level of education								
Junior secondary	0.149^{***}	0.149^{***}	0.126^{***}	0.229^{***}	0.088^{*}	0.183^{***}	0.097^{*}	0.137^{**}
	(4.29)	(2.83)	(2.72)	(3.97)	(1.88)	(2.67)	(1.84)	(2.14)
Senior secondary	0.453^{***}	0.582^{***}	0.366^{***}	0.602^{***}	0.251^{***}	0.529^{***}	0.306^{***}	0.474^{***}
	(10.53)	(8.40)	(6.58)	(10.04)	(3.51)	(7.09)	(4.42)	(5.42)
Semibachelor	0.872^{***}	1.114^{***}	0.693^{***}	1.018^{***}	0.665^{***}	0.916^{***}	0.704^{***}	0.915^{***}
	(15.92)	(13.36)	(9.44)	(15.58)	(3.23)	(10.68)	(7.23)	(7.57)
Bachelor and above	1.191^{***}	1.501^{***}	0.981^{***}	1.335^{***}	0.733^{***}	1.296^{***}	0.904^{***}	1.018^{***}
	(20.06)	(16.23)	(12.58)	(19.25)	(2.72)	(14.51)	(7.46)	(7.77)
Good English skills	0.150^{***}	0.147^{**}	0.115^{*}	0.154^{***}	0.158	0.205^{***}	0.055	0.103
	(3.28)	(2.24)	(1.80)	(3.55)	(1.00)	(3.61)	(0.58)	(0.87)
Number of observations	4,223	1,797	2,426	2,288	1,935	1,586	1,435	1,202
Adjusted R-squared	0.53	0.56	0.48	0.45	0.23	0.48	0.38	0.46

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. "Good English skills" is a dummy variable which indicates whether a respondent's English skills (including speaking and listening) are at or above the standard proficiency level (=1) or not (=0). Full specification is in model 5 of Table 2. For "level of education," the reference category is "at or below primary level," following Meng and Kidd (1997).
Sources: Chinese General Social Survey (CGSS) and authors' calculations.

that female workers benefit more from having higher education than men. Similarly, urban residents are rewarded more than rural residents with the same level of college education, which is consistent with findings from Qian and Smyth (2008b) and Wang (2012).

Given such convexities in the earnings function, income inequality is unlikely to be reduced through school education unless equality in access to higher education is ensured.[18] This is also confirmed by the fact that educational endowments (schooling as well as skills) are distributed unequally in the PRC. The average number of years of schooling in Shanghai is 13.8, which is clearly higher than in the full sample (9.7), the eastern region including Shanghai (11.6), the eastern region excluding Shanghai (11.4), the central region (8.9), and the western region (8.1). Moreover, the percentage of respondents that have good English skills in Shanghai is also higher (43.1%) than in the full sample (11.2%), the eastern region including Shanghai (20.1%), the eastern region excluding Shanghai (17.8%), the central region (6.3%), and the western region (5.4%).

VI. Conclusion

In this paper, we have reexamined the economic returns to education in the PRC using a recent dataset that is representative of all provinces. When the endogeneity problem is not addressed, OLS estimates underestimate the true returns to schooling in the PRC. The IV estimates yield a much higher return to schooling—20.9% compared with the OLS estimate of 7.8%. In addition to commonly used instruments such as father's and mother's education, we used parental death when the respondent was 14 years old, which proved to be a strong excluded instrument in the first stage regression.

In general, our estimates are much higher than what has been reported in earlier studies on the PRC, particularly those that used prereform labor market datasets. This confirms that returns to education have steadily increased following the process of transition toward a market economy. Our evidence also confirms that individuals in coastal and urban locations (particularly nonstate sector employees) and young workers with market-relevant language skills were rewarded with higher returns to their education than their counterparts in rural and inland locations. The findings support the conclusions of recent studies that it took about 2 decades for the PRC to raise their workers' respective returns to education to the 10% level (Hung 2008; Meng, Shen, and Xue 2013).

The transition of the Chinese labor market from a centrally planned to a market-oriented system has contributed to a significant increase in earnings inequality by increasing the rewards for education and work experience. The

[18] For evidence on the role of higher education in explaining income inequality in the PRC, see Yang and Qiu (2016).

estimated return is much larger for higher education compared with secondary education. Market reforms may have also increased the price of unobserved skills (Meng, Shen, and Xue 2013). This may explain why we find a systematic labor market advantage enjoyed by those with English language skills and why the return is highest in coastal provinces where private sector jobs have the highest concentration. This finding is consistent with the evidence that schooling contributes to labor market performance in educationally advanced countries by enhancing labor market relevant functional literacy skills. Given our evidence on the convexities in returns to education and the significance of human capital as a determinant of labor market performance in postreform PRC, policies that improve access to cognitive skills are likely to reduce income inequality and boost economic growth in the coming decades.

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Appendix Table A1. **Distribution of Sample Individuals by Work Status**

		N	**Waged Work (Agricultural)**	**Waged Work (Nonagricultural)**	**Self-Employed**	**In Labor Force but Unemployed**	**Not in Labor Force**
Without age limitation	Full sample	11,724	24.9%	29.0%	9.8%	6.7%	29.6%
	Female	6,079	25.1%	23.2%	7.5%	6.3%	37.9%
	Male	5,645	24.8%	35.2%	12.3%	7.1%	20.6%
	Urban	7,173	4.4%	39.0%	12.4%	7.3%	36.9%
	Rural	4,551	57.2%	13.2%	5.7%	5.7%	18.2%
Female: 16–55 years old Male: 16–60 years old	Full sample	8,644	24.5%	38.1%	12.5%	7.2%	17.7%
	Female	4,279	25.5%	31.8%	10.1%	6.9%	25.7%
	Male	4,365	23.6%	44.2%	15.0%	7.5%	9.7%
	Urban	5,363	4.0%	50.7%	15.7%	8.1%	21.5%
	Rural	3,281	58.1%	17.5%	7.4%	5.8%	11.2%

Continued.

Appendix Table A1. *Continued.*

		N	Waged Work (Agricultural)	Waged Work (Nonagricultural)	Self-employed	In Labor Force but Unemployed	Not in Labor Force
Female:	Full sample	7,747	26.3%	38.2%	13.3%	7.2%	15.0%
25–55	Female	3,809	27.3%	31.6%	10.8%	6.9%	23.4%
years old	Male	2,938	25.4%	44.6%	15.6%	7.4%	7.0%
Male:	Urban	4,745	4.5%	51.7%	16.9%	8.1%	18.8%
25–60 years old	Rural	3,002	60.9%	16.8%	7.6%	5.6%	9.1%

Source: Chinese General Social Survey (CGSS).

Appendix Table A2. **Descriptive Statistics for Waged Workers**

	Mean	SD
Monthly employment income (renminbi)	1,631.37	2,283.98
Personal characteristics		
Years of experience	27.86	10.06
Female*	0.43	0.49
Minority*	0.09	0.29
Nonagricultural *hukou**	0.40	0.49
Currently married*	0.89	0.31
Schooling and cognitive skills		
Years of education (years of schooling)	9.70	4.45
Level of education:		
*Bachelor and above**	0.11	0.31
*Semibachelor**	0.11	0.31
*Senior secondary**	0.19	0.49
*Junior secondary**	0.30	0.46
*Primary and below (base group)**	0.29	0.45
Good English skills*	0.11	0.32
Health capital		
Height (centimeters)	165.38	7.49
Self-reported health status:		
*Bad**	0.12	0.32
*Normal (base group)**	0.21	0.40
*Good**	0.67	0.47
Body mass index (BMI):		
*BMI < 18.5, underweight**	0.07	0.25
*18.5 ≤ BMI < 25, normal (base group)**	0.72	0.45
*25 ≤ BMI < 30, overweight**	0.19	0.39
*BMI ≥ 30, obese**	0.02	0.14
Excluded instruments (IV model)		
$\text{Education}_{\textit{Father}}$ (in years)	5.27	4.61
$\text{Education}_{\textit{Mother}}$ (in years)	3.38	4.30
Parent died when respondent was 14 years old*	0.03	0.18
Labor force participation identifying variable (Heckman model)		
Nonlabor income received from bequest (renminbi)	30.15	707.22

Continued.

Appendix Table A2. *Continued.*

	Mean	SD
Geographic location		
Rural*	0.46	0.50
Eastern region*	0.38	0.48
Central region*	0.34	0.47
Western region*	0.28	0.45

IV = instrumental variable, SD = standard deviation.
Note: *indicates dummy variables equal to 1 if true, and otherwise equal to 0.
Sources: Chinese General Social Survey (CGSS) and authors' calculations.

Appendix Table A3. **First Stage Regression of Instrumental Variable and Heckman Models (full sample estimates only)**

	IV First Stage (individual's schooling)	Heckman First Stage (labor force participation)
Personal characteristics		
Age	0.035	0.044***
	(0.72)	(12.90)
Age squared	−0.001	−0.001***
	(1.50)	(14.01)
Female	−0.801***	−0.181***
	(5.84)	(15.89)
Minority	−0.109	−0.001
	(0.66)	(0.01)
Nonagricultural *hukou*	2.241***	−0.016*
	(16.34)	(1.81)
Currently married	0.315*	−0.005
	(1.93)	(0.48)
Schooling and cognitive skills		
Years of education		0.005***
		(5.07)
Good English skills	2.454***	0.061***
	(14.62)	(5.09)
Health capital		
Height (centimeters)	0.024***	−0.001
	(2.64)	(0.30)
Self-reported health status:		
Bad	−0.827***	−0.039***
	(4.67)	(3.33)
Good	0.108	0.029***
	(0.89)	(3.38)
Body mass index (BMI):		
BMI < 18.5, underweight	−0.203	0.001
	(1.05)	(0.07)
25 ≤ BMI < 30, overweight	0.130	−0.023**
	(1.06)	(2.49)
BMI ≥ 30, obese	−0.379	−0.021
	(1.12)	(0.79)

Continued.

Appendix Table A3. *Continued.*

	IV First Stage (individual's schooling)	**Heckman First Stage (labor force participation)**
Family background (instruments)		
Parent died when respondent was 14 years old (yes = 1)	-0.857^{***}	
	(3.00)	
$\text{Education}_{Father}$ (years)	0.138^{***}	
	(9.60)	
$\text{Education}_{Mother}$ (years)	0.122^{***}	
	(7.71)	
Labor force participation identifying variable		
Nonlabor income received from bequest (renminbi)		-0.012^{***}
		(3.93)
Geographic location		
Rural	-1.682^{***}	0.106^{***}
	(12.19)	(11.98)
Eastern region	0.535^{***}	0.005
	(4.43)	(0.54)
Western region	-0.497^{***}	0.026^{***}
	(3.98)	(2.85)
Constant	4.394^{**}	
	(2.38)	
Adjusted R-squared/Pseudo R-squared	0.54	0.17
Number of observations	4,223	6,618
F-test of significance: parental death only	19.03^{***}	
F-test of significance: parental education variables only	151.61^{***}	

IV = instrumental variable.

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Early parental death along with father's and mother's education are used as excluded instruments in the IV model. Nonlabor income received from bequest is used as an excluded identifying variable in the Heckman model.

Sources: Chinese General Social Survey (CGSS) and authors' calculations.

The Labor Productivity Gap between the Agricultural and Nonagricultural Sectors, and Poverty and Inequality Reduction in Asia

Katsushi Imai, Raghav Gaiha, and Fabrizio Bresciani*

The objective of this paper is to examine how agricultural and nonagricultural labor productivities have grown over time and whether the growth pattern affected poverty in low- and middle-income economies in Asia. We first examine whether labor productivities in the agricultural and nonagricultural sectors have converged, finding evidence that they did not as the latter have grown faster. We then confirm that both agricultural and nonagricultural labor productivities have converged across economies and that the convergence effect is stronger for the nonagricultural sector. We have also observed that, despite the relatively slower growth in agricultural labor productivity, the agricultural sector played an important role in promoting nonagricultural labor productivity and thus in nonagricultural growth. Finally, we have found some evidence that the labor productivity gap reduces rural and urban poverty, as well as national-level inequality.

Keywords: agricultural labor productivity, Asia, inequality, labor productivity gap, poverty
JEL codes: C23, I32, J24, O13

I. Introduction

The objective of this paper is to examine (i) how labor productivities in the agricultural and nonagricultural sectors in Asia have grown over time, and (ii) whether the growth pattern—proxied by the labor productivity gap between the two sectors—affected poverty and inequality in low- and middle-income economies in Asia. We focus on these economies because the interaction between the agricultural and nonagricultural sectors has become increasingly important as these

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economies have experienced structural transformation. We will first investigate the convergence of labor productivity in the agricultural and nonagricultural sectors with a focus on both intersectoral convergence and within-sector convergence across different economies over time.

The issue of intersectoral convergence versus divergence is reviewed in the literature, which investigates allocations or misallocations of inputs into the agricultural and nonagricultural sectors. For instance, using microlevel data, Gollin, Lagakos, and Waugh (2013) found that a large gap between the two sectors persists, suggesting the misallocation of labor at the macro level. However, the extent of the gap and how it has changed over time differs across economies depending on their initial capital and labor endowments, the stage of economic development, and the nature of their public policies. As the degree of the misallocation of resources in dual-economy settings explains variations in national income and productivity growth (Vollrath 2009), it is important to examine how the gap has changed over time.

To investigate whether the growth pattern impacts poverty and inequality in low- and middle-income economies in Asia, we draw upon the large empirical literature to test the convergence hypothesis in line with the neoclassical growth model: that is, whether poorer economies or regions grow faster than richer economies or regions (Barro 1991, Barro and Sala-i-Martin 1992, Barro et al. 1991). For instance, Barro et al. (1991) and Barro and Sala-i-Martin (1992) used state-level data on personal income for 48 states in the United States (US) during 1940–1963 and found clear evidence of convergence. As for convergence across economies, while the earlier literature suggests that there was convergence across a wide range of economies (Barro [1991] observes 98 economies during 1960–1985) and that the convergence was also observed for productivity growth (Baumol, Nelson, and Wolff 1994), it has been debated whether the convergence occurred for a subset of economies or for different specifications (Levine and Renelt 1992, Quah 1996). The results partly depend on the extent to which the economies are integrated, for instance, through international trade (Ben-David 1996). Given that East and South Asian economies are becoming more integrated, an interesting question is whether productivity converged among Asian economies.

We will also investigate whether the gap is associated with poverty and inequality reduction in rural and urban areas. While the literature has focused on the poverty-reducing effect of agricultural sector income or productivity growth, little is known about whether the gap between agricultural and nonagricultural productivity influences poverty or inequality.[1] A point of departure is that we treat the labor productivity gap as endogenous by using the fixed-effects instrumental-variable (FE-IV) model, where the cropping pattern is used as an instrument. Finally, we

[1] See Imai, Gaiha, and Bresciani (2016) for the evidence for Asia.

will discuss whether the labor productivity gap will dynamically affect the labor allocation between rural and urban sectors.

Our paper draws upon the following three strands of the literature. The first is the literature on the empirical investigations of the gap between agricultural and nonagricultural productivities in the dual-economy model, consisting of the traditional and modern sectors. A seminal work in this strand of the literature is Gollin, Lagakos, and Waugh (2013), who used both national accounts and household data to show that value added per worker is much higher in the nonagricultural than agricultural sector in developing economies. They call this the "agricultural productivity gap." As Gollin, Lagakos, and Waugh (2013, p. 942) note, the investigation of the agricultural productivity gap has been viewed as an important topic in the early literature on development economics as it can offer valuable insights into the analysis of economic growth and inequality in developing economies (e.g., Lewis 1955, Kuznets 1971). In recent years, the agricultural and nonagricultural sectors have become more integrated within economies through structural transformation, while the agricultural (or nonagricultural) sector of one economy has become more closely linked with the same sector of other economies under globalization. Given the nature of the data that Gollin, Lagakos, and Waugh (2013) used, their analysis is essentially static. However, it is important to analyze the gap in a dynamic context. Drawing upon the panel data of Asian economies, the present study focuses on how agricultural and nonagricultural labor productivities have grown, with their interactions taken into account. It also estimates the effect of the gap on poverty and inequality.

Second, our study is closely related to the large body of the literature on the role of the agricultural sector in development and the reduction of poverty and inequality (e.g., Christiaensen, Demery, and Kuhl 2011). A point of departure of the recent literature (Christiaensen, Demery, and Kuhl 2011; Imai, Cheng, and Gaiha 2017) is that the role of agriculture is captured by dynamic interactions between the agriculture and nonagricultural sectors. The present study extends these arguments and focuses on the effect of the labor productivity gap between the two sectors on poverty and inequality.

Third, the present study is also closely related to the literature on structural transformation, in particular rural transformation (or agricultural transformation), and its effect on development and/or poverty in low- and middle-income economies in Asia and elsewhere (e.g., Reardon and Timmer 2014, Dawe 2015, Barrett et al. 2017). As the structural transformation implies a closer and more intricate relationship between the agricultural and nonagricultural sectors, our empirical investigation of the gap between agricultural and nonagricultural productivity can provide useful insight into the literature on structural transformation.

The rest of the paper is organized as follows. In the next section, we briefly summarize the theoretical foundations underlying our empirical investigation. In section III, we examine the convergence of labor productivity in the agricultural and nonagricultural sectors. Section IV estimates the effects of the labor productivity gap on poverty, inequality, and the sectoral population share. The final section offers our concluding observations.

II. Theoretical Foundations

Our empirical investigation of the gap between agricultural and nonagricultural labor productivity is associated with a large body of theoretical literature on the dual-economy model, which originated from Arthur Lewis (1954) and was later developed by many authors (e.g., Dixit 1973, Mundlak 2000). More recently, Vollrath (2009) constructs a dual-economy model in which the productivity differences between the two sectors arise endogenously. In Vollrath's model, agricultural production is a constant returns to scale function of labor effort and land (Vollrath 2009, p. 8). Total agricultural production is denoted as

$$Y_t^A = A_t^A F\left(R, E_t^A\right) \tag{1}$$

where Y_t^A is agricultural production at time t (and superscript A denotes the agricultural sector), A_t^A is total factor productivity of the agricultural sector, R is the total amount of land (or resources in general) in the agricultural sector, and E_t^A is the total labor effort: that is, $E_t^A = s_t a_t L_t$. F is a well-behaved function with constant returns to scale. Net income for a representative farmer in the agricultural sector is

$$I_t^A = p_t^A A_t^A F\left(r_t, s_t\right) - \rho_t r_t \tag{2}$$

where r_t is the land employed by the farmer at time t. Each individual has a unit of time, with the share $s_t \in (0, 1)$ allocated to productive work in the agricultural sector and the remaining $1 - s_t$ spent in nonfarm activity at time t. ρ_t is the rental price of land, and p_t^A is the price of agricultural goods relative to manufactured goods.

The manufacturing (nonagricultural) sector is assumed to be perfectly competitive so that labor effort is paid its marginal product (Vollrath 2009, p. 9). The wage rate per unit of effort in the nonagricultural sector is specified as

$$w_t^M = A_t^M w\left(a_t\right) \tag{3}$$

where the wage rate depends on the productivity of nonagricultural sector, A_t^M, as well as on a well-behaved function w of the number of people in agriculture, a_t ($w' > 0$ and $w'' > 0$), given the assumption that the nonagricultural sector is competitive, while the agricultural sector is not. These properties imply that the nonagricultural wage increases as the number of people in the nonagricultural sector $(1 - a_t)$ decreases. Net income for nonagricultural workers is simply defined by

$$I_t^M = w_t^M s_t \tag{4}$$

Under these settings, Vollrath (2009, p. 11) showed that in equilibrium a dual economy exists where nonagricultural workers allocate more time to productive work than agricultural workers, and the marginal product of a worker is higher for nonagricultural (manufacturing) workers.[2] As a result, gross domestic product (GDP) per capita can be increased by a transfer of labor from the agricultural sector to the nonagricultural sector. Vollrath's model (2009, p. 13) also implies that sustained increases in agricultural productivity will help industrialize the economy, but this will be accompanied by a growing disparity in productivity between sectors. On the contrary, increases in nonagricultural productivity will not only industrialize the economy but also induce agricultural workers to work more efficiently.[3] This model prediction is intuitively valid given close interactions between the two sectors through migration, particularly in emerging economies such as India, the People's Republic of China, and Viet Nam.

The above model would predict, in our empirical context, that the gap in labor productivity between the agricultural and nonagricultural sectors expands as the economy grows. As the gap in labor productivity between the two sectors implies an improvement in relative productivity of the nonagricultural sector, it is likely to reduce poverty. So, we will test the hypotheses directly related to Vollrath (2009) that (i) the labor productivity gap between the agricultural and nonagricultural sectors expands over time, and (ii) the labor productivity gap between the two sectors reduces poverty. As we will discuss later, our empirical results are broadly consistent with Vollrath (2009).

Vollrath's (2009) model also implies that agricultural productivity and nonagricultural productivity interact in a complicated way. However, the model does not explicitly consider the interactions with factors outside the economy. Assuming the concavity of the production function in both sectors, we will empirically investigate whether agricultural productivity will converge or not across Asian economies by taking account of the effect of the lagged nonagricultural productivity on agricultural productivity. The convergence of nonagricultural productivity will also be examined by incorporating the effect of agricultural productivity on nonagricultural productivity. This empirical model is oriented in the literature to test the convergence of economic growth (Barro 1991, Barro and Sala-i-Martin 1992, Barro et al. 1991).

Vollrath (2009) predicts that in the long term the agricultural sector's productivity growth will exacerbate the inefficiencies of a dual economy and

[2] See Vollrath (2009, pp. 8–11) for details on how equations (1)–(4) will lead to the results.

[3] See Vollrath (2009, pp. 12–13 and the Appendix) for more details.

produce slower overall growth than will nonagricultural sector productivity improvements, and therefore the dual economy will disappear. This is consistent with empirical observations of developed Asian economies such as Japan and the Republic of Korea. While both of these economies improved their agricultural productivity in the late 20th century, the GDP share of the agricultural sector declined as they industrialized and eventually achieved higher overall productivity. In the meantime, the overall inequality of these economies remained relatively low and stable.[4] However, Vollrath (2009) lacks two aspects. First, the effect of the persistence of the dual economy on income distribution is not explicitly analyzed. Second, focusing on the long-term effect, Vollrath's model may not fully capture the positive role of agriculture on economic growth and the reduction of poverty and inequality, which is important in most low- and middle-income economies in Asia such as India. For instance, Ravallion and Datt (1996) used 35 household surveys of India between 1951 and 1991 and found that the growth of the primary sector (mainly agriculture) and the tertiary sector (mainly services) reduced national, rural, and urban poverty significantly, while growth of the secondary sector (mainly manufacturing) increased national poverty. They also showed that rural growth is more important for poverty reduction than urban growth. It is evident that a separate theoretical model is necessary to analyze the effect of a dual economy on income distribution and poverty.

Some authors have explored the relationship between growth and income distribution with a focus on the dual economy (e.g., Robinson 1976, Bourguignon 1990, Fields 1993, Bourguignon and Morrisson 1998). Bourguignon (1990) offers a theoretical ground for Kuznets' hypothesis in detail. The dual economy is modeled in a general equilibrium framework by taking account of the entire distribution, which generates a Lorenz curve rather than summary measures. Bourguignon (1990, p. 219) first derived a proposition that a "necessary and sufficient condition for growth to shift the Lorenz curve of the income distribution upward is that the share of the traditional sector in GDP increases with growth." That is, an increase of the share of the agricultural sector in the growth process tends to reduce inequality. However, as Bourguignon notes, it is unlikely that the agricultural sector share increases with growth. Bourguignon (1990, pp. 226–27) then derives the proposition that a "necessary condition for growth to be unambiguously egalitarian, despite a fall in the GDP share of the traditional sector, is that capital–labor substitution be inelastic in the modern sector," implying that "observing a falling GDP share of the traditional sector, together with elastic capital–labor substitution in the modern sector, is sufficient to rule out unambiguously egalitarian growth in a dual economy." That is, the model predicts that the disparity between the

[4]The income Gini coefficient of the Republic of Korea declined from 0.34 in 1965 to 0.31 in 1993 (Choo 1991) and that of Japan fell from 0.29 in 1966 to 0.28 in 1998 (based on the Family Income and Expenditure Survey from Moriguchi and Saez 2008). Both economies experienced a decline in the GDP share of agriculture during the respective review period.

agricultural and nonagricultural sectors tends to increase inequality with elastic capital–labor substitution in the nonagricultural (modern) sector. Bourguignon's model motivates our empirical analysis of the relationship between the agricultural–nonagricultural labor productivity gap and inequality and poverty.

III. Convergence of Labor Productivity in the Agricultural and Nonagricultural Sectors

Drawing upon the theoretical discussion in the last section, this section will examine the relationship between agricultural labor productivity and nonagricultural labor productivity with a focus on whether (i) these two converge or diverge over time, (ii) agricultural labor productivity converges across different economies, and (iii) nonagricultural labor productivity converges across different economies. For (ii) and (iii), the intersectoral effects are also taken into account in one case. That is, the effect of lagged nonagricultural labor productivity on agricultural labor productivity is considered. For (iii), the effect of lagged agricultural labor productivity on nonagricultural labor productivity is taken into account. For simplicity, the labor productivity of the agricultural (nonagricultural) sector is defined as value added in the agricultural (nonagricultural) sector divided by the number of workers in the agricultural (nonagricultural) sector.

Table 1 compares labor productivity in these sectors by economy and region, and for Asia as a whole. The comparison is also made for the entire period as well as before and after the year 2000. Table 1 reports labor productivity growth as well as the labor productivity gap as defined by the gap between the logarithm of agricultural value added per worker and the logarithm of value added per worker in the nonagricultural sector. Consistent with earlier literature (e.g., Martin and Mitra 2001, Bernard and Jones 1996), nonagricultural labor productivity is higher in all cases except the Federated States of Micronesia before 2000. Also, the labor productivity gap is higher after 2000 in all cases except Fiji. Our results strongly confirm the labor productivity divergence between the two sectors. That is, nonagricultural labor productivity was higher than agricultural labor productivity to start with and that the gap has expanded over time.

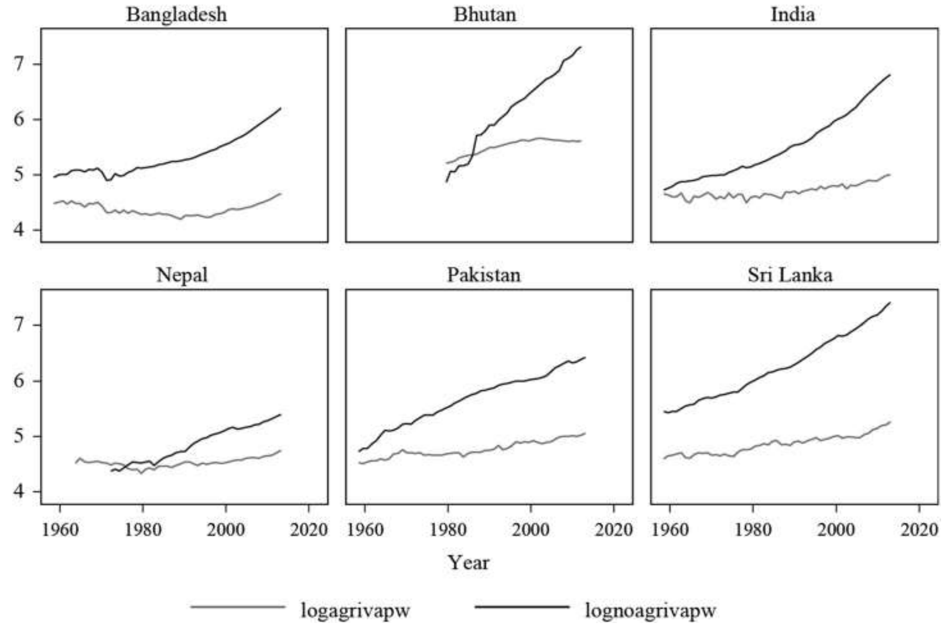
However, there is a great degree of heterogeneity in terms of the speed of divergence. For instance, in a few economies (e.g., Indonesia and the Federated States of Micronesia), the gap has only moderately increased, but in other economies (e.g., Bhutan, India, and the People's Republic of China), the gap dramatically increased after 2000. It is thus safe to conclude that there is no evidence of labor productivity convergence between the agricultural and nonagricultural sectors. This is due to the fact that while agricultural labor productivity has grown substantially since 2000, nonagricultural labor productivity has grown even faster in many economies.

Table 1. **Labor Productivity Growth in the Agricultural and Nonagricultural Sectors, and the Labor Productivity Gap (in level) in These Sectors**

	Total			Before 2000			After 2000		
	Agricultural Labor Productivity Growth[a]	**Nonagricultural Labor Productivity Growth[b]**	**Labor Productivity Gap[c]**	**Agricultural Labor Productivity Growth[a]**	**Nonagricultural Labor Productivity Growth[b]**	**Labor Productivity Gap[c]**	**Agricultural Labor Productivity Growth[a]**	**Nonagricultural Labor Productivity Growth[b]**	**Labor Productivity Gap[c]**
South Asia									
Bangladesh	0.33	2.40	**0.95**	−0.41	1.49	**0.82**	2.57	5.15	**1.39**
Bhutan	1.30	7.90	**0.66**	2.13	8.38	**0.29**	0.06	7.14	**1.28**
India	0.66	4.01	**0.81**	0.37	3.20	**0.59**	1.53	6.47	**1.52**
Nepal	0.50	2.62	**0.34**	0.002	2.78	**0.22**	1.79	2.29	**0.61**
Pakistan	1.00	3.29	**0.91**	0.93	3.33	**0.78**	1.25	3.15	**1.28**
Sri Lanka	1.29	3.76	**1.40**	1.03	3.36	**1.21**	2.04	4.97	**1.99**
Total	0.82	3.77	**0.88**	0.55	3.36	**0.71**	1.56	4.83	**1.34**
East and Southeast Asia; Pacific									
Cambodia	2.72	7.25	**0.52**	1.93	5.66	**0.13**	3.23	7.99	**0.74**
PRC	2.96	7.34	**0.74**	2.78	6.54	**0.31**	3.51	9.75	**2.06**
Fiji	0.86	3.63	**2.96**	0.34	3.99	**2.87**	−0.66	0.97	**1.82**
Indonesia	1.40	4.38	**1.34**	1.09	4.34	**1.15**	2.32	4.51	**1.91**
Lao PDR	1.98	5.50	**0.33**	1.97	3.60	**0.10**	1.99	7.68	**0.62**
Malaysia	0.62	4.47	**1.78**	0.22	4.95	**1.50**	1.52	3.41	**2.52**
FSM	0.12	−0.27	**1.09**	−14.20	−6.31	**1.01**	0.74	0.19	**1.09**
Philippines	0.35	1.74	**1.72**	0.07	1.20	**1.64**	1.22	3.34	**1.97**
Timor-Leste	−2.90	4.87	**1.08**	—	—	—	−2.90	4.87	**1.08**
Viet Nam	2.19	5.85	**1.18**	1.70	5.70	**0.94**	2.70	6.02	**1.46**
Total	1.15	3.68	**1.06**	0.96	3.14	**0.90**	1.48	4.64	**1.34**
Asia Total	0.84	3.44	**1.07**	0.24	2.56	**0.90**	2.04	5.16	**1.42**

FSM = Federated States of Micronesia, Lao PDR = Lao People's Democratic Republic, PRC = People's Republic of China.
Notes:
[a]Agricultural labor productivity growth = DLog (agricultural value added per worker)
[b]Nonagricultural labor productivity growth = DLog (nonagricultural value added per worker)
[c]Labor productivity gap = Log (nonagricultural value added per worker) − Log (agricultural value added per worker)
Source: Authors' calculations based on World Bank. 2016. World Development Indicators 2016. https://openknowledge.worldbank.org/handle/10986/23969.

Figure 1. **The Gap between Nonagricultural Labor Productivity** (nonagricultural value added per worker) **and Agricultural Labor Productivity** (agricultural value added per worker) **in South Asia by Economy**

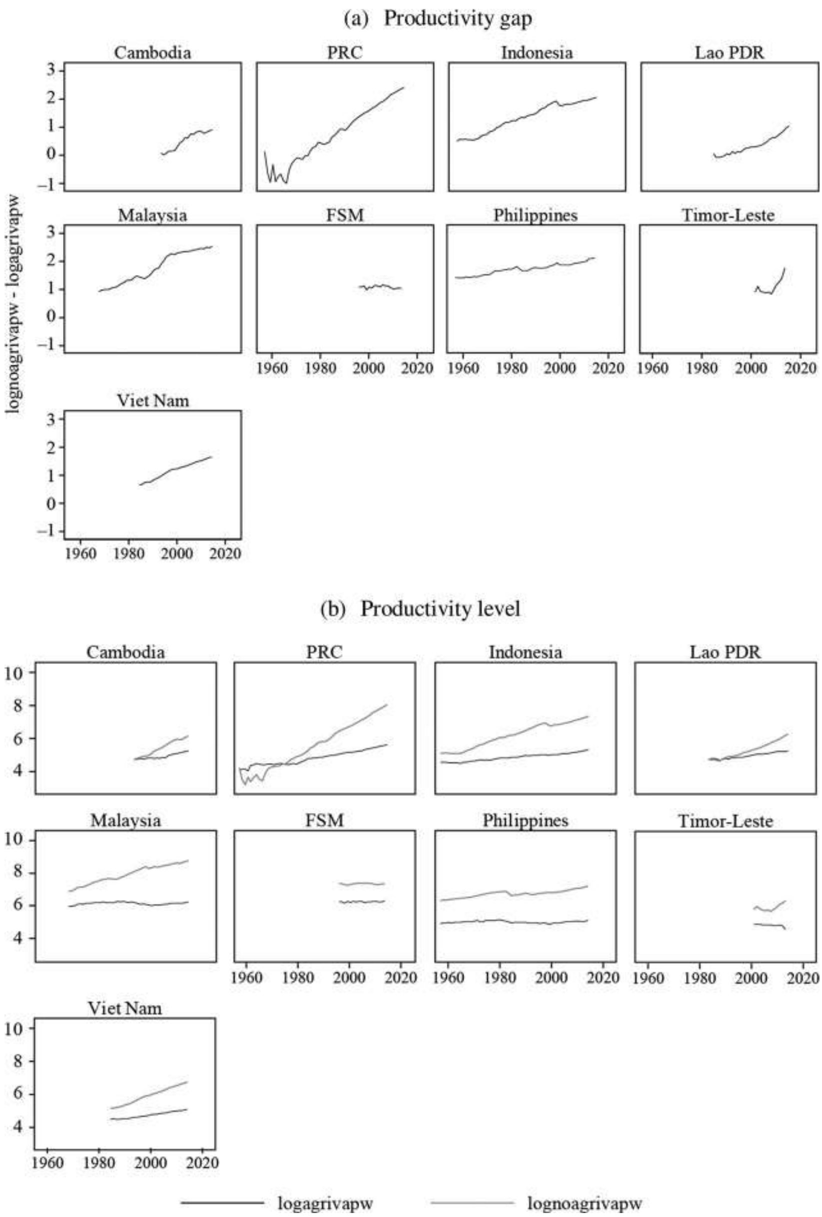


logagrivapw = logarithm of agricultural value added per worker, lognoagrivapw = logarithm of nonagricultural value added per worker.
Source: Authors' calculations based on World Bank. 2016. World Development Indicators 2016. https://openknowledge.worldbank.org/handle/10986/23969.

Figures 1 and 2 confirm these results graphically. Figure 1 plots labor productivity in the agricultural and nonagricultural sectors in South Asian economies over time. The productivity gap was initially small in many economies (in the 1960s and 1970s), but it has expanded over the years. Figure 2 indicates that the above results are broadly similar for East and Southeast Asian economies. If we aggregate these data, the divergence of labor productivity between the agricultural and nonagricultural sectors can be confirmed for all of Asia.

Next, we will examine whether agricultural labor productivity (or nonagricultural labor productivity) has converged across different economies based on the following simple static model (FE model) and dynamic panel model (system generalized method of moments). The idea is similar to Ghosh (2006), who examined the convergence of agricultural productivity among Indian states during 1960–2001. He found that there was significant divergence in labor productivity, particularly after the early 1990s, while there was no significant convergence or divergence in land productivity and per capita agricultural output. To take account

Figure 2. **The Gap between Agricultural Labor and Nonagricultural Labor Productivity in East and Southeast Asia, by Economy**



FSM = Federated States of Micronesia, Lao PDR = Lao People's Democratic Republic, logagrivapw = logarithm of agricultural value added per worker, lognoagrivapw = logarithm of nonagricultural value added per worker, PRC = People's Republic of China.

Source: Authors' calculations based on World Bank. 2016. World Development Indicators 2016. https://openknowledge.worldbank.org/handle/10986/23969.

of the business cycle, we have taken the 5-year averages and estimate the same models as follows. We have redefined the time periods as $t = 1$ for 1960–1964, $t = 2$ for 1965–1969, . . . , and $t = 11$ for 2010–2014. A selection of the economies is guided by the availability of variables: 37 middle-income and low-income economies have been chosen from Asia and the Pacific.

First, the static model (FE model) is specified as

$$d \log AGLP_{it} = \beta_0 + \beta_1 \log AGLP_{it-1} + \beta_2 T + X_{it} \cdot \beta_3 + \beta_4 d \log NAGLP_{it-1} + \mu_i + \varepsilon_{it} \tag{5}$$

where $d \log AGLP_{it}$ stands for the annual agricultural labor productivity growth at time t for economy i. $\log AGLP_{it-1}$ is the level of agricultural productivity one period earlier in order to capture the convergence effect following the empirical literature to test the Solow growth model. Our main hypothesis for convergence is to test whether β_1 is negative.

T is the linear time trend. X_{it} is a vector of control variables, such as the logarithm of schooling years, the logarithm of share of the mining sector in GDP (in order to capture the economy's resource dependency), and the lagged level of inequality (based on the Gini coefficient). A selection of explanatory variables draws upon the recent literature, which investigated the interactions between agricultural growth and nonagricultural growth (Christiaensen, Demery, and Kuhl 2011; Imai, Cheng, and Gaiha 2017). The average years of total schooling is based on the Barro–Lee data, which has been commonly used in the empirical macroeconomics literature as it is a broad measure of the human capital stock of the economy.[5] It is assumed that as the economy's educational attainment improves, agricultural or nonagricultural labor productivity improves. The GDP share of the mining sector captures the extent to which the economy relies on natural resources, which may undermine sectoral labor productivity. The degree of inequality in various ways influences the sectoral labor productivity. For instance, if there exists a threshold (based on the nutritional requirement) below which workers cannot work efficiently in the labor market, a high level of inequality may undermine either agricultural or nonagricultural labor productivity. $d \log NAGLP_{it-1}$ is the lagged annual nonagricultural productivity growth to capture the transmission effect of labor productivity growth in the nonagricultural sector. This draws upon Vollrath's (2009) model, which showed that nonagricultural labor productivity enhances agricultural labor productivity over time in a dual-economy setting. μ_i is the economy's unobservable fixed effect (e.g., cultural or institutional factors). ε_{it} is an error term. We estimate this model with and without control variables, or

[5] For more details, see Barro–Lee Educational Attainment Dataset. http://www.barrolee.com/.

the nonagricultural labor productivity growth term, while the results are robust to inclusion (exclusion) of a few other explanatory variables.

As an extension, equation (1) has been estimated using the dynamic panel model (system generalized method of moments) drawing upon the Blundell and Bond (1998) robust estimator:

$$\begin{aligned} d\log AGLP_{it} = {} & \beta_0 + \beta_1 d\log AGLP_{it-1} + \beta_2 \log AGLP_{it-1} + \beta_3 T \\ & + \beta_4 d\log NAGLP_{it-1} + \varepsilon_{it} \end{aligned} \tag{6}$$

Here, d denotes the first difference. The lagged dependent variable captures the persistent effect of agricultural labor productivity growth. Control variables have been dropped as they are statistically insignificant.

Exactly the same models can be estimated for nonagricultural labor productivity growth by static and dynamic panel models as in equations (7) and (8). The same models have been applied to subsamples for South Asia and for East and Southeast Asia:

$$\begin{aligned} d\log NAGLP_{it} = {} & \beta_0 + \beta_1 \log NAGLP_{it-5} + \beta_2 T + X_{it} \cdot \beta_3 + \beta_4 d\log AGLP_{it-1} \\ & + \mu_i + \varepsilon_{it} \end{aligned} \tag{7}$$

$$\begin{aligned} d\log NAGLP_{it} = {} & \beta_0 + \beta_1 d\log NAGLP_{it-1} + \beta_2 \log NAGLP_{it-5} + \beta_3 T \\ & + \beta_4 d\log AGLP_{it-1} + \mu_i + \varepsilon_{it} \end{aligned} \tag{8}$$

In Table 2, the above models are estimated by using the 5-year average data. Here, the presence of convergence effect can be tested by checking whether the lagged agricultural labor productivity (agricultural value added per worker [$t-1$]) is negative and statistically significant in Cases 1–4, and whether lagged nonagricultural labor productivity (nonagricultural value added per worker [$t-1$]) is negative and statistically significant in Cases 5–8. The result of a positive effect of agricultural productivity on nonagricultural productivity (Cases 1–4) is important as this is consistent with the prediction of Vollrath's (2009) model that there is diffusion from the agricultural sector. This is important in terms of the literature on structural transformation in Asia (Reardon and Timmer 2014), which suggests that the transformation of the agricultural sector (e.g., commercialization and product diversification) is becoming closely linked to changes in dietary patterns; supply chain and retail revolution; and integrated labor, land, and credit markets. Here, the whole process of structural transformation implies a positive diffusion effect of agricultural labor productivity on nonagricultural labor productivity. However, contrary to Vollrath's prediction, a positive effect of nonagricultural labor productivity on agricultural labor productivity was not observed as many Asian

Table 2. **Convergence of Labor Productivity in the Agricultural and Nonagricultural Sectors** (Asia, 5-year average)

	Dependent Variable: Agricultural Labor Productivity Growth				**Dependent Variable: Nonagricultural Labor Productivity Growth**			
Model Variables	**Fixed Effects Case 1**	**Fixed Effects Case 2**	**Fixed Effects Case 3**	**SGMM Case 4**	**Fixed Effects Case 5**	**Fixed Effects Case 6**	**Fixed Effects Case 7**	**SGMM Case 8**
Agricultural labor productivity growth ($t-1$)				**0.331****	**0.318*****		**0.281***	**0.340****
				(0.141)	**(0.117)**		**(0.160)**	**(0.145)**
Nonagricultural labor productivity growth ($t-1$)		−0.0401	**−0.100****	**−0.154****				0.0136
		(0.0555)	**(0.0418)**	**(0.0779)**				(0.0756)
Agricultural labor productivity ($t-1$)	**–4.27e-06****	−3.56e-06	**−2.91e-05***	**−2.61e-06****				
	(1.91e-06)	(2.19e-06)	**(1.45e-05)**	**(1.22e-06)**				
Nonagricultural labor productivity ($t-1$)					**−0.000111*****	**−9.56e-05*****	**−0.000124*****	**−2.73e-05*****
					(2.28e-05)	**(1.77e-05)**	**(3.19e-05)**	**(7.75e-06)**
Log share of the mining sector in GDP			0.00377				0.0119	
			(0.0101)				(0.0202)	
Log schooling years			−0.0366				0.00883	
			(0.103)				(0.144)	
Inequality index ($t-1$)			0.00424				0.00850*	
			(0.00259)				(0.00430)	
Linear time trend	0.0197**	0.0102**	0.0203	0.00956**	0.0200***	0.0268***	0.0188	0.00446
	(0.00732)	(0.00484)	(0.0118)	(0.00386)	(0.00655)	(0.00750)	(0.0196)	(0.00473)
Constant	−0.118	−0.0144	−0.138	−0.00652	0.208	0.123	−0.147	0.171
	(0.0625)	(0.0462)	(0.211)	(0.0377)	(0.0485)	(0.0450)	(0.200)	(0.0545)
Observations	177	155	102	155	185	222	123	184
R-squared	0.054	0.033	0.197		0.253	0.160	0.257	
Number of economies	37	37	23	37	37	38	23	37

GDP = gross domestic product, SGMM = system generalized method of moments.
Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Source: Authors' calculations based on World Bank. 2016. World Development Indicators 2016. https://openknowledge.worldbank.org/handle/10986/23969.

economies were primarily dependent on the agricultural sector during our data period.

In Table 2, we confirm that labor productivity converges in both the agricultural and nonagricultural sectors, and the convergence effect is significant in all the cases except Case 2. This implies "a catching-up effect" in which the economies with relatively low agricultural labor productivity tend to catch up with those having relatively high agricultural labor productivity. The catching up effect is also found for nonagricultural labor productivity.

We have also found that lagged nonagricultural labor productivity growth deters agricultural labor productivity growth (Cases 3 and 4). This is consistent with the theoretical model of Vollrath (2009) that an improvement of nonagricultural productivity induces agricultural workers to work more efficiently. However, the result is reversed when we use the annual panel data in which nonagricultural labor productivity is lagged by 5 years. Here, lagged nonagricultural labor productivity growth is found to promote agricultural labor productivity growth as predicted by the theoretical model.[6]

On the other hand, we have found, based on the 5-year average panel, that lagged agricultural labor productivity growth promotes nonagricultural labor productivity growth (Cases 5, 7, and 8). In Case 8, the lagged agricultural productivity growth is treated as an endogenous variable. Other covariates are mostly statistically insignificant, but a large lagged inequality increases nonagricultural labor productivity growth in Case 7.

We have estimated the same models using the 5-year average data only for South Asia. A statistically significant convergence effect is found in the case of agricultural labor productivity growth. For the cross-sectoral effects, lagged agricultural labor productivity growth is found to promote nonagricultural labor productivity growth. For South Asia, a higher level of inequality tends to reduce overall agricultural labor productivity growth with some lag. Given that inequality can dampen the productivity of the disadvantaged group of agricultural workers or poor smallholders, this is a plausible result.[7] When we replicate the same regressions for East and Southeast Asia, we find that convergence effects are generally found to be significant. For the cross-sectoral effect, lagged agricultural labor productivity growth positively affects nonagricultural labor productivity growth.[8]

[6]The results based on the annual panel will be provided on request.

[7]For South Asian economies, the Gini coefficient is positively correlated with the agricultural commercialization index based on the extent to which an agricultural product is processed (Imai, Gaiha, and Bresciani 2016); the coefficient of correlation is 0.067. For East and Southeast Asian economies, the correlation is negative with a coefficient of –0.4. This could explain the negative correlation between inequality and agricultural labor productivity for South Asia, though the causality will have to be examined carefully in future studies.

[8]The disaggregated results will be provided on request.

IV. Effects of the Labor Productivity Gap between the Agricultural and Nonagricultural Sectors on Poverty, Inequality, and the Sectoral Population Share

We have so far examined the pattern of (i) the convergence of labor productivity between the agricultural and nonagricultural sectors, and (ii) the convergence of agricultural or nonagricultural productivity across different economies. Overall, agricultural labor productivity growth has promoted nonagricultural productivity growth and the sectoral gap has widened, while the between-economy disparity of the sectoral labor productivity has narrowed. These findings are broadly consistent with the theoretical model of Vollrath (2009).

An interesting empirical question is how this process will dynamically affect poverty and inequality as well as labor allocation across different sectors over time. As we discussed in section II, the theoretical model implies that an increase of the sectoral gap tends to be generally less egalitarian, or that there is an increase in inequality when both sectors grow (Bourguignon 1990). However, it is not straightforward to answer the question because of the difficulty in disentangling the complex causal links from the labor productivity gap between the agricultural and nonagricultural sectors to poverty (or inequality or the sectoral population share). For instance, an increase in the labor productivity gap may imply a divergence: that is, a change toward higher nonagricultural labor productivity (reflecting technological development) and/or lower or more stagnant agricultural productivity. On the other hand, a reduction in the gap may imply a change toward convergence due to stagnant nonagricultural labor productivity and/or an increase in agricultural labor productivity. However, while the larger gap affects poverty or inequality, the higher poverty rates or inequality might also influence the gap. For instance, poor people in rural areas cannot invest in a profitable investment in agriculture that would require a certain amount of investment in physical and human capital (e.g., machinery or high-yielding crops), which hinders the growth of labor productivity in agricultural areas. Thus, there is a need for instrumenting the labor productivity gap because it may be endogenous.

We have tackled the endogeneity by instrumenting the labor productivity gap by (i) the lagged agricultural product diversity index (Imai, Gaiha, and Bresciani 2016) and (ii) the lagged logarithm of the production share of the mining sector in GDP.[9] The first instrument is used as a proxy for agricultural transformation by

[9]This draws upon Remans et al. (2014), who use an index called the Shannon Entropy Diversity Metric to capture production diversity at the country level using FAOSTAT. It is defined as $H' = -\sum_{i=1}^{R} p_i \ln p_i$ where R is the number of agricultural products and p_i is the share of production for the item, i, available from FAOSTAT. The production share, p_i, is defined in terms of the monetary value at a local price for each product, i. If the country produces more agricultural products, including processed and unprocessed crops, and the monetary value of all products is more evenly divided among different items, the diversity index, H', takes a larger value. On the contrary, if the country produces a smaller number of agricultural products and the monetary value of one or two specific products is large, H' is smaller.

Imai, Gaiha, and Bresciani (2016), and is supposed to affect the labor productivity gap, mainly by influencing agricultural labor productivity. However, the change of the production pattern itself cannot directly influence poverty or inequality. We cannot deny the possibility that the process of specialization could increase poverty, for instance, as there may be less demand for manual labor; but we can reasonably assume that poverty can change through adjustments in farm production or income (per worker). The second instrument could also reduce the labor productivity gap because dependence on the mining sector could deter the overall effort for technological progress in the industrial sector, without directly affecting poverty. The reliance on the mining sector could affect poverty directly (e.g., the impoverishment of manual workers in the mining sector), but we assume that this does not have a direct impact on poverty, particularly in rural areas. We assume that the productivity or income effect is larger than the direct effect on poverty, while we admit limitations in using the second instrument.[10] We have applied the IV model in the panel framework using the FE-IV model, whereby the unobservable country effect is taken into account. Because we focus on the relatively longer-term effect, we use only the 5-year average data.

In the first stage, we will estimate the determinants of the labor productivity gap between the two sectors:

$$\begin{aligned} Gap_{it-1} = {} & \beta_0 + \beta_1 d\log AGLP_{it-1} + \beta_2 d\log NAGLP_{it-1} + \beta_3 S_{it-1} + \beta_4 Mining_{it-2} \\ & + \beta_5 Product\ Diversity_{it-2} + \mu_i + \varepsilon_{it} \end{aligned} \tag{9}$$

Here, t stands for each 5-year period: $t = 1$ for 1960–1964, $t = 2$ for 1965–1969, $\ldots, t = 11$ for 2010–2014. Gap_{it-1} is the first lag of normalized difference between nonagricultural value added per worker and agricultural value added per worker (at purchasing power parity [PPP] in US dollars divided by 1,000). $d\log AGLP_{it-1}$ is the lag of the first difference in log of agricultural value added per worker: that is, the agricultural labor productivity growth during the preceding period. Likewise, $d\log NAGLP_{it-1}$ is the nonagricultural labor productivity growth during the preceding period. S_{it-1} is the lag of schooling years. μ_i is the unobservable country fixed effect and ε_{it} is an error term (independent and identically distributed).

Instruments for the labor productivity gap between the agricultural and nonagricultural sectors are the second lag of the production share of the mining sector ($Mining_{it-2}$) and the second lag of the agricultural product diversity index. These instruments, despite the limitations, are justified on the following grounds. Since the mining sector share is a variable closely associated with the (broadly predetermined) factor endowment of the economy, it will have a direct effect on the economy's labor allocations across different sectors, including the

[10]These sets of instruments are the best candidates given the data availability.

rural agricultural sector, rural nonagricultural sector (nonmining or mining), and urban nonagricultural sector (nonmining or mining). Depending on the degree of dependence on mining resources, the allocation of labor across sectors and worker efforts in each sector are influenced directly. It is surmised here that the effect of the mining sector share first influences sectoral labor productivity, rather than poverty. While the mining sector share may influence poverty directly (e.g., through the impoverishment of mining workers), we assume that it mainly influences the relative sectoral productivity. The second instrument, the product diversity index, affects agricultural labor productivity directly as more diversified production implies the economy's adoption of profitable and marketable agricultural products (e.g., vegetables, fruits, meat). The index also influences nonagricultural labor productivity as the introduction of these products influences the productivity of the food processing sector. However, it is unlikely that the product diversity index directly affects poverty or inequality. These instruments, despite the limitations, have been validated by specification tests.

In the second stage, poverty is estimated by the (instrumented) labor productivity gap as well as other determinants:

$$\begin{aligned} Poverty_{it} &= \gamma_0 + \gamma_1 \widehat{Gap}_{it-1} + \gamma_2 d\log AGLP_{it-1} + \gamma_3 d\log NAGLP_{it-1} + \gamma_4 S_{it-1} \\ &\quad + \theta_i + e_{it} \end{aligned} \tag{10}$$

Equations (9) and (10) are estimated using the FE-IV model. Poverty is defined in various ways, including (i) the national poverty headcount, or poverty gap, based on the international poverty line of \$1.9 (extreme poverty) or \$3.1 (moderate poverty) per day at PPP in 2011 (World Bank 2016); (ii) the rural poverty headcount, poverty gap, or poverty gap squared, based on \$1.25 (extreme poverty) or \$2 (moderate poverty) at PPP in 2005; and (iii) the same urban poverty indexes in (ii), based on household data in rural areas.[11] In one case, we have replaced poverty by the Gini coefficient evaluated at the national or subnational level (for rural and urban areas separately). Finally, given the data limitations, we have derived the population share of the rural sector, nonagricultural sector, and urban sector, and used each share as a dependent variable in the second-stage regression (Imai, Gaiha, and Garbero 2017). This aims to examine how the labor productivity gap will influence the labor allocation in the middle to long run. In all cases, the endogeneity of the labor productivity gap is instrumented.

First, we have estimated national poverty in the second stage (the upper left panel of Table 3).[12] In the first stage, one of the instruments, the agricultural product

[11] The difference in the definitions of rural, urban, and national poverty reflects the data availability. Poverty estimates for (ii) and (iii) have been provided by the Strategy and Knowledge Department of the International Fund for Agricultural Development.

[12] A full set of the regression results will be provided upon request. We provide only the second-stage results in Table 3.

Table 3. **Effects of the Labor Productivity Gap between the Agricultural and Nonagricultural Sectors on Poverty and Inequality**
(second stage of the FE-IV model)

Variables	**Poverty Headcount ($1.9)**	**Poverty Gap ($1.9)**	**Poverty Headcount ($3.1)**	**Poverty Gap ($3.1)**	**Rural Poverty Headcount ($1.25)**	**Rural Poverty Gap ($1.25)**	**Rural Poverty Gap Squared ($1.25)**	**Rural Poverty Headcount ($2)**	**Rural Poverty Gap ($2)**	**Rural Poverty Gap Squared ($2)**
Gap ($t-1$)	**−0.224**	**0.081**	**−0.074**	**−0.394**	**−1.620****	**−1.633****	**−1.291**	**−1.117****	**−1.357****	**−1.465****
	(0.481)	**(0.464)**	**(0.601)**	**(0.459)**	**(0.734)**	**(0.797)**	**(2.664)**	**(0.504)**	**(0.593)**	**(0.662)**
Agricultural productivity growth ($t-1$)	−3.445	−3.894	−2.793	−3.063	−1.176	−1.537	2.961	−0.904	−1.008	−1.152
	(2.940)	(2.857)	(3.207)	(2.942)	(1.736)	(2.086)	(2.841)	(1.109)	(1.422)	(1.660)
Nonagricultural productivity growth ($t-1$)	0.553	0.395	0.154	0.373	0.159	0.360	−1.132	0.190	0.172	0.214
	(2.366)	(2.309)	(2.615)	(2.358)	(1.073)	(1.313)	(1.172)	(0.679)	(0.886)	(1.040)
Log schooling years ($t-1$)	−1.660	−1.613	−1.746	−1.470	−0.776	−1.368	−8.573**	−0.174	−0.584	−0.932
	(1.085)	(1.023)	(1.224)	(1.056)	(0.888)	(0.931)	(4.119)	(0.592)	(0.704)	(0.799)
Observations	77	77	77	77	45	45	45	45	45	45
R-squared	0.251	0.190	0.170	0.273	0.479	0.557	0.561	0.455	0.506	0.524
Number of economies	11	11	11	11	12	12	12	12	12	12

Continued.

Table 3. *Continued.*

Variables	Urban Poverty Headcount ($1.25)	Urban Poverty Gap ($1.25)	Urban Poverty Gap Squared ($1.25)	Urban Poverty Headcount ($2)	Urban Poverty Gap ($2)	Urban Poverty Gap Squared ($2)	National Gini	Rural Gini	Urban Gini	Rural Share	Rural Non–agri. Share	Urban Share
Gap ($t-1$)	**−19.400**	**−3.317****	**−2.074**	**−1.864*****	**−2.058*****	**−6.854**	**−4.636*****	**0.136**	**−0.0115**	**−24.46****	**30.81*****	**5.032***
	(12.740)	**(1.583)**	**(1.891)**	**(0.488)**	**(0.716)**	**(4.967)**	**(1.174)**	**(0.147)**	**(0.0971)**	**(8.294)**	**(8.281)**	**(2.535)**
Agricultural productivity growth ($t-1$)	26.210*	−0.525	0.316	−0.188	−0.0250	8.909*	6.316	−0.281	−0.198	−12.42	5.940	−5.097
	(14.18)	(1.702)	(1.711)	(1.052)	(1.287)	(5.084)	(3.925)	(0.183)	(0.142)	(21.900)	(17.650)	(7.491)
Nonagricultural productivity growth ($t-1$)	−15.68**	−0.564	−0.749	−0.174	−0.450	−5.528**	−6.143**	0.0261	0.00750	5.547	−9.953	8.586*
	(5.859)	(1.064)	(1.114)	(0.658)	(0.769)	(2.070)	(2.766)	(0.106)	(0.086)	(14.990)	(19.43)	(5.048)
Log schooling years ($t-1$)	−11.65	0.261	−0.702	−0.135	−0.737	−5.265	8.673***	−0.0299	0.234*	46.34***	−39.37***	−8.656
	(13.97)	(1.631)	(2.090)	(0.618)	(1.113)	(7.249)	(2.851)	(0.177)	(0.137)	(8.679)	(8.875)	(7.405)
Observations	44	42	39	43	42	42	77	45	43	24	24	68
R-squared	0.271	0.542	0.428	0.689	0.689	0.256	0.063	−0.003	0.356	0.686	0.629	0.034
Number of economies	12	12	11	12	12	12	12	12	12	6	6	10

FE-IV = fixed effects instrumental variable.

Notes: "Gap" refers to the normalized difference between nonagricultural value added per worker and agricultural value added per worker (at purchasing power parity in United States dollars divided by 1,000). Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Values inside the parentheses below the column headings are the poverty lines.

Source: Authors' calculations based on World Bank. 2016. World Development Indicators 2016. https://openknowledge.worldbank.org/handle/10986/23969.

diversity in the preceding period, will reduce the labor productivity gap. That is, if the structural transformation in the rural sector progresses and agricultural production is more diversified, then the gap will be reduced, presumably because agricultural sector productivity will catch up with nonagricultural productivity. However, the first lagged agricultural productivity growth increases the gap. This is counterintuitive, but if agricultural productivity growth promotes nonagricultural growth without a lag, the period with faster agricultural productivity growth may even match the period with faster nonagricultural growth. The coefficient estimate of nonagricultural labor productivity growth is negative, but not statistically significant.[13] Education tends to increase the gap.

The question arising from the analysis in the last section is why the labor productivity gap has grown in some economies and not in other economies. It is not easy to provide a definite answer, but our results imply that the agricultural transformation reduces the gap and that improved human capital widens the gap.

In the second stage, we do not find any evidence that the gap influences poverty at the national level with the coefficient estimate being negative (except the second column) and statistically insignificant (the upper left panel of Table 3).[14] We find that the number of schooling years is negative and statistically significant. The F-statistic of excluded instruments is 16.34, which is above the threshold of 10, and the Sargan overidentification test of all instruments is not significant (p-value of 0.331), validating the IV estimation.

Next, we examine whether the labor productivity gap has affected poverty. Because the sample is reduced, the results from the first stage have changed slightly. For instance, nonagricultural productivity growth is now negative and significant, while one of the instruments, the productivity–diversity index, is now positive and significant. So, with a smaller sample, the progress of the agricultural transformation tends to increase the labor productivity gap. The reason is not clear, but in this case the agricultural transformation may have an instant impact on improving both agricultural and nonagricultural labor productivity, with the magnitude of the latter being comparatively larger.

In the second stage, the increase of the labor productivity gap tends to reduce poverty in the rural regions regardless of the choice of poverty thresholds and for all different measures of poverty (e.g., headcount, poverty gap, and poverty gap squared except the third column for extreme poverty gap squared as shown

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[13] The correlation between the labor productivity gap and nonagricultural labor productivity growth is positive with a correlation coefficient of 0.034. The correlation coefficient between the gap and agricultural labor productivity growth is 0.036. Not surprisingly, the correlation coefficient between the agricultural and nonagricultural sector growth terms is high at 0.614. The highest variance inflation factor of the first-stage regression is 2.44, which is below the threshold of 10 and which would justify the inclusion of labor productivity growth in both sectors at the same time.

[14] We have also estimated the second-stage regressions by using the FE model without using IV. In this case, the sample size is larger, but we have found that the lagged labor productivity gap reduces significantly both extreme and moderate poverty, for both the headcount ratio and poverty gap.

in the upper right panel of Table 3). That is, as nonagricultural labor productivity grows faster than agricultural labor productivity, rural poverty significantly declines in every dimension, including the share of the poor, the depth of rural poverty, and inequality among the rural poor. This result may not be consistent with the theoretical prediction by Bourguignon (1990) as the model suggests that the gap between the agricultural and nonagricultural sectors tends to increase inequality given elastic capital–labor substitution assumed in the modern sector. However, Vollrath's (2009) model implies that as nonagricultural labor productivity increases, the efficiency of workers in the agricultural sector improves. If this helps the rural poor escape from poverty, we expect that nonagricultural labor productivity growth has the effect of reducing rural poverty. Here, the test of excluded instruments (F-statistic) is 9.55, which is below the threshold of 10, partly because of the small sample size, and so the results need to be interpreted with caution. The Sargan statistic is not significant, justifying the use of IV.[15]

We have also estimated urban poverty in the second stage of the FE-IV model. The results are shown in the lower left panel of Table 3. We have found that the size of the poverty-reducing effect is much larger for urban poverty than rural poverty. That is, as the gap between nonagricultural and agricultural labor productivity expands, both urban poverty and rural poverty decrease, but urban poverty tends to decline at a much faster rate. However, the results will have to be interpreted with caution, particularly in cases where the F-statistic for excluded instruments in the first stage is low (columns 2 and 3).

Finally, we have estimated the effect of the lagged labor productivity gap on the Gini coefficient at the national, rural, and urban levels. As the sample sizes differ, the result in the first column cannot be compared with the results in the second and third columns. However, after controlling for the endogeneity of the labor productivity gap, we have found evidence that the gap significantly reduces the national Gini coefficient (the lower right panel of Table 3). In this case, the first-stage F-statistic is larger than 10. The result is robust if we do not instrument the labor productivity gap or if we use the smaller sample for which disaggregated inequality data are available.

Using the disaggregated data, we have also estimated the effects of the lagged labor productivity gap on the sectoral population share, drawing upon Imai, Gaiha, and Garbero (2017). The results will have to be interpreted with caution, specifically in the first and the second columns (due to the small sample size) where the specification tests for IV do not validate the specifications. However, we have found some evidence that the labor productivity gap reduces the rural population share and increases the share of the rural nonagricultural sector. When we use a larger sample size, we have found that the lagged productivity gap

[15]The lagged labor productivity gap is no longer statistically significant in explaining rural poverty for the larger sample in the FE model without IV.

increases the population share of the urban sector significantly. These results are broadly consistent with the theoretical model of Vollrath (2009) where increases in nonagricultural productivity will help industrialize the economy and induce agricultural laborers to work more efficiently, while the share of the agricultural sector declines over time. If this process benefits much of the population in rural and urban areas, inequality is likely to decline over time. However, our result is not consistent with Bourguignon's (1990) model, which implies that the gap between the agricultural and nonagricultural sectors tends to increase inequality.

In sum, we have found that the increase in the lagged labor productivity gap, which is treated as endogenous, will reduce both urban and rural poverty as well as national-level inequality. In particular, there is robust evidence confirming that the labor productivity gap reduces urban poverty evaluated at the poverty threshold of $2 per day.

V. Conclusions

First, we have examined whether labor productivities in the agricultural and nonagricultural sectors have converged by using the 5-year average panel dataset. We have found robust evidence that nonagricultural labor productivity and agricultural labor productivity did not converge; the former has grown faster and the gap has increased significantly over time.

We have also observed that within Asia (i) agricultural labor productivity has converged across economies, (ii) nonagricultural labor productivity has converged across economies, and (iii) the convergence effect is stronger for the nonagricultural sector. Agricultural labor productivity growth was found to promote nonagricultural productivity growth with some lag. That is, despite the slower growth in agricultural labor productivity, the agricultural sector played an important role in promoting nonagricultural labor productivity and thus in nonagricultural growth. As we used the 5-year average panel data, we can identify the middle- to long-term effects by controlling for short-term fluctuations.

In the second part of the study, we examined whether the labor productivity gap between the agricultural and nonagricultural sectors reduced poverty, inequality, and the sectoral population shares over time. While the results vary depending on the specifications, we have found some evidence that the labor productivity gap reduces both urban and rural poverty over time as well as national-level inequality. The gap also increases the share of the population in the urban sector.

Our results provide the following policy implications. While improvement in agricultural labor productivity also brings about improvement in nonagricultural labor productivity, the latter has increased faster than the former over time, resulting in a gap between the two sectors. The widening gap was found to reduce poverty and inequality. These results are important in light of the literature on structural transformation in Asia (e.g., Reardon and Timmer 2014; Imai, Gaiha, and Bresciani 2016), which underscores diffusion from the agricultural sector. Our results suggest that as the agricultural sector experiences structural changes, it plays a central role in improving nonagricultural labor productivity and reducing poverty and inequality within an economy. Policy makers need to facilitate the process of structural transformation (e.g., commercialization and product diversification of agriculture; revolutions in supply chain and retail networks; and integration of labor, land, and credit markets) to improve agricultural labor productivity and reduce poverty and inequality.

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Kuznets Revisited: What Do We Know about the Relationship between Structural Transformation and Inequality?

Çinar Baymul and Kunal Sen*

This paper revisits the Kuznets postulate that structural transformation will be associated with increasing inequality using comparable time series data for 32 developing and recently developed economies for the post-1950 period. We find that structural transformation in the majority of our economies has resulted in the movement of workers from agriculture to services, and not to manufacturing. Economies show different paths of structural transformation that cut across geographical regions, being either structurally underdeveloped, structurally developing, or structurally developed. We see clear differences in the structural transformation–inequality relationship depending on the stage of structural transformation that a particular economy is in, as well as across regions. We do not see a Kuznets-type relationship between manufacturing employment share and inequality when we take into account the different paths of industrialization that economies in our dataset have followed. On the other hand, inequality unambiguously increases with structural transformation if the movement of workers from agriculture is to services.

Keywords: agriculture, inequality, Kuznets, manufacturing, services, structural transformation
JEL codes: O50

I. Introduction

In recent decades, most developing and emerging economies have seen large shifts of workers from agriculture to the manufacturing and service sectors (Dabla-Norris et al. 2013; Felipe, Mehta, and Rhee 2015). At the same time, in several economies, inequality has increased (Berg and Ostry 2011, United Nations Development Programme 2013, Milanović 2016). In a famous 1955 paper, Kuznets argued that as low-income economies industrialize, inequality will increase over time as workers move from low-productivity agriculture to high-productivity

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manufacturing, which may lead to an increase in overall inequality, though the process of industrialization will also accelerate economic growth (Lewis 1954).

Two complications arise when considering Kuznets' thesis from the viewpoint of today. Firstly, very few economies have followed successful industrialization strategies since Kuznets published his article, and some economies may well be undergoing "premature deindustrialization" (Rodrik 2016). It is not clear what would be the inequality implications of the mixed record on industrialization in developing economies. Secondly, as we will show in this paper, much of the shift of workers from agriculture has been to services and not to manufacturing. Services, in general, tend to have lower levels of productivity than manufacturing, so it is not obvious that structural change that is biased toward services is necessarily as inequality enhancing as the agriculture-to-manufacturing shift in employment.

In this paper, we revisit the stylized facts of structural transformation and inequality, using comparable data on these measures for a range of low-, middle-, and (now) high-income economies in Asia, Africa, and Latin America for the period 1950–2010.[1] We ask whether there is a positive relationship between structural transformation and inequality, as hypothesized by Kuznets, and whether this relationship differs across economies that have followed different paths of structural transformation, and across regions.

In section II, we first provide a summary of the main theoretical underpinnings of the Kuznets process. In section III, we describe the data used in the paper. In section IV, we document the patterns of structural transformation across economies and classify them according to their stage of structural transformation. In section V, we present the stylized facts on the relationship between structural transformation and inequality. In section VI, we look at the regional differences in the structural transformation–inequality relationship. In section VII, we present our conclusions.

II. The Kuznets Process

In his classic 1955 paper, Kuznets suggested that in the early phase of economic development, inequality will increase. At a later phase of economic development, as governments follow redistributive policies combining progressive taxation with welfare spending, inequality may decrease. The core of Kuznet's argument on the relationship between inequality and development is captured in the following paragraph extracted from his 1955 paper:

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[1]The end year is 2012 in some cases and the start year differs across economies, depending on data availability. By structural transformation, we mean the movement of workers from low-productivity agriculture to higher-productivity services and manufacturing (McMillan, Rodrik, and Verduzco-Gallo 2014).

> An invariable accompaniment of growth in developed countries is the shift away from agriculture, a process usually referred to as industrialization and urbanization. The income distribution of total population in the simplest model may therefore be viewed as a combination of the total income distributions of the rural and urban populations. What little we know of the structure of the two component income distributions reveals that a) the average per capita income of the rural population is usually lower than that of the urban; b) inequality in the percentage shares within the distribution for the rural population is somewhat narrower than that in the urban population . . . Operating with this simple model, what conclusions do we reach? First, all other conditions being equal, the increasing weight of the urban population means an increasing share for the more unequal of the two component distributions. Second, the relative difference in per capita income between the rural and urban populations does not necessarily shift downward in the process of economic growth; indeed, there is some evidence to suggest that it is stable at best and tends to widen because per capita productivity in urban pursuits increases more rapidly than in agriculture. If this is so, inequality in total income distribution should increase (Kuznets 1955, 7–8).

The Kuznets process of widening inequality with structural transformation—that is, the movement of workers away from agriculture—can be described as comprising two subprocesses: (i) the movement of the population from a sector characterized by lower mean income to a sector characterized by higher mean income, and (ii) the movement of the population from a sector with low within-sector inequality to a sector with higher within-sector inequality. If both subprocesses work in the same direction—that is, if the movement of workers is from a sector with both a low mean and low variance in incomes to a sector with a higher mean and high variance in incomes—then structural transformation will unambiguously increase inequality. However, if the movement of workers is from a sector with a low mean but higher variance in income to a sector with a higher mean but lower variance in income, then it is less obvious that inequality will necessarily increase.

In Kuznets' view, the sector from which workers were moving out from is clearly agriculture. However, the sector that is absorbing the labor movement is left ambiguous in the 1955 paper; while it is most likely industry, it could be services as well. The two defining features of this sector are that it should have both higher mean income and within-sector inequality than the agricultural sector for the Kuznets process to hold. Both these features may not hold for any particular economy in the process of structural transformation. For example, if the movement of workers away from agriculture is mostly to the informal service sector such as retail trade and restaurants, it is not clear that such a transfer is necessarily a move to a sector with higher mean income. It is also possible that the agricultural sector in any particular economy has high inequality if the land distribution is concentrated among a few elites. In this case, if the movement of workers is from agriculture to a sector with relatively low inequality such as a labor-intensive manufacturing, inequality may not increase with structural transformation and may even decline.

What the above discussion shows is that whether the Kuznets process holds for any particular economy depends on the specific characteristics of the path of structural transformation that the economy follows. For example, are workers moving from an agricultural sector that has high land inequality or is the agricultural sector in this economy characterized by more equal land distribution? And, is the movement of workers to a sector with relatively low mean incomes such as low-productivity services or to a sector with high within-sector inequality such as mining or capital-intensive manufacturing? Previous empirical research on the Kuznets process does not have an unambiguous finding of inequality first increasing and then decreasing with economic development (Anand and Kanbur 1993a, 1993b; Milanović 2000; Lindert and Williamson 2003; Roine and Waldenström 2015). However, much of this literature has focused on the growth–inequality relationship, and there is a large gap in the literature on understanding the structural transformation–inequality relationship. This is a crucial omission, given the relevance of the debates around structural transformation and inequality in contemporary development policy.

III. Data

In this section, we describe the data used in the analysis of structural transformation, inequality, and poverty.

A. Structural Transformation

Data on structural transformation in economies are taken from the Groningen Growth and Development Centre's (GGDC) 10-Sector Database. The GGDC database includes data from 42 economies covering the 1950–2012 period. We have excluded advanced market economies from Europe, along with Japan and the United States, which left us with 32 economies from four geographic regions. Table 1 provides a list of economies in our sample with the time period that the data cover for each economy. The GGDC database consists of annual series for the gross value-added output and the number of people employed in agriculture, mining, manufacturing, utilities, construction, trade services, transport services,

Table 1. **List of Economies in the Sample**

Region	Abbreviation	Economy	Value Added Data Period	Employment Data Period
Africa	BWA	Botswana	1964–2010	1964–2010
	EGY	Egypt	1960–2012	1960–2012
	ETH	Ethiopia	1961–2010	1961–2010
	GHA	Ghana	1960–2010	1960–2010
	KEN	Kenya	1964–2010	1969–2010
	MWI	Malawi	1966–2010	1966–2010
	MUS	Mauritius	1970–2010	1970–2010
	MOR	Morocco	1960–2012	1960–2012
	NGA	Nigeria	1960–2010	1960–2011
	SEN	Senegal	1970–2010	1970–2010
	ZAF	South Africa	1960–2010	1960–2010
	TZA	Tanzania	1960–2010	1960–2010
	ZMB	Zambia	1965–2010	1965–2010
Asia	HKG	Hong Kong, China	1974–2011	1974–2011
	IND	India	1950–2012	1960–2010
	INO	Indonesia	1960–2012	1961–2012
	MAL	Malaysia	1970–2011	1975–2011
	PRC	People's Republic of China	1952–2010	1952–2011
	PHI	Philippines	1971–2012	1971–2012
	KOR	Republic of Korea	1953–2011	1963–2011
	SIN	Singapore	1960–2012	1970–2011
	TAP	Taipei,China	1961–2012	1963–2012
	THA	Thailand	1951–2011	1960–2011
Latin America	ARG	Argentina	1950–2011	1950–2011
	BOL	Bolivia	1950–2011	1950–2010
	BRA	Brazil	1950–2011	1950–2011
	CHL	Chile	1950–2011	1950–2012
	COL	Colombia	1950–2011	1950–2010
	CRI	Costa Rica	1950–2011	1950–2011
	MEX	Mexico	1950–2011	1950–2012
	PER	Peru	1950–2011	1960–2011
	VEN	Venezuela	1950–2012	1950–2011

Source: Groningen Growth and Development Centre (GGDC). 1950–2012. "GGDC 10-Sector Database." https://www.rug.nl/ggdc/productivity/10-sector/ (accessed March 1, 2018).

business services, government services, and personal services. We have grouped these 10 sectors into four main categories:

(i) Agricultural sector = agriculture

(ii) Manufacturing industry = manufacturing

(iii) Nonmanufacturing industry = mining + utilities + construction

(iv) Service sector = trade services + transport services + business services + government services + personal services

Gross value-added data are taken from national income accounts of the various economies and compiled according to the United Nations System of National Accounts. The 10 sectors have been classified using the International Standard Industrial Classification, Revision 3.1. Using this classification of manufacturing instead of the narrower Standard International Trade Classification implies that primary processed products are also included in the definition of manufacturing. Employment is defined as “all persons engaged,” thus including all paid employees as well as self-employed and family workers. This implies that the GGDC employment data include both the formal and informal sectors. The primary source of the employment data is the population census, supplemented by labor force and business surveys (Timmer and de Vries 2009; Timmer, de Vries, and de Vries 2016).

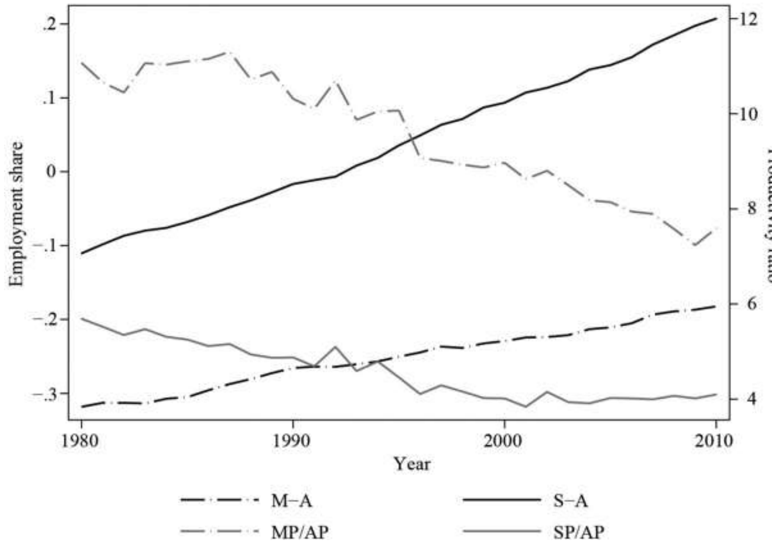
The share of employment for the four main categories is calculated by dividing the number of people employed in each category by the total number of people employed in the economy in a given year. Productivity in each category is calculated by dividing the value-added output in constant 2005 local currency by the number of people employed.

As noted by Diao, McMillan, and Rodrik (2017), GGDC provides the highest quality data available on sectoral output and employment for developing economies. However, it is also subject to certain limitations, which can raise concerns when the data are used to calculate productivity. The first set of limitations relates to the quality of the source data and the extent to which they include the informal sector. The quality of data on the sectoral value-added output published by national statistical agencies of underdeveloped economies can be unsatisfactory, and whether the data successfully account for the informal sector depends on the quality of the national sources. On the other hand, as the annual series on the number of people employed in each sector are obtained from census data and household surveys by the GGDC researchers, they are more likely to capture informal employment. (Appendix 1 discusses other sources of sectoral employment data and their limitations.)

B. Income Inequality

Income inequality data are taken from the standardized income inequality dataset computed by Baymul and Shorrocks (forthcoming). The Gini coefficient, calculated from household surveys, is the most commonly used measure of inequality. However, due to conceptual and methodological differences between household surveys, the comparability of inequality data is an issue that troubles empirical researchers. The standardized dataset used in this research tries to enhance comparability by adjusting all available data that exceeds a quality threshold from various sources through a regression adjustment method that

Figure 1. **Shifts in Employment between Sectors and Relative Labor Productivity**



M–A = share of (manufacturing–agriculture), S–A = share of (services–agriculture), MP/AP = manufacturing productivity/agriculture productivity, SP/AP = services productivity/agriculture productivity.
Source: Groningen Growth and Development Centre.

includes an extensive list of independent variables. Despite generating the highest number of individual annual observations per economy compared with any other available dataset, the number of observations still varies between economies.

In this paper, we use Gini coefficients that indicate the net income per capita inequality.[2] However, standardized income inequality data are prone to measurement errors made in source data. Measurement errors could be especially problematic in least developed economies where the quality of the data collection methods is questionable.

IV. Patterns of Structural Transformation

A striking feature of structural transformation in our sample of 32 economies is that the movement of employment from agriculture has been mostly to services (Figure 1). We observe an agriculture-to-manufacturing shift in employment for an appreciably long period only for East and Southeast Asian economies and for Mauritius. Even for this set of economies, the share of manufacturing in total

[2]We confine our analysis to using net income Gini as the measure of inequality as the relationship between structural transformation and other measures of inequality such as the income share of the top 10% or bottom 40% of the population is broadly similar to the relationship between structural transformation and net income Gini (results available upon request).

employment shows a hump shape in the case of Hong Kong, China; Malaysia; Mauritius; the Republic of Korea; Singapore; and Taipei,China; which suggests that the share of employment in manufacturing has reached its peak and is now falling steadily over time.

A second striking feature of structural transformation is that the shift of employment from agriculture to services has been accompanied by falling productivity in the service sector compared with agriculture (Figure 1).[3] The large shift of employment from agriculture to services accompanied by the falling relative productivity of services suggests that structural transformation in most developing economies (barring a few economies in Asia) has not been growth enhancing. This has implications for the possible effects that structural transformation may have on inequality, which we explore in the next section. We also observe a similar falling ratio of manufacturing to agricultural productivity, though the relative productivity of manufacturing is far higher than that of services.

Economies in our sample show three different paths or stages of structural transformation. There are economies where agriculture is still the largest sector in terms of the share of employment in the most recent time period available. In our sample, these economies are Ethiopia, India, Kenya, Malawi, Nigeria, Senegal, Tanzania, and Zambia. These economies are all in Sub-Saharan Africa except for India. We call these economies structurally underdeveloped. The next set of economies are where more people are employed in the service sector than in agriculture, with agriculture being the second-largest sector. These economies are Bolivia, Botswana, Brazil, Colombia, Costa Rica, Egypt, Ghana, Indonesia, Morocco, the People's Republic of China, Peru, the Philippines, Thailand, and South Africa. We call them structurally developing economies. These economies span all three continents included in our study: Africa, Asia, and Latin America. The final set of economies has more people employed in the manufacturing sector than in agriculture. These economies are Argentina; Chile; Hong Kong, China; Malaysia; Mauritius; Mexico; the Republic of Korea; Singapore; Taipei,China; and Venezuela. These economies are either in East Asia or Latin America, with the exception of Mauritius, which is in Africa. We call these economies structurally developed.

Figure 2 presents summary graphs of the path of structural transformation between 1980 and 2010 by level of structural development. We see that the share of employment in services in structurally developed economies surpasses the share of employment in agriculture prior to 1980, while the share of employment in the manufacturing sector has stayed relatively stable with a slight decrease in the relative productivity of manufacturing. Despite decreasing relative productivity compared with agriculture, the labor share of both services

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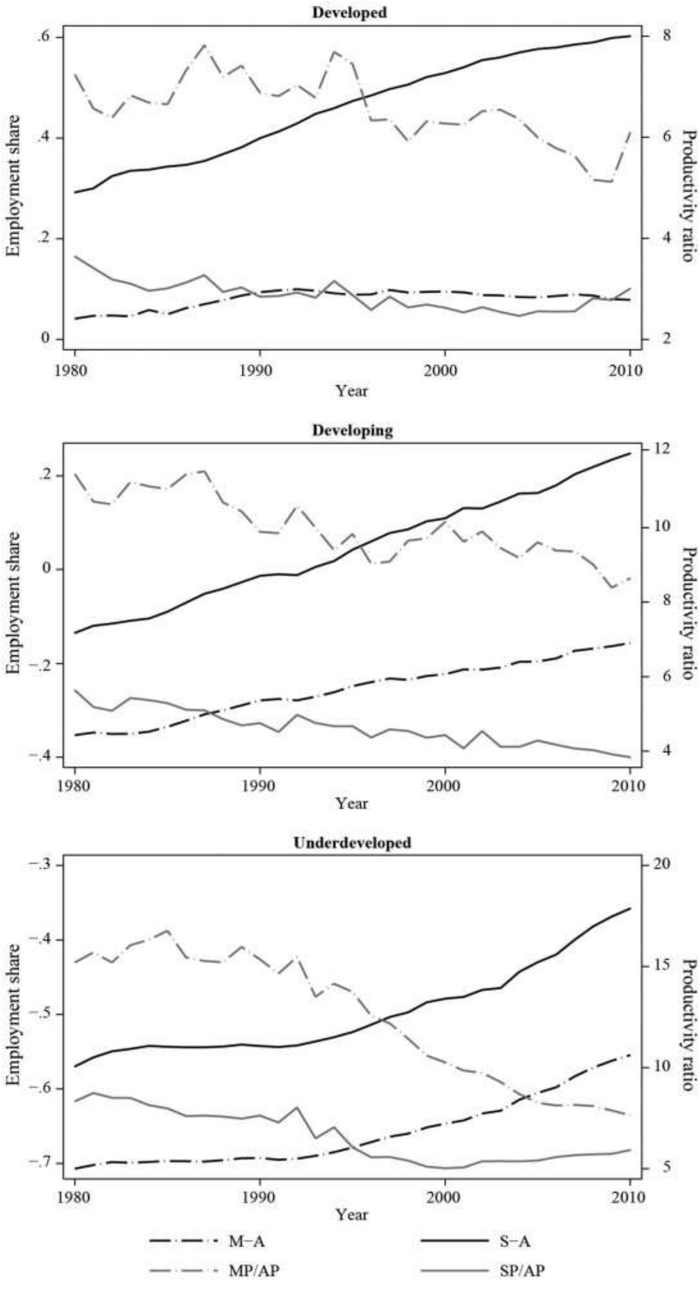
[3]The figures on productivity would be sensitive to price movements such as a terms-of-trade shock to agriculture. However, purchasing power parity measures of sectoral output are not available in the GGDC data.

Figure 2. **Shifts in Employment between Sectors and Relative Labor Productivity by Stage of Structural Transformation**



M–A = share of (manufacturing–agriculture), S–A = share of (services–agriculture), MP/AP = manufacturing productivity/agriculture productivity, SP/AP = services productivity/agriculture productivity.
Source: Groningen Growth and Development Centre.

and manufacturing increases over the 30-year period for structurally developing and underdeveloped economies. Structurally underdeveloped economies started to experience significant labor shifts from agriculture to other sectors only from the middle of the 1990s onward.

V. Structural Transformation and Inequality

As we have noted in the previous section, the movement of labor away from agriculture in the process of economic development can either be toward manufacturing or services. We first look at the relationship between structural transformation and inequality when the share of employment in agriculture is falling. We then look at the manufacturing employment–inequality relationship, followed by the services employment–inequality relationship. In each case, we first look at the pooled relationship between structural transformation and inequality, where we measure inequality by the net income per capita Gini. We then focus on our three economy groups, which we have categorized by their stage of structural transformation: (i) structurally developed, (ii) structurally developing, and (iii) structurally underdeveloped.[4]

A. Agriculture versus Inequality

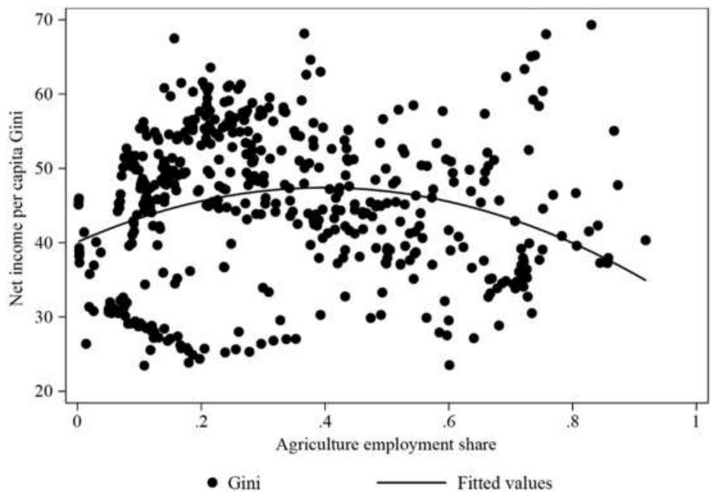
In the overall sample, we see evidence of the Kuznets curve with an increase in inequality, whether measured by the net income Gini or the income share of the bottom 40% of the population, and then a decrease with a fall in the share of employment in agriculture (Figure 3). In structurally developed economies, we see that as the share of agriculture in employment decreases, inequality follows an inverted U-shaped pattern (Figure 4). It first increases, peaking when agriculture's employment share is around 20% of total employment. Inequality declines once its share drops below this level. In structurally developing and underdeveloped economies, we only witness the first half of the transformation, where agriculture's share has not declined below 20% yet for most economies and inequality has been increasing while agriculture's share drops.

B. Manufacturing versus Inequality

In the overall sample, we see a clear negative relationship between the share of employment in manufacturing and inequality (Figure 5). As the share of manufacturing increases in structurally developed economies, inequality decreases (Figure 6). There is weaker evidence of this relationship for developing and underdeveloped economies; the likely reason being that they have not yet reached

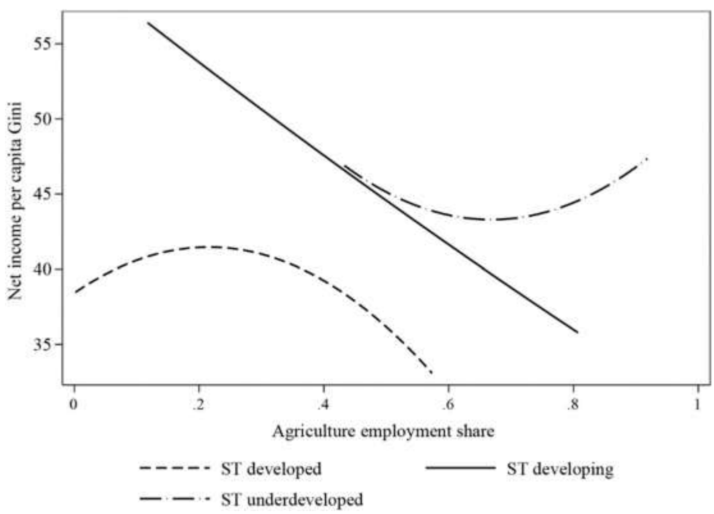
[4] All estimates of group averages presented in this section use unweighted averages.

Figure 3. **Agriculture Employment Share versus Income Inequality**



Sources: Groningen Growth and Development Centre (GGDC). 1950–2012. “GGDC 10-Sector Database.” https://www.rug.nl/ggdc/productivity/10-sector/ (accessed March 1, 2018); Baymul and Shorrocks (forthcoming).

Figure 4. **Agriculture Employment Share versus Income Inequality by Development Level**

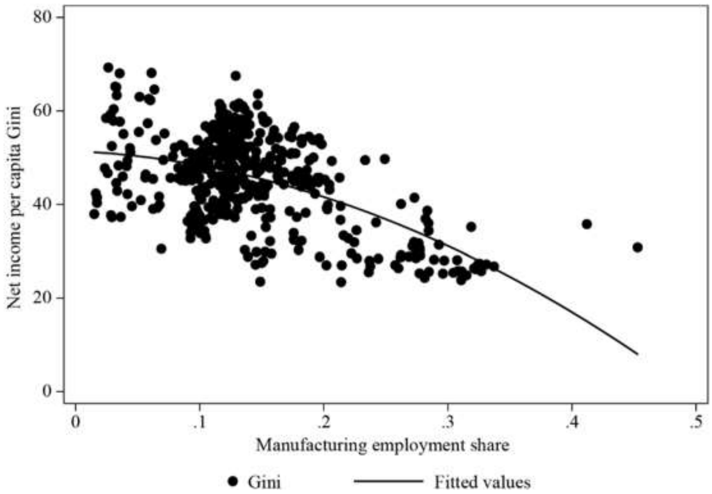


ST = Structurally.
Sources: Groningen Growth and Development Centre (GGDC). 1950–2012. “GGDC 10-Sector Database.” https://www.rug.nl/ggdc/productivity/10-sector/ (accessed March 1, 2018); Baymul and Shorrocks (forthcoming).

the level of development that is necessary to foster a more equal distribution of income.

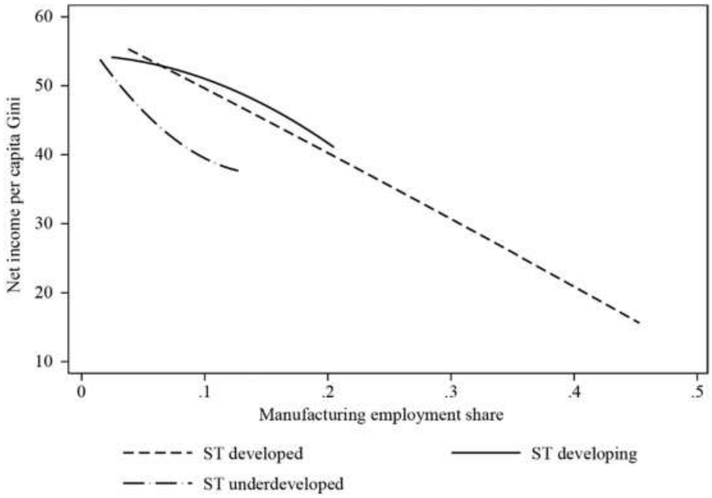
Figure 7 shows that the marginal effect of an increase in manufacturing employment share on inequality is very different, depending on whether the

Figure 5. **Manufacturing Employment Share versus Income Inequality**



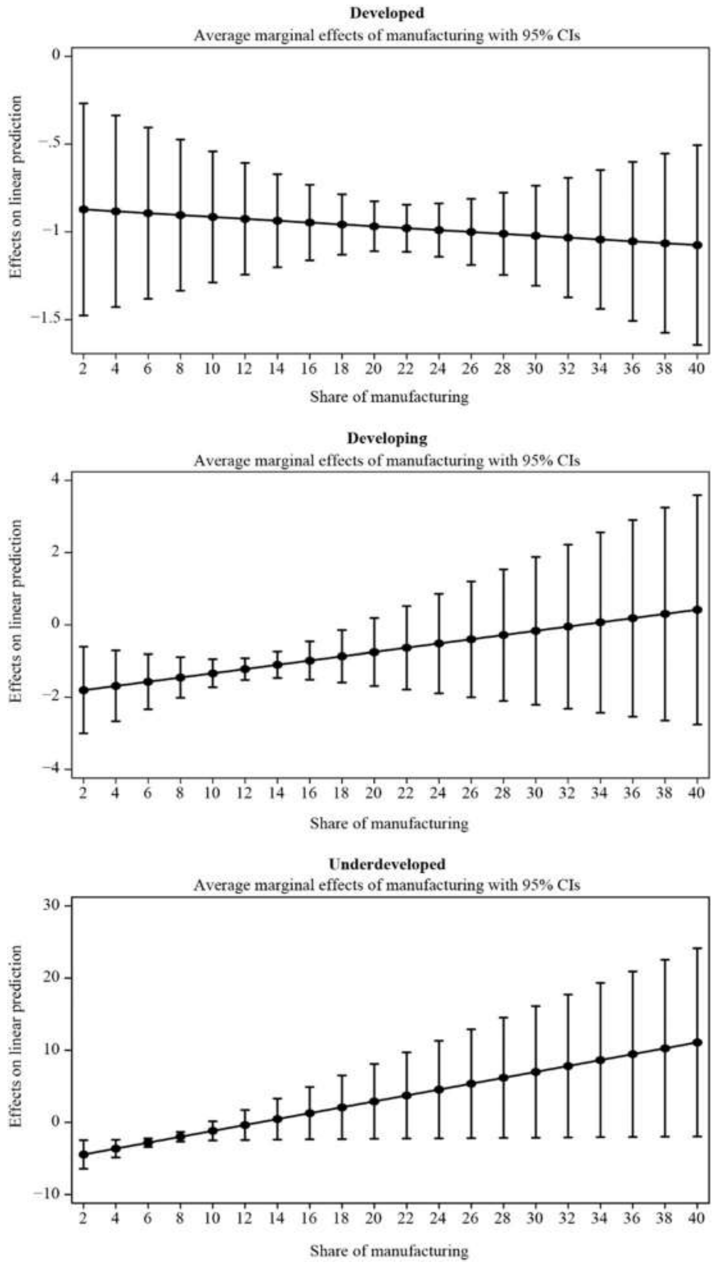
Sources: Groningen Growth and Development Centre (GGDC). 1950–2012. "GGDC 10-Sector Database." https://www.rug.nl/ggdc/productivity/10-sector/ (accessed March 1, 2018); Baymul and Shorrocks (forthcoming).

Figure 6. **Manufacturing Employment Share versus Income Inequality by Development Level**



ST = Structurally.
Sources: Groningen Growth and Development Centre (GGDC). 1950–2012. "GGDC 10-Sector Database." https://www.rug.nl/ggdc/productivity/10-sector/ (accessed March 1, 2018); Baymul and Shorrocks (forthcoming).

Figure 7. **Marginal Effect of Manufacturing Employment Share on Inequality by Stage of Structural Transformation**



CIs = confidence intervals.
Note: Both Gini (dependent variable) and share of manufacturing (manfindustry_share) are measured as a percentage.
Sources: Groningen Growth and Development Centre (GGDC). 1950–2012. "GGDC 10-Sector Database." https://www.rug.nl/ggdc/productivity/10-sector/ (accessed March 1, 2018); Baymul and Shorrocks (forthcoming).

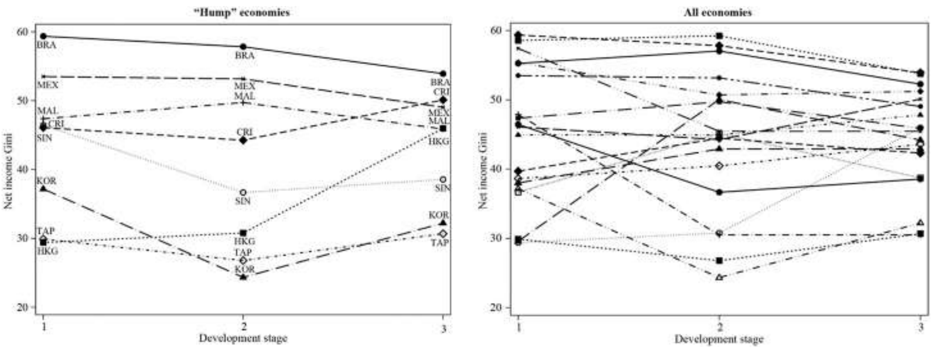
economy is structurally developed, developing, or underdeveloped. Marginal effects are calculated through ordinary least squares regressions, with estimates presented in columns (I) and (III) of Table A2.1. Samples for regression models are given in Table A2.5. For structurally developed economies, an increase in the manufacturing employment share unambiguously decreases inequality, and there is a relative fall in the marginal effect of the manufacturing employment share on inequality as this share increases over time. For structurally developing economies where the manufacturing employment share ranges from around 2% to 20%, an increase in the manufacturing employment share decreases inequality. We see a similar phenomenon for structurally underdeveloped economies where the manufacturing employment share varies from around 2% to 10%. This indicates that, on the whole, structural transformation that is related to an increase in the manufacturing employment share is associated with decreasing inequality.

However, one problem in assessing the relationship between manufacturing employment share and inequality is that the share of manufacturing in total employment does not show a clear monotonic relationship with time. This is in contrast with the behavior of the shares of agriculture and services in total employment, both of which show a clear monotonic relationship with time. (In the case of agriculture, its share in total employment falls over time for our sample economies; in the case of services, its share increases more or less continuously over time for our sample economies.)

Economies exhibit the following patterns in the share of manufacturing in total employment over time: (i) a "hump" (increasing, then decreasing); (ii) continuously increasing; (iii) continuously decreasing; and (iv) no discernible movement. This suggests that a scatter plot of inequality against the manufacturing employment share may simply be capturing cross-sectional differences in the relationship of inequality with the manufacturing employment share across the sample economies, in contrast to the scatters of inequality against the agricultural and services employment shares, which capture both time series and cross-sectional variation in the relationship. (In the case of the inequality–agriculture scatter, a movement in the graph from right to left in the horizontal axis is a movement in time; in the case of the inequality–services scatter, a movement in the graph from left to right in the horizontal axis is a movement in time.)

In order to further analyze the relationship between inequality and manufacturing employment share, we have separated the economies in which we observe a hump in manufacturing employment. We define these humps as a steady increase in manufacturing from time t to time $t + 1$, and then a decrease from $t + 1$ onward. Hence, economies reach the peak level of employment in manufacturing at $t + 1$, where t can be different for each economy. We call the increase in manufacturing in time period t, Development Stage 1; the peak at $t + 1$, Development Stage 2; and the subsequent decline, Development Stage 3.

Figure 8. **Inequality in Different Development Stages**

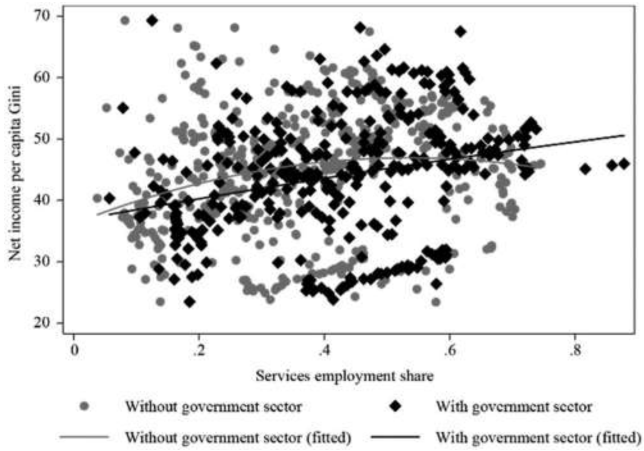


Sources: Groningen Growth and Development Centre (GGDC). 1950–2012. "GGDC 10-Sector Database." https://www.rug.nl/ggdc/productivity/10-sector/ (accessed March 1, 2018); Baymul and Shorrocks (forthcoming).

Taking the closest net income Gini coefficients corresponding to each stage for each economy, we produced the graphs in Figure 8. Graphs on the left-hand side show the movement of Gini coefficients through the three development stages for economies in which we observe the hump. Other economies might be on the first or third stage of development during the entire time period of the sample. Graphs depicting the same relationship are on the right-hand side for all economies. We do not observe any meaningful relationship between income inequality and the development stages of different economies. Whether we confine our analysis to the economies with a hump shape in their manufacturing employment share or include all economies for which we have inequality data over the time period, we do not observe a common relationship between the manufacturing employment share and inequality over time across our sample economies. This clearly shows the lack of a Kuznets-type inverted U-shaped relationship across all economies, with a great deal of heterogeneity in the response of inequality to manufacturing-driven structural transformation across economies. In fact, we do not see a Kuznets-type relationship for any of the 32 economies in our sample.[5] In addition, in the cases of the Republic of Korea; Singapore; and Taipei,China; we see a decrease in inequality as the manufacturing employment share increases to its peak level, which is then followed by an increase.

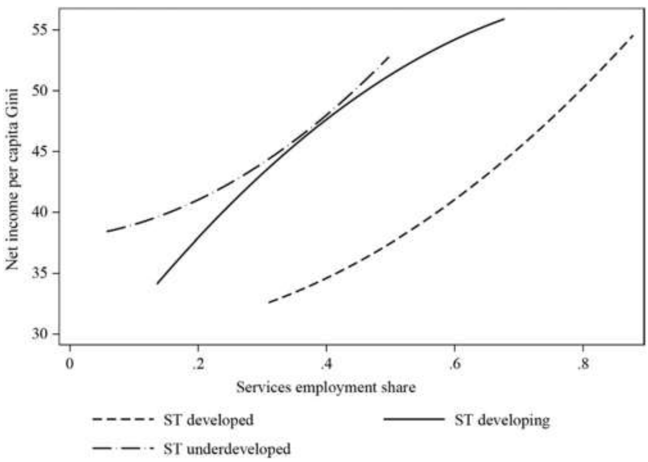
[5] We supplement our analysis of the relationship between the manufacturing employment share and inequality by including economies in the database on manufacturing employment shares compiled by Felipe and Mehta (2016). In this database, smaller economies in the Pacific and Central America, and some other South Asian economies such as Bangladesh and Pakistan, are included. However, our findings on the lack of a relationship between the manufacturing employment share and inequality remains the same with this expanded data (results available on request).

Figure 9. **Services Employment Share versus Income Inequality**



Sources: Groningen Growth and Development Centre (GGDC). 1950–2012. "GGDC 10-Sector Database." https://www.rug.nl/ggdc/productivity/10-sector/ (accessed March 1, 2018); Baymul and Shorrocks (forthcoming).

Figure 10. **Services Employment Share versus Income Inequality by Development Level**



ST = structurally.
Sources: Groningen Growth and Development Centre (GGDC). 1950–2012. "GGDC 10-Sector Database." https://www.rug.nl/ggdc/productivity/10-sector/ (accessed March 1, 2018); Baymul and Shorrocks (forthcoming).

C. Services versus Inequality

A higher share of service sector employment is associated with higher inequality in all economy groups, with the correlation being especially strong in structurally developing economies (Figures 9, 10).

Thus, we observe a very different behavior of inequality to increases in the services employment share compared with what we observed with the increases in the manufacturing employment share.

Looking at the marginal effects, the effect of an increase in the services employment share on inequality is unambiguously positive, irrespective of an economy's stage of structural transformation (Figure 11). Secondly, even though the overall effect of services-driven structural transformation is positive, there is a decline in the marginal effect of the increase in the services employment share on inequality across all economy groups. In other words, as the service sector employment share increases, inequality increases at a decelerating rate.

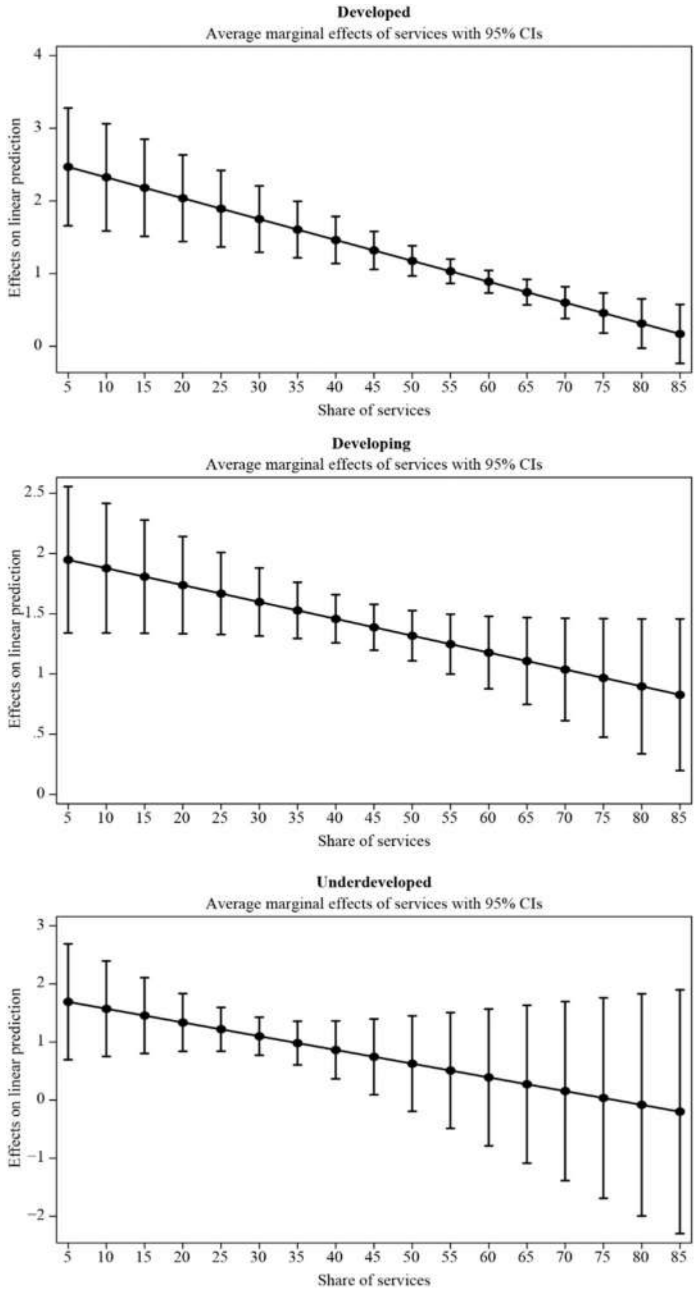
Robustness Tests

We conduct three further tests to check the robustness of our results. Firstly, we use the gross Gini instead of the net Gini to see the direct effect of structural transformation on market inequality, prior to taxes and transfers. We present the regression results in Table A2.2. Next, we confine our analysis to the post-1970 period as there was not a significant structural transformation in most developing economies during the 1960s. We present the regression results in Table A2.3. Finally, we use the sectoral employment data from the International Labour Organization (ILO). These data are seen as being poor quality as they are directly obtained from the statistical agencies of the economies concerned and are not subject to consistency checks in the same way as the GGDC data. (For a discussion of the weaknesses of these data, see Diao, McMillan, and Rodrik [2017].) By using these data, we more than double the number of observations to 1,148. We present the regression results in Table A2.4 and the plots of the marginal effects of manufacturing and services on inequality in Figures A2.1 and A2.2, respectively.

When we use gross Gini instead of net Gini, we do not find any difference in our results in terms of the manufacturing and services employment shares on inequality, either by structural transformation group or region. The sign and significance of the coefficients of the manufacturing employment share and its square, and the interaction of these two variables with structural transformation groups and with regions, generally remain the same compared with the results in Table A2.1 and columns (I) and (II) in Table A2.2. Similarly, we do not find any discernible difference in the sign and significance of the coefficients of the services employment share and its square and the interaction of these two variables with structural transformation groups and with regions compared with Table A2.1 and columns (III) and (IV) in Table A2.2. We also get identical results with the post-1970 employment data (Table A2.3).

When we use the ILO data, we find that the marginal effect of the manufacturing employment share on inequality changes from negative to positive for structurally developed economies, but that there is no change in the effect of the

Figure 11. **Marginal Effect of Services on Inequality by Economy Groups**



CIs = confidence intervals.
Note: Both Gini (dependent variable) and share of services (servwithgov_share) are measured as a percentage.
Sources: Groningen Growth and Development Centre (GGDC). 1950–2012. "GGDC 10-Sector Database." https://www.rug.nl/ggdc/productivity/10-sector/ (accessed March 1, 2018); Baymul and Shorrocks (forthcoming).

manufacturing employment share on inequality for structurally underdeveloped and developing economies for relevant ranges of the manufacturing employment shares compared with Figure 7 (Table A2.4 and Figures A2.1, A2.2).

VI. Regional Differences in the Relationship between Structural Transformation and Inequality

Are there differences in the relationship between structural transformation and inequality across regions? In particular, is the relationship for Asia different than for Africa and Latin America? With respect to manufacturing, we see that the marginal effect of the manufacturing employment share on inequality is very similar for Asia and Africa (Figure 12).[6] An increase in the manufacturing employment share is first associated with a decrease in inequality, though every percentage point increase in the manufacturing employment share leads to a smaller decrease in inequality, up to a point where a further increase in the manufacturing employment share is not associated with any decrease in inequality (that is, the marginal effect turns from negative to zero).[7] However, in the case of Latin America, an increase in the manufacturing employment share is initially associated with an increase in inequality, though after this share reaches a critical level of 10%, inequality starts decreasing with an increase in the manufacturing employment share. Though Asia and Africa show similar paths of inequality with respect to manufacturing-driven structural transformation, it is important to note that African economies have witnessed far lower levels of industrialization than Asian economies. The highest maximum level of manufacturing employment share for an African economy is 32.2% (Mauritius in 1990), while the average manufacturing employment share for our sample of African economies for the last year for which data are available is 18.5%. In contrast, the highest maximum level of manufacturing employment share for an Asian economy is 45.3% (Hong Kong, China in 1976), while the average manufacturing employment share for the last year in which data are available is 27.5%. This suggests that for most African economies, a 1 percentage point increase in the manufacturing employment share will be associated with a large decline in inequality, compared with most Asian economies where further manufacturing-driven structural transformation is unlikely to be associated with declining inequality.

With respect to services, we see something completely different: we now observe that the relationship of services-driven structural transformation and inequality is very similar for Asia and Latin America (Figure 13). An increase in the service sector share of employment is associated with an increase in

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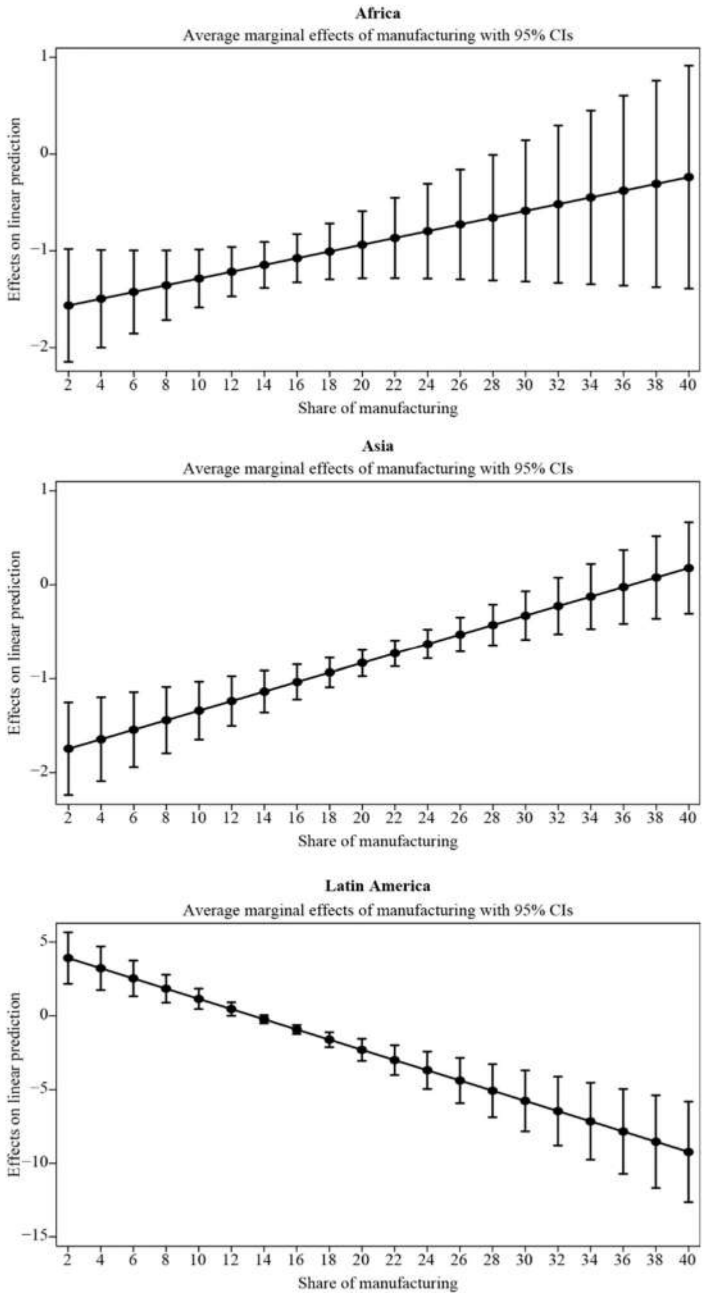
[6]We include Middle East and North African economies in the African region, along with Sub-Saharan African economies.

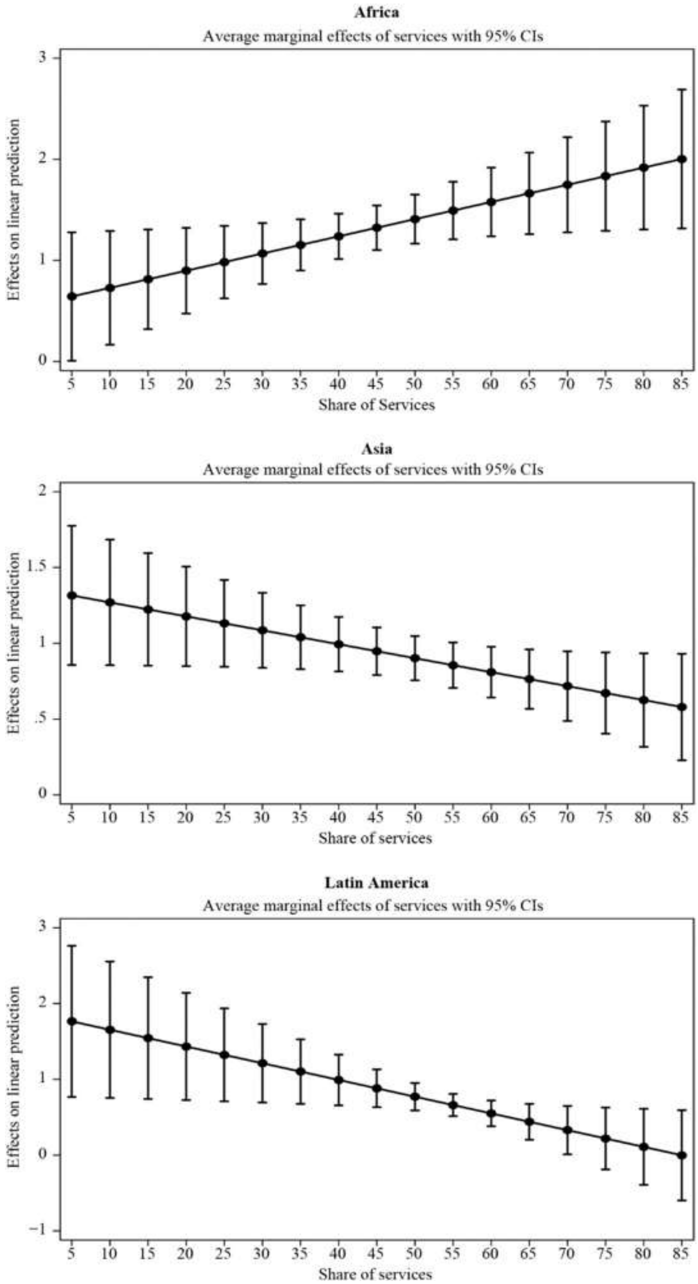
[7]Figures 12 and 13 are based on regression estimates presented in columns (II) and (IV) of Table A2.1.

Figure 12. **Marginal Effect of Manufacturing on Inequality by Region**



CIs = confidence intervals.
Note: Both Gini (dependent variable) and share of services (servwithgov_share) are measured as a percentage.
Sources: Groningen Growth and Development Centre (GGDC). 1950–2012. "GGDC 10-Sector Database." https://www.rug.nl/ggdc/productivity/10-sector/ (accessed March 1, 2018); Baymul and Shorrocks (forthcoming).

Figure 13. **Marginal Effect of Services on Inequality by Region**



CIs = confidence intervals.

Note: Both Gini (dependent variable) and share of services (servwithgov_share) are measured as a percentage.

Sources: Groningen Growth and Development Centre (GGDC). 1950–2012. "GGDC 10-Sector Database." https://www.rug.nl/ggdc/productivity/10-sector/ (accessed March 1, 2018); Baymul and Shorrocks (forthcoming).

inequality in both regions. However, the marginal effect of services-driven structural transformation on increases in inequality declines over time. Given the large and steady increases in the share of services in employment in most Latin American and Asian economies in recent years, this suggests that inequality will increase in these economies for some time, but that the rate of change of inequality will fall over time.[8] In contrast, in Africa, services-driven structural transformation is associated with increasing inequality, and the rate of change of inequality with an increase in the services employment share is actually increasing. This suggests that for many African economies, as workers gradually move from agriculture to services (with stagnant manufacturing employment in most economies), inequality will increase at an increasing rate for some time to come.

VII. Conclusions

A long-held view in the literature on economic development is that inequality increases with structural transformation as workers move from a low-inequality sector such as agriculture to high-inequality sectors such as manufacturing and services. This is commonly known as the Kuznets process. We revisit the relationship between structural transformation and inequality using comparable data for 32 developing and recently developed economies for the period 1950–2010.

Firstly, we find that structural transformation in the majority of our 32 economies has entailed a move of workers from agriculture to services, and not to manufacturing. Further, the move of workers from agriculture to services (and, wherever it has occurred, to manufacturing) has been accompanied by a fall in the relative productivity of services and manufacturing compared with agriculture (barring a few economies in East and Southeast Asia). The economies in our sample have shown different paths of structural transformation that cut across geographical regions. A set of economies can be categorized as structurally developed if the number of workers employed in manufacturing exceeds the number of workers employed in agriculture. Five Asian economies figure in this list—Hong Kong, China; Malaysia; the Republic of Korea; Singapore; and Taipei,China—along with Argentina, Chile, Mauritius, Mexico, and Venezuela. Structurally underdeveloped economies have agriculture as the largest sector in terms of the number of people employed in the most recent time period available. In our sample, only one Asian economy figures in this list, India, along with Ethiopia, Kenya, Malawi, Nigeria, Senegal, Tanzania, and Zambia. Structurally developing economies are those where more people are employed in the service sector than in agriculture, with agriculture being the second-largest sector. Four Asian economies figure in this list—Indonesia, the People's Republic of China, the Philippines, and Thailand—along with Bolivia,

[8]Following the referee's suggestion, we have excluded Singapore and Hong Kong, China from our analysis with no change in our findings.

Botswana, Brazil, Colombia, Costa Rica, Egypt, Ghana, Morocco, Peru, and South Africa.

If we look at the relationship of the employment share of agriculture in total employment and inequality, we see a Kuznets-type, inverted-U relationship for structurally developed economies. For structurally developing and underdeveloped economies, a lower employment share in agriculture is accompanied by higher inequality. However, we do not observe a Kuznets-type relationship between the share of manufacturing in total employment and inequality. This is particularly evident when we take into account the different paths of industrialization that developing economies have followed. In fact, in contrast to what was postulated by Kuznets, there is a fall in inequality with an increase in the manufacturing employment share for all economies. We also see clear regional differences in the structural transformation–inequality relationship in the case of manufacturing, with an increase in the employment share of the latter associated with falling inequality in Africa and Asia, but with increasing inequality in Latin America.

In the case of services, we see that the effect of an increase in the services employment share on inequality is unambiguously positive, irrespective of an economy's stage of structural transformation. However, we also find that there is a decline in the marginal effect of the increase in the services employment share on inequality across all economy groups, so that the rate of increase in inequality as the services employment share increases declines over time. We also find that an increase in inequality with services-driven structural transformation is evident for Africa, Asia, and Latin America. However, the rate of increase in inequality falls over time in Asia and Latin America, in contrast with Africa where the rate of change of inequality increases over time, suggesting that the evolution of inequality will be very different in Asia and Latin America compared with Africa as all three regions see significant shift of workers from agriculture to services.

Our paper did not attempt to explain why we see such a heterogeneous response of inequality to structural transformation across economies, and why the effect of manufacturing-driven structural transformation on inequality is different from that of services-driven structural transformation. For Asia, the high rates of manufacturing-driven structural transformation and the relatively benign effect of such a pattern provides more of a win–win scenario of structural transformation into manufacturing, leading to both economic growth and falling inequality. This is a scenario that is very different from that envisaged by Kuznets and many others in the development community in which structural transformation was inevitably associated with rising inequality. Why Asia has had such a favorable scenario is an avenue for further research.

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Appendix 1. Alternate Sources of Employment Data

There are two additional sources of data, apart from the GGDC database, on sectoral employment at the economy level. The first is the World Bank's World Development Indicators (WDI), which covers more economies than the GGDC. However, the WDI only reports total shares of labor in agriculture, industry, and services. The industry sector consists of mining, construction, public utilities, and manufacturing. The service sector consists of wholesale and retail trade and restaurants and hotels; transport, storage, and communications; financing, insurance, real estate, and business services; and community, social, and personal services. The WDI dataset does not break down industry employment data by manufacturing and nonmanufacturing (e.g., mining, construction, utilities) and services employment by subsectors. The aim of our analysis is to examine the impact of manufacturing and service subsectors on inequality. Since the WDI does not offer information on subsectoral allocations of employment, we are unable to use the data it provides.

A second source of employment data is the ILO's database, ILOSTAT, which provides detailed information on the number of people working in each sector for a majority of the economies in our sample since the 1950s. The data are based mostly on labor force surveys and supplemented by censuses and other minor sources. However, even though ILOSTAT offers the largest sample size and time scale, the comparability of this dataset is limited as concept definitions and population coverage differ between economies and over time. The frequency of the data collected also varies between economies and disregards all impacts of seasonality on the labor force. For these reasons, the GGDC 10-Sector Database is our preferred data source.

Appendix 2. Tables and Figures

Table A2.1. **Regression Results; Dependent Variable: Net Gini**

	I	II		III	IV
Agriculture	0.11	0.30***	Agriculture	1.01***	0.99***
	(0.07)	(0.05)		(0.15)	(0.09)
Agriculture^2	−0.0052***	−0.0056***	Agriculture^2	−0.0014	−0.0036**
	(0.0009)	(0.0007)		(0.0019)	(0.0015)
Manufacturing (Man)	−1.92***	−1.63***	Services	2.02***	0.56
	(0.72)	(0.34)		(0.34)	(0.36)
Manufacturing^2	0.0292	0.0175	Services^2	−0.0070*	0.0085**
	(0.0289)	(0.0111)		(0.0037)	(0.0039)
Developed	−13.36**		Developed	−13.77	
	(5.79)			(13.57)	
Underdeveloped (Und)	14.41**		Underdeveloped	6.29	
	(5.96)			(7.34)	

Continued.

Table A2.1. *Continued.*

	I	II		III	IV
Developed × Man	1.06		Developed ×	0.59	
	(0.79)		Services	(0.55)	
Developed × Man^2	−0.0319		Developed ×	−0.0074	
	(0.0298)		Services^2	(0.0053)	
Und × Man	−3.34**		Und × Services	−0.21	
	(1.55)			(0.50)	
Und × Man^2	0.1752*		Und × Services^2	−0.0048	
	(0.1036)			(0.0088)	
Asia		−5.06*	Asia		−15.93***
		(2.78)			(4.72)
Latin America (LAM)		−45.93***	Latin America		−15.69
		(7.71)			(15.82)
Asia × Man		−0.21	Asia × Services		0.80***
		(0.38)			(0.26)
Asia × Man^2		0.0079	Asia × Services^2		−0.0131***
		(0.0066)			(0.0034)
LAM × Man		6.25***	LAM × Services		1.31**
		(1.07)			(0.60)
LAM × Man^2		−0.1905***	LAM × Services^2		−0.0195***
		(0.0361)			(0.0059)
No. of observations	478	478		330	330
R–squared	0.55	0.66		0.57	0.66

Notes: Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Column (I) is a regression with manufacturing employment share, the square of manufacturing employment share, and the interaction of these two variables with a structural transformation group. Column (II) is a regression with manufacturing employment share, the square of manufacturing employment share, and the interaction of these two variables with the region the economy is in. Column (III) is a regression with services employment share, the square of services employment share, and the interaction of these two variables with the structural transformation group. Column (IV) is a regression with services employment share, the square of services employment share, and the interaction of these two variables with the structural transformation group.
Source: Authors' calculations.

Table A2.2. **Regression Results, Dependent Variable: Gross Gini**

	I	II		III	IV
Agriculture	0.073	0.28***	Agriculture	0.89***	1.00***
	(0.075)	(0.05)		(0.17)	(0.11)
Agriculture^2	−0.005***	−0.006***	Agriculture^2	−0.00	−0.004**
	(0.001)	(0.0007)		(0.002)	(0.002)
Manufacturing (Man)	−2.11***	−1.65***	Services	1.91***	0.43
	(0.74)	(0.36)		(0.38)	(0.41)
Manufacturing^2	0.037	0.017	Services^2	−0.01*	−0.01***
	(0.03)	(0.012)		(0.00)	(0.004)
Developed	−10.05*		Developed	−13.79	
	(5.96)			(15.01)	
Underdeveloped (Und)	11.21*		Underdeveloped	0.17	
	(6.12)			(8.12)	
Developed × Man	0.79		Developed ×	0.50	
	(0.81)		Services	(0.60)	

Continued.

Table A2.2. *Continued.*

	I	II		III	IV
Developed × Man^2	−0.030		Developed × Services^2	−0.006	
	(0.031)			(0.006)	
Und × Man	−3.01*		Und × Services	−0.03	
	(1.59)			(0.55)	
Und × Man^2	0.160		Und × Services^2	−0.01	
	(0.107)			(0.01)	
Asia		−2.66	Asia		−14.71***
		(2.94)			(5.35)
Latin America (LAM)		−44.29***	Latin America		−17.52
		(8.12)			(17.93)
Asia × Man		−0.47	Asia × Services		0.74**
		(0.40)			(0.29)
Asia × Man^2		0.014	Asia × Services^2		−0.013***
		(0.012)			(0.004)
LAM × Man		6.00***	LAM × Services		1.37**
		(1.13)			(0.68)
LAM × Man^2		−0.183***	LAM × Services^2		−0.020***
		(0.038)			(0.007)
No. of observations	478	478		330	330
R–squared	0.55	0.64		0.51	0.60

Notes: Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Column (I) is a regression with manufacturing employment share, the square of manufacturing employment share, and the interaction of these two variables with a structural transformation group. Column (II) is a regression with manufacturing employment share, the square of manufacturing employment share, and the interaction of these two variables with the region the economy is in. Column (III) is a regression with services employment share, the square of services employment share, and the interaction of these two variables with the structural transformation group. Column (IV) is a regression with services employment share, the square of services employment share, and the interaction of these two variables with the structural transformation group.
Source: Authors' calculations.

Table A2.3. **Regression Results, Dependent Variable: Net Gini; Sample Confined to Post-1970s Period**

	I	II		III	IV
Agriculture	0.094	0.30***	Agriculture	1.08***	1.02***
	(0.080)	(0.05)		(0.16)	(0.10)
Agriculture^2	−0.005***	−0.006***	Agriculture^2	−0.003	−0.004***
	(0.001)	(0.0007)		(0.002)	(0.002)
Manufacturing (Man)	−1.90**	−1.66***	Services	1.87***	0.39
	(0.73)	(0.35)		(0.35)	(0.39)
Manufacturing^2	0.029	0.018	Services^2	−0.006	−0.01**
	(0.03)	(0.011)		(0.004)	(0.004)
Developed	−13.36**		Developed	−22.76	
	(6.11)			(15.29)	
Underdeveloped (Und)	16.29**		Underdeveloped	9.83	
	(6.56)			(8.67)	
Developed × Man	1.03		Developed × Services	0.91	
	(0.83)			(0.59)	

Continued.

Table A2.3. *Continued.*

	I	II		III	IV
Developed × Man^2	−0.032		Developed × $Services^2$	-0.01^{*}	
	(0.031)			(0.006)	
Und × Man	-3.69^{**}		Und × Services	−0.34	
	(1.66)			(0.57)	
Und × Man^2	0.19^{*}		Und × $Services^2$	−0.003	
	(0.109)			(0.01)	
Asia		-5.10^{*}	Asia		-18.13^{***}
		(3.07)			(5.56)
Latin America (LAM)		-48.34^{***}	Latin America		−27.38
		(8.67)			(19.96)
Asia × Man		−0.16	Asia × Services		0.91^{***}
		(0.41)			(0.29)
Asia × Man^2		0.006	Asia × $Services^2$		-0.014^{***}
		(0.012)			(0.004)
LAM × Man		6.65^{***}	LAM × Services		1.74^{**}
		(1.23)			(0.74)
LAM × Man^2		-0.21^{***}	LAM × $Services^2$		-0.023^{***}
		(0.04)			(0.007)
No. of observations	455	455		312	312
R–squared	0.56	0.66		0.58	0.66

Notes: Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Column (I) is a regression with manufacturing employment share, the square of manufacturing employment share, and the interaction of these two variables with a structural transformation group. Column (II) is a regression with manufacturing employment share, the square of manufacturing employment share, and the interaction of these two variables with the region the economy is in. Column (III) is a regression with services employment share, the square of services employment share, and the interaction of these two variables with the structural transformation group. Column (IV) is a regression with services employment share, the square of services employment share, and the interaction of these two variables with the structural transformation group.
Source: Authors' calculations.

Table A2.4. **Regression Results, Dependent Variable: Net Gini Using ILO Data**

	I	II		III	IV
Agriculture	0.774^{***}	0.403^{***}	Agriculture	1.40^{***}	0.64^{***}
	(0.043)	(0.035)		(0.07)	(0.07)
$Agriculture^2$	-0.011^{***}	-0.006^{***}	$Agriculture^2$	-0.006^{***}	−0.001
	(0.001)	(0.001)		(0.001)	(0.001)
Manufacturing (Man)	7.33^{***}	−0.343	Services	-6.64^{***}	1.63^{***}
	(1.73)	(0.241)		(1.43)	(0.21)
$Manufacturing^2$	-0.33^{***}	0.012	$Services^2$	0.075^{***}	-0.01^{***}
	(0.07)	(0.008)		(0.013)	(0.001)
Developed	58.13		Developed	-204.80^{***}	
	(10.24)			(38.87)	
Underdeveloped (Und)	52.01^{***}		Underdeveloped	-183.78^{***}	
	(10.36)			(38.90)	
Developed × Man	-9.29^{***}		Developed × Services	8.70^{***}	
	(1.74)			(1.44)	

Continued.

Table A2.4. *Continued.*

	I	II		III	IV
Developed × Man^2	0.36***		Developed × Services^2	−0.087***	
	(0.07)			(0.013)	
Und × Man	−9.05**		Und × Services	7.03***	
	(1.80)			(1.44)	
Und × Man^2	0.35***		Und × Services^2	−0.063***	
	(0.07)			(0.013)	
Asia		8.388*	Asia		9.17*
		(4.72)			(5.48)
Latin America (LAM)		−14.93***	Latin America		2.71
		(4.81)			(9.45)
Asia × Man		−1.85***	Asia × Services		−0.78***
		(0.45)			(0.23)
Asia × Man^2		0.05***	Asia × Services^2		−0.008***
		(0.01)			(0.002)
LAM × Man		−0.02	LAM × Services		−0.30
		(0.49)			(0.34)
LAM × Man^2		0.01	LAM × Services^2		0.001
		(0.01)			(0.003)
No. of observations	1141	1141		1141	1141
R-squared	0.46	0.59		0.52	0.59

ILO = International Labour Organization.
Notes: Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Column (I) is a regression with manufacturing employment share, the square of manufacturing employment share, and the interaction of these two variables with a structural transformation group. Column (II) is a regression with manufacturing employment share, the square of manufacturing employment share, and the interaction of these two variables with the region the economy is in. Column (III) is a regression with services employment share, the square of services employment share, and the interaction of these two variables with the structural transformation group. Column (IV) is a regression with services employment share, the square of services employment share, and the interaction of these two variables with the structural transformation group.
Source: Authors' calculations.

Table A2.5. **Regression Sample**

Region	Economy	Regression 1 and Regression 2	Regression 3 and Regression 4	First and Last Year
Africa	Botswana	8	8	1985–2010
	Egypt	6		1975–2012
	Ethiopia	5	5	1995–2011
	Ghana	8	8	1987–2006
	Kenya	5	5	1992–2006
	Malawi	5	5	1985–2009
	Mauritius	6	6	1980–2007
	Morocco	10		1960–2007
	Nigeria	8	8	1975–2010
	Senegal	5	5	1990–2010
	South Africa	8	8	1990–2011
	Tanzania	6	6	1969–2011
	Zambia	8		1991–2010

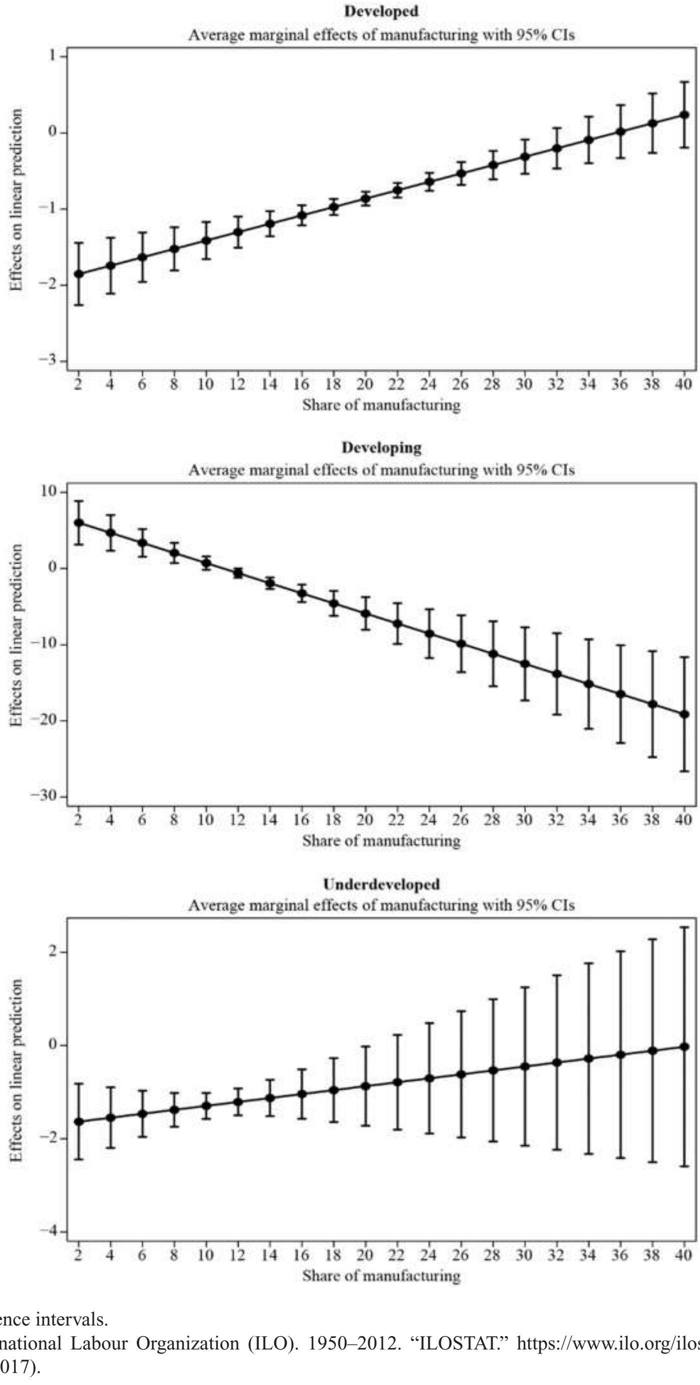
Continued.

Table A2.5. *Continued.*

Region	Economy	Regression 1 and Regression 2	Regression 3 and Regression 4	First and Last Year
Asia	Hong Kong, China	6	6	1976–2011
	India	32	32	1960–2010
	Indonesia	17	17	1984–2012
	Malaysia	10	10	1979–2009
	People's Republic of China	21	21	1981–2011
	Philippines	12	12	1971–2012
	Republic of Korea	19		1965–2010
	Singapore	10		1974–2011
	Taipei,China	43	43	1964–2012
	Thailand	23	23	1962–2011
Latin America	Argentina	29	29	1969–2011
	Bolivia	17		1989–2009
	Brazil	29	29	1979–2011
	Chile	16		1968–2011
	Colombia	20		1991–2010
	Costa Rica	25	25	1981–2011
	Mexico	19	19	1963–2012
	Peru	19		1969–2011
	Venezuela	23		1981–2011

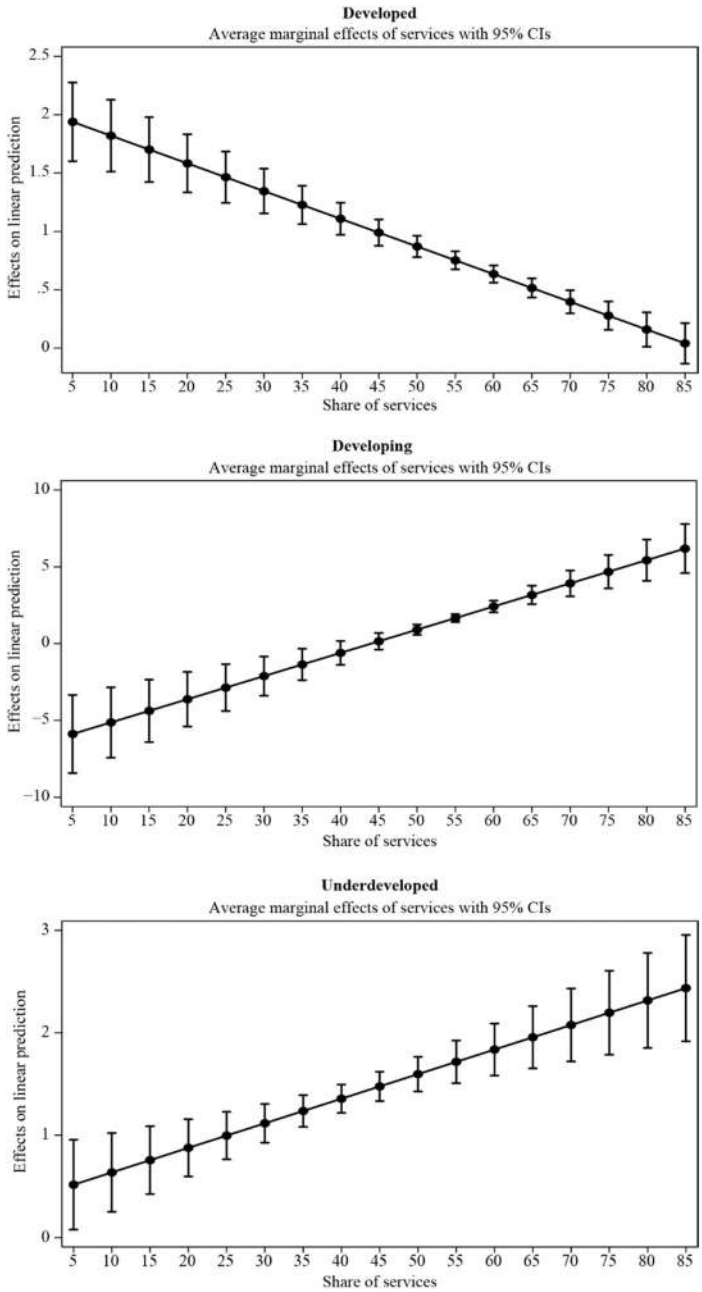
Source: Authors' compilation.

Figure A2.1. **Marginal Effect of Manufacturing Employment Share on Inequality by Stage of Structural Transformation Using ILO Data**



CIs = confidence intervals.
Source: International Labour Organization (ILO). 1950–2012. “ILOSTAT.” https://www.ilo.org/ilostat/ (accessed October 13, 2017).

Figure A2.2. **Marginal Effect of Services Employment Share on Inequality by Stage of Structural Transformation Using ILO Data**



CIs = confidence intervals.
Source: International Labour Organization (ILO). 1950–2012. “ILOSTAT.” https://www.ilo.org/ilostat/ (accessed October 13, 2017).

The Long-Run Determinants of Indian Government Bond Yields

Tanweer Akram and Anupam Das*

This paper investigates the long-term determinants of the nominal yields of Indian government bonds (IGBs). It examines whether John Maynard Keynes' supposition that the short-term interest rate is the key driver of the long-term government bond yield holds over the long run, after controlling for key economic factors. It also appraises if the government fiscal variable has an adverse effect on government bond yields over the long run. The models estimated in this paper show that in India the short-term interest rate is the key driver of the long-term government bond yield over the long run. However, the government debt ratio does not have any discernible adverse effect on IGB yields over the long run. These findings will help policy makers to (i) use information on the current trend of the short-term interest rate and other key macro variables to form their long-term outlook about IGB yields, and (ii) understand the policy implications of the government's fiscal stance.

Keywords: government bond yields, India, interest rates, monetary policy
JEL codes: E43, E50, E60, G10, O16

I. Introduction

John Maynard Keynes (1930) contends that the central bank's monetary policy is the most important driver of the long-term interest rate. He believes that the central bank's actions influence the long-term interest rate primarily through the effect of policy rates on the short-term interest rate and other tools of monetary policy. In *The General Theory of Employment, Interest, and Money*, Keynes (2007 [1936]) reiterates the importance of the central bank's influence on the long-term interest rate, even though he acknowledges that interest rates have psychological, social, and conventional foundations, and arise from investors' liquidity preferences.

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This paper examines whether Keynes' supposition that the short-term interest rate is the key driver of the long-term government bond yield holds in India over the long run after controlling for various key economic factors, such as inflationary pressure and measures of economic activity. It also appraises if government fiscal variables, such as the ratio of government debt to nominal gross domestic product (GDP), have an adverse long-run effect on government bond yields in India. Akram and Das (2015a and 2015b) report that Keynes' conjectures hold in India for the short-run horizon. They also find that government fiscal variables do not appear to exert upward pressure on Indian government bond (IGB) yields. However, they do not examine if these results hold over a long-run horizon. This paper fills that critical lacunae.

Understanding the determinants of government bond yields in India over the long-run horizon is important not just for scholarly reasons but also for policy purposes and policy modeling, particularly for discerning the effects of fiscal and monetary policy on IGB yields. Understanding the drivers of government bond yields in emerging markets such as India has crucial implications for the government's fiscal and macroeconomic policy mix. It is also relevant for fixed income investment and portfolio allocation, as well as the management of government debt.

India's institutional features, its economic rise, and the evolution of its financial system make it worthwhile to examine the long-run trends in its government bond market. First, India's financial markets are in the development stage. While India has liberalized its economy and many aspects of its financial system, there are still various restrictions. Its bond market is not as deep as those of advanced capitalist economies such as Japan, the United Kingdom, and the United States (US). The country's banking system is dominated by state-owned or state-controlled financial institutions, and its fixed income investors in the local currency bond market are largely confined to investing in government securities since the depth and liquidity of corporate bonds and other fixed income securities are limited. It is, hence, appropriate to inquire whether Keynes' supposition regarding the link between the short-term interest rate and the long-term interest rate holds in the institutional and structural circumstances of emerging market economies such as India. Second, whether the central bank's setting of the policy rate(s) and other monetary policy actions influence the long-term interest rate over the long run in India has meaningful policy implications for monetary transmission mechanisms. If the evidence suggests that the central bank can decisively affect the long-term interest rate, not just in the short run but also over the long run, this would show that the Government of India has considerable policy space. If no such relationship can be established, then this would mean that its policy space is rather restrictive and narrow. Hence, it is important to examine what conjectures are empirically warranted in India and other emerging markets.

The paper is organized as follows. Section II sets the foundation for the empirical investigation. First, it discusses Keynes' view on interest rates and provides the theoretical framework. Second, it summarizes Keynes' stance on the loanable funds theory and explains why he rejects this theory. Third, it presents a simple two-period model of government bond yields. Fourth, it recounts the stylized facts about government bond yields and government debt ratios. Fifth, it briefly reviews the relevant literature on government bond yields in emerging market economies. Section III describes the data, the behavioral equations to be estimated, and the econometric methodology applied here. Section IV reports the empirical findings. Section V analyzes the policy implications of the results and concludes. Appendix 1 presents the details of the simple two-period model of government bond yields used in the paper. Appendix 2 presents additional regressions to examine the effects of credit growth, global investors' risk appetite, and the nominal effective exchange rate on government bond yields.

II. Theoretical Framework, Model, Institutional Background, Stylized Facts, and Brief Review of the Literature

A. The Keynesian Framework

This paper investigates the long-run determinants of IGB yields based on Keynes' (1930 and 2007 [1936]) views. Keynes holds that the central bank's actions play the decisive role in setting the long-term interest rate on government bonds (Kregel 2011). He argues against the classical view of interest rates based on the loanable funds theory as represented in Cassel (1903), Marshall (1890), Taussig (1918), and the classical economists.

The central bank's ability to influence the long-term interest rate arises from its ability to set the policy rate and anchor the short-term interest rate around the policy rates, and to use various other tools of monetary policy (Keynes 1930). He acknowledges that interest rates have a foundation based on human psychology, social conventions, herd mentality, and liquidity preferences (Keynes 2007 [1936]). Nevertheless, the most immediate and important driver of long-term government bond yields are the central bank's actions as manifested through its ability to (i) influence the short-term interest rate by setting the policy rate, and (ii) use a wide range of tools of monetary policy including expanding and contracting its balance sheet as it deems appropriate. Keynes relies on Riefler's (1930) pioneering empirical analysis of the behavior of interest rates on US government securities (Kregel 2011). He also observes that current conditions and the investor's near-term outlook affect the investor's long-term outlook. Keynes believes that since the investor does not have a firm basis for estimating the mathematical expectations of the unknown and uncertain future, the investor resorts to forming an outlook of the future based on past and current conditions. As a result, the factors that affect the short-term interest rate also affect the long-term interest rate.

Keynes' view on the drivers of long-term government bond yields is in contrast to that of conventional views in macroeconomics and finance. The conventional view is that government debts and deficits have a decisive effect on government bond yields. Other things held constant, if government debts and/or government deficits (both as a share of nominal GDP) increase (decrease), then government bond yields will rise (decline). This view relies on the loanable funds theory of interest rates. For Keynes, liquidity preferences and the central bank's actions are largely responsible for interest rates as manifested in the yield curve for gilt-edged (government) securities and other fixed income instruments in an economy.

Among others, Ardagna, Caselli, and Lane (2007); Baldacci and Kumar (2010); Gruber and Kamin (2012); Lam and Tokuoka (2013); Poghosysan (2014); and Tokuoka (2012) represent the conventional view. In contrast, Akram (2014); Akram and Das (2014a, 2014b, 2015a, 2015b, 2017a, 2017b, and 2017c); and Akram and Li (2016, 2017a, and 2017b) have argued that the short-term interest rate and pace of inflation are the key drivers of interest rates on government bonds. Moreover, they argue that if other things are held constant, the government fiscal variable has hardly any influence on government bond yields. This view is based on their interpretation of Keynes. It is supported with empirical work on the determinants of government bond yields in the eurozone, India, Japan, and the US. As mentioned earlier, Akram and Das' (2015a and 2015b) empirical work on India has merely explored the short-run dynamics. This paper examines whether the same hypothesis holds true for India in the long run.

B. Keynes' Stance on the Loanable Funds Theory of Interest Rates

Keynes rejected the loanable funds theory of interest rates. According to the proponents of this theory, the interest rate is primarily determined by the demand and supply of loanable funds. The loanable funds theory has a distinguished pedigree. It is endorsed in classical economics such as Cassel (1903), Böhm-Bawerk (1959), Hayek (1933 and 1935), Marshall (1890), Pigou (1927), Ricardo (1817), von Mises (1953), and Wicksell (1962 [1936]). Keynes rejects the loanable funds theory because he believes it is insufficient to determine interest rates solely on the basis of knowledge of the demand for investment and the supply of savings. He criticizes the loanable funds theory for neglecting the roles of national income, the marginal propensity to consume, and liquidity preference in the determination of interest rates. In his view, the "rate of interest is the reward for parting with liquidity for a specified time" (Keynes 2007 [1936], p. 167). It follows that the interest rate is "a measure of the unwillingness of those who possess money to part with their liquid control over it." Liquidity preference is quite central to Keynes' view on the interest rate. Liquidity preference arises from fundamental uncertainty about future economic and financial conditions, and the divergence among investors about their outlook for the future. Interest rates have institutional and behavioral foundations. Hence, for Keynes, institutions like the central bank and investors' psychology and social orientation, as manifested in herding and the formation of long-term expectations, play decisive roles in the determination of the interest rate, rather than just the demand and supply of loanable funds. The demand and the supply of loanable funds are outcomes of income, the propensity to consume, and liquidity preference, which occur within a context that consists of institutions, such as the central bank, and amid investors' psychology that is guided by animal spirits, instincts, and social conventions.

C. A Simple Two-Period Model of Government Bond Yields

A simple model, based on Akram and Das' (2014 and 2015) and Akram and Li's (2016 and 2017a) interpretations of Keynes' views, is presented here to show the connection between the current short-term interest rate and the long-term interest rate.

To simplify the exposition, a two-period horizon is used. There are two periods: $t = 1, 2$. The long-term interest rate on a government bond in period 1 is r_{LT}; the short-term interest rates on a Treasury bill in period 1 and period 2 are, respectively, r_1 and r_2; the expected short-term interest rate in period 2 is Er_2; the 1-year, 1-year forward rate is $f_{1,1}$; the term premium is z; the current rate of inflation in period 1 is π_1; the actual rate of inflation in period 2 is π_2; the expected rate of inflation in period 2 is $E\pi_2$; the current growth rate in period 1 is g_1; the actual growth rate in period 2 is g_2; the expected growth rate in period 2 is Eg_2; the government fiscal variable in period 1 is ν_1; the government fiscal variable in period 2 is ν_2; and the expected government fiscal variable in period 2 is $E\upsilon_2$.

It can be shown that the long-term interest rate is a function of either (i) the short-term interest rates in period 1 and period 2, and the growth rate and the rate of inflation in period 2; or (ii) the short-term interest rates in period 1 and period 2, and the growth rate, the rate of inflation, and the government fiscal variable in period 2. Hence, the models of the determinants of the long-term bond yields take the following forms:

$$r_{LT} = F^7 (r_1, r_2, g_2, \pi_2) \tag{1}$$

$$r_{LT} = F^8 (r_1, r_2, g_2, \pi_2, \nu_2) \tag{2}$$

A detailed derivation of the above models is presented in Appendix 1.

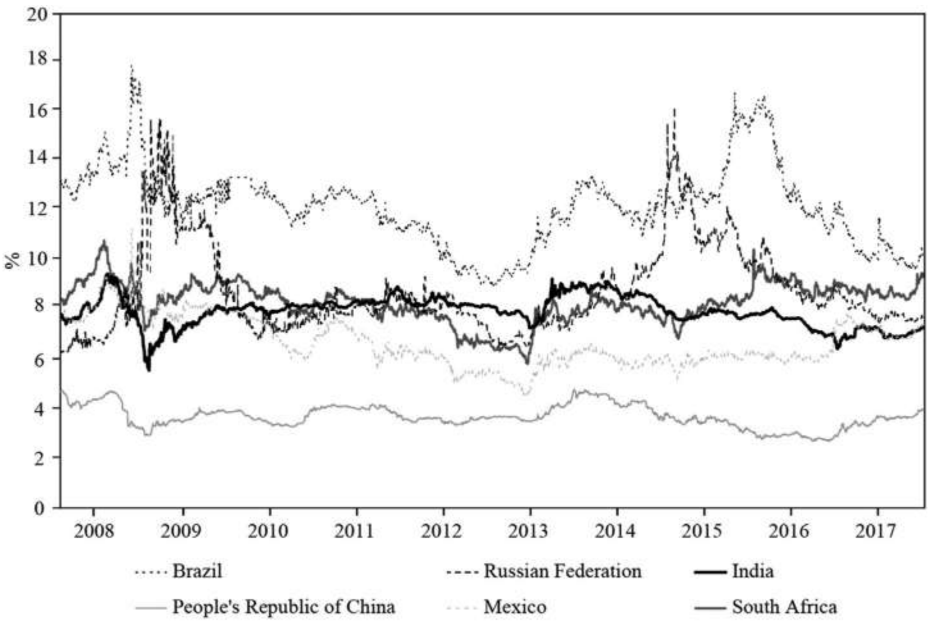
It is appropriate to incorporate the government fiscal variable in the model of the long-term interest rate for several reasons. First, government fiscal variables affect the long-term interest rate in the standard IS–LM Keynesian models. Second, it is also included in the standard theoretical and empirical literature, including Ardagna, Caselli, and Lane (2007); Baldacci and Kumar (2010); and other studies cited in section II.A. Third, since the paper assesses whether Keynes' conjecture regarding the importance of the short-term interest rate in driving the long-term interest rate is more warranted than that of the conventional view, it is necessary to empirically estimate the effect of government fiscal variables on the long-term interest rate. Ruling out, a priori, the role of the government fiscal variable on the long-term interest rate would be arbitrary and could be regarded as an ad hoc and unjustified maneuver. Undoubtedly, the empirical findings of this and other studies that find support for the Keynesian perspective can influence the choice of variables in the construction of models of the long-term interest rate in the future.

D. Institutional Background

Akram and Das (2015a and 2015b) provide the institutional background to the monetary policy framework, the government bond market, and monetary–fiscal coordination in India. Yanamandra (2014) gives additional perspective on monetary policy making in India in light of economic reforms, modernization, and recent developments, while Chakraborty (2016) provides a detailed description and analysis of the country's monetary–fiscal policy mix and monetary–fiscal coordination. Jácome et al.'s (2012) survey of global practices among central banks in extending credit and coordinating with the national Treasury includes a description of Indian laws, regulations, and practices related to its Treasury and central bank.

India enjoys monetary sovereignty as defined by Wray (2012). The Government of India issues its own currency, the rupee. The country's central bank, the Reserve Bank of India (RBI), sets the policy rates and can use a wide range of monetary policy tools. The RBI enjoys a wide range of authority and control over the country's financial system. The Government of India has the legal and political authority to collect taxes from households, businesses, financial institutions, and other organizations. The country's sovereign debt is predominantly issued in its own currency, the rupee. The multifaceted roles played by the RBI in the payment system, monetary policy, financial stability policy, and policy coordination with the Treasury gives it the operational ability to influence government bonds' nominal yields by setting and changing the short-term interest rate and using other tools of monetary policy as it deems appropriate. RBI (2014) provides a detailed institutional description of the IGB market, while RBI (various years) *Annual Reports* give useful summaries of the central bank's monetary policy and background. The 2009 report presents a valuable perspective on the operational aspects of monetary–fiscal coordination in India.

Figure 1. **The Evolution of 10-Year Government Bond Yields in Selected Emerging Market Economies**



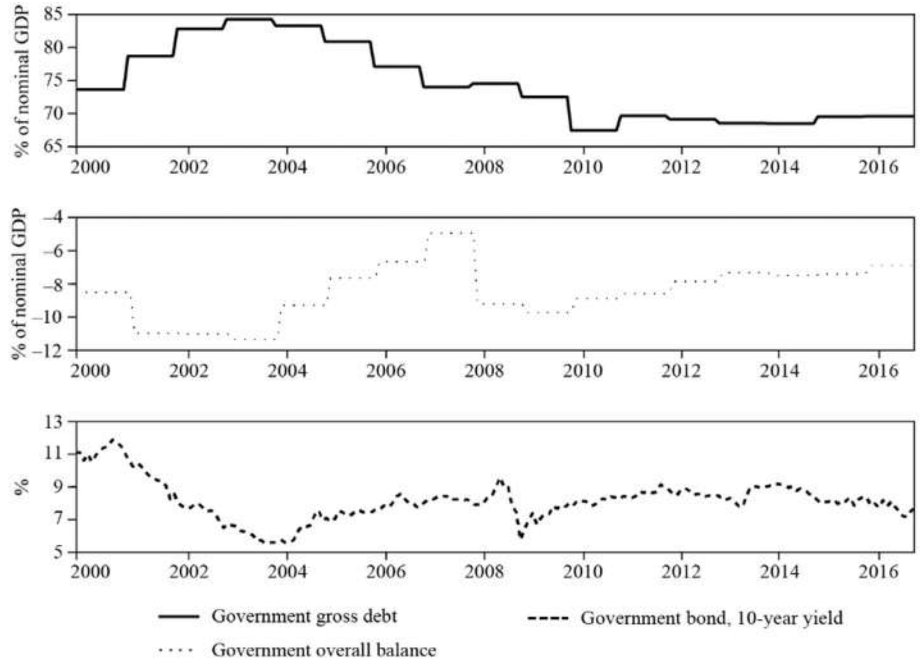
Source: Macrobond. Various years. Macrobond subscription services (accessed September 13, 2017).

E. Stylized Facts

A set of figures are presented in this section to highlight important stylized facts related to IGBs and government finance. Figure 1 compares the evolution of 10-year government bond yields in India with that of other major emerging markets, such as Brazil, Mexico, the People's Republic of China, the Russian Federation, and South Africa. It shows that since the global financial crisis, government bond yields in India have been generally higher than in the People's Republic of China and Mexico, but lower than in Brazil. Government bond yields in the Russian Federation and South Africa have been more volatile than those in India. In recent years, as commodity prices tumbled, financial flows to emerging markets weakened, and their central bank policy rates increased, and government bond yields in the Russian Federation and South Africa rose.

Figure 2 shows the evolution of key government fiscal variables in India such as the (i) ratio of gross government debt to nominal GDP, (ii) ratio of government fiscal balance to GDP, and (iii) 10-year government bond yield. It shows that the government debt-to-GDP ratio rose from 70% to nearly 85% in the early 2000s, but subsequently declined to around 70% as the country's annual fiscal

Figure 2. **The Evolution of Key Government Fiscal Variables in India**



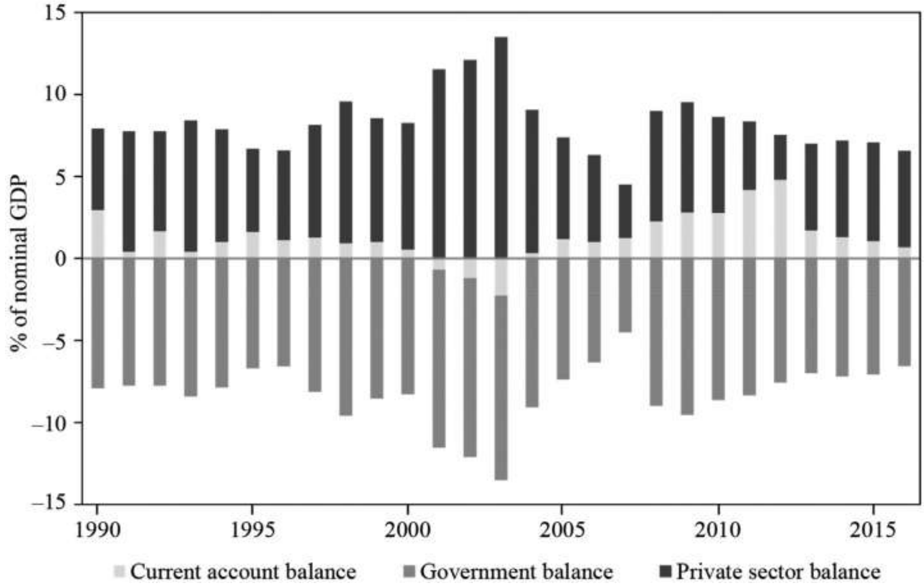
GDP = gross domestic product.
Source: Macrobond. Various years. Macrobond subscription services (accessed September 13, 2017).

balance improved from a deficit of around 11% of GDP in the early 2000s to a deficit of just 4% of GDP in the 2010s. Since the beginning of the 2010s, India's government debt ratio has been stable at around 70%, while its fiscal deficit has hovered around 7% of GDP. The figure also suggests that, prima facie, the evolution of government bonds yields in India is not directly affected by government fiscal conditions.

Figure 3 shows the evolution of the sector balances as a share of nominal GDP in India. It uses annual flow data to display (i) the government balance, (ii) the private sector balance, and (iii) the current account balance. It visually shows that the flow of government dissaving is equal to private sector saving and the rest of the world's saving in Indian rupees.

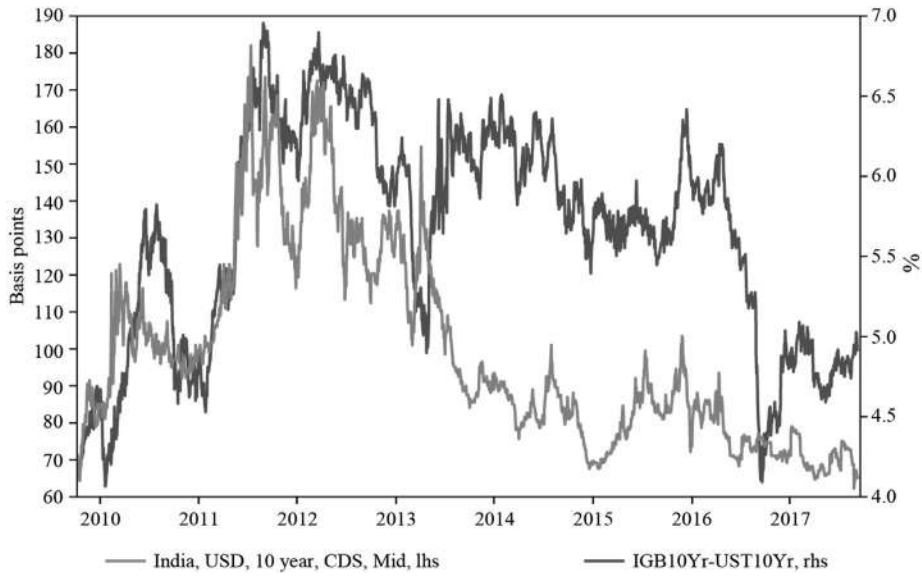
Figure 4 displays that the changing relationship between the credit default swap (CDS) premium on IGBs and the spread between the nominal yields of 10-year IGBs and 10-year US Treasury notes since 2010. It shows that the correlation can change drastically. Between 2010 and 2013, the CDS premium and the yield spread were tightly correlated. However, since 2014, the correlation between the CDS premium and the yield spread has been quite weak.

Figure 3. **The Evolution of Sector Balances in India**



GDP = gross domestic product.
Source: Macrobond. Various years. Macrobond subscription services (accessed September 12, 2017).

Figure 4. **The Evolution of Credit Default Swap Premiums and Yield Spreads**



CDS = credit default swap, IGB10Yr = 10-year Indian government bond yield, lhs = left-hand side, rhs = right-hand side, USD = United States (US) dollar, UST10Yr = 10-year US Treasury note yield.
Source: Macrobond. Various years. Macrobond subscription services (accessed September 12, 2017).

F. A Brief Review of the Literature on Government Bond Yields

There is a substantial literature on government bonds yields, including on the determinants of government bond yields in emerging markets such as India. Nevertheless, the debate on the determinants of bond yields and the relative importance of the key drivers is still unsettled.

We examine the findings of recent studies on government bond yields to ascertain how relevant these are to the question that this paper addresses. Andritzky (2012) provides a useful database on the investor base for government securities and investigates the effect of the composition of the investor base on government bond yields. Even though the study relies on G20 advanced economies and the eurozone, a key finding appears to be relevant for emerging markets. An increase in the share of bonds held by institutional or nonresidents by 10 percentage points is correlated with a decline in bond yields by about 25–40 basis points (bps). Asonuma, Bakhache, and Hesse (2015) find that an increase in domestic bank holdings of government bonds reduces bond yields and provides fiscal space for the sovereign authorities. Ebeke and Lu (2014) argue that the rise in foreign holdings of local currency government bonds in emerging markets has led to a decline in bond yields but a rise in their volatility, particularly since the global financial crisis. Acharya and Steffen (2015) provide an insightful analysis of the cause of the divergence of bond yields between the core of the eurozone and its periphery. They also discuss the vital role played by the "carry trade" of eurozone banks in causing the widening of the spread. The results of Ardagna, Caselli, and Lane (2007) are in line with the conventional wisdom cited earlier in the introduction. They claim that an increase of 1 percentage point in the ratio of the primary deficit leads to (i) an increase in the current long-term interest rate by 10 bps and (ii) cumulative increases in the long-term interest rate by 150 bps after 10 years. These and other results in the conventional literature on government bond yields are interesting. However, the conventional literature does not probe sufficiently the key role of the central bank in influencing government bond yields in emerging markets. Hence, a Keynesian perspective may provide a more insightful analysis of the decisive factors and may be more pertinent for understanding government bond yields in India.

This view is reinforced by the empirical literature on IGBs, which largely refutes the conventional view that higher (lower) government debt or government deficits induce higher (lower) government bond yields. Chakraborty's (2016) detailed and careful institutional and empirical study finds that there is no evidence of any link between fiscal deficit and interest rates in India. Vinod, Chakraborty, and Karun (2014) use the maximum entropy bootstrap method and report that the government fiscal deficit ratio is not significant for interest rate determination in India. Chakraborty (2012), applying asymmetrical vector autoregressive models, finds that an increase in the fiscal deficit ratio does not lead to a rise in interest rates. Akram and Das (2015a and 2015b) show that changes in the short-term interest rate, after controlling for other crucial variables such as changes in the rates of inflation and economic activity, take a lead role in driving the changes of the nominal yields of IGBs. Additional results show that higher fiscal deficits do not appear to exert upward pressures on government bond yields. Findings from Akram and Das (2015a and 2015b) are, however, valid solely for the short run. One of the important goals of the current paper is to examine if the findings from Akram and Das (2015a and 2015b) hold over the long-run horizon.

The next section introduces behavioral equations, time series data, and econometric methods to examine the role of the short-term interest rate, the rate of inflation, the government fiscal variable, and other key macroeconomics variables to determine the nominal yields on IGBs over the long-run horizon.

III. Data, Behavioral Equations, and Methods

A. Data[1]

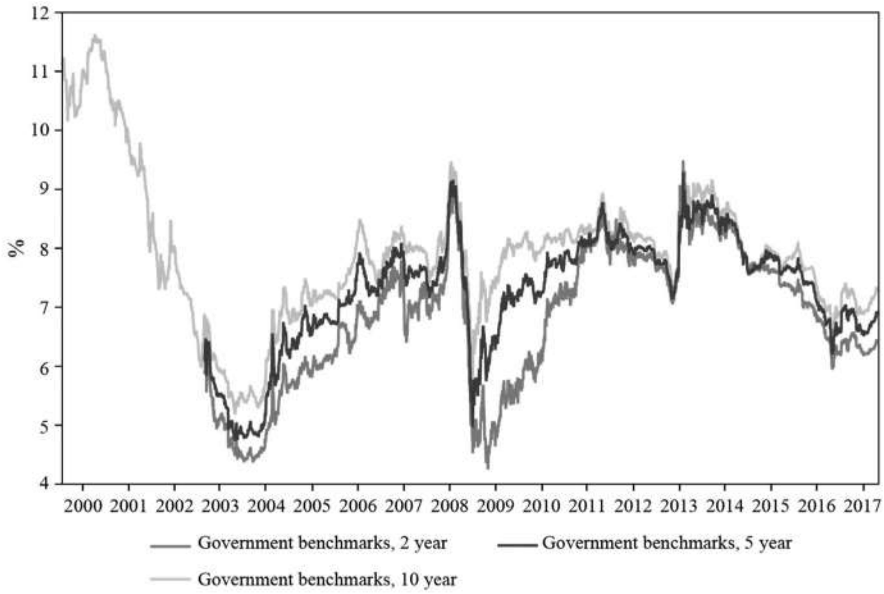
For the purpose of econometric estimations, time series data on the nominal yields of long-term IGBs, the short-term interest rate, the rate of inflation, the growth of industrial production, and government fiscal variables are used.

Nominal yields on Indian Treasury bills with 3-month maturities are used for the short-term interest rate, while the nominal yields on IGBs of various tenors—including 2-year, 3-year, 5-year, 7-year, and 10-year maturities—are used to represent long-term government bond yields. The RBI (2014) classifies government securities with a maturity of less than 1 year as short-term securities, and those with a maturity of 1 year or more as long-term securities.

Figure 5 shows the evolution of nominal yields of IGBs. Figure 6 shows the evolution of the short-term interest rate along with the RBI's policy rates (repo rates and reverse repo rates). The rate of inflation is defined as the year-on-year percentage change in the total consumer price index for all items. Growth in industrial production is the year-on-year percentage change in the index of industrial activity in India. The ratio of government debt to nominal GDP is used here as the government fiscal variable. The ratio of private sector credit (from all sectors) to nominal GDP is used to measure credit growth. The Institute for International Monetary Affairs' index of the volatility in global bond markets is a proxy for global investors' risk appetite. An increase (decrease) in volatility in global bond markets means that investors' perception of and appetite for risk has risen (declined). The nominal effective exchange rate, calculated by the Bank for International Settlements, is the exchange rate used here. The data of all the variables are collected from Macrobond's (various years) data services. Table 1 provides a

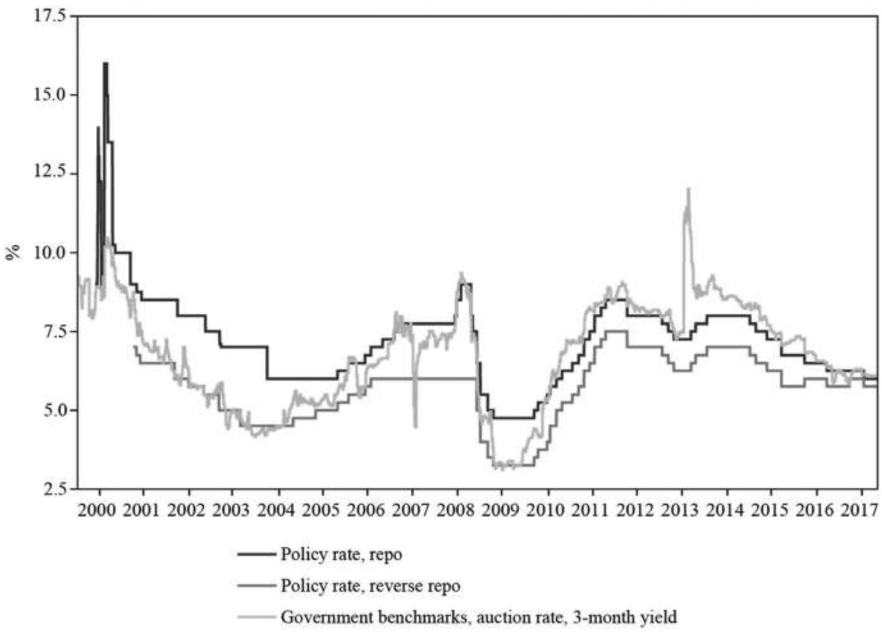
[1]The dataset used in the empirical part of this paper is available upon request to bona fide researchers for the replication and verification of the results.

Figure 5. **The Evolution of Indian Government Bond Yields of Selected Tenors**



Source: Macrobond. Various years. Macrobond subscription services (accessed July 12, 2017).

Figure 6. **The Evolution of Policy Rates and Short-Term Interest Rates in India**



Source: Macrobond. Various years. Macrobond subscription services (accessed July 12, 2017).

Table 1. **Summary of the Data and Variables**

Variable Labels	Data Description, Date Range	Frequency	Sources
Indian Short-Term Interest Rates			
TB3M; TB3M_Q	Government benchmarks, auction rate, 3-month % yield; Jan 1999–Oct 2015; Q1 1999–Q3 2015	Daily; converted to monthly	Reserve Bank of India; Macrobond converted to quarterly
Indian Government Bond Yields			
IGB2YR; IGB2YR_Q	Government bond, 2-year % yield; Mar 2003–Oct 2015; Q2 2003–Q3 2015	Daily; converted to monthly	Clearing Corporation of India; Macrobond converted to quarterly
IGB3YR; IGB3YR_Q	Government bond, 3-year % yield; Mar 2003–Oct 2015; Q2 2003–Q3 2015	Daily; converted to monthly	Clearing Corporation of India; Macrobond converted to quarterly
IGB5YR; IGB5YR_Q	Government bond, 5-year % yield; Mar 2003–Oct 2015; Q2 2003–Q3 2015	Daily; converted to monthly; converted to quarterly	Clearing Corporation of India; Macrobond
IGB7YR; IGB7YR_Q	Government bond, 7-year % yield; Mar 2003–Oct 2015; Q2 2003–Q2 2015	Daily; converted to monthly; converted to quarterly	Clearing Corporation of India; Macrobond
IGB10YR; IGB10YR_Q	Government bonds, 10-year % yield; Jan 1999–Oct 2015; Q1 1999–Q2 2015	Daily; converted to monthly; converted to quarterly	Clearing Corporation of India; Macrobond
Inflation			
TCPIYOY; TCPIYOY_Q	India, consumer price index, total, % change, year on year; Jan 2007–Oct 2015; Q1 2007–Q2 2015	Monthly; converted to quarterly	*The Economist*; Macrobond
Economic Activity			
IPIYOY; IPIYOY_Q	Industrial production, % change, year on year; Jan 1999–Oct 2015; Q1 1999–Q2 2015	Monthly; converted to quarterly	Central Statistical Organisation, India; Macrobond
Government Fiscal Variable			
DRATIO_Q	Government debt, % of nominal GDP; Q1 1999–Q2 2015	Quarterly	Indian Ministry of Commerce and Industry; Macrobond
Credit Growth			
CREDIT	Credit from all sectors to the private sector, % of nominal GDP; Jan 1999–Dec 2015	Quarterly; converted to monthly using cubic interpolation	Bank for International Settlements; Macrobond
Investors' Risk Appetite			
RISK	Global bond market volatility index; Jan 1999–Dec 2015	Daily; converted to monthly	Institute for International Monetary Affairs; Macrobond
Exchange Rate			
NEER	Nominal effective exchange rate index, broad; Jan 1999–Dec 2015	Monthly	Bank for International Settlements; Macrobond

GDP = gross domestic product, Q = quarter.
Source: Authors' compilation.

summary of the data and detailed descriptions of the variables. The monthly time series dataset runs from March 1999 to October 2015, while the quarterly dataset includes time series variables from the third quarter of 2003 to the second quarter of 2015.

Both monthly and quarterly data are used to examine the determinants of nominal yields of long-term government bonds. Indian government fiscal data is available only in quarterly form. Hence, the debt-to-GDP ratio is included only in the quarterly equations.

B. Behavioral Equations

A set of behavioral equations for monthly data and for quarterly data are constructed in concordance with the model based on the Keynesian framework presented earlier. These behavioral equations readily lend themselves to empirical testing. The specific-to-general approach is deployed here. For the monthly dataset, the long-term government bond yields are first regressed individually with the short-term interest rate, inflation, and the growth rate of industrial production. The dependent variables are then regressed with the short-term interest rate and inflation, and the short-term interest rate and growth rate. In the general form of the behavioral equation, the long-term interest rate is determined by all three explanatory variables including the short-term interest rate, rate of inflation, and growth rate. The general equation takes the following form:

$$r_{LT} = \alpha_1 + \alpha_2 r_1 + \alpha_3 \pi_1 + \alpha_4 g_1 \tag{3}$$

The same approach is used when the quarterly dataset is employed to examine the determinants of long-term bond yields in India. However, to understand the effects of the government fiscal variable on government bond yields, the ratio of government debt to nominal GDP is included in the general equation of the quarterly dataset. Hence, the behavioral equation can be written in the following manner:

$$r_{LT} = z_1 + z_2 r_1 + z_3 \pi_1 + z_4 g_1 + z_5 v_1 \tag{4}$$

C. Econometric Methodology

The first step is to examine the nature of the data. The presence of unit roots in most macroeconomic variables is fairly common (Nelson and Plosser 1982). Hence, estimating the long-run relationships of stationary variables using standard cointegration techniques (e.g., Johansen cointegration) is inconsistent. Therefore, unit root tests on the variables used in this paper are imperative. Conventional research has used both the Augmented Dickey–Fuller (ADF) (Dickey and Fuller 1979, 1981) and the Phillips–Perron (PP) (Phillips and Perron 1988) tests to

Table 2. **Unit Root Tests for Monthly Variables**

Variable	DFGLS	ADF	PP
IGB2YR	−1.29	−1.72	−1.86
ΔIGB2YR	-1.76^{*}	-11.57^{***}	-11.57^{***}
IGB3YR	−1.26	−1.81	−1.97
ΔIGB3YR	-2.01^{**}	-7.60^{***}	-11.54^{***}
IGB5YR	−1.26	−1.95	−2.03
ΔIGB5YR	-2.44^{**}	-7.87^{***}	-11.38^{***}
IGB7YR	−1.27	−2.06	−2.06
ΔIGB7YR	-2.74^{***}	-7.96^{***}	-11.18^{***}
TB3M	−1.57	−2.57	−2.58
ΔTB3M	-2.15^{**}	-17.09^{***}	-17.13^{***}
TCPIYOY	-1.63^{*}	−1.89	−1.99
ΔTCPIYOY	-9.47^{***}	-9.51^{***}	-9.48^{***}
IPIYOY	-1.92^{*}	-4.67^{***}	-13.66^{***}
ΔIPIYOY	−0.97	-9.73^{***}	-47.57^{***}
CREDIT	0.30	−1.54	−1.64
ΔCREDIT	−0.98	−2.48	-6.99^{***}
NEER	0.48	−0.52	−0.27
ΔNEER	-0.79^{*}	-11.21^{***}	-11.04^{***}
RISK	-4.93^{***}	-4.93^{***}	-4.86^{***}
ΔRISK	−0.97	-17.18^{***}	-19.01^{***}

ADF = Augmented Dickey–Fuller, CREDIT = credit to the private sector as percentage of GDP, DFGLS = Dickey–Fuller Generalized Least Squares, IGB2YR = 2-year government bond yield, IGB3YR = 3-year government bond yield, IGB5YR = 5-year government bond yield, IGB7YR = 7-year government bond yield, IPIYOY = year-on-year percentage change in industrial production, NEER = nominal effective exchange rate, PP = Phillips–Perron, RISK = global bond market volatility index, TB3M = 3-month government auction rate, TCPIYOY = year-on-year percentage change in consumer price index.
Notes: ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. The null hypothesis of all three tests is that the series contains unit roots.
Source: Authors' calculations.

identify the existence of unit roots. Elliott, Rothenberg, and Stock (1996) proposed the Dickey–Fuller Generalized Least Square (DFGLS) test, which is a modified version of the standard ADF test. According to the DFGLS procedure, the data are detrended before testing for stationarity. Different versions of the ADF, PP (with no constant and trend, constant and no trend, and constant and trend), and DFGLS tests (with constant but without trend, and constant and trend) are applied in this paper. All of these versions produce similar results. Due to space constraints, only the results with constant but without trend are presented here. All remaining results are available upon request.[2] Unit root results for monthly variables are displayed in Table 2 and the results for quarterly variables are displayed in Table 3. For the monthly dataset, most variables are nonstationary at levels and stationary at the first difference. The year-on-year percentage change in consumer price index is found to be nonstationary at levels and stationary at the first difference by two out of three

[2]For additional results, the interested reader may want to consult the working paper version (Akram and Das 2017a) of this study and/or contact the authors.

Table 3. **Unit Root Tests for Quarterly Variables**

Variable	DFGLS	ADF	PP
IGB2YR_Q	−1.51	−2.05	−2.05
ΔIGB2YR_Q	−6.10***	−7.47***	−7.48***
IGB3YR_Q	−1.60	−2.27	−2.14
ΔIGB3YR_Q	−6.36***	−8.06***	−8.36***
IGB5YR_Q	−1.72*	−2.54	−2.30
ΔIGB5YR_Q	−6.58***	−8.51***	−9.59***
IGB7YR_Q	−1.81*	−2.72	−2.47
ΔIGB7YR_Q	−6.77***	−6.81***	−10.14***
TB3M_Q	−1.59	−2.16	−2.57
ΔTB3M_Q	−1.87*	−8.52***	−8.60***
TCPIYOY_Q	−1.93*	−2.36	−2.44
ΔTCPIYOY_Q	−6.46***	−6.56***	−6.65***
IPIYOY_Q	−1.70*	−4.64***	−4.58***
ΔIPIYOY_Q	−6.55***	−6.53***	−14.18***
DRATIO_Q	−1.27	−2.21	−4.00***
ΔDRATIO_Q	−0.87	−2.60*	−11.21***

ADF = Augmented Dickey–Fuller, DFGLS = Dickey–Fuller Generalized Least Squares, DRATIO_Q = government debt as percentage of nominal gross domestic product, IGB2YR_Q = 2-year government bond yield, IGB3YR_Q = 3-year government bond yield, IGB5YR_Q = 5-year government bond yield, IGB7YR_Q = 7-year government bond yield, IPIYOY_Q = year-on-year percentage change in industrial production, PP = Phillips–Perron, TB3M_Q = 3-month government auction rate, TCPIYOY_Q = year-on-year percentage change in consumer price index.

Notes: ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. The null hypothesis of all three tests is that the series contains unit roots.

Source: Authors' calculations.

tests. The year-on-year percentage change in industrial production (IPIYOY) and the global bond market volatility index are stationary at levels. Thus, most variables are integrated of order one, I(1). All three tests suggest that IPIYOY is stationary at levels; that is, I(0). Similar results are found for the quarterly variables. Government bond as a percentage of GDP is found to be stationary at levels by the PP test, and nonstationary at levels by the ADF and DFGLS tests. Therefore, all quarterly variables are either I(0) or I(1).

Given the results from the unit root tests, it is appropriate to estimate the long-run cointegrating relationships using the autoregressive distributive lag (ARDL) proposed by Pesaran and Shin (1998) and Pesaran, Shin, and Smith (2001). The ARDL bounds test approach is based on the ordinary least squares estimation of a conditional unrestricted error correction model for cointegration analysis. The ARDL technique is more appealing than the Johansen cointegration technique (Johansen and Juselius 1990) because the latter requires that the variables are integrated of the same order of I(1). However, the ARDL approach is not constrained by the outcomes of unit root tests. It is applicable irrespective of whether the regressors in the model are purely I(0), purely I(1), or mutually cointegrated. In the present case, most variables are I(1) with the exception of IPIYOY and DRATIO_Q (i.e., government debt as percentage of nominal

Table 4. **Autoregressive Distributive Lag Bounds Test Results for IGB2YR** (monthly data)

Equation		**F-statistic**
4.1) IGB2YR $= \beta_0 + \beta_1$TB3M		3.93
4.2) IGB2YR $= \beta_2 + \beta_3$TCPIYOY		2.97
4.3) IGB2YR $= \beta_4 + \beta_5$IPIYOY		1.46
4.4) IGB2YR $= \beta_6 + \beta_7$TB3M $+ \beta_8$TCPIYOY		**6.52****
4.5) IGB2YR $= \beta_9 + \beta_{10}$TB3M $+ \beta_{11}$IPIYOY		2.99
4.6) IGB2YR $= \beta_{12} + \beta_{13}$TB3M $+ \beta_{14}$TCPIYOY $+ \beta_{15}$IPIYOY		**4.81***
	Long-Run Relationships	
Variable	**Equation 4.4**	**Equation 4.6**
TB3M	0.51***	0.51***
	(0.04)	(0.05)
TCPIYOY	−0.01	−0.00
	(0.04)	(0.04)
IPIYOY	—	−0.00
		(0.01)
Constant	3.60***	3.60***
	(0.48)	(0.54)
Time period	Dec 2006–Oct 2015	Feb 2007–Oct 2015
Number of observations	107	105

IGB2YR = 2-year government bond yield, IPIYOY = year-on-year percentage change in industrial production, TB3M = 3-month government auction rate, TCPIYOY = year-on-year percentage change in consumer price index.

Notes: ***, **, and * represent 1%, 5%, and 10% levels of significance, respectively. Standard errors are in parentheses. Lower bound values are 6.84, 4.94, and 4.04 for 1%, 5%, and 10% levels of significance, respectively. Upper bound values are 7.84, 5.73, and 4.78 for 1%, 5%, and 10% levels of significance, respectively.

Source: Authors' calculations.

GDP), which are I(0). Moreover, the ARDL technique allows different variables to take different optimal numbers of lags, while this is not permitted in the Johansen cointegration approach. Therefore, the ARDL technique, which will accommodate both I(0) and I(1) variables, is used in this paper to estimate the long-run relationships between long-term government bond yields and other control variables.

IV. Empirical Results

A. Monthly Results

The ARDL bounds test results generated from monthly variables are presented in Tables 4–8. When the short-term interest rate is included with inflation, in most cases the computed F-statistic based on a Wald test exceeds the upper bound value at the 5% level. In the case of the 2-year government bond yield, the computed F-statistic exceeds the upper bound value at the 10% level when the

Table 5. **Autoregressive Distributive Lag Bounds Test Results for IGB3YR** (monthly data)

Equation	**F-statistic**
5.1) IGB3YR $= \beta_{16} + \beta_{17}$TB3M	4.60
5.2) IGB3YR $= \beta_{18} + \beta_{19}$TCPIYOY	2.64
5.3) IGB3YR $= \beta_{20} + \beta_{21}$IPIYOY	2.03
5.4) IGB3YR $= \beta_{22} + \beta_{23}$TB3M $+ \beta_{24}$TCPIYOY	**8.37*****
5.5) IGB3YR $= \beta_{25} + \beta_{26}$TB3M $+ \beta_{27}$IPIYOY	3.70
5.6) IGB3YR $= \beta_{28} + \beta_{29}$TB3M $+ \beta_{30}$TCPIYOY $+ \beta_{31}$IPIYOY	**6.20****

Long-Run Relationships

Variable	**Equation 5.4**	**Equation 5.6**
TB3M	0.39***	0.38***
	(0.04)	(0.05)
TCPIYOY	−0.01	−0.01
	(0.04)	(0.04)
IPIYOY	—	−0.01
		(0.01)
Constant	4.74***	4.81***
	(0.47)	(0.55)
Time period	Dec 2006–Oct 2015	Feb 2007–Oct 2015
Number of observations	107	105

IGB3YR = 3-year government bond yield, IPIYOY = year-on-year percentage change in industrial production, TB3M = 3-month government auction rate, TCPIYOY = year-on-year percentage change in consumer price index.
Notes: *** and ** represent 1% and 5% levels of significance, respectively. Standard errors are in parentheses. Lower bound values are 6.84, 4.94, and 4.04 for 1%, 5%, and 10% levels of significance, respectively. Upper bound values are 7.84, 5.73, and 4.78 for 1%, 5%, and 10% levels of significance, respectively.
Source: Authors' calculations.

short-term rate is included in the equation with both inflation and the industrial production index (equation 4.6). The null hypothesis of no cointegration is rejected whenever the F-statistic value is higher than the upper bound value. This analysis confirms the presence of a long-run relationship among long-term government bond yields, the short-term interest rate, the rate of inflation, and the growth of industrial production. It enables the estimation of the long-run coefficients of the short-term interest rate and other control variables. The coefficients of the short-term interest rate are always positive and statistically significant at the 1% level. The size of this coefficient tends to be smaller as the tenor of the government bond rises. These results suggest that in the long run the short-term interest rate strongly influences long-term government bond yields in India.

B. Quarterly Results

Estimated results using quarterly data are presented in Tables 9–13. When the short-term 3-month interest rate is included with inflation and the ratio of

Table 6. **Autoregressive Distributive Lag Bounds Test Results for IGB5YR** (monthly data)

Equation	**F-statistic**
6.1) IGB5YR = $\beta_{32} + \beta_{33}$TB3M	3.84
6.2) IGB5YR = $\beta_{34} + \beta_{35}$TCPIYOY	3.65
6.3) IGB5YR = $\beta_{36} + \beta_{37}$IPIYOY	2.37
6.4) IGB5YR = $\beta_{38} + \beta_{39}$TB3M + β_{40}TCPIYOY	**10.56*****
6.5) IGB5YR = $\beta_{41} + \beta_{42}$TB3M + β_{43}IPIYOY	4.08
6.6) IGB5YR = $\beta_{44} + \beta_{45}$TB3M + β_{46}TCPIYOY + β_{47}IPIYOY	**7.74****

Long-Run Relationships

Variable	**Equation 6.4**	**Equation 6.6**
TB3M	0.26***	0.25***
	(0.04)	(0.04)
TCPIYOY	−0.00	−0.00
	(0.04)	(0.04)
IPIYOY	—	−0.01
		(0.01)
Constant	5.86***	5.98***
	(0.43)	(0.53)
Time period	Dec 2006–Oct 2015	Feb 2007–Oct 2015
Number of observations	107	105

IGB5YR = 5-year government bond yield, IPIYOY = year-on-year percentage change in industrial production, TB3M = 3-month government auction rate, TCPIYOY = year-on-year percentage change in consumer price index.
Notes: *** and ** represent 1% and 5% levels of significance, respectively. Standard errors are in parentheses. Lower bound values are 6.84, 4.94, and 4.04 for 1%, 5%, and 10% levels of significance, respectively. Upper bound values are 7.84, 5.73, and 4.78 for 1%, 5%, and 10% levels of significance, respectively.
Source: Authors' calculations.

government debt to nominal GDP, the computed F-statistic value is mostly higher than the upper bound value. Long-run coefficients of the short-term interest rate are positive when significant. The magnitude of this coefficient lies between 0.13 and 0.53. The coefficient of the ratio of government debt to nominal GDP is mostly negative and significant at the 1% level, suggesting that in the long run a higher debt ratio tends to reduce the nominal yields of IGBs. This is contrary to the conventional wisdom. Quarterly data allow the use of government fiscal variables but a clear limitation is that these results are based on a smaller number of observations.

C. The Main Finding and Its Relevance

The main finding is that the short-term interest rate is a key driver of the long-term interest rate on IGBs in both the short run and the long run. This finding has important policy implications. For example, it suggests that the RBI's monetary policy decisions not only have an immediate effect on the long-term interest rate and the Treasury yield curve, but also on the direction and the level of the

Table 7. **Autoregressive Distributive Lag Bounds Test Results for IGB7YR** (monthly data)

Equation	*F*-statistic
7.1) IGB7YR $= \beta_{48} + \beta_{49}$TB3M	4.02
7.2) IGB7YR $= \beta_{50} + \beta_{51}$TCPIYOY	**5.63**
7.3) IGB7YR $= \beta_{52} + \beta_{53}$IPIYOY	2.59
7.4) IGB7YR $= \beta_{54} + \beta_{55}$TB3M $+ \beta_{56}$TCPIYOY	**10.60*****
7.5) IGB7YR $= \beta_{57} + \beta_{58}$TB3M $+ \beta_{59}$IPIYOY	4.09
7.6) IGB7YR $= \beta_{60} + \beta_{61}$TB3M $+ \beta_{62}$TCPIYOY $+ \beta_{63}$IPIYOY	**7.70****

Long-Run Relationships

Variable	Equation 7.2	Equation 7.4	Equation 7.6
TB3M	—	0.19***	0.18***
		(0.03)	(0.04)
TCPIYOY	0.03	0.02	0.01
	(0.08)	(0.04)	(0.04)
IPIYOY	—	—	−0.01
			(0.01)
Constant	7.71***	6.40***	6.53***
	(0.62)	(0.43)	(0.52)
Time period	Dec 2006–Oct 2015	Dec 2006–Oct 2015	Feb 2007–Oct 2015
Number of observations	107	107	105

IGB7YR = 7-year government bond yield, IPIYOY = year-on-year percentage change in industrial production, TB3M = 3-month government auction rate, TCPIYOY = year-on-year percentage change in consumer price index.
Notes: *** and ** represent 1% and 5% levels of significance, respectively. Standard errors are in parentheses. Lower bound values are 6.84, 4.94, and 4.04 for 1%, 5%, and 10% levels of significance, respectively. Upper bound values are 7.84, 5.73, and 4.78 for 1%, 5%, and 10% levels of significance, respectively.
Source: Authors' calculations.

long-term interest rate over a longer horizon. The results obtained are robust. Additional regressions estimated in Appendix 2 show that the coefficient of the short-term interest rate is positive and statistically significant, at least at the 5% level, even after controlling for variables such as credit growth, global investors' risk appetite, and the nominal effective exchange rate. Therefore, the main finding that the short-term interest rate is the most important determinant of long-term bond yields does not change with adjustments to the specifications.

These results reinforce the findings in Akram and Das' (2015a and 2015b) recent studies on IGBs in which they report that changes in the short-term interest rate are important determinants of changes in long-term government bond yields in India. Whereas Akram and Das (2015a and 2015b) established the results for the short run, the current study extends this for the long run.

V. Policy Implications and Conclusion

The empirical results reported here support Keynes' conjecture that the central bank's actions, through its influence on the short-term interest rate and its use

Table 8. **Autoregressive Distributive Lag Bounds Test Results for IGB10YR** (monthly data)

Equation	F-statistic
8.1) IGB10YR $= \beta_{64} + \beta_{65}$TB3M	4.73
8.2) IGB10YR $= \beta_{66} + \beta_{67}$TCPIYOY	**7.51****
8.3) IGB10YR $= \beta_{68} + \beta_{69}$IPIYOY	3.60
8.4) IGB10YR $= \beta_{70} + \beta_{71}$TB3M $+ \beta_{72}$TCPIYOY	**9.42*****
8.5) IGB10YR $= \beta_{73} + \beta_{74}$TB3M $+ \beta_{75}$IPIYOY	3.07
8.6) IGB10YR $= \beta_{76} + \beta_{77}$TB3M $+ \beta_{78}$TCPIYOY $+ \beta_{79}$IPIYOY	**6.83****

Long-Run Relationships

Variable	Equation 8.2	Equation 8.4	Equation 8.6
TB3M	—	0.14***	0.13***
		(0.04)	(0.04)
TCPIYOY	0.04	0.03	0.02
	(0.05)	(0.04)	(0.04)
IPIYOY	—	—	−0.01
			(0.01)
Constant	7.74***	6.87***	6.99***
	(0.45)	(0.44)	(0.53)
Time period	Dec 2006– Oct 2015	Dec 2006– Oct 2015	Feb 2007– Oct 2015
Number of observations	107	107	105

IGB10YR = 10-year government bond yield, IPIYOY = year-on-year percentage change in industrial production, TB3M = 3-month government auction rate, TCPIYOY = year-on-year percentage change in consumer price index.
Notes: *** and ** represent 1% and 5% levels of significance, respectively. Standard errors are in parentheses. Lower bound values are 6.84, 4.94, and 4.04 for 1%, 5%, and 10% levels of significance, respectively. Upper bound values are 7.84, 5.73, and 4.78 for 1%, 5%, and 10% levels of significance, respectively.
Source: Authors' calculations.

Table 9. **Autoregressive Distributive Lag Bounds Test Results for IGB2YR_Q** (quarterly data)

Equation	F-statistic
9.1) IGB2YR_Q $= \gamma_0 + \gamma_1$TB3M_Q $+ \gamma_2$DRATIO_Q	2.67
9.2) IGB2YR_Q $= \gamma_3 + \gamma_4$TCPIYOY_Q $+ \gamma_5$DRATIO_Q	1.68
9.3) IGB2YR_Q $= \gamma_6 + \gamma_7$IPIYOY_Q $+ \gamma_8$DRATIO_Q	2.21
9.4) IGB2YR_Q $= \gamma_9 + \gamma_{10}$TB3M_Q $+ \gamma_{11}$TCPIYOY_Q $+ \gamma_{12}$DRATIO_Q	1.16
9.5) IGB2YR_Q $= \gamma_{13} + \gamma_{14}$TB3M_Q $+ \gamma_{15}$IPIYOY_Q $+ \gamma_{16}$DRATIO_Q	2.03
9.6) IGB2YR_Q $= \gamma_{17} + \gamma_{18}$TB3M_Q $+ \gamma_{19}$TCPIYOY_Q $+ \gamma_{20}$IPIYOY_Q $+ \gamma_{21}$DRATIO_Q	1.01

DRATIO_Q = government debt as percentage of nominal gross domestic product, IGB2YR_Q = 2-year government bond yield, IPIYOY_Q = year-on-year percentage change in industrial production, TB3M_Q = 3-month government auction rate, TCPIYOY_Q = year-on-year percentage change in consumer price index.
Note: Lower bound values are 6.84, 4.94, and 4.04 for 1%, 5%, and 10% levels of significance, respectively. Upper bound values are 7.84, 5.73, and 4.78 for 1%, 5%, and 10% levels of significance, respectively.
Source: Authors' calculations.

Table 10. **Autoregressive Distributive Lag Bounds Test Results for IGB3YR_Q** (quarterly data)

Equation	***F*-statistic**
10.1) IGB3YR_Q = $\gamma_{22} + \gamma_{23}$TB3M_Q + γ_{24}DRATIO_Q	**5.51****
10.2) IGB3YR_Q = $\gamma_{25} + \gamma_{26}$TCPIYOY_Q + γ_{27}DRATIO_Q	2.19
10.3) IGB3YR_Q = $\gamma_{28} + \gamma_{29}$IPIYOY_Q + γ_{30}DRATIO_Q	2.51
10.4) IGB3YR_Q = $\gamma_{31} + \gamma_{32}$TB3M_Q + γ_{33}TCPIYOY_Q + γ_{34}DRATIO_Q	**6.17****
10.5) IGB3YR_Q = $\gamma_{35} + \gamma_{36}$TB3M_Q + γ_{37}IPIYOY_Q + γ_{38}DRATIO_Q	2.21
10.6) IGB3YR_Q = $\gamma_{39} + \gamma_{40}$TB3M_Q + γ_{41}TCPIYOY_Q + γ_{42}IPIYOY_Q + γ_{43}DRATIO_Q	1.09

Long-Run Relationships

Variable	**Equation 10.1**	**Equation 10.4**
TB3M_Q	0.53***	0.44***
	(0.07)	(0.03)
TCPIYOY_Q	—	0.00
		(0.03)
IPIYOY_Q	—	—
DRATIO_Q	−2.39***	0.69
	(0.82)	(0.61)
Constant	7.36***	3.21***
	(1.55)	(0.85)
Time period	Q3 2003–Q2 2015	Q1 2007–Q2 2015
Number of observations	48	34

DRATIO_Q = government debt as percentage of nominal gross domestic product, IGB3YR_Q = 3-year government bond yield, IPIYOY_Q = year-on-year percentage change in industrial production, TB3M_Q = 3-month government auction rate, TCPIYOY_Q = year-on-year percentage change in consumer price index.
Notes: *** and ** represent 1% and 5% levels of significance, respectively. Standard errors are in parentheses. Lower bound values are 5.15, 3.79, and 3.17 for 1%, 5%, and 10% levels of significance, respectively. Upper bound values are 6.36, 5.52, and 4.14 for 1%, 5%, and 10% levels of significance, respectively.
Source: Authors' calculations.

of the tools of monetary policy, are the main drivers of the long-term interest rate. In the case of India, the actions of the RBI affect the long-term interest rate. The long-term interest rate on IGBs is positively associated with the short-term interest rate on Indian Treasury bills after controlling for the relevant variables such as the rate of inflation, growth of industrial production, and debt ratio. A higher (lower) long-term interest rate on IGBs is associated with a higher (lower) short-term interest rate, higher (lower) rate of inflation, and faster (slower) pace of industrial production. The results show that a higher level of government indebtedness does not have an adverse effect on IGBs' nominal yields, contrary to the conventional view. These findings concur with the results obtained in Akram and Das' (2015a and 2015b) studies of the short-term dynamics of IGBs. The findings also align with those obtained in studies by Chakraborty (2012 and 2016) and Vinod, Chakraborty, and Karun (2014), which use quite different econometric and statistical methods.

Table 11. **Autoregressive Distributive Lag Bounds Test Results for IGB5YR_Q** (quarterly data)

Equation	*F*-statistic
11.1) IGB5YR_Q = $\gamma_{44} + \gamma_{45}$TB3M_Q + γ_{46}DRATIO_Q	**5.13****
11.2) IGB5YR_Q = $\gamma_{47} + \gamma_{48}$TCPIYOY_Q + γ_{49}DRATIO_Q	3.45
11.3) IGB5YR_Q = $\gamma_{50} + \gamma_{51}$IPIYOY_Q + γ_{52}DRATIO_Q	3.81
11.4) IGB5YR_Q = $\gamma_{53} + \gamma_{54}$TB3M_Q + γ_{55}TCPIYOY_Q + γ_{56}DRATIO_Q	**9.00*****
11.5) IGB5YR_Q = $\gamma_{57} + \gamma_{58}$TB3M_Q + γ_{59}IPIYOY_Q + γ_{60}DRATIO_Q	3.97
11.6) IGB5YR_Q = $\gamma_{61} + \gamma_{62}$TB3M_Q + γ_{63}TCPIYOY_Q + γ_{64}IPIYOY + γ_{65}DRATIO_Q	**6.63*****

Long-Run Relationships

Variable	Equation 11.1	Equation 11.4	Equation 11.6
TB3M_Q	0.41***	0.26***	0.21***
	(0.09)	(0.04)	(0.07)
TCPIYOY_Q	—	−0.03	−0.11
		(0.05)	(0.08)
IPIYOY_Q	—	—	−0.03
			(0.02)
DRATIO_Q	−3.06***	1.54	1.67
	(1.04)	(0.92)	(1.08)
Constant	9.52***	3.73**	4.67**
	(1.98)	(1.36)	(1.83)
Time period	Q3 2003–Q2 2015	Q1 2007–Q2 2015	Q1 2007–Q2 2015
Number of observations	48	34	34

DRATIO_Q = government debt as percentage of nominal gross domestic product, IGB5YR_Q = 5-year government bond yield, IPIYOY_Q = year-on-year percentage change in industrial production, TB3M_Q = 3-month government auction rate, TCPIYOY_Q = year-on-year percentage change in consumer price index.
Notes: *** and ** represent 1% and 5% levels of significance, respectively. Standard errors are in parentheses. Lower bound values are 5.15, 3.79, and 3.17 for 1%, 5%, and 10% levels of significance, respectively. Upper bound values are 6.36, 5.52, and 4.14 for 1%, 5%, and 10% levels of significance, respectively.
Source: Authors' calculations.

The findings reported in this paper have implications for policy debates in India and other emerging markets with monetary sovereignty that issue government debt mostly in their own currencies. The findings are also relevant for ongoing debates over fiscal policy, the sustainability of government debt, monetary policy, monetary–fiscal coordination and the policy mix during economic fluctuations, and macroeconomic and monetary theory (Bindseil 2004, Fullwiler 2008 and 2016, Kregel 2011, Sims 2013a and 2013b, Tcherneva 2011, Woodford 2001, and Wray 2003 [1998] and 2012). First, the results show that the RBI can exert a strong influence on IGB yields by affecting the short-term interest rates. The RBI can affect the short-term interest rates on Indian Treasury bills through setting the repo rate and the reverse repo rate (Figure 6). These findings support Keynes' conjecture about the influence of a sovereign central bank on long-term interest rates. Second, the results also suggest that, contrary to the conventional wisdom, higher government indebtedness does not raise IGBs' nominal yields. While this

Table 12. **Autoregressive Distributive Lag Bounds Test Results for IGB7YR_Q (quarterly data)**

Equation	***F*-statistic**
12.1) IGB7YR_Q = $\gamma_{66} + \gamma_{67}$TB3M_Q + γ_{68}DRATIO_Q	**4.89****
12.2) IGB7YR_Q = $\gamma_{69} + \gamma_{70}$TCPIYOY_Q + γ_{71}DRATIO_Q	**4.50****
12.3) IGB7YR_Q = $\gamma_{72} + \gamma_{73}$IPIYOY_Q + γ_{74}DRATIO_Q	**4.62****
12.4) IGB7YR_Q = $\gamma_{75} + \gamma_{76}$TB3M_Q + γ_{77}TCPIYOY_Q + γ_{78}DRATIO_Q	**10.04*****
12.5) IGB7YR_Q = $\gamma_{79} + \gamma_{80}$TB3M_Q + γ_{81}IPIYOY_Q + γ_{82}DRATIO_Q	3.81
12.6) IGB7YR_Q = $\gamma_{83} + \gamma_{84}$TB3M_Q + γ_{85}TCPIYOY_Q + γ_{86}IPIYOY_Q + γ_{87}DRATIO_Q	2.44

Long-Run Relationships

Variable	**Equation 12.1**	**Equation 12.2**	**Equation 12.3**	**Equation 12.4**
TB3M_Q	0.35***	—	—	0.18***
	(0.10)			(0.05)
TCPIYOY_Q	—	0.02	—	−0.04
		(0.10)		(0.05)
IPIYOY_Q	—	—	−0.02	—
			(0.04)	
DRATIO_Q	−3.22***	1.67	−4.97***	1.71*
	(1.14)	(2.16)	(1.57)	(0.98)
Constant	10.40***	5.18	15.71***	4.27***
	(2.17)	(3.51)	(2.53)	(1.43)
Time period	Q3 2003–Q2 2015	Q1 2007–Q2 2015	Q3 2003–Q2 2015	Q1 2007–Q2 2015
Number of observations	48	34	48	34

DRATIO_Q = government debt as percentage of nominal gross domestic product, IGB7YR_Q = 7-year government bond yield, IPIYOY_Q = year-on-year percentage change in industrial production, TB3M_Q = 3-month government auction rate, TCPIYOY_Q = year-on-year percentage change in consumer price index.
Notes: *** and ** represent 1% and 5% levels of significance, respectively. Standard errors are in parentheses. Lower bound values are 5.15, 3.79, and 3.17 for 1%, 5%, and 10% levels of significance, respectively. Upper bound values are 6.36, 5.52, and 4.14 for 1%, 5%, and 10% levels of significance, respectively.
Source: Authors' calculations.

finding is contrary to the conventional view, which is derived from the loanable funds perspective, it is fully in concordance with Keynes' views and modern money theory (Fullwiler 2008 and 2016, Kregel 2011, and Wray 2003 [1998] and 2012), which holds that increased government expenditures result in rising central bank reserves and banking deposits in the financial system because the central bank credits the banks in order to facilitate the government's borrowing and expenditures. Third, the results suggest that Indian policy makers can use appropriate models—based on information on the current trend of short-term interest rates, government debt ratios, and other key macro variables—to form their long-term outlook about IGBs' nominal yields and understand the implications of the government's fiscal stance on the government bond market. Of course, the use of such models requires judgment and prudence, and carries with it model risks and limitations.

Keynes claims that the central bank has a decisive influence on long-term interest rates. He believes that short-term interest rates and other monetary policy

Table 13. **Autoregressive Distributive Lag Bounds Test Results for IGB10YR_Q (quarterly data)**

Equation	*F*-statistic
13.1) IGB10YR_Q = $\gamma_{88} + \gamma_{89}$TB3M_Q + γ_{90}DRATIO_Q	**6.82*****
13.2) IGB10YR_Q = $\gamma_{91} + \gamma_{92}$TCPIYOY_Q + γ_{93}DRATIO_Q	**5.51****
13.3) IGB10YR_Q = $\gamma_{94} + \gamma_{95}$IPIYOY_Q + γ_{96}DRATIO_Q	**7.88*****
13.4) IGB10YR_Q = $\gamma_{97} + \gamma_{98}$TB3M_Q + γ_{99}TCPIYOY + γ_{100}DRATIO_Q	**10.66*****
13.5) IGB10YR_Q = $\gamma_{101} + \gamma_{102}$TB3M_Q + γ_{103}IPIYOY_Q + γ_{104}DRATIO_Q	4.14
13.6) IGB10YR_Q = $\gamma_{105} + \gamma_{106}$TB3M_Q + γ_{107}TCPIYOY_Q + γ_{108}IPIYOY_Q + γ_{109}DRATIO_Q	3.93

Long-Run Relationships

Variable	Equation 13.1	Equation 13.2	Equation 13.3	Equation 13.4
TB3M_Q	0.29	—	—	0.13**
	(0.20)			(0.05)
TCPIYOY_Q	—	0.03	—	−0.05
		(0.08)		(0.06)
IPIYOY_Q	—	—	0.04	—
			(0.07)	
DRATIO_Q	−5.41***	1.53	−7.52***	1.75*
	(2.18)	(1.78)	(2.16)	(1.02)
Constant	14.67***	5.48*	19.90***	4.85***
	(4.42)	(2.90)	(3.56)	(1.48)
Time period	Q3 1999–Q2 2015	Q1 2007–Q2 2015	Q3 1999–Q2 2015	Q1 2007–Q2 2015
Number of observations	64	34	64	34

DRATIO_Q = government debt as percentage of nominal gross domestic product, IGB10YR_Q = 10-year government bond yield, IPIYOY_Q = year-on-year percentage change in industrial production, TB3M_Q = 3-month government auction rate, TCPIYOY_Q = year-on-year percentage change in consumer price index.
Notes: *** and ** represent 1% and 5% levels of significance, respectively. Standard errors are in parentheses. Lower bound values are 5.15, 3.79, and 3.17 for 1%, 5%, and 10% levels of significance, respectively. Upper bound values are 6.36, 5.52, and 4.14 for 1%, 5%, and 10% levels of significance, respectively.
Source: Authors' calculations.

actions drive long-term interest rates and that an investor's long-term outlook is mostly shaped by the investor's near-term outlook and assessment of current conditions. This paper shows that Keynes' conjecture has empirical support in India over the long-run horizon by extending Akram and Das' (2015a and 2015b) findings for the short-run horizon to the long-run horizon for the case of India. It contributes to the nascent literature—such as Akram (2014) and Akram and Das (2014a and 2014b) on Japan; Akram and Das (2017b and 2017c) on the eurozone; and Akram and Li (2016, 2017a, and 2017b) on the US—on this topic of examining whether Keynes' conjecture holds in various countries. Further research should extend this to a wider range of countries—both advanced capitalist economies and emerging markets and other developing areas—and apply a broad spectrum of suitable econometric methods to establish whether these findings can be generalized and determine under which institutional contexts they are warranted.

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Appendix 1. Derivation of the Two-Period Model of Government Bond Yields

The long-term interest rate on the 2-year government bond depends on the short-term interest rate on Treasury securities in period 1 and the 1-year, 1-year forward rate (equation A1). The 1-year, 1-year forward rate is based on an investor's expectation of the short-term interest rate on Treasury securities in period 2 and the term premium (equation A2). However, the expected short-term interest rate on Treasury securities in period 2 and the term premium is a function of the investor's expectation of growth and inflation in period 2 (equation A3). Hence, the 1-year, 1-year forward rate is merely the sum of the expected short-term interest rate on the Treasury bill in period 2 and a function of the expected growth rate and expected inflation in the same period (equation A4). This implies that the forward rate is a function of expected short-term interest rates on Treasury securities, the expected growth rate, and expected rate of inflation in period 2 (equation A5). Since the long-term interest rate is a function of the short-term interest rate on the Treasury securities in period 1 and the 1-year, 1-year forward rate (equation A6), it follows that the long-term interest rate is a function of the short-term interest rate in period 1, and a function of the expected short-term interest rate, expected growth rate, and expected rate of inflation in period 2 (equation A7).

Keynes' view is that the investor resorts to the present and the past. The investor relies on his view of the near-term future to form his conception of the long-term future since it is not really possible to have a proper mathematical expectation of the unknown and uncertain future. Hence, for the investor, the expected short-term interest rate in period 2 is based on the actual short-term interest rate in period 1 (equation A8), the expected growth rate in period 2 is based on the actual growth rate in period 1 (equation A9), and the expected rate of inflation in period 2 is based on the actual rate of inflation in period 1 (equation A10). Similarly, the expected government fiscal variable in period 2 is based on the government fiscal variable in period 1 (equation A11). These Keynesian assumptions results in a model (equation A12) where the long-term interest rate is a function of either (i) the current short-term interest rate, the current growth rate, and current inflation (equation A13); or (ii) the current short-term interest rate, the current growth rate, current inflation, and the current government fiscal variable (equation A14).

The Keynesian view that an investor's expectation of key economic variables depends largely on current conditions or the investor's assessment of current conditions may appear intriguing and counterintuitive. But if key economic variables follow a Markov process (equation A15, equation A16, equation A17, and equation A18), then the Keynesian view of the trajectory of expected values of these variables is entirely reasonable. Empirical and behavioral studies of the investor's expectations of the interest rate and the rate of inflation show that Keynes' conjectures have considerable support (Clark and Davig 2008; Faust and Wright 2013; Mavroedis, Plagborg-Møller, and Stock 2014).

In contrast, under rational expectations where Lucasian assumptions of perfect foresight hold, the investor's expected short-term interest rates, expected growth rate, expected inflation, and expected government fiscal variable would equal, respectively, the actual short-term interest rates, growth rate, rate of inflation, and government fiscal variable in period 2 (equation A19, equation A20, equation A21, and equation A22). This would result in the long-term interest rate being a function of either (i) the current short-term interest rate, growth rate, and rate of inflation in period 2 (equation A23); or (ii) the current short-term interest rate, growth rate, rate of inflation, and government fiscal variable in period 2 (equation A24).

The model is represented in the following system of equations:

$$(1+r_{LT})^2 = (1+r_1)(1+f_{1,1}) \tag{A1}$$

$$f_{1,1} = Er_2 + z \tag{A2}$$

$$Er_2 + z = F^1(Eg_2, E\pi_2) \tag{A3}$$

$$f_{1,1} = Er_2 + F^2(Eg_2, E\pi_2) \tag{A4}$$

$$f_{1,1} = F^3(Er_2, Eg_2, E\pi_2) \tag{A5}$$

$$r_{LT} = F^4(r_1, f_{1,1}) \tag{A6}$$

$$r_{LT} = F^4\left(r_1, F^3(Er_2, Eg_2, E\pi_2)\right) \tag{A7}$$

The Keynesian assumptions imply that the following hold:

$$Er_2 = r_1 \tag{A8}$$

$$Eg_2 = g_1 \tag{A9}$$

$$E\pi_2 = \pi_1 \tag{A10}$$

$$E\nu_2 = \nu_1 \tag{A11}$$

Incorporating Keynesian assumptions into the model leads to the following:

$$r_{LT} = F^4\left(r_1, F^3(r_1, g_1, \pi_1)\right) \tag{A12}$$

$$r_{LT} = F^5(r_1, g_1, \pi_1) \tag{A13}$$

Extending the model to include the government fiscal variable results in the following:

$$r_{LT} = F^6(r_1, g_1, \pi_1, \upsilon_1) \tag{A14}$$

If the variables in period 2 are to follow a simple Markov process, these variables can be modeled in the following terms:

$$r_2 = \Lambda_1 + \Lambda_2 r_1 \tag{A15}$$

$$g_2 = \Lambda_3 + \Lambda_4 g_1 \tag{A16}$$

$$\pi_2 = \Lambda_5 + \Lambda_6 \pi_1 \tag{A17}$$

$$\upsilon_2 = \Lambda_7 + \Lambda_8 \upsilon_1 \tag{A18}$$

In the above equations, the restrictions on the parameters are as follows: $0 < \Lambda_2 < 1, 0 < \Lambda_4 < 1, 0 < \Lambda_6 < 1$, and $0 < \Lambda_8 < 1$.

It is useful to contrast the Keynesian model with a Lucasian (rational expectations) model. Under rational expectations:

$$Er_2 = r_2 \tag{A19}$$

$$Eg_2 = g_2 \tag{A20}$$

$$E\pi_2 = \pi_2 \tag{A21}$$

$$E\upsilon_2 = \upsilon_2 \tag{A22}$$

Under Lucasian assumptions, the long-term rates are modeled, respectively, without and with government fiscal variable, as follows:

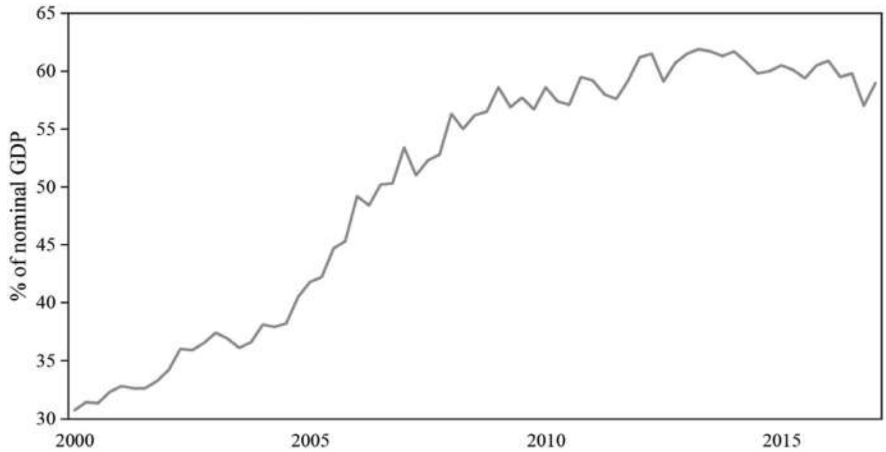
$$r_{LT} = F^7 (r_1, r_2, g_2, \pi_2) \tag{A23}$$

$$r_{LT} = F^8 (r_1, r_2, g_2, \pi_2, \upsilon_2) \tag{A24}$$

Appendix 2. The Effects of Credit Growth, Global Risk Appetite, and the Nominal Effective Exchange Rate on Indian Government Bond Yields

While this paper is based on a Keynesian perspective on government bond yields, it can be worthwhile to examine the view that a number of other macroeconomic variables—such as credit growth, global investors' risk appetite, the index of the nominal effective exchange rate, and financial flows—could have marked effects on government bond yields. Increased (decreased) access to credit should lead to higher (lower) demand for government bonds and hence would cause bond prices to rise (fall) and bond yields to decline (increase). The appreciation (depreciation) of the Indian rupee should lead to lower (higher) bond yields because investors, particularly foreign investors, are compensated for the increase

Figure A2.1. **The Evolution of Credit to the Private Sector in India**



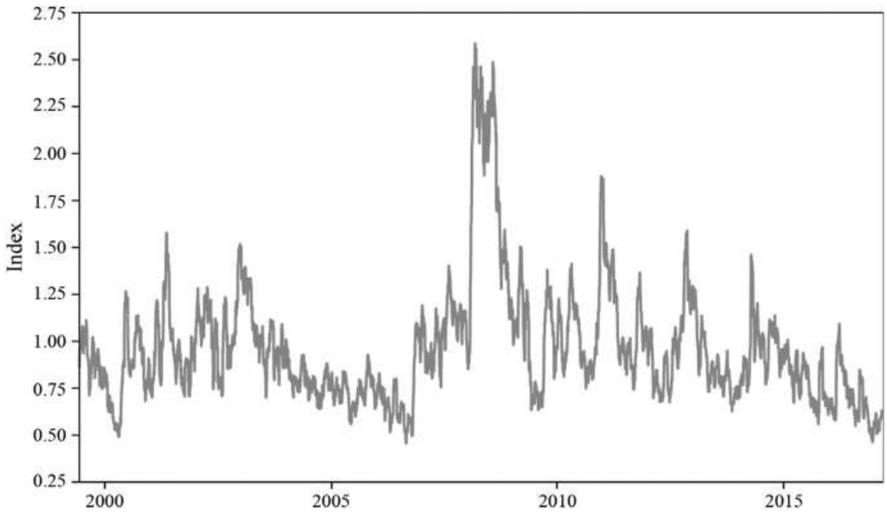
GDP = gross domestic product.
Source: Macrobond. Various years. Macrobond subscription services (accessed September 13, 2018).

(reduction) in the value of the currency. Increased (decreased) perception of risk, as measured by higher (lower) volatility in global bond markets, should lead to higher (lower) government bond yields in India. This appendix examines whether any of these variables have a discernable influence on government bond yields as posited.

The hypothesis that credit growth, global investors' risk appetite, and the exchange rate matter is supported in some of the findings reported in the recent empirical literature on the determinants of government bond yields. Arslanalp and Poghosyan (2014) show that an increase in the share of government debt held by foreign investors can explain a reduction in long-term government bond yields. Ebeke and Lu (2014) report that foreign holdings of local currency government bonds in emerging markets exert downward pressure on government bond yields, though they note that an increase in such holdings is associated with somewhat increased yield volatility in the post-Lehman period. Other researchers have explored the effects of overall credit growth and the exchange rate on government bond yields in emerging markets.

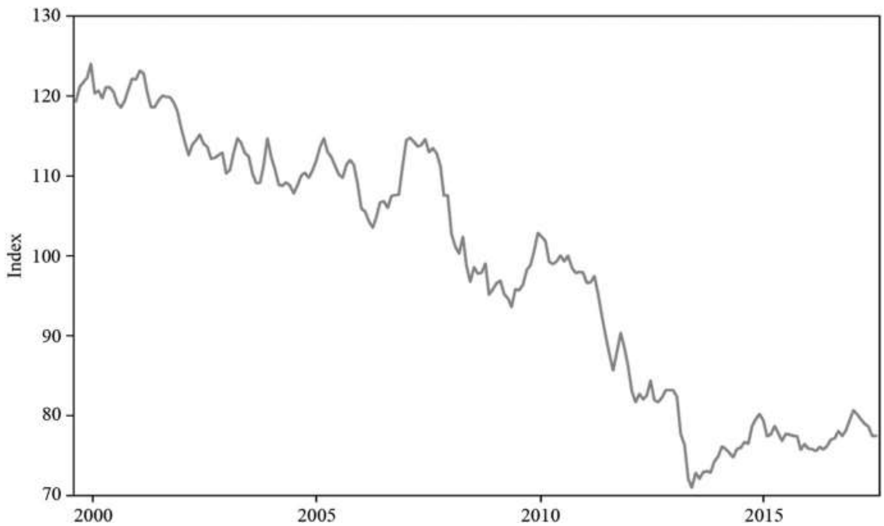
The evolution of some of these additional variables for India is shown in the figures below. Figure A2.1 shows that the ratio of overall credit to nominal gross domestic product steadily increased for many years before stabilizing in recent years. Figure A2.2 depicts the evolution of volatility in global bond markets. Volatility in government bond markets rose sharply during both the global financial crisis and the eurozone debt crisis. Such volatility is a good proxy for global investors' risk appetite. Figure A2.3 displays the evolution of the nominal effective exchange rate for the Indian rupee. The Indian rupee depreciated steadily versus

Figure A2.2. **The Evolution of Risk as Measured by the Global Market Volatility Index**



Source: Macrobond. Various years. Macrobond subscription services (accessed September 13, 2018).

Figure A2.3. **The Evolution of the Nominal Effective Exchange Rate of the Indian Rupee**



Source: Macrobond. Various years. Macrobond subscription services (accessed September 13, 2018).

the United States dollar between 2000 and 2014. Since 2014, it has appreciated modestly and has been fairly stable.

After controlling for the short-term interest rate, rate of inflation, growth of industrial production, and debt ratio, the effects of credit growth, global risk

Table A2.1. **Autoregressive Distributive Lag Bounds Test Results for IGB2YR (monthly data)**

Equation	***F*-statistic**
B1.1) IGB2YR = $\beta_0 + \beta_1$TB3M + β_2CREDIT + β_3NEER + β_4RISK	**9.86**
B1.2) IGB2YR = $\beta_5 + \beta_6$TCPIYOY + β_7CREDIT + β_8NEER + β_9RISK	**5.79**
B1.3) IGB2YR = $\beta_{10} + \beta_{11}$IPIYOY + β_{12}CREDIT + β_{13}NEER + β_{14}RISK	**8.03**
B1.4) IGB2YR = $\beta_{15} + \beta_{16}$TB3M + β_{17}TCPIYOY + β_{18}CREDIT + β_{19}NEER + β_{20}RISK	**7.58**
B1.5) IGB2YR = $\beta_{21} + \beta_{22}$TB3M + β_{23}IPIYOY + β_{24}CREDIT + β_{24}NEER + β_{27}RISK	**8.58**
B1.6) IGB2YR = $\beta_{28} + \beta_{29}$TB3M + β_{30}TCPIYOY + β_{31}IPIYOY + β_{32}CREDIT + β_{33}NEER + β_{34}RISK	**5.99**

Long-Run Relationships

Variable	**Equation B1.1**	**Equation B1.2**	**Equation B1.3**	**Equation B1.4**	**Equation B1.5**	**Equation B1.6**
TB3M	0.46^{***}	—	—	0.47^{***}	0.47^{***}	0.45^{***}
	(0.04)			(0.03)	(0.04)	(0.04)
TCPIYOY	—	0.05	—	−0.20	—	−0.04
		(0.15)		(0.03)		(0.04)
IPIYOY	—	—	0.00	—	−0.02	−0.01
			(0.05)		(0.02)	(0.02)
CREDIT	0.07^{***}	0.10	0.16^{***}	0.06	0.08^{***}	0.07
	(0.01)	(0.27)	(0.04)	(0.05)	(0.01)	(0.06)
NEER	0.01^{***}	0.02	0.03	0.01	0.02^{**}	0.01
	(0.01)	(0.06)	(0.03)	(0.01)	(0.01)	(0.01)
RISK	-1.07^{***}	-3.26^{***}	-4.07^{***}	-0.89^{***}	-1.28^{***}	-1.04^{***}
	(0.19)	(0.75)	(1.11)	(0.18)	(0.26)	(0.27)
Constant	−0.28	2.82	−0.61	0.30	−1.44	0.08
	(0.99)	(19.83)	(4.49)	(3.54)	(1.24)	(4.14)
Time period	May 2003–Oct 2015	Mar 2007–Oct 2015	Aug 2009–Oct 2015	Mar 2007–Oct 2015	Jul 2003–Oct 2015	Feb 2007–Oct 2015
Number of observations	150	104	147	107	148	105

CREDIT = credit to the private sector as percentage of gross domestic product, IGB2YR = 2-year government bond yield, IPIYOY = year-on-year percentage change in industrial production, NEER = nominal effective exchange rate, RISK = global bond market volatility index, TB3M = 3-month government auction rate, TCPIYOY = year-on-year percentage change in consumer price index.
Notes: *** represents 1% level of significance. Standard errors are in parentheses.
Source: Authors' calculations.

appetite, and the nominal effective exchange rate on the nominal yields of Indian government bonds (IGBs) of various tenors are examined using monthly data. Autoregressive distributive lag bounds test results are obtained. When the computed F-statistic value is higher than the upper bound value, the long-run relationships are estimated.

The results of the empirical investigation are presented in Tables A2.1–A2.5. An increase in the ratio of credit to nominal GDP leads to slightly higher IGB yields rather than lower yields. The coefficient for the index of the nominal

Table A2.2. **Autoregressive Distributive Lag Bounds Test Results for IGB3YR (monthly data)**

Equation	***F*–statistic**
B2.1) IGB3YR = $\beta_{35} + \beta_{36}$TB3M + β_{37}CREDIT + β_{38}NEER + β_{39}RISK	**8.73**
B2.2) IGB3YR = $\beta_{40} + \beta_{41}$TCPIYOY + β_{42}CREDIT + β_{43}NEER + β_{44}RISK	**5.96**
B2.3) IGB3YR = $\beta_{45} + \beta_{46}$IPIYOY + β_{47}CREDIT + β_{48}NEER + β_{49}RISK	**8.04**
B2.4) IGB3YR = $\beta_{50} + \beta_{51}$TB3M + β_{52}TCPIYOY + β_{53}CREDIT + β_{54}NEER + β_{55}RISK	**6.35**
B2.5) IGB3YR = $\beta_{56} + \beta_{57}$TB3M + β_{58}IPIYOY + β_{59}CREDIT + β_{60}NEER + β_{61}RISK	**7.82**
B2.6) IGB3YR = $\beta_{62} + \beta_{63}$TB3M + β_{64}TCPIYOY + β_{65}IPIYOY + β_{66}CREDIT + β_{67}NEER + β_{68}RISK	**5.02**

Long-Run Relationships

Variable	**Equation B2.1**	**Equation B2.2**	**Equation B2.3**	**Equation B2.4**	**Equation B2.5**	**Equation B2.6**
TB3M	0.35***	—	—	0.36***	0.35***	0.34***
	(0.04)			(0.04)	(0.04)	(0.04)
TCPIYOY	—	0.06	—	−0.02	–	−0.01
		(0.09)		(0.03)		(0.04)
IPIYOY	—	—	−0.01	—	–0.01	−0.01
			(0.04)		(0.02)	(0.02)
CREDIT	0.09***	−0.06	0.14***	0.04	0.09***	−0.02
	(0.01)	(0.14)	(0.03)	(0.05)	(0.01)	(0.05)
NEER	0.01***	−0.02	0.03	0.01	0.02**	−0.01
	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)
RISK	−0.97***	−2.78***	−3.06***	−0.66***	–1.07***	−0.73***
	(0.18)	(0.64)	(0.75)	(0.17)	(0.22)	(0.23)
Constant	−0.58	15.39	−0.24	2.46	–1.02	7.35*
	(0.99)	(1.014)	(3.27)	(4.00)	(1.22)	(3.92)
Time period	May 2003–Oct 2015	Jan 2007–Oct 2015	Aug 2003–Oct 2015	Dec 2006–Oct 2015	Jul 2003–Oct 2015	Feb 2007–Oct 2015
Number of Observations	150	106	147	107	148	105

CREDIT = credit to the private sector as percentage of gross domestic product, IGB3YR = 3-year government bond yield, IPIYOY = year-on-year percentage change in industrial production, NEER = nominal effective exchange rate, RISK = global bond market volatility index, TB3M = 3-month government auction rate, TCPIYOY = year-on-year percentage change in consumer price index.
Notes: *** represents 1% level of significance. Standard errors are in parentheses.
Source: Authors' calculations.

effective exchange rate is positive. This implies that as the Indian rupee appreciates (depreciates), IGB yields rise (fall). The estimated coefficient on risk shows that as risk (as measured by global bond market volatility) rises (falls), IGB yields decline (increase).

The results from the additional regressions estimated in this Appendix suggest that the ratio of credit to nominal GDP, nominal effective exchange rate, and investors' risk appetite (volatility) in global bond markets are not important drivers of IGB yields in India. However, the short-term interest rate is always found to be

Table A2.3. **Autoregressive Distributive Lag Bounds Test Results for IGB5YR (monthly data)**

Equation	***F*–statistic**
B3.1) IGB5YR = $\beta_{69} + \beta_{70}$TB3M + β_{71}CREDIT + β_{72}NEER + β_{73}RISK	**6.60**
B3.2) IGB5YR = $\beta_{74} + \beta_{75}$TCPIYOY + β_{76}CREDIT + β_{77}NEER + β_{78}RISK	**5.60**
B3.3) IGB5YR = $\beta_{79} + \beta_{80}$IPIYOY + β_{81}CREDIT + β_{82}NEER + β_{83}RISK	**6.51**
B3.4) IGB5YR = $\beta_{84} + \beta_{85}$TB3M + β_{86}TCPIYOY + β_{87}CREDIT + β_{88}NEER + β_{89}RISK	**4.02**
B3.5) IGB5YR = $\beta_{90} + \beta_{91}$TB3M + β_{92}IPIYOY + β_{93}CREDIT + β_{94}NEER + β_{95}RISK	**5.88**
B3.6) IGB5YR = $\beta_{96} + \beta_{97}$TB3M + β_{98}TCPIYOY + β_{99}IPIYOY + β_{100}CREDIT + β_{101}NEER + β_{102}RISK	**5.23**

Long-Run Relationships

Variable	**Equation B3.1**	**Equation B3.2**	**Equation B3.3**	**Equation B3.4**	**Equation B3.5**	**Equation B3.6**
TB3M	0.21***	—	—	0.23***	0.21***	0.21***
	(0.05)			(0.05)	(0.05)	(0.04)
TCPIYOY	—	0.02	—	0.01	—	0.01
		(0.06)		(0.04)		(0.04)
IPIYOY	—	—	−0.01	—	−0.02	−0.02
			(0.03)		(0.02)	(0.02)
CREDIT	0.09***	−0.02	0.13***	−0.05	0.10	−0.03
	(0.01)	(0.09)	(0.02)	(0.06)	(0.01)	(0.05)
NEER	0.01*	−0.01	0.02	−0.01	0.02*	−0.01
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
RISK	−0.78***	−1.79***	−2.05***	−0.34	−0.89***	−0.73***
	(0.22)	(0.40)	(0.51)	(0.22)	(0.27)	(0.23)
Constant	0.31	11.65*	0.20	10.30**	−0.68	9.54**
	(1.36)	(6.85)	(2.45)	(4.22)	(1.70)	(3.91)
Time period	Jan 2007–Oct 2015	Dec 2006–Oct 2015	Aug 2003–Oct 2015	Dec 2006–Oct 2015	Jul 2003–Oct 2015	Feb 2007–Oct 2015
Number of observations	150	107	147	107	148	105

CREDIT = credit to the private sector as percentage of gross domestic product, IGB5YR = 5-year government bond yield, IPIYOY = year-on-year percentage change in industrial production, NEER = nominal effective exchange rate, RISK = global bond market volatility index, TB3M = 3-month government auction rate, TCPIYOY = year-on-year percentage change in consumer price index.

Notes: ***, **, and * represent 1%, 5%, and 10% levels of significance, respectively. Standard errors are in parentheses.

Source: Authors' calculations.

positive and statistically significant, irrespective of the equations used to estimate the determinants of long-term government bond yields. This particular result is robust and insensitive to any changes in the specification. This result supports Keynes' contention in the case of India.

Table A2.4. **Autoregressive Distributive Lag Bounds Test Results for IGB7YR (monthly data)**

Equation	***F*–statistic**
B4.1) IGB7YR = $\beta_{103} + \beta_{104}$TB3M + β_{105}CREDIT + β_{106}NEER + β_{107}RISK	**3.17**
B4.2) IGB7YR = $\beta_{108} + \beta_{109}$TCPIYOY + β_{110}CREDIT + β_{111}NEER + β_{112}RISK	**2.90**
B4.3) IGB7YR = $\beta_{113} + \beta_{114}$IPIYOY + β_{115}CREDIT + β_{116}NEER + β_{117}RISK	**5.91**
B4.4) IGB7YR = $\beta_{118} + \beta_{119}$TB3M + β_{120}TCPIYOY + β_{121}CREDIT + β_{122}NEER + β_{123}RISK	**4.28**
B4.5) IGB7YR = $\beta_{124} + \beta_{125}$TB3M + β_{126}IPIYOY + β_{127}CREDIT + β_{128}NEER + β_{129}RISK	**4.97**
B4.6) IGB7YR = $\beta_{130} + \beta_{131}$TB3M + β_{132}TCPIYOY + β_{133}IPIYOY + β_{134}CREDIT + β_{135}NEER + β_{136}RISK	**3.69**

Long-Run Relationships

Variable	**Equation B4.1**	**Equation B4.3**	**Equation B4.4**	**Equation B4.5**	**Equation B4.6**
TB3M	0.22***	—	0.18***	0.15**	0.18***
	(0.08)		(0.05)	(0.06)	(0.05)
TCPIYOY	—	—	0.03	–	0.03
			(0.04)		(0.05)
IPIYOY	—	−0.02	—	–0.02	−0.02
		(2.28)		(0.02)	(0.02)
CREDIT	0.09***	0.13***	−0.07	0.10***	−0.08
	(0.02)	(0.02)	(0.06)	(0.02)	(0.06)
NEER	0.02*	0.02	−0.02	0.02*	−0.01
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
RISK	−0.19	−1.69***	−0.15	–0.83***	−0.28
	(0.41)	(0.45)	(0.24)	(0.30)	(0.31)
Constant	−0.17	−0.02	11.89***	–0.40	12.39***
	(1.90)	(0.03)	(4.41)	(1.86)	(4.59)
Time period	Jan 2007–Oct 2015	Aug 2003–Oct 2015	Dec 2006–Oct 2015	Jul 2003–Oct 2015	Feb 2007–Oct 2015
Number of Observations	150	147	107	148	105

CREDIT = credit to the private sector as percentage of gross domestic product, IGB7YR = 7-year government bond yield, IPIYOY = year-on-year percentage change in industrial production, NEER = nominal effective exchange rate, RISK = global bond market volatility index, TB3M = 3-month government auction rate, TCPIYOY = year-on-year percentage change in consumer price index.

Notes: ***, **, and * represent 1%, 5%, and 10% levels of significance, respectively. Standard errors are in parentheses.

Source: Authors' calculations.

Table A2.5. **Autoregressive Distributive Lag Bounds Test Results for IGB10YR (monthly data)**

Equation	***F*-statistic**
B5.1) IGB10YR = $\beta_{137} + \beta_{138}$TB3M + β_{139}CREDIT + β_{140}NEER + β_{141}RISK	**3.51**
B5.2) IGB10YR = $\beta_{142} + \beta_{143}$TCPIYOY + β_{144}CREDIT + β_{145}NEER + β_{146}RISK	**2.89**
B5.3) IGB10YR = $\beta_{147} + \beta_{148}$IPIYOY + β_{149}CREDIT + β_{150}NEER + β_{151}RISK	**2.83**
B5.4) IGB10YR = $\beta_{152} + \beta_{153}$TB3M + β_{154}TCPIYOY + β_{155}CREDIT + β_{156}NEER + β_{157}RISK	**4.19**
B5.5) IGB10YR = $\beta_{158} + \beta_{159}$TB3M + β_{160}IPIYOY + β_{161}CREDIT + β_{162}NEER + β_{163}RISK	**3.08**
B5.6) IGB10YR = $\beta_{164} + \beta_{165}$TB3M + β_{166}TCPIYOY + β_{167}IPIYOY + β_{168}CREDIT + β_{169}NEER + β_{170}RISK	**3.59**

Long-Run Relationships

Variable	**Equation B5.1**	**Equation B5.4**	**Equation B5.5**	**Equation B5.6**
TB3M	0.66***	0.17***	0.66***	0.17***
	(0.15)	(0.05)	(0.15)	(0.05)
TCPIYOY	—	0.07*	—	0.07
		(0.04)		(0.04)
IPIYOY	—	—	−0.05	−0.01
			(0.07)	(0.02)
CREDIT	0.04	−0.09	0.05	−0.10
	(0.04)	(0.06)	(0.05)	(0.06)
NEER	0.04	−0.01	0.06	−0.01
	(0.03)	(0.01)	(0.04)	(0.01)
RISK	2.04*	−0.00	1.72	0.08
	(1.08)	(0.24)	(1.17)	(0.31)
Constant	−4.69	12.88***	−6.74	13.17***
	(4.83)	(4.51)	(6.36)	(4.66)
Time period	Mar 1999–Oct 2015	Dec 2006–Oct 2015	Jun 1999–Oct 2015	Feb 2007–Oct 2015
Number of observations	199	107	197	105

CREDIT = credit to the private sector as percentage of gross domestic product, IGB10YR = 10-year government bond yield, IPIYOY = year-on-year percentage change in industrial production, NEER = nominal effective exchange rate, RISK = global bond market volatility index, TB3M = 3-month government auction rate, TCPIYOY = year-on-year percentage change in consumer price index.

Notes: ***, **, and * represent 1%, 5%, and 10% levels of significance, respectively. Standard errors are in parentheses.

Source: Authors' calculations.

The Effectiveness of Credit Policy: Evidence from the Republic of Korea

JIHO LEE*

In response to the global financial crisis and subsequent Great Recession, central banks embarked on a variety of unconventional measures. Among others, credit policy has been widely employed in many advanced economies. However, credit policy is far less understood than unconventional monetary policy by both policy makers and academic scholars. This paper sheds new light on what credit policy is, how it differs from other central bank policies, and what its risks and limitations might be. In particular, I examine whether credit policy has been effective in stimulating the real economy in the Republic of Korea.

Keywords: credit policy, fiscal aspects of central banking, quantitative easing and credit easing, unconventional monetary policy
JEL codes: E40, E50, E52, E58, E60

I. Introduction

Prior to the 2008–2009 global financial crisis, mainstream macroeconomists seemed to have reached an international consensus regarding the central bank's mandates and monetary policy.[1] The two main features of the consensus were the necessities of central bank independence and flexible inflation targeting. Under this paradigm, a central bank's job description was straightforward: to minimize volatility in inflation and output. For example, according to the popular Taylor (1993) rule, a central bank should set short-term interest rates in response to the deviation of inflation from its desired or target level (inflation gap) and the deviation of output from its potential output level (output gap). Flexible inflation targeting, together with central bank independence, had appeared to achieve price stability and deliver macroeconomic stability in advanced economies and many emerging market economies, at least until the global financial crisis (Eichengreen et al. 2011). The so-called Great Moderation period was viewed as the heyday of central banks.

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[1]See, for example, Goodfriend (2007), Mishkin (2007), and Woodford (2007).

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The global financial crisis and subsequent Great Recession, however, brought unprecedented changes to the world's central bank landscape.[2] In response, many central banks lowered short-term interest rates to effectively zero and increased aggregate bank reserves enormously; the extraordinary times required extraordinary measures. The precrisis consensus view of central banks was also highly criticized as focusing too narrowly on inflation and output gaps.[3]

Today, the proper mandates and roles of central banks are thus more highly contentious topics than ever before among academics and policy makers around the world. Historically, it was not uncommon for crises to change the mandates and functions of central banks (Goodhart 2010, Reis 2013).[4] After the experience of the so-called Great Inflation of the 1970s, which combined with poor real economic performance, many countries assigned a sole mandate of price stability to their independent central banks. At the current juncture, however, criticism of the previous consensus has broadly evolved into two strands.

The first criticism is that central banks seemed to underestimate their ex ante role with respect to financial stability. Where low policy rates are consistent with low inflation, they may still contribute to excess credit growth and the build-up of asset bubbles, and thus sow the seeds of financial imbalance. Prior to the crisis, it was often argued that central banks should not target asset prices or try to prick a bubble. They were only to mop up the mess after a bubble had burst by injecting sufficient liquidity to avoid a financial and macroeconomic meltdown. But one key lesson from the recent crisis is that microprudential policy focusing solely on the health of individual financial institutions is not sufficient for systemwide financial stability. Further, central banks are often requested to adopt macroprudential policy, which addresses risks to the financial system as a whole in pursuit of financial stability (Yellen 2014).[5]

Another important social demand is that central banks should play a more active role in facilitating the flow of credit when financial institutions reduce their lending for the sake of deleveraging following financial market turmoil. I believe that credit policy—by which a central bank directly or indirectly channels credit to private entities and lowers specific interest rates in order to restore the functioning of a particular market—has the potential to serve the aforementioned purpose. The problem is that since credit policy is not a standard policy of central banks it is not

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[2]For postwar recessions in the United States (US), the deep contractions of 1973–1975 and 1980–1982 were each also called the Great Recession (Blinder 2013). This paper uses the term Great Recession to refer to the economic slump observed during the late 2000s.

[3]Larry Summers (2014) rebukes the precrisis consensus view as follows: "What has happened in the last few years suggests the second moment—the volatility of output around its normal level—is second-order relative to the first moment—the average level of output through time."

[4]This is also true for the development of economics. Issing (2012) argues that the development of economics is not driven by either cycles or trends but by severe crises.

[5]As a result, many countries have established committees responsible for mitigating systemic risks such as the Financial Policy Committee in the United Kingdom (UK), the European Systemic Risk Board, and the Financial Stability Oversight Council in the US.

well established. Therefore, a key motivation of this paper is to develop a conceptual framework for credit policy and to shed light on what credit policy is and how it differs from a central bank's other policies.

Then, more importantly, I attempt to investigate whether credit policy has been effective in stimulating the real economy. Unfortunately, there have been so few attempts to examine the effects of credit policy, partly because the available datasets are very limited (Churm et al. 2015).[6] In stark contrast, there is a large amount of literature on the effects of unconventional monetary policy such as quantitative easing (QE).[7] To fill this gap, I choose to use the Korean dataset for credit policy effectiveness because the Bank of Korea (BOK) has a long history of utilizing modern credit policy since March 1994.[8]

Before proceeding further, it would be useful to review a brief history of credit policy in the Republic of Korea (The Bank of Korea 2012). In March 1994, the BOK replaced automatic rediscounts with Aggregate Credit Ceiling Loans as a modern credit policy tool. Under this scheme, the BOK has provided loans to banks at a slightly lower rate than its policy rate within a certain ceiling set by the BOK's Monetary Policy Committee. Since then, the BOK has gradually retreated from credit policy to promote the market mechanism in financial resource allocation.[9]

After the global financial crisis, the need for credit policy reemerged, but for different reasons. In response, the BOK lowered its policy rate steeply from 5.25% in October 2008 to 2% in February 2009, its lowest level since the policy rate target began to be announced in May 1999. Nevertheless, severe uncertainty in financial markets and risk aversion have broken the last segment in monetary policy transmission channels that linked financial conditions and the real economy. In particular, many small and medium-sized enterprises (SMEs), which heavily rely on banks for funding in bankcentric financial systems such as in the Republic of Korea, have been denied access to credit at affordable interest rates.

Another contributing factor to resurrect credit policy is that the effective lower bound for the policy rate could be higher in the Republic of Korea compared to major advanced economies, potentially due to the concerns about sudden capital outflows. Against these backdrops, the BOK has strengthened its credit policy through the Bank Intermediated Lending Support Facility, which replaced the

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[6]A recent study exploring the effectiveness of credit policy failed to find a statistically significant direct effect of the incentive mechanisms in the UK's Funding for Lending Scheme (FLS) for banks to increase their lending to SMEs (Havrylchyk 2016). It pointed out limited data availability as a potential explanation for this failure.

[7]A number of authors have already conducted substantial research on the effectiveness of QE programs. See, for example, Gagnon et al. (2011), Krishnamurthy and Vissing-Jorgensen (2012), and D'Amico and King (2013) for the US; and Joyce et al. (2011) and Joyce and Tong (2012) for the UK.

[8]Indeed, the Bank of Korea Act makes this point clear under Article 1 as follows: "The purpose of this Act shall be to establish the Bank of Korea and to contribute to the sound development of the national economy by pursuing price stability through the formulation and implementation of efficient monetary and credit policies."

[9]When this lending scheme was adopted, the BOK seemed to regard it as a transitional stage in the evolution of the central bank's lending facilities.

existing Aggregate Credit Ceiling Loans. With this new facility, the BOK raised the ceiling and broadened the scope of the previous lending facility.[10]

The rest of the paper is organized as follows. Section II briefly describes recently implemented unconventional monetary policy measures and presents a conceptual framework for credit policy. Section III examines whether credit policy has promoted real economic activity with Korean data. Section IV discusses potential risks for implementing credit policy tools and emphasizes that the bar for the use of credit policy should be higher than for conventional polices. Finally, section V concludes.

II. Conceptual Framework

A. Recently Implemented Unconventional Measures

In response to the 2008–2009 financial crisis and subsequent Great Recession, major central banks embarked upon the use of various unconventional policy tools once their policy rates had nearly reached the zero lower bound. Many of these programs initially attempted to alleviate financial market distress. Thereafter, the purpose of those programs was broadened to stimulate the anemic real economy (Fawley and Neely 2013).

One good example is the United States (US) Federal Reserve's QE program, which involved central bank purchases of securities financed by the creation of bank reserves held at the central bank.[11] The purchases included a substantial amount of long-term securities, such as US Treasury securities and mortgage-backed securities (MBS). Its main goal is to put downward pressure on long-term yields to support economic growth. QE is believed to work through two main channels: the portfolio balance channel and the signaling channel.[12]

Analogously, the Bank of England (BOE) undertook a series of asset purchases, mostly government debt, via an asset purchase facility beginning in

[10]The BOK seems mindful of striking a balance between improved credit flows and possible market distortion caused by credit policy. In 2013, the governor of the BOK stated: "Going forward, we plan to monitor and critically review the performance of the funding program and any associated side effects. Such efforts will guide us to a better design of credit policy that can strike the right balance between improved credit flows to where most needed and possible market inefficiencies that credit policy itself can create." Nevertheless, central banks should do their best to avoid distorting or replacing the market mechanism through excess interventions.

[11]A similar idea was proposed by Milton Friedman (1969) and referred to as helicopter money, which is an expansionary fiscal policy–whether an increase in public spending or a tax cut–financed by a permanent increase in the money stock. Recently, the idea of helicopter money has received great attention, partly because monetary policy alone may be inadequate to spur economic recovery amid very low inflation (Buiter 2014, Gali 2014, Turner 2015, Bernanke 2016). But a key difference between QE and helicopter money is that the former involves a transitory increase of the money stock while the latter involves a permanent increase.

[12]The signaling channel involves asset purchases leading market participants to revise downward their expectations of future short-term interest rates. On the other hand, the portfolio balance channel, affecting term and risk premiums, involves the reinvestment of the proceeds from asset sales into substitutable assets, pushing up asset prices in general (Bean et al. 2015, Bernanke 2017).

March 2009 (Bank of England 2014). In July 2012, the BOE introduced the Funding for Lending Scheme (FLS) to lend long-term, low-interest funds to banks in an effort to boost SMEs.[13] On the other hand, the European Central Bank (ECB) started by extending the range of collateral it accepts for monetary operations, and from 2015 bought €60 billion worth of bonds from banks each month.[14]

In April 2013, the Bank of Japan announced a program of quantitative and qualitative easing that involved a doubling of the monetary base, a lengthening of the expected average maturity of Japanese government bond purchases, and an increase in central bank purchases of risky assets such as stocks. Also in Asia following the global financial crisis, the BOK strengthened its credit policy using the Bank Intermediated Lending Support Facility, which aims to encourage commercial banks to lend more to SMEs. Under this scheme, the BOK offered lower-interest loans to banks in order to compensate for the additional credit risk costs associated with bank loans to SMEs struggling to access credit, even amid ample aggregate liquidity, due to heightened uncertainty in financial markets and risk aversion.

It is clear from the above that even though major central banks have used QE programs, their focuses differ slightly. For instance, the ECB and the Bank of Japan have focused on direct lending to banks–reflecting the bankcentric structure of their financial systems–while the Federal Reserve and the BOE preferred to expand their respective monetary bases by purchasing bonds.

More recently, many central banks have embarked on forward guidance by which central banks signal their willingness to keep monetary policy ultraloose until their economies regain some strength. Both QE and forward guidance aim to directly affect the longer-end of the yield curve. A key difference between them is that QE directly changes long-term interest rates largely through term premia, while forward guidance changes long-term interest rates through future short-term interest rates. By launching forward guidance, central banks sought to counter the upward pressure on market expectations of future rates, enabling them to plan their spending and investment decisions with more confidence.[15]

Given the complex and evolving nature of recent unconventional measures, they cannot be easily understood, at least in a systematic way, if they are simply classified as unconventional policies as a whole. Hence, it may be useful to review these unconventional policy tools to understand what they are and how they

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[13] In April 2013, the BOE made changes to the duration, method, and eligibility criteria of the FLS to encourage banks to lend more to SMEs. In November 2015, the BOE announced a 2-year extension of the FLS.

[14] The ECB carried out two rounds of long-term refinancing operations for European banks in December 2011 and February 2012.

[15] Precisely for this purpose, in early 2013, the ECB and the BOE introduced forward guidance, expressing a commitment to maintain monetary easing, in response to rising concerns regarding the Federal Reserve's QE tapering. However, a critical concern regarding forward guidance is that such guidance could raise uncertainty if the recovery is faster than anticipated.

differ from central banks' conventional instruments (International Monetary Fund 2013).

B. Conceptual Framework for Credit Policy

Goodfriend (2011) has proposed a good starting point in conceptualizing credit policy. He divides central bank operations into monetary policy and credit policy.[16] In his categorization, monetary policy refers to open market operations that expand or contract bank reserves and currency by buying or selling Treasury securities. On the other hand, credit policy shifts the composition of central bank assets, holding their total amount fixed. In other words, credit policy involves lending to particular borrowers or acquiring non-Treasury securities with the proceeds from the sale of Treasuries.[17] Surely, in principle, any monetary policy is a credit policy as credit is the main transmission channel of monetary policy.[18] But there is still a key distinction between the two policies. That is, monetary policy contributes to a broad easing in financial market conditions, but credit policy facilitates funding conditions of specific sectors that have difficulty in accessing credit. In this context, credit policy could be viewed as a debt-financed fiscal policy.[19]

Armed with this overview, this paper proposes to categorize the current policies of central banks into monetary policy, credit policy, and macroprudential policy. In this classification, monetary policy can be further divided into conventional and unconventional monetary policies. While conventional monetary policy can be summarized as adjusting central banks' policy rate at the very short end of the yield curve, unconventional monetary policy can take many different forms, such as large purchases of government bonds and forward guidance.

On the other hand, credit policy intends to ease credit conditions in the economy and affect capital flows or credit allocation in the private sector by making

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[16] Goodfriend (2011) also discusses the interest-on-reserves policy adopted by the Federal Reserve in the midst of the global financial crisis, which pays and adjusts interest on bank reserve balances at the central bank. I do not discuss it here, however, partly because target reserves and required reserves were remunerated by central banks such as the BOE and the ECB even before the crisis. In those cases, that policy is a part of the corridor system within the monetary policy operating framework (Lee 2016).

[17] The fiscal authorities then receive interest on the credit assets instead of interest on the Treasuries held by the central bank.

[18] In practice, however, central banks can employ a mix of monetary and credit policies. Some of the unconventional monetary policy actions recently taken by major central banks had a direct or indirect impact on credit allocation as well as on liquidity volume. Moreover, credit policy can complement an accommodative monetary policy stance. As noted by Bernanke, Gertler, and Gilchrist (1998), a properly working credit market is a critical prerequisite for the transmission of monetary policy. As a consequence, credit policy could not only facilitate the flow of credit in the economy but also help restore the channels of monetary policy transmission.

[19] There is a key distinction between credit policy and fiscal policy, especially in the Republic of Korea. The reason is that credit is allocated by commercial banks' own decision via an incentivized scheme rather than by a government or central bank decision.

changes to the composition of a central bank's assets.[20] In this vein, Richmond Federal Reserve President Jeffrey Lacker also saw the MBS purchases under the third stage of QE, which was introduced in September 2012, as an example of central bank credit policy (Lacker 2012). Therefore, the following actions can be classified as credit policy as they were intended to encourage sector-specific credit allocation: (i) the Federal Reserve's funding support for nonbank financial institutions (e.g., American International Group) and direct purchase of MBS; (ii) FLS and purchases of corporate bonds and commercial bills by the BOE; and (iii) funding support for stronger growth by the Bank of Japan. In the same vein, the Bank of Korea has recently revamped its Bank Intermediated Lending Support Facility in an effort to incentivize commercial banks to lend more funds to highly promising SMEs that have little collateral.

Finally, macroprudential policy aims to moderate the procyclicality of the financial system. Thus, credit policy and macroprudential policies could overlap because both policies often involve some form of credit control or credit allocation aimed at specific sectors (Shin 2015). In spite of these similarities, the two policies apparently differ in their priorities. Macroprudential policy mainly aims to restrict the growth of credit from the perspective of systemic risk management, whereas credit policy pays close attention to credit availability, in either the overall economy or particular sectors, and aims to rectify failures in financial intermediation.

III. Effectiveness of Credit Policy in the Republic of Korea

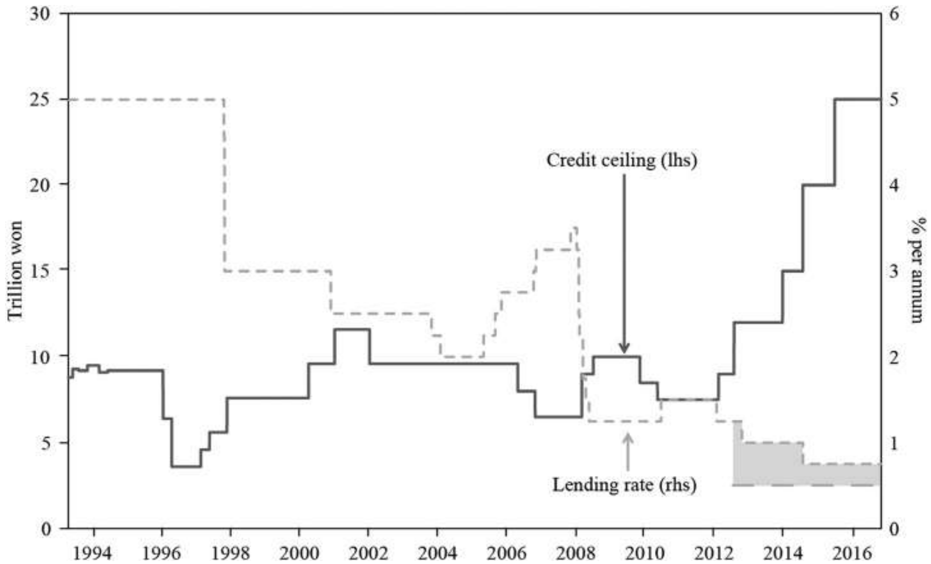
In this section, I evaluate whether credit policy has promoted real economic activity, tackling the question with Korean data. This choice is motivated by the fact that the BOK has a long history of utilizing modern credit policy. One reason for this long tradition is that the Republic of Korea's financial system has maintained a bankcentric structure. Figure 1 shows changes in the amount of the BOK's credit ceiling and its lending rate.

I examine the impact of credit policy on the real economy in two steps in reverse order. Unlike many studies on QE that analyzed its impact on interest rates, corporate bond yields, and exchange rates, I believe that a more important question is whether credit policy has indeed promoted real economic activity.[21] Hence, I first examine which interest rates or spreads are relevant in stimulating the real economy. Then, I check which interest rates or spreads were affected by the BOK's credit policy.

[20]According to Her Majesty's Treasury (2013), credit easing refers to measures aimed at easing credit conditions for businesses that do not have ready access to capital markets by giving them access to cheaper bank loans and nonbank sources of finance.

[21]A few studies have looked at the macroeconomic effect of QE using a vector autoregressive approach (Baumeister and Benati 2012, Weale and Wieladek 2015).

Figure 1. **Changes in the Bank of Korea's Credit Ceiling and Lending Rate**



lhs = left-hand side, rhs = right-hand side.
Source: The Bank of Korea.

A. Which Interest Rate Spreads Are Relevant in Promoting the Real Economy?

The first question to address is which interest rate or interest rate spreads are more important in promoting economic activity. Specifically, are credit spreads more important than term spreads? To answer this question, I modify the existing methodology that uses the slope of the yield curve (term spreads) to predict future real economic activity (Hamilton and Kim 2002; Favero, Kaminska, and Soderstrom 2005; Wright 2006; Rudebusch, Sack, and Swanson 2007).[22]

First, I use monthly data rather than quarterly data because some Korean financial market data are available only from the 2000s. Hence, the data I use span from January 2001 to July 2017. Also, I choose the annual growth of industrial production in the Republic of Korea as a dependent variable. To compute the growth rate, the log of monthly industrial production with no seasonal adjustments is used. Second, I include the real policy rate and two credit spreads as independent variables, as well as one term spread. For example, the real policy rate is defined

[22] For example, Rudebusch, Sack, and Swanson (2007) employ the following forecasting equation:

$$Y_{t+4} - Y_t = \beta_0 + \beta_1(Y_t - Y_{t-4}) + \beta_2(i_t^{(n)} - i_t) + \varepsilon_t$$

where Y_t is the log of real GDP at time t and $i_t^{(n)}$ is the n-quarter interest rate.

as the BOK's Base Rate minus the annual inflation rate. The first credit spread is the interest rate gap between high-quality (AA−) 3-year corporate bonds and 3-year Treasury bonds: that is, $i_t^{AA-} - i_t^{3yr}$, where the latter is the risk-free government bond interest rate. The second one is the interest rate gap between low-quality (BBB−) 3-year corporate bonds and high-quality (AA−) 3-year corporate bonds: that is, $i_t^{BBB-} - i_t^{AA-}$.[23] Finally, the term spread is computed as the difference between the 3-year Treasury bond rate and the 91-day certificate of deposit rate.[24]

As a preliminary step, I verify the stationarity of the variables above using the Augmented Dickey–Fuller test. The test results, reported in Table A1 in the Appendix, show that most variables are stationary. The only exception is the credit spread between low-quality and high-quality 3-year corporate bonds, $i_t^{BBB-} - i_t^{AA-}$, which is found to be $I(0)$.[25] But, conventional unit root tests are often biased to falsely find the existence of a unit root if the series are stationary with a structural break (Perron 1989, Hansen 2001). Therefore, I further implement unit root tests with a breakpoint for $i_t^{BBB-} - i_t^{AA-}$. This is largely motivated by the fact that the sample period contains the 2008–2009 global financial crisis and that the crisis could sharply widen the credit premia. Indeed, Table A2 suggests that $i_t^{BBB-} - i_t^{AA-}$ is stationary with a structural break in October 2008. Here the structural breakpoint is selected to minimize Dickey–Fuller *t*-statistics. Intuitively, this breakpoint seems consistent with the collapse of Lehman Brothers in September 2008. Having said that, I include a dummy variable in the equation for the period September 2008–June 2009 to address concerns about the potential structural break around the global financial crisis.

Now, I estimate a forecasting equation for real economic activity as follows:

$$Y_{t+12} - Y_t = \alpha + \beta_1 RBR_t + \beta_2\left(i_t^{3yr} - i_t^{91d}\right) + \beta_3\left(i_t^{AA-} - i_t^{3yr}\right) + \beta_4\left(i_t^{BBB-} - i_t^{AA-}\right) + Dum_{0809} + \varepsilon_t \qquad (1)$$

where Y is the log of monthly industrial production; RBR is the real policy rate and is calculated as $i_t^{BR} - 100(\log p_t - \log p_{t-12})$, where p is the consumer price index and i_t^{BR} is the BOK's Base Rate; $i_t^{3yr} - i_t^{91d}$ is the term spread; and $i_t^{AA-} - i_t^{3yr}$ and $i_t^{BBB-} - i_t^{AA-}$ are credit spreads. Finally, Dum_{0809} is a dummy variable with a value of 1 for the period September 2008–June 2009.

[23]Corporate credit spreads are assumed to reflect compensation for expected default; compensation for the uncertainty about the probability of default; and differences between government and corporate bonds in terms of liquidity, regulation, and tax (Churm and Panigirtzoglou 2005).

[24]Since there is no short-term Treasury bill rate available in the Republic of Korea, in practice the 91-day certificate of deposit rate has been widely used as a proxy for it.

[25]In addition, Kwiatkowski–Phillips–Schmidt–Shin test results, which are not reported here, reinforced this finding (Kwiatkowski et al. 1992). It is well established in the literature that many interest rates are often found to be nonstationary (Campbell and Clarida 1987, Newbold et al. 2001), partly because those time series are not immune to structural breaks.

Table 1. **Forecasting Equations for Industrial Production Growth**

Dependent Variable: $Y_{t+12} - Y_t$	RBR_t	$i_t^{3yr} - i_t^{91d}$	$i_t^{BBB-} - i_t^{3yr}$	$i_t^{AA-} - i_t^{3yr}$	$i_t^{BBB-} - i_t^{AA-}$	**J-statistics**
(1)	−0.07	1.13**		−0.55	−0.55**	12.65
	(0.35)	(0.46)		(1.04)	(0.24)	[0.12]
(2)	−0.07	1.30**	−0.58**			11.36
	(0.31)	(0.48)	(0.24)			[0.13]

Y = monthly industrial production, RBR_t = Bank of Korea's real Base Rate, i_t^{3yr} = 3-year Treasury bond rate, i_t^{91d} = 91-day certificate of deposit rate, i_t^{AA-} = high-quality (AA−) 3-year corporate bond rate, i_t^{BBB-} = low-quality (BBB−) 3-year corporate bond rate.
Note: Coefficient estimates are shown with their standard errors in parentheses. Significant coefficients at the 10%, 5%, and 1% levels are superscripted with *, **, and ***, respectively. Each regression includes a constant and a dummy variable (2008:9 to 2009:6) that are not reported. P-values of J-statistics are reported in square brackets.
Source: Author's calculations.

In the above equation, if industrial production growth is a determinant of any of the right-hand-side variables in the model, an ordinary least squares regression that does not take into account this endogeneity problem will yield biased and inconsistent parameter estimates. To address this concern, I estimate the above model using a single equation generalized method of moments estimator. In particular, I use the lagged values of regressors and a set of US financial variables as instruments.[26] An important caveat here is that equation (1) is only a reduced-form relationship that has no economic structure. However, this is the common approach in the literature to investigate whether the term spreads and the credit spreads have significant predictive power for future real economic activity.

Table 1 presents the empirical results in two different specifications. The null hypothesis that all the instruments are exogenous cannot be rejected based on the J-test results for overidentifying restrictions in Table 1. Furthermore, Cragg–Donald F-statistics of 16.55 in the first-row setting and 46.72 in the second, which exceed the rule-of-thumb criterion 10, suggest that the instruments are relevant (Cragg and Donald 1993). Next, I focus on four β's: (i) real policy rate, (ii) term spread, (iii) high-quality corporate spread, and (iv) low-quality corporate spread. In particular, the term spread captures the slope of the term structure, reflecting both expectations of the path of future short rates and the pure term premium, while the two credit spread terms in equation (1) capture risk factors.

Note first that all coefficients on the real Base Rate in rows 1 and 2 are of the expected negative sign but not statistically significant. Second, the coefficients on the term spread in both settings are positive and significantly different from zero. That is, an increase in the term spread forecasts higher future industrial production.

[26] I include three financial variables retrieved from the Federal Reserve Economic Data of the Federal Reserve Bank of St. Louis. The first variable is the US term spread, which is calculated as the spread between the 10-Year Treasury Constant Maturity and 3-Month Treasury Constant Maturity. The second is the US credit spread, computed as the spread between Moody's Seasoned Baa Corporate Bond and the 10-Year Treasury Constant Maturity. The third is the US real federal funds rate.

Table 2. **Vector Autoregressive Estimates, January 2001–July 2017**

	ΔY_t	RBR_t	$i_t^{3yr} - i_t^{91d}$	$i_t^{BBB-} - i_t^{3yr}$
ΔY_{t-1}	0.20^{***}	−0.01	−0.001	0.01
	(0.07)	(0.01)	(0.01)	(0.01)
RBR_{t-1}	0.01	0.90^{***}	0.02	−0.02
	(0.22)	(0.04)	(0.02)	(0.02)
$i_{t-1}^{3yr} - i_{t-1}^{91d}$	2.53^{***}	0.07	0.92^{***}	-0.14^{***}
	(0.37)	(0.06)	(0.03)	(0.03)
$i_{t-1}^{BBB-} - i_{t-1}^{3yr}$	-0.62^{***}	-0.05^{*}	0.03^{**}	0.98^{***}
	(0.17)	(0.03)	(0.01)	(0.01)
$\bar{R}^2$	0.49	0.86	0.87	0.98

ΔY_t = growth of monthly industrial production compared with the same month of previous year, RBR_t = Bank of Korea's real Base Rate, i_t^{3yr} = 3-year Treasury bond rate, i_t^{91d} = 91-day certificate of deposit rate, i_t^{BBB-} = low-quality (BBB−) 3-year corporate bond rate.
Notes: The values in parentheses denote standard errors. Significant coefficients at the 10%, 5%, and 1% levels are superscripted with *, **, and ***, respectively. A constant and a dummy variable are included in the VAR estimation.
Source: Author's calculations.

The finding that a rise in the long-term rate relative to the short-term rate predicts higher future real activity is consistent with the existing empirical evidence in Rudebusch, Sack, and Swanson (2007), and Walsh (2014). Most interestingly, in row 2, the coefficient on the credit spread ($i_t^{BBB-} - i_t^{3yr}$) is of the expected negative sign and statistically significant. In particular, as displayed in row 1, most of these effects appear to come from the credit spread between low-quality (BBB−) 3-year corporate bonds and high-quality (AA−) 3-year corporate bonds: ($i_t^{BBB-} - i_t^{AA-}$). On the other hand, the coefficient on the credit spread between high-quality 3-year corporate bonds and 3-year Treasury bonds ($i_t^{AA-} - i_t^{3yr}$) is negative but not statistically significant in row 1.

The results in Table 1 suggest that central bank policy makers should focus on reducing the credit spreads, particularly between high-grade corporate bonds and low-grade corporate bonds. The reason is that a rise in the term spread may just reflect the expectation of stronger economic growth in the future. Importantly, this finding implies that QE, mainly working through the term premium channel, might have little effect on the real economy.

To explore further the effects of interest rate spreads on real economic activity, I estimate a vector autoregressive (VAR) model with the growth of industrial production, the real Base Rate, and term and credit spreads. Table 2 reports the results of the VAR estimation.[27]

[27]Both a constant and a dummy variable are included in the VAR estimation. We also estimated a VAR model with two credit spreads separately $i_t^{AA-} - i_t^{3yr}$ and $i_t^{BBB-} - i_t^{AA-}$, rather than an aggregate credit spread ($i_t^{BBB-} - i_t^{3yr}$) with similar results.

Table 3. **F-Statistics of Granger Causality Tests, November 2000–July 2017**

	Lag					
	1	**2**	**3**	**4**	**5**	**6**
Credit Ceiling ⇒ Real Base Rate[a]	0.58	0.38	0.31	0.21	0.56	0.73
Real Base Rate[a] ⇒ Credit Ceiling	0.05	0.54	1.33	0.98	0.92	0.76
Credit Ceiling ⇒ Term Spread[b]	0.40	0.60	1.33	1.76	1.39	1.14
Term Spread[b] ⇒ Credit Ceiling	6.18**	3.59**	2.43*	1.81	1.89	1.58
Credit Ceiling ⇒ Credit Spread[c]	2.02	1.68	1.75	0.95	0.76	0.62
Credit Spread[c] ⇒ Credit Ceilings	1.14	2.30	1.69	1.26	1.03	0.86
Credit Ceiling ⇒ Credit Spread[d]	0.01	3.32**	2.19*	1.68	0.58	0.64
Credit Spread[d] ⇒ Credit Ceiling	1.15	1.26	0.99	0.64	0.57	0.57

[a] $RBR = i_t^{BR} - 100(\log p_t / \log p_{t-12})$ where p is the consumer price index
[b] $i_t^{3yr} - i_t^{91d}$
[c] $i_t^{AA-} - i_t^{3yr}$
[d] $i_t^{BBB-} - i_t^{AA-}$
i_t^{BR} = Bank of Korea's Base Rate, i_t^{3yr} = 3-year Treasury bond rate, i_t^{91d} = 91-day certificate of deposit rate, i_t^{AA-} = high-quality (AA−) 3-year corporate bond rate, i_t^{BBB-} = low-quality (BBB−) 3-year corporate bond rate.
Note: The symbols *, **, *** in the superscript denote significance at the 10%, 5%, and 1% levels, respectively.
Source: Author's calculations.

The risk-free term spread again has a positive sign and is statistically significant. Similar to the result in Table 1, the risk spread captured by the difference between the BBB–rate and the 3-year Treasury rate is of a negative sign and statistically significant. Therefore, this corroborates the previous finding that credit policy would be effective only if it is capable of lowering credit spreads.[28]

B. Which Interest Rate Spreads Were Affected by the Bank of Korea's Credit Policy?

The evidence in the previous section suggests that, to be effective, the BOK's credit policy needs to tighten the credit spreads. Narrowing in the term spread seems to just reflect the rising expectation of future economic activity. This brings us back to the first question posed earlier: which interest rate spreads have been affected by the BOK's credit policy?

To answer the question, I carry out Granger causality tests.[29] Table 3 reports the F-statistics of the tests between the BOK's credit ceiling—as a measure of credit policy—and the real Base Rate, term spreads, and credit spreads. In the table, I

[28] In the preliminary analysis, which is not reported here, I also examined whether credit policy could increase retail sales–proxy for household consumption. I found little evidence that retail sales are meaningfully affected either by credit spreads or credit policy. Potentially, this finding implies that credit policy is more effective in boosting business activities than household consumption, given that there is escalating global concern about subdued wage growth and worsening inequality recently.

[29] For X and Y, when Y can be better explained on the basis of past X's and past Y's than on the basis of past Y's alone, a causal relationship exists from X to Y according to Granger (1969).

present test results with various lags because previous studies claimed that results of Granger tests can be sensitive to the lag length structure (Hamilton 1994). The sample period runs from November 2000 to July 2017 because of the credit spread of ($i_t^{BBB-} - i_t^{AA-}$), where i_t^{BBB-} is available only from November 2000.

The Granger causality tests support the notion that a change in the BOK's credit ceiling affects the credit spread of $i_t^{BBB-} - i_t^{AA-}$. On the other hand, there is little evidence that the credit spread of $i_t^{BBB-} - i_t^{AA-}$ affects the amount of the credit ceiling. Together with the previous finding that the credit spread rather than the term spread is important in stimulating real economic activity, the current finding is encouraging. These two findings jointly imply that the BOK's credit policy has been effective in promoting the real economy.

More importantly, the BOK's credit policy does not seem to affect or be affected by the real Base Rate. Moreover, there is little evidence that the BOK's credit policy may affect the credit spread of $i_t^{AA-} - i_t^{TB3}$. These results are consistent with the objective of the BOK's credit policy, which is in fact targeted at the improvement of funding conditions for SMEs with relatively lower credit ratings.

However, there are at least a few caveats to this approach. First, Granger causality is not necessarily true causality if two variables of interest are driven by a common third process. In this case, one might still fail to reject the alternative hypothesis of Granger causality. Second, this exercise cannot provide any estimate of the quantitative impacts scaled by the size of the credit policy. Instead, it simply assesses the statistical significance of the effects.

IV. Potential Risks

Unconventional monetary policy like QE is often claimed to pose critical risks to the economy, partly because it takes a central bank close to the political arena (Stein 2012). Similarly, several policy makers and economists have identified the potential risks for implementing credit policy tools.

The first and most severe concern is that credit policy invades the territory of the fiscal authorities and puts central bank independence in jeopardy, which could undermine the credibility and effectiveness of the central bank in its conventional role (Goodfriend 2011). For this reason, Rajan (2013, p. 10) warns that expansive credit policy, pursued in an attempt to revamp economic activity, can be "a step into the dark." But perceptions of timidity and caution in central banking also have the potential to threaten the independence of central banks. Moreover, most central bank policies have fiscal aspects and implications, and it appears a reasonable idea for a central bank to implement credit policy in close cooperation with the Treasury and to strengthen its accountability to Congress or Parliament.[30]

[30]The Federal Reserve and the US Department of the Treasury issued a statement in March 2009 on the delineation of responsibilities between the two institutions. While the statement indicated that "decisions to influence

Second, the central bank may face strong political pressure and criticism from the public.[31] Central banks could be criticized for subsidizing bank lending, which is the inherent role of banks. Furthermore, credit policy could escalate financial stability concerns because it incentivizes risk-taking among banks and thus could weaken their asset qualities, even if this were exactly what the central bank aimed at achieving. An even bigger challenge is that an exit from credit policy could be more difficult than that from QE because it involves specific beneficiaries such as SMEs.

As a consequence, the bar for the use of nonconventional policies should be higher than for conventional policies. This is in part because the effects of those policies on economic activity and inflation are uncertain and their potential costs are well beyond those associated with standard policies (Bernanke 2012). Hence, the former president of the ECB, Jean-Claude Trichet, argues that four conditions should be met for implementing unconventional measures. They must first be independent from the standard measures; second, they must be targeted at helping restore a more normal functioning of monetary and financial markets with a limited amount of interventions; third, they must be transitory by nature; and fourth, they must not be intended to fine-tune the transmission mechanism of conventional monetary policy (Trichet 2013). Of course it is easy to state this as a principle but harder to know how to implement it in practice. Therefore, a careful cost–benefit analysis is really required to assess the net impact on social welfare.

V. Conclusion

After presenting a conceptual framework for credit policy along with other related policies, this paper highlighted that the Bank of Korea's credit policy indeed has been effective in stimulating real economic activity. I find evidence that the risk premium rather than the term premium is relevant to promoting the real economy, and that the implementation of the BOK's credit policy affects the risk premium. Therefore, credit policy can be more effective than QE, which mainly aims at reducing the term premium, particularly when the economy suffers from a rising credit risk premium due to a credit crunch.

Until the early 2000s, credit policy played a relatively minor role in advanced economies. Now, however, there is growing recognition that the conventional approach to central banking needs to be fundamentally rethought. Using interest

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the allocation of credit are the province of the fiscal authorities," and pledged the Treasury's help in removing the Maiden Lane assets from the Federal Reserve's balance sheet, it largely reaffirmed the Federal Reserve's continued long-term use of its emergency lending powers. See, US Department of the Treasury and US Federal Reserve. 2009. "The Role of the Federal Reserve in Preserving Financial and Monetary Stability: Joint Statement by the Treasury and the Federal Reserve." 23 March. http://federalreserve.gov/newsevents/press/monetary/20090323b.htm.

[31] More often than not, the fiscal authorities favor expansive credit policy ex ante, but they preserve the option to criticize central bank actions ex post (Goodfriend 2012). In the same vein, central banks may often choose to lend rather than risk a potential panic by not lending, even though they lend at very low interest rates with poor collateral.

rates as the main monetary policy tool was initially considered a radical step for central banks to stabilize inflation and the macroeconomy. But, with the benefit of hindsight, it has proven to be effective.

In summary, credit policy represents a useful addition to central banks' toolkit. After all, central banks cannot plead ignorance as justification for doing nothing. At the same time, since we do not yet have a full understanding of this mechanism, deeper research is needed to ascertain its longer-term benefits and unintended consequences.

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Appendix: Tests for Unit Root

Table A1 presents the Augmented Dickey–Fuller test results for the presence of a unit root in ΔY_t, RBR_t, $i_t^{3yr} - i_t^{91d}$, $i_t^{AA-} - i_t^{3yr}$, and $i_t^{BBB-} - i_t^{AA-}$. The results strongly support the assumption of the nonexistence of a unit root in ΔY_t, RBR_t, $i_t^{3yr} - i_t^{91d}$, and $i_t^{AA-} - i_t^{3yr}$. The only exception is $i_t^{BBB-} - i_t^{AA-}$, which is found to be $I(1)$ because its difference is stationary.

But, conventional unit root tests are often biased to falsely find the existence of a unit root if the series are stationary with a structural break (Perron 1989, Hansen 2001). Therefore, I further implement unit root tests with a breakpoint for $i_t^{BBB-} - i_t^{AA-}$. This is largely motivated by the fact that the sample period contains the 2008–2009 global financial crisis and that the crisis could sharply widen the credit premia. Table A2 presents the Augmented Dickey–Fuller test results for the presence of a unit root with a structural break in $i_t^{BBB-} - i_t^{AA-}$. It suggests that the credit premia are stationary with a structural break in October 2008. Here, the structural break point is selected to minimize Dickey–Fuller t-statistics. Intuitively, this break point seems consistent with the collapse of Lehman Brothers in September 2008.

Table A1. **Augmented Dickey–Fuller Tests for the Presence of a Unit Root**

	Lag Length			
	1	**2**	**3**	**4**
ΔY_t	−4.24	−3.17	−3.38	−3.45
RBR_t	−3.07	−2.74	−2.92	−3.22
$i_t^{3yr} - i_t^{91d}$	−3.68	−3.80	−3.33	−2.92
$i_t^{AA-} - i_t^{3yr}$	−4.32	−4.39	−2.96	−2.97
$i_t^{BBB-} - i_t^{AA-}$	−1.31	−1.48	−1.52	−1.25
<Critical Values>				
1%	−3.46			
5%	−2.88			
10%	−2.57			

ΔY_t = growth of monthly industrial production compared with the same month of previous year, i_t^{3yr} = 3-year Treasury bond rate, i_t^{91d} = 91-day certificate of deposit rate, i_t^{AA-} = high-quality (AA−) 3-year corporate bond rate, i_t^{BBB-} = low-quality (BBB−) 3-year corporate bond rate, RBR_t = Bank of Korea's real Base Rate.
Notes: Figures are t-statistics when the estimated model includes a constant. Critical values are from MacKinnon (1996).
Source: Author's calculations.

Table A2. **Augmented Dickey–Fuller Tests for the Presence of a Unit Root with a Structural Break**

	Lag Length			
	1	**2**	**3**	**4**
$i_t^{BBB-} - i_t^{AA-}$	−6.85	−5.35	−5.12	−4.89
<Critical Values>				
1%	−4.95			
5%	−4.44			
10%	−4.19			

i_t^{AA-} = high-quality (AA−) 3-year corporate bond rate, i_t^{BBB-} = low-quality (BBB−) 3-year corporate bond rate.

Notes: Figures are *t*-statistics when the estimated model includes a constant and a structural break in October 2008. The break date is selected to minimize Dickey–Fuller *t*-statistics. Critical values are from Perron (1989).

Source: Author’s calculations.

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