Export Destinations and Skill Premium: Evidence from Chinese Manufacturing Industries

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Abstract

This paper examines the relationship between average income of export destinations and skill premium in a developing country, using Chinese manufacturing industry-level data from 1995 to 2008. To do so, we construct weighted average GDP per capita across destinations employing within-industry export share to each destination as the weight, and then link it with industry-level wages and skill premium. Empirical evidence shows a positive correlation between average destination income and average wages, which is consistent with existing literature. More importantly, we find that industries that export more to high-income destinations tend to pay a higher skill premium, suggesting that skilled workers benefit more from high-income exports than unskilled workers on average. IV estimates confirm causality and the positive relationship identified is robust to the inclusion of additional control variables. However, the positive relationship only applies to ordinary export whereas processing export reveals that exporting to high-income destinations induces a reduction in skill premium. This is consistent with the fact that processing production generally involves simple assembly and primarily requires low-skilled workers. Our results also reveal a stronger effect during the post-WTO accession period when China integrated into world economy rapidly. Our paper contributes to the understanding of the role of export destinations in the uneven distribution effects of globalisation for workers with different skill levels in developing countries.

Key Words: Export destinations; Skill premium; Manufacturing industries; China
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1 Introduction

Wage effects of trade openness have been widely documented in the trade literature. The traditional Stolper-Samuelson theorem predicts that relative returns to unskilled labour rise and hence the skill premium declines in labour-abundant developing countries with increasing trade openness. However, empirical evidence provides little support for this prediction. Although trade liberalisation that occurred in developing countries led them to be more integrated into the world economy, the skill premium has increased simultaneously (see Goldberg and Pavcnik, 2007 for a survey). Recent studies have emphasised the role of export destinations, particularly high-income destinations, in affecting the rising demand for skilled workers and in shaping wage inequality between skilled and unskilled workers (e.g. Brambilla et al., 2012 and Brambilla and Porto, 2016). This is because exporting to rich destinations is often associated with the production of high-quality products, with specialised exporting services or technology upgrading that is complimentary with skills (Matsuyama, 2007; Verhoogen, 2008). While existing papers primarily focus on outcome variables like skill utilisation and average wages, relatively few have studied the differential wage effects for workers with different skill levels.[1]

The main purpose of this paper is to investigate the relationship between export destinations and skill premium using Chinese manufacturing industry data from 1995 to 2008. In particular, provided that existing papers like Brambilla and Porto (2016) present a positive association between income level of export destinations and average wages, we are more interested in whether the composition of export destinations differently affects wages of workers with different skills. China provides a compelling case to exploit this issue. First, as a representative middle-income developing country, China has observed a substantial increases in the wage gap between skilled and unskilled workers (Sheng and Yang, 2016), which has been witnessed in quite a few other developing countries (Goldberg and Pavcnik, 2007). Second, during our sample period, China has integrated further into the world economy, especially after 2001 when China joined the WTO. The share of China's export in world total exports almost tripled from only 3.18% in 1995 to

[1]An exception is Pellandra (2015) who explicitly distinguishes wages for skilled from unskilled workers when investigating the wages effects of exporting to high-income destinations using Chilean firm-level data.

9.15% in 2008, and the total value of manufacturing exports grew from 136.80 billion USD in 1995 to 1.40 trillion in 2008 (see Fig. A.1 and Fig. A.2). In particular, manufacturing exports to high-income destinations increased drastically from 111.67 billion USD to 947.00 billion during this period.

In theory, export destination and skill premium can be linked through two channels. The most plausible one is perhaps quality upgrading: given that consumers in rich countries have a greater demand for high-quality goods, firms that export to these markets have to upgrade the quality of their products. Quality upgrading requires more skilled workers and firms need to pay higher wages to skilled workers to sustain quality production, which in turn induces an increase in the skill premium (Verhoogen, 2008). This idea relies on a crucial assumption, namely that consumers have non-homothetic preferences in the exporting market, and on the supply side that there is complementarity of the production of quality products and skills. Brambilla et al. (2012) examines this idea using Argentinean manufacturing firms' data and find that exporters to high-income destinations hire more skilled workers than other exporters and non-exporters. This paper is perhaps most closely related to Brambilla and Porto (2016) who exploit the effects of export destination on average wages. Based on country-industry-level data, they find that industries exporting to rich countries tend to pay higher average wages. In addition, they find evidence that supports the quality upgrading mechanism. That is, the quality of products is higher for industries that ship products to high-income destinations, and the production of high-quality goods are related to higher average wages. Relative to their work, this paper differs in that we distinguish differential wage effects for skilled and unskilled workers. This is important for developing countries like China with high income inequality since even if exporting to high-income countries tends to raise average wages, it is likely that workers with different skill levels are affected unevenly.

An alternative channel is export-induced technology change. The intuition is that with the presence of fixed technology investment costs, increased revenue from exports may motivate firms to invest more on skill-intensive technologies (Yeaple, 2005; Bustos, 2011a,b). Notice that this mechanism does not depend on the characteristics of export destinations. However, if exporting to high-income destinations is more profitable, firms or industries that export more to those markets are expected to hire more skilled workers and to observe an increase in the skill premium.

Based on these theories, the current paper aims to identify a causal link between export destination and skill premium. To this end, we calculate the weighted average GDP per capita across export destinations using the share of export to each destination as the weight for each industry following Brambilla and Porto (2016), and then examine whether industries that export more to high-income destinations witness a higher skill premium. However, one challenge is that data on wages for workers with different skill levels are rarely available at the industry level for China. This paper relies on the World Input-Output database (WIOD) which primarily provides input-output tables for a sample of countries but also reports industry-level data on employment, labour compensation and working hour shares for different skill levels, and China is fortunately among the sample countries. Although this database does not directly provide data on the skill premium, it is possible to reckon these data based on labour compensation and working hour shares. The second challenge is that our main explanatory variable might be endogeneous if there are unobservable factors that affect within-industry export structure to each destination and skill premium simultaneously. Our strategy is to use predicted export share based on bilateral exchange rates to calculate the weighted average destination income, which serves as an instrument for the actual average income across destinations (Park et al., 2010; Brambilla and Porto, 2016; Bastos et al., 2016).

We find a positive correlation between average destination income and average wages, which is consistent with the findings in Brambilla and Porto (2016). By distinguishing wages for skilled and unskilled workers, we find that exporting to high-income destinations is positively correlated with wages for both types of workers but the correlation is stronger for skilled than for unskilled workers, which implies a positive link with skill premium. Using predicted export share weighted average GDP per capita across destinations as the instrument, our IV estimation identifies a causal positive relationship between average destination income and the skill premium. This suggests that shipping more products to high-income destinations induces an increase in the wage disparity between skilled and unskilled workers within industries. Our results are robust to the inclusion of various important control variables like the relative supply of skilled workers and import share weighted average source country income. Considering the important role of processing trade in China (Koopman et al., 2012; Dai et al., 2016), we disaggregate total exports into ordinary and processing exports, and calculate the weighted average GDP per capita across destinations using ordinary and processing exports share as the weight separately. The empirical results find a positive association between average destination income and the skill premium only for the case of ordinary exports. In contrast, industries with an increase in processing exports to high-income destinations tend to be associated with a reduction in the skill premium. This is not surprising given that processing production is involved with simple assembly of imported parts into final goods and mainly requires low-skilled workers (Upward et al., 2013). This finding is crucial for developing countries like China that are deeply integrated into global value chains in the sense that industrial policies affecting the balance of ordinary and processing exports will affect the relative wages of skilled and unskilled workers.

The remainder of this paper is organised as follows. In the next section, we briefly present potential mechanisms that link export destination and the skill premium and relevant empirical evidence. Section 3 shows our empirical strategy. Section 4 describes data sources and the construction of our main variables, skill premium and export weighted average GDP per capita across destinations. In Section 5 we report the main regression results as well as some robustness checks and Section 6 concludes.

2 Theoretical Mechanism and Empirical Evidence

The relationship between export destination and the skill premium in developing countries has received a great deal of attention in recent years. One important channel through which variations in export destinations may affect the skill premium is quality upgrading. The basic idea is that firms export higher-quality products to richer markets than they sell in domestic and poorer markets, whereas production of those high-quality products requires skilled workers and therefore is associated with increasing payments for skilled relative to unskilled workers. Verhoogen (2008) is among the first that documents the quality upgrading mechanism. His model is built on three crucial assumptions. First, as in Melitz

(2003) model, firms are heterogenous in productivity and only the most productive firms are able to export due to the presence of fixed costs to enter foreign markets. Second, products are differentiated in quality and consumer's preferences are non-homothetic, such that consumers with higher income value product quality more than those with lower incomes. Third, in the production side, producing high-quality goods requires skilled workers, and firms need to pay high enough wages to those workers to motivate effort. On the top of these assumptions, exchange rate devaluation induces the most productive firms to increase exports, upgrade quality, raise employment of high-skilled workers and pay higher wages compared to less productive firms, which widens the wage gap between skilled and unskilled workers within industries. Based on Mexican manufacturing firm-level data, Verhoogen (2008) investigates differences in exports, quality of goods and wages of white-collar workers versus blue-collar workers for firms that are heterogenous in initial productivity when facing 1994 peso crisis, with empirical findings that are consistent with the theoretical predictions.

Brambilla et al. (2012) directly relate variation in export destination with utilisation of skills. They incorporate the quality upgrading mechanism proposed by Verhoogen (2008) into their model and argue that consumers in high-income countries value the quality of products more than those in low-income countries. As such, to satisfy consumer demand in high-income markets, firms that target those markets must upgrade their product quality and employ more high-skilled workers, which makes exporting to high-income destinations *per se* more skill-intensive. An alternative mechanism that they consider is the "required services" channel. It means that reaching consumers in foreign markets requires additional services compared to selling in the domestic market, such as marketing research and communicating with foreign clients, which induces greater use of skilled workers who are specialised in international business, foreign languages, etc, as in Matsuyama (2007). These required services differ by export destination, since countries are differentiated in geographic location, culture, business models, and so on. To test these two mechanisms, Brambilla et al. (2012) employ firm and customs data for Argentinean manufacturing firms and explores the impact of exogenous shocks arising from devaluation in Brazil in 1999. They find that exporters to high-income destinations hire more skilled workers and pay higher average wages than other exporters and domestic firms. They also find strong evidence that supports both the quality upgrading and required service mechanisms. While the data used in Brambilla et al. (2012) only allow to observe average wages, Pellandra (2015) explores the effects of exporting to high-income destinations on wages for skilled and unskilled workers separately using Chilean firm-level data combined with customs records. The empirical results show that firms that export to at least one high-income country experience a significant increase in both employment and wages for skilled workers from the year they export whereas the impact on unskilled workers is insignificant.

A recent paper that links export destination and wages with an emphasis of the quality upgrading mechanism at the industry level is Brambilla and Porto (2016), to which this paper is mostly related. They express the quality channel as a combination of quality valuation (demand side) and quality provision (supply side) mechanisms. Similar to the idea in Verhoogen (2008) and Brambilla et al. (2012), the former argues that consumers in richer countries have greater demand for higher-quality goods and the latter suggests that the provision of high-quality goods requires more intensive use of skilled workers and consequently induces higher average wages at the industry level. As such, industries that export more to high-income destinations are expected to have higher quality exports on average and to pay higher average wages. Based on manufacturing industry data of 82 countries, they empirically examine the relationship between exporting to high-income destinations and average industrial wages and find a positive causal link. They also find strong evidence that supports the quality valuation and quality provision mechanisms. However, the positive association between high-income exports and average industrial wages is built on the assumption that average wages increase following the rise in wages of skilled workers, with the wages for unskilled workers remaining constant. While their data do not allow wages for workers with different skill levels to be observed, their paper implicitly examines the differential effects on wages for skilled and unskilled workers and on skill premium. The present research will explicitly examine the differential wage effects by skill and the effects on the skill premium.

A number of other papers also document the quality valuation and quality provision mechanisms. On the demand side, using data on bilateral industry-level trade flows between 60 countries, Hallak (2006) identifies a positive relationship between income per capita and demand for quality. On the supply side, based on Portuguese firm-level data, Bastos and Silva (2010) find that unit value tends to be higher for goods that are shipped to high-income destinations. Similar findings are found in Manova and Zhang (2012) who focus on Chinese manufacturing firms. However, unit values, commonly used as a measure of quality, not only reflect product quality but also reflect mark-ups. Input quality may be relatively unaffected by mark-ups. Bastos et al. (2016) re-visit the income-based quality choice using detailed Portuguese firm-product-level data by focusing on the quality of inputs. Empirical results reveal a significant and positive association between average destination income and input prices, indicating that firms export higher-quality products to rich countries and in doing so require high-quality inputs. Using firms' innovation activities as proxies for quality, Crinò and Epifani (2012) uncover a strong negative correlation between R&D intensity and the share of exports to low-income destinations using Italian manufacturing firm-level data, which is consistent with the hypothesis that export quality is positively correlated with destination income.

A second channel that may link export destination and the skill premium is export-induced technology upgrading. The intuition is that in the presence of fixed technology adoption costs, increases in exports reduce such fixed costs per unit and make it more profitable, which stimulates firms to invest more on technology and skill upgrading and hence results in a widening of the skill premium. In a general equilibrium model, Yeaple (2005) assumes that firms can choose technologies and workers with various skill levels. A reduction in trade costs increases firms' incentives to expand exports, adopt new technologies that favour high-skilled workers, and pay higher wages to skilled workers. Building on Yeaple's model, Bustos (2011b) argues that increases in revenue from rising exports induce firms to upgrade technology. In a related paper, Bustos (2011a) argues that a reduction in trade partners' tariff rates encourages the most productive firms to shift their production technology so as to be more skill-intensive. As a result, trade-induced reallocation of market share towards more productive firms induces an increase in the relative demand for skilled workers and in the skill premium. For Argentinean manufacturing firms, Bustos (2011a) finds that the reduction in Brazil's tariffs led the most productive firms to upgrade skills but other firms to downgrade. Notice that this channel emphasises the importance of export *per se* other than variation in exporting destination. If exporting to richer countries is more profitable due to the fact that firms charge higher prices in those markets as in

Manova and Zhang (2012), income of export destination matters. In other words, firms that export to high-income destinations invest more on skill-intensive technologies and increase the demand for skilled labour and the skill premium.

Empirical evidence that supports the association between export destination and the skill premium is also provided by a few other empirical papers. Milner and Tandrayen-Ragoobur (2007) explore potential differences in the wage effects of exporting status for firms that export to African market and for those exporting to other markets using Sub-Saharan African employer-employee matched dataset. They find that exporting to African markets is associated with a positive wage premium whereas exporting to outside African markets generates a negative wage premium. They attribute such differences to the differential degree in competitiveness in those two sorts of markets. Specifically, African markets are relatively more protected and less competitive than other markets. As a result, exporters to outside African markets are found with greater pressure to reduce production costs due to greater competition in the local market. Using matched employer-employee dataset of South Africa, Rankin and Schöer (2013) examine the relationship between export destination and average wages for workers with different skill levels. In particular, they compare firms that export to Southern African Development Community (SADC) countries that are poorer than South Africa and those exporting to European Union (EU) and North American Free Trade Agreement (NAFTA) countries that are richer than South Africa. Empirical results show that SADC exporters pay relatively lower average wages and skill premium, whereas firms exporting to EU and NAFTA destinations pay higher average wages and a higher skill premium than non-exporters on average, which is consistent with the findings in Verhoogen (2008) and Brambilla et al. (2012).

3 Empirical Strategy

Econometric Specification

The main objective of this paper is to identify the effects of export destination on skill premia at the industry level. To this end, we first present the main methodology used to empirically examine the correlation between export destination and skill premium, and then discuss potential identification issues.

Consider the following specification:

$$sp_{it} = \alpha + \beta wagdppc_{it} + \mathbf{x}_{it}^{'}\gamma + \theta_t + \theta_i + \epsilon_{it} \tag{1}$$

where i indexes industry and t indexes year. The dependent variable sp_{it} is skill premium defined as the logarithm of the average wage ratio of skilled to unskilled workers. $wagdppc_{it}$ is a measure of export destination income level, which will be defined later. $\mathbf{x}_{it}$ is a vector of control variables that vary across specifications. θ_t and θ_i are year fixed effects and industry fixed effects that control for the potential effects of common shocks to all industries across years and for time-invariant industry specific factors. ϵ_{it} is a mean-zero error term. Notice that our main interest is the measure of average destination income $wagdppc_{it}$. Its coefficient β captures to what extent the skill premium varies according to changes in average income in export destinations.

Following Brambilla and Porto (2016), we define export destination income level as weighted average GDP per capita across export destinations using within-industry export share to each destination as the weight:

$$wagdppc_{it} = ln\left(\sum_{d} exsh_{idt} \times gdppc_{d,1995}\right) \tag{2}$$

where i, d, and t denote industry, destination country, and year, respectively. $gdppc_{d,1995}$ is GDP per capita of destination d in real terms at the start year for our sample, and $exsh_{idt}$ is the export share to destination d in total industrial exports in year t, which captures the composition effects of exports within industries. Note that the use of GDP per capita in the initial year treats GDP per capita as a predetermined characteristic and is to avoid possible endogeneity issues with contemporaneous income (Bastos et al., 2016). As such, variations in weighted average GDP per capita across time are primarily attributed to changes in the exposure to different export destinations. In the later discussion, we allow destination GDP per capita to vary across time and our results do not change much.

Identification Issues

Equation (1) attempts to establish a link between the industrial skill premium and the income level of export destinations. However, even after controlling for various covariates, the main regressor, the export share weighed average GDP per capita, is likely to be endogenous if there are unobserved factors that affect the destination composition of exports within industries and the skill premium simultaneously. One potential source of endogeneity is that exporters are usually more productive and often pay higher average wages (Bernard and Bradford Jensen, 1999). The productivity differences between exporters and non-exporters are not captured by aggregate industrial productivity, and such omission could introduce downward bias of the estimates. Another factor could be labour market institutions like minimum wages. Due to variations in skill composition within firms and within industries, firms and industries with a higher proportion of unskilled labour that are paid relatively low wages might be more constrained by the pressure of minimum wages. An increase in minimum wages that mainly benefits the low-paid workers will build up production costs and impose a downward pressure on exports, which could lead to a reduction in the skill premium.

To deal with the endogeneity issue and to explore the causal relationship between skill premia and export destinations, we estimate Equation (1) with instrumental variables (IV) approach. An ideal instrument variable would explain variations in average income levels of export destinations but is not correlated with the unobserved confounding factors as discussed above. Our strategy is to construct the instrument variable from exogenous variations in the exporting market following the literature (Revenga, 1992; Park et al., 2010; Bustos, 2011b; Brambilla et al., 2012; Brambilla and Porto, 2016). One candidate is bilateral exchange rates. The intuition is that if a foreign currency appreciates, imported products from China can be priced lower in terms of local currency and the demand for China's products will rise. Since the endogeneity of the weighted average destination income only comes from export shares, we first predict the export share to each destination from the following regression:

$$exsh_{idt} = \alpha_0 + \delta exchr_{dt} + \phi_d + \phi_t + v_{idt} \tag{3}$$

where $exchr_{dt}$ is bilateral exchange rate between China and destination d in real term. ϕ_d and ϕ_t are destination and year fixed effects respectively.[2] v_{idt} is an error term. A rise in the exchange rate means an appreciation of the local currency and is expected to lead to higher export share to that destination. Therefore, we expect δ to be positive.

After estimating Equation (3), we predict the export share to each destination $ex\hat{s}h_{idt}$ and calculate the instrument for $wagdppc$ as follows:

$$wag\hat{d}ppc_{it} = ln\left(\sum_d ex\hat{s}h_{idt} \times gdppc_{d,1995}\right) \tag{4}$$

Finally, we estimate Equation (1) using $wag\hat{d}ppc_{it}$ as the instrument for $wagdppc_{it}$.

4 Data

4.1 Industry-level data on wages and other characteristics

Industry-level data on wages for workers with different skill levels are relatively scarce in China. The main data source on wages and the skill premium in this study is the Socio Economic Accounts (SEA) from World Input-Output Database (WIOD).[3] WIOD is a new database that provides time series of input-output tables from 1995 to 2011 for forty countries based on various sources of officially released data, and China is one of those countries. As a sub-database of WIOD, SEA provides industry-level data on employment, capital stocks, gross output, etc., for each sample country. Though SEA does not report wages for workers with different skill levels directly, it contains data on total labour compensation, total working hours, labour compensation share and working hour share for high-skilled, medium-skilled and low-skilled workers, which makes it possible to back out hourly labour compensation for each type of workers and to calculate the skill premium accordingly.[4]

[2] In the later estimation, we estimate Equation (3) separately for each industry. Therefore, industry fixed effects are not included in the specification.

[3] All WIOD datasets are available from http://www.wiod.org. User guide of to this database can be found from Timmer et al. (2015).

[4] Calculation of hourly labour compensation for high-skilled, medium-skilled, and low-skilled workers proceeds in two steps. First, based on total labour compensation and labour compensation shares of workers with different skills, we calculate total labour compensation for each group of workers for each industry. Total working hours for each group of workers are calculated analogously. Second, average hourly labour compensation are calculated as total labour compensation divided by total working hours

For China, industry-level data on employment, labour compensation, working hours, etc., are available from 1995 to 2009 from this source.[5] Note that those data for workers with different skill levels at the industry level are not readily available from other sources. To generate consistent and comparable industry-level relative wage series, SEA combines comprehensive data from various officially released data sources, including various issues of China Statistical Yearbook, China Industrial Economic Statistics Yearbook, China Labour Statistical Yearbook, census data like Industrial Censuses and Economic Censuses, as well as individual-level data from China Household Income Project surveys.[6] Skill classification is based on the individual's educational attainment. That is, low-skilled workers are those with middle school education or below, medium-skilled workers are those with high school education and technical secondary school education, and high-skilled workers are those with college education or above. In the later stage of discussion, we translate these three skill groups into skilled and unskilled groups. In particular, skilled workers include high-skilled and medium-skilled ones and unskilled workers are low-skilled ones. We also shift medium-skilled workers to the unskilled group as a robustness check. Average hourly wages for skilled and unskilled workers are the ratio of total labour compensation over total working hours for these two groups, respectively. The skill premium is thus defined as the logarithm of the average hourly wage ratio of skilled to unskilled workers.

Industry-level data on wages and other industrial characteristics are reported for 35 WIOD industries, which include 14 manufacturing industries. Given that this paper seeks to link wages and exports, non-tradable industries without exports are excluded from this study.[7] Note that the main mechanism linking export destination and the skill premium is quality and technology upgrading, and we do not expect too much upgrading in quality or technology attributed to exports for industries such agriculture, mining and quarrying, and water, electricity, and gas supply, the main exporting products of which are raw natural sources. Therefore, we constrain our discussion to manufacturing industries throughout the paper, with a sample of 14 industries spanning 1995 to 2008.

for each skill group.

[5]Due to the fact that industrial skill premiums in 2009 are completely the same as in 2008, which is assumed by the data source, we restrict our sample from 1995 to 2008 in the main discussion. As what will be shown later, the main findings do not change much with 2009 being left out.

[6]For more details, see the WIOD SEA documents from http://www.wiod.org/publications/source_docs/SEA_Sources.pdf.

[7]Here exports specifically denote exports in goods.

Information on other industry-level characteristics are also taken from WIOD. Those data include industrial exports, gross output, gross fixed capital formation (GFCF), and various price indices.

4.2 Export weighted average GDP per capita across export destinations

To calculate the export share to each destination, data on exports to each destination at the industry level is required. These data are obtained from the World Integrated Trade Solution (WITS) database at 3-digit level of International Standard Industrial Classification (ISIC) Revision 3. To combine with wage data, we aggregate the 3-digit ISIC Rev.3 industry codes into WIOD broad industry classifications. Time series on GDP per capita, GDP deflator, Consumer Price Index (CPI), and exchange rates are from the World Bank Indicator Database.[8]

One important feature of China's exports is the high proportion of processing exports, which account for over 50% in total exports (Koopman et al., 2012). In particular, industries with high proportion of processing exports are ones that are often considered as relatively technologically sophisticated ones, such as machinery and equipment (Amiti and Freund, 2010; Koopman et al., 2012). However, processing production is simple assembly of imported parts into final products and does not require much technology upgrading or high skill inputs. Thus, exports of processing goods, especially to high-income destinations, may not have as strong effects as exports of ordinary goods on the skill premium. To distinguish potential different effects of ordinary exports and processing exports, we calculate the within-industry processing and ordinary export shares to various destinations, which are utilised as the weights to compute weighted average GDP per capita separately. Data on processing and ordinary exports are available at 4-digit HS level between 2001 and 2008 from DRCNET Statistical Database, an official database of Development Research Center of the State Council of China.[9]

[8]http://databank.worldbank.org/data. Taiwan province of China is an important export destination whereas its data is not available from the World Bank Indicator Database. For the purpose of completeness, data on Taiwan province of China are collected from various issues of Taiwan Statistical Data Book.

[9]To calculate processing/ordinary export share to each destination within industries, we classify 4-digit HS level data into industry level combining 6-digit HS level export data from WITS database and relevant

Table 1: Summary statistics of industrial skill premium and weighted average GDP per capita across export destinations in manufacturing industries: 1995-2008

	A: Skill premium				B: Weighted average GDP per capita			
	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1995	0.088	0.025	0.052	0.123	12.171	0.135	11.942	12.405
1996	0.096	0.020	0.067	0.124	12.190	0.135	11.931	12.434
1997	0.105	0.015	0.082	0.126	12.181	0.115	11.996	12.406
1998	0.114	0.010	0.098	0.128	12.177	0.118	11.939	12.411
1999	0.123	0.005	0.114	0.130	12.204	0.121	11.956	12.424
2000	0.133	0.001	0.132	0.134	12.190	0.119	11.998	12.414
2001	0.143	0.005	0.135	0.150	12.183	0.133	11.901	12.413
2002	0.154	0.011	0.138	0.167	12.165	0.126	11.910	12.389
2003	0.156	0.007	0.147	0.168	12.146	0.132	11.847	12.382
2004	0.169	0.010	0.156	0.186	12.134	0.113	11.956	12.325
2005	0.178	0.012	0.164	0.200	12.093	0.122	11.863	12.277
2006	0.188	0.014	0.172	0.215	12.029	0.115	11.860	12.205
2007	0.189	0.009	0.178	0.209	11.943	0.117	11.788	12.119
2008	0.198	0.016	0.180	0.226	11.813	0.120	11.638	12.001

Notes: This table shows summary statistics of industrial skill premium and export weighed average GDP per capita across export destinations in manufacturing industries. Industrial skill premium is defined as the ratio of real hourly wage of skilled workers over real hourly wage of unskilled workers (in logarithm) for each manufacturing industry. Export weighted GDP per capita across export destinations is defined as Equation (2). S.D. denotes standard deviations, Min. and Max. denote minimum value and maximum value respectively.

Table 1 provides summary statistics on the skill premium and export weighted average GDP per capita from 1995 to 2008, the period of this study. It shows in Panel A that average skill premium (in natural logarithm) for manufacturing industries increased continuously from 0.088 in 1995 to 0.198 in 2008. In Panel B, export weighted average GDP per capita (in natural logarithm), however, fluctuated between 12.17 and 12.20 before 2001 and decreased afterwards from 12.18 in 2001 to 11.81 in 2008. Such reduction is mainly attributed to the decline of the share of exports going to Hong Kong and Japan, both of which ranked on the top of China's export destinations in terms of real GDP per capita, and to which China exported more than 40% of its total exports in 1995 and reduced this

concordance tables.

share to around 20% in 2008 (See Figure A.3). The time-series of average skill premium and export weighted GDP per capita do not indicate a systematic relationship between the two. However, the different patterns of weighted average GDP per capita before and after 2001 motivate us to explore the possible differences in the relationship between the two in the pre- and post-WTO accession periods.

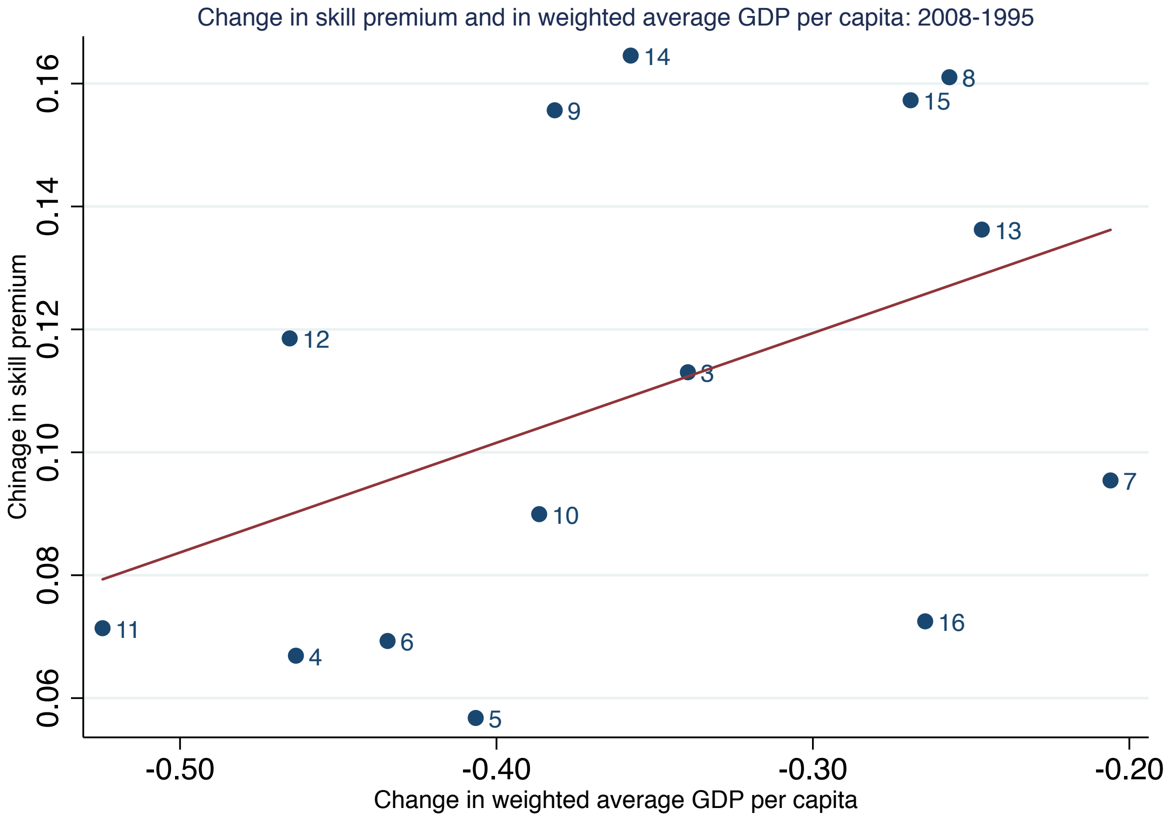

Figure 1: Change in skill premium and in weighted average GDP per capita in manufacturing industries: 2008-1995

Notes: The straight line is a fitted line of the OLS regression: $\Delta sp_{i,2008-1995} = \alpha + \beta \Delta wagdppc_{i,2008-1995} + \epsilon_i$, where $\Delta sp_{i,2008-1995}$ is change in skill premium in industry i between 1995 and 2008, and $\Delta wagdppc_{i,2008-1995}$ is change in export weighted average GDP per capita in industry i between 1995 and 2008. The estimated coefficient of $\Delta wagdppc_{i,2008-1995}$, β, is 0.18 with robust standard error being 0.09 (p=0.08) and the partial R^2 being 0.19. Concordance of industry code and industry name is shown in Table A.4 in the Appendix.

Recall that the data used in this paper is at the industry level. Simple averages across industries, as shown in Table 1, hide industrial variation in relative wages and in weighted average GDP per capita. Figure 1 shows the scatter plots of changes in industrial skill premium against changes in weighted average GDP per capita between 1995 and 2008.

It shows that all industries observed an reduction in weighted average GDP per capita, the same as the overall trend in Table 1. Importantly, industries with lower reductions in weighted average GDP per capita, such as machinery, not elsewhere classified (13) and transport equipment (15), experienced a relatively higher rise in the skill premium. The estimated correlation coefficient between the two is positive and significant at the 10% level, which provides some supportive evidence of a potential positive relationship between average destination income and the skill premium. We explore this relationship empirically in the next section.

5 Skill Premium and Average Export Destination Income: Regression Results

In this section, we empirically explore the relationship between skill premium and income levels of export destinations. We start from estimating Equation (1) to examine the association between the two, then address the endogeneity issues, and finally check the robustness of the relationship.

5.1 Main results

Table 2 reports the baseline OLS-FE regression results. In Columns (1), we present the relationship between skill premium and average income across export destinations conditional only on year fixed effects and industry fixed effects. Note that year fixed effects control for common shocks to all industries in each year, such as Asian financial crisis in around 1997 and 1998. Industry fixed effects account for all time-invariant industry-specific characteristics, such as initial differences in productivity and in skill intensity. The estimated coefficient is positive and significant. Specifically, an industry with a 10% higher average income across export destinations has a 1.07% higher skill premium.

Note that the skill premium is calculated based on wage data of all workers, including those working in exporting firms and those in non-exporting firms. Wage adjustments in non-exporting firms must be indirectly via the effects on exporting firms. However, the export share used to calculate weighted average GDP per capita only captures the composition of export destinations within industries, but does not account for the scale effects, that is, differences in the degree of exposure to exports across industries. For example, an industry with a high share of export to the U.S. but a low total export value would observe high weighted average GDP per capita across destinations but we would not expect strong effects on wages due to the relatively low exposure to export. To control for the scale effects, we include the share of exports in industrial output as a control variable. Following Goldberg and Pavcnik (2005) and Kumar and Mishra (2008), who study trade liberalisation and industrial the wage premium in Columbia and India respectively, we include industry-level capital as an additional control variable, measured as the logarithm of real gross fixed capital formation (GFCF). Data on GFCF and relevant price indices are from WIOD SEA database.

Regression results for the extended specifications are shown in Columns (2) to (4). The coefficient on export share in gross output is negative, suggesting that industries that are more exposed to exports tend to have lower skill premia, though this effect is not statistically significant. In contrast, industrial capital is positively correlated with the skill premium. The coefficients on export weighted average GDP per capita, however, increase slightly compared to the basic result in Column (1) and stay highly significant, indicating that accociation between skill premium and weighted average income is robust to the inclusion of these two important controls.

Another important factor that affects wages is productivity. The argument is that more productive firms are more likely to pay higher wages through rent sharing. Following Brambilla and Porto (2016), we add labour productivity, calculated as the real output per worker, as a further control variable. As is shown in Column (5), productivity effects are positive and highly significant, suggesting that more productive industries have higher skill premia on average. Conditional on productivity, the basic pattern between the skill premium and weighted average destination income is not affected. However, one apparent change is the coefficient on the logarithm of GFCF that changes from positive to negative. Given that more capital-intensive industries are often more productive ones, we leave out GFCF in Column (6) but the main result does not vary much.

Table 2: Skill premium and weighted average GDP per capita across export destinations in manufacturing industries: OLS-FE regressions, 1995-2008

	(1)	(2)	(3)	(4)	(5)	(6)
Export weighted average GDP p/c	0.107***	0.109***	0.115***	0.116***	0.075***	0.081***
	(3.972)	(3.917)	(4.151)	(4.080)	(3.500)	(3.897)
Export share		-0.008		-0.005	-0.064**	-0.058**
		(0.263)		(0.173)	(2.604)	(2.411)
Ln(GFCF)			0.042***	0.042***	-0.022**	
			(4.234)	(4.177)	(2.193)	
Productivity					0.044***	0.040***
					(10.134)	(10.945)
Constant	-1.215***	-1.243***	-1.552***	-1.569***	-1.177***	-1.340***
	(3.711)	(3.676)	(4.383)	(4.345)	(4.416)	(5.564)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	196	196	196	196	196	196
R^2	0.901	0.901	0.906	0.906	0.941	0.940

Notes: This table shows the OLS-FE regression results of skill premium on export weighted average GDP per capita across export destinations in manufacturing industries. Skilled workers are defined as those with high school education or above. Others are identified as unskilled workers. Export share denotes the share of total exports in gross output in each industry. GFCF denotes gross fixed capital formation. Productivity is labour productivity, calculated as real output per worker. Robust standard errors are computed in all specifications.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Absolute t values in parentheses.

The baseline results show a positive relationship between the skill premium and weighted average destination income. However, an increase in skill premium could be either from higher wage growth for skilled than for unskilled workers, or from wage rise for skilled workers combined with wage decline for unskilled workers. To clarify, we run regressions with average wages for skilled and for unskilled workers as the dependent variable separately, and the results are reported in Appendix Table A.2. It is evident that export weighted average GDP per capita is positively correlated with average wages for both skilled and unskilled workers, which is consistent with Brambilla and Porto (2016) who find a positive correlation with average industrial wages. However, the coefficient is larger in magnitude for skilled than for unskilled workers, which is accounted for the rising skill premium. This pattern is robust to the inclusion of various control variables.[10]

Due to the potential endogeneity of the weighted average destination income, we cautiously interpret the results in Table 2 as correlation or association instead of causality. To identify whether the positive correlation between weighted average destination income and the skill premium is a causal relationship, we estimate Equation (1) with instrumental variables. As discussed earlier, to construct an instrument for the weighted average destination income, we first estimate Equation (3) to predict the export share to each destination that is attributed to the exogenous changes in exchange rates. In particular, we run regressions for each industry separately following Brambilla and Porto (2016) and the regression results are reported in Appendix Table A.3. Conditional on year fixed effects and destination fixed effects, the estimated coefficient on the bilateral exchange rate variable is positive and statistically significant for 12 out of 14 industries. It implies that an appreciation of foreign currency is associated with a rise in the share of China's exports to that destination. In addition, the R^2 is over 0.90 for 10 industries, suggesting that the overall fit of the model is good. Using the predicted export share to each destination, we calculate weighted average GDP per capita for each industry and use it as the instrument for our main regressor to estimate Equation (1) utilising the two-stage least squares (2SLS) approach.

In Table 3, we report the IV estimation results. Specifically, Panel A shows the first-stage regression results. Columns (1) to (6) correspond to various specifications controlling for alternative additional variables as in Table 2. We find a positive correlation between our instrument and the endogeneous regressor, and this correlation is statistically significant. This positive correlation is robust throughout all specifications. Moreover, the R^2 of the first-stage regression is always over 0.95 across the different specifications, indicating an overall good fit of the model. The second-stage regression, as shown in Panel B, shows that the coefficient of the weighted average destination income is significantly positive and is robust to the inclusion of various control variables. These results confirm a causal

[10] As mentioned earlier, we leave out 2009 from our sample considering that skill premium in 2009 is the same as in 2008 due to assumptions that imposed by the data source. However, we also check whether this affects our main findings by repeating the above regressions with inclusion of 2009. As shown in Table A.1 in the Appendix, all estimated coefficients are similar to ones in Table 2. This allows us to safely leave out 2009 in all subsequent regressions.

Table 3: Skill premium and weighted average GDP per capita across export destinations in manufacturing industries: IV regressions, 1995-2008

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First-stage results						
Predicted export weighted average GDP p/c	0.436**	0.504**	0.456**	0.519**	0.482**	0.480**
	(2.359)	(2.542)	(2.412)	(2.570)	(2.275)	(2.320)
Export share		0.260***		0.254***	0.194***	0.233***
		(5.670)		(5.115)	(3.584)	(4.735)
Ln(GFCF)			-0.076*	-0.066	-0.117**	
			(1.807)	(1.543)	(2.444)	
Productivity					0.037**	0.018
					(2.237)	(1.169)
Constant	7.432***	6.656***	7.659***	6.870***	7.161***	6.716***
	(3.695)	(3.084)	(3.840)	(3.208)	(3.197)	(3.035)
R^2	0.952	0.956	0.952	0.957	0.958	0.957
Panel B: Second-stage results						
Export weighted average GDP p/c	0.371**	0.336**	0.338**	0.312**	0.242**	0.242**
	(2.243)	(2.444)	(2.270)	(2.455)	(2.440)	(2.426)
Export share		-0.059		-0.048	-0.090***	-0.089***
		(1.419)		(1.224)	(3.160)	(2.979)
Ln(GFCF)			0.056***	0.052***	-0.003	
			(3.769)	(3.954)	(0.176)	
Productivity					0.036***	0.036***
					(5.600)	(7.491)
Constant	-4.491**	-4.052**	-4.457**	-4.101**	-3.283***	-3.295***
	(2.198)	(2.390)	(2.349)	(2.551)	(2.637)	(2.752)
R^2	0.833	0.855	0.858	0.872	0.917	0.917
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	196	196	196	196	196	196

Notes: This table shows the IV regression results of skill premium on export weighted average GDP per capita across export destinations in manufacturing industries. Panel A shows the first-stage regression results and Panel B shows the second-stage regression results. Instrument for weighted average GDP per capita is weighted average GDP per capita across destinations using the predicted export share as the weight. All other variables are defined the same as in earlier tables. Robust standard errors are computed in all specifications.

* p <0.1, ** p <0.05, *** p <0.01. Absolute t values in parentheses.

relationship and suggest that an increase in exports to high-income destinations widens the wage gap between skilled and unskilled workers within industries. For example, the estimated coefficient in Column (1) implies that a 10% increase in average destination income causes the skill premium to rise by 3.71%. Compared with the OLS-FE results in Table 2, the IV estimated coefficients are larger, indicating that the OLS-FE estimation results are downwardly biased.

5.2 Robustness checks

In this section, we check the robustness of our main results by considering various specifications. These robustness checks include using alternative measures of the dependent variable or of the main regressor, and controlling for additional variables.

Alternative skill measures

As mentioned above, the skill premium is defined as the ratio of the wages of skilled and unskilled workers, where skilled workers are those with high-school education or above. Taking the advantage that our main data source of wages, the WIOD, reports wage data for high-, medium- and low-skilled workers, we consider an alternative measure of skills in this section. Specifically, we shift the medium-skilled workers from the skilled group to the unskilled group. As such, skilled workers are those with college education or above and others are now identified as the unskilled workers. The skill premium therefore measures the wage gap between college or above diploma holders (high-skilled workers) and others (medium- and low-skilled workers). We replicate the above regressions using the revised skill premium definition as the dependent variable.

Table 4 presents the results. In Panel A we show the OLS-FE regression results. It is evident that the revised skill premium and the export weighted average GDP per capita across destinations are still positively correlated, though the estimated coefficient is less significant. Panel B reports the IV estimation results. The coefficient of the weighted average destination income is significantly positive and is robust across specifications, suggesting that industries that ship more goods to high-income destinations pay higher

Table 4: Skill premium and weighted average GDP per capita across export destinations in manufacturing industries: Alternative skill measures, 1995-2008

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS-FE estimation						
Export weighted average GDP p/c	0.017**	0.017*	0.019**	0.018**	0.008	0.010
	(2.076)	(1.969)	(2.224)	(2.098)	(1.102)	(1.391)
Export share		0.001		0.002	-0.012*	-0.010
		(0.162)		(0.231)	(1.664)	(1.419)
Ln(GFCF)			0.008***	0.008***	-0.007**	
			(3.079)	(3.068)	(2.171)	
Productivity					0.011***	0.009***
					(6.240)	(6.473)
Constant	0.095	0.100	0.028	0.035	0.129	0.077
	(0.945)	(0.972)	(0.266)	(0.321)	(1.448)	(0.894)
R^2	0.994	0.994	0.994	0.994	0.995	0.995
Panel B: IV estimation						
Export weighted average GDP p/c	0.062**	0.058**	0.056**	0.053***	0.035*	0.035*
	(2.032)	(2.402)	(2.216)	(2.651)	(1.654)	(1.684)
Export share		-0.008		-0.006	-0.016	-0.015
		(0.449)		(0.350)	(1.118)	(1.044)
Ln(GFCF)			0.011***	0.010***	-0.004	
			(4.524)	(4.506)	(0.662)	
Productivity					0.009***	0.009***
					(4.440)	(6.190)
Constant	-0.468	-0.410	-0.462	-0.420*	-0.209	-0.226
	(1.241)	(1.389)	(1.453)	(1.695)	(0.778)	(0.933)
R^2	0.993	0.993	0.993	0.994	0.995	0.995
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	196	196	196	196	196	196

Notes: This table checks an alternative definition of skills. Medium-skilled workers are treated as being unskilled. As such, skilled workers are those with college education or above (high-skilled), and unskilled workers include all others that have technical school education, high school education or below (medium-skilled and low-skilled). Panel A reports the OLS-FE regression results and Panel B report the IV regression results. Instrument for export weighted average GDP per capita is defined as in Equation (4). Other variables are defined the same as in earlier tables. Robust standard errors are computed in all specifications. * p <0.1, ** p <0.05, *** p <0.01. Absolute t values in parentheses.

wages for skilled than unskilled workers. Compared with the results in Table 2 and in Table 3, the estimated coefficients are smaller in magnitudes in all specifications. This means that the high to medium and low skills wage gap resulted from exposure to high-income exports is smaller than high and medium to low skill wage gap, which implies that medium-skilled workers are less disadvantaged than low-skilled workers relative to the highest skilled workers. Overall, the results in Table 3 provide supportive evidence for our main argument.

Time-variant GDP per capita

In all above regressions, we use GDP per capita in 1995 to calculate the weighted average destination income to avoid potential endogeneity problems. In this section, we allow destination income to vary across years and use this time-variant GDP per capita to calculate industry-level weighted average income. As such, this variable captures not only variations in the exposure to different export destinations but also changes in income levels at each destination over the years. Using the revised weighted average income across destinations as the main regressor, we repeat the above regressions. Notice that the dependent variable, skill premium, is our preferred (original) measure, i.e. the wage differential between workers with high-school education or above and others.

In Table 5, we report both OLS-FE and IV regression results. The estimated correlation between skill premium and weighted average destination income is positive and highly significant across specifications. Accounting for the endogeneity of the weighted average GDP per capita, the positive relationship remains significant. One may notice that the estimated coefficients are similar to those in our baseline results as shown in Table 2. This confirms that our main results are not sensitive to the changes in destination income over time. However, variations in trade partners' income could potentially affect exports and wages in Chinese market, which introduces additional endogeneity problem. Therefore, using the initial value of destination income is our preferred specification (Bastos et al., 2016; Brambilla and Porto, 2016).

Table 5: Skill premium and weighted average GDP per capita across export destinations in manufacturing industries: Time-variant GDP per capita, 1995-2008

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS-FE estimation						
Export weighted average GDP	0.073***	0.073***	0.077***	0.076***	0.051***	0.055***
	(3.036)	(3.042)	(3.161)	(3.132)	(2.749)	(2.974)
Export share		-0.001		0.002	-0.063**	-0.055**
		(0.036)		(0.073)	(2.499)	(2.240)
Ln(GFCF)			0.038***	0.039***	-0.026***	
			(3.802)	(3.761)	(2.636)	
Productivity					0.045***	0.041***
					(10.484)	(10.813)
Constant	-0.796***	-0.799***	-1.067***	-1.061***	-0.875***	-1.029***
	(2.736)	(2.751)	(3.470)	(3.467)	(3.839)	(4.869)
R^2	0.897	0.897	0.902	0.902	0.939	0.938
Panel B: IV estimation						
Export weighted average GDP p/c	0.285**	0.261**	0.264**	0.245**	0.182***	0.182***
	(1.985)	(2.236)	(2.172)	(2.438)	(3.719)	(3.640)
Export share		-0.048		-0.039	-0.087	-0.082
		(0.617)		(0.545)	(1.437)	(1.443)
Ln(GFCF)			0.047***	0.045***	-0.015	
			(3.624)	(3.184)	(0.813)	
Productivity					0.040***	0.038***
					(5.640)	(6.986)
Constant	-3.408*	-3.109**	-3.458**	-3.210**	-2.497***	-2.565***
	(1.932)	(2.170)	(2.245)	(2.519)	(4.028)	(4.474)
R^2	0.837	0.853	0.855	0.866	0.918	0.918
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	196	196	196	196	196	196

Notes: This table shows the robustness of main findings by allowing GDP per capita of destinations to vary across time. Panel A shows OLS-FE regression results and Panel B shows IV regression results. All other variables are defined the same as in earlier tables. Robust standard errors are computed in all specifications. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Absolute t values in parentheses.

Relative supply of skilled labour

The supply of skilled labour is an important factor that affects average wages and the skill premium. As Acemoglu (1998) documents, new technologies are skill-biased by nature. Increasing the supply of skilled labour enables the market to upgrade skill-complementary technologies, which further induces a rise in the demand for skilled workers and an increase in the skill premium. Consequently, the effects of increasing the supply of skilled labour on the skill premium depend on two competing forces: one is the traditional *substitution effect* which has a downward pressure on the skill premium, and the other is the *directed technology effect*, which raises the skill premium as a result of the faster upgrading of skill-complementary technologies.

During our sample period, China experienced a rapid growth in the supply of skilled labour (See Figure A.4). In particular, China launched a college expansion programme that aimed to increase college enrolment rate. Since then, the number of college admissions surged from 1.1 million in 1998 to 6.8 million in 2011 (Li et al., 2014), leading to a large increase in the supply of skilled labour in the labour market. Provided that this policy change is a nationwide event, year fixed effects that are included in previous regressions could control for the common impacts of the policy change. However, if manufacturing industries are affected disproportionately, our regression results would suffer from omitted variable biases. This is true because manufacturing industries differ from each other in skill intensity. To control for this, we include a measure of relative supply of skills in the regressions. Similar to Acemoglu (2002), the relatively supply of skills are defined as ratio of total hours worked by skilled and unskilled workers. Data on total working hours by different skill levels at the industry level are from WIOD SEA database.

Columns (1) and (4) in Table 6 report the OLS and IV estimation results with relative skill supply as an additional control variable. Its coefficient is positive and highly significant, implying that industries with a greater supply of skilled labour tend to have higher skill premia. This is consistent with the *directed technology effect* proposed in Acemoglu (1998) and suggests that the positive technology effect dominates the negative substitution effect.

The coefficient on export weighted average destination income remains positive, though we lose significance in the IV estimation.

Table 6: Skill premium and weighted average GDP per capita across export destinations in manufacturing industries: Robustness Checks, 1995-2008

	Panel A: OLS-FE estimation			Panel B: IV estimation		
	(1)	(2)	(3)	(4)	(5)	(6)
Export weighted average GDP p/c	0.043***	0.079***	0.045***	0.035	0.313**	0.054*
	(5.323)	(3.483)	(5.384)	(1.041)	(2.324)	(1.661)
Export share	-0.007	-0.090***	-0.014	-0.006	-0.131***	-0.016
	(0.798)	(3.671)	(1.597)	(0.552)	(3.652)	(1.518)
Ln(GFCF)	0.007	-0.022**	0.007	0.007	0.005	0.008
	(1.205)	(2.142)	(1.145)	(0.989)	(0.225)	(1.142)
Productivity	0.007***	0.045***	0.008***	0.007***	0.034***	0.008***
	(3.173)	(10.059)	(3.585)	(3.371)	(4.264)	(3.551)
Relative skill supply	0.362***		0.357***	0.364***		0.355***
	(24.442)		(25.034)	(23.579)		(23.707)
Import weighted average GDP p/c		-0.024***	-0.006		-0.029***	-0.006*
		(2.749)	(1.633)		(2.906)	(1.729)
Constant	-0.803***	-0.946***	-0.753***	-0.713*	-3.849**	-0.887**
	(7.196)	(3.235)	(6.659)	(1.681)	(2.328)	(2.221)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	196	196	196	196	196	196
R^2	0.991	0.945	0.991	0.991	0.898	0.991

Notes: This table shows robustness checks that examine the relationship between skill premium and export weighted average GDP per capita across export destinations in Chinese manufacturing industries. Panel A shows OLS-FE regression results and Panel B shows IV regression results. Relative supply of skilled labour is measured as the ratio of total working hours by skilled workers over those by unskilled workers, where skilled and unskilled workers are defined the same as before. Import weighted average GDP per capita is defined as weighted average GDP per capita across import source economies using the share of imports from each economy in total industrial imports as the weight. Other variables are defined the same as in earlier tables. Robust standard errors are computed in all specifications.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Absolute t values in parentheses.

Imports from high-income economies

Along with rapidly growing exports following the WTO accession, another prominent feature of China's trade is the rapid increase in imports, due to factors such as tariff rates reduction, rising incomes and the exposure of exports. As documented in Li et al. (2014) and Raveh and Reshef (2016), imports of capital goods and intermediate goods from advanced economies, especially R&D intensive capital goods and high-quality intermediate inputs, are complementary to skills and therefore are related to increasing skill premium in developing countries. Indeed, a large proportion of China's imports are intermediate and capital goods, with imports of consumption goods accounting for a fairly small proportion (See Figure A.5). Analogously to the construction of export weighted average GDP per capita across export destinations, we generate weighted average GDP per capita across import source economies using import share as the weight and include it in the regression to account for the role of imports from high-income economies. Notice that a higher value of this variable indicates that one industry imports more from high-income economies.

Interestingly, the estimated coefficient of import weighted average GDP per capita is significantly negative, as shown in Columns (2) and (5) in Table 6, suggesting that imports from high-income economies appear to benefit unskilled workers more than skilled workers. One potential reason is that a large proportion of China's imports (of both intermediate and capital goods) are for processing production (Amiti and Freund, 2010; Koopman et al., 2012).[11] Even if imports from high-income economies are embodied with advanced technology, processing production is only involved with simple assembling of imported parts into final goods and does not require much in terms of skills. As such, increasing imports from advanced economies that are used for processing production drive up the relative demand for unskilled workers and therefore are related to a reduction in the skill premium. More importantly, the estimated coefficient on export weighted average destination income does not change much with the inclusion of imports.

In Columns (3) and (6), we include both relative supply of skills and the import weighted average GDP per capita as control variables. It is evident from both OLS and IV results

[11] As shown in Table 1 in Koopman et al. (2012), almost half of intermediate and capital goods imports are used for processing exports production.

that the variable of interest remains positive and significant. It is worthwhile to mention that in specifications that control for relative supply of skills, the coefficient of average destination income is much lower than that in specifications when not controlled for, which indicates that omitting this crucial factor biases our main results upwards.

5.3 Additional supporting evidence

Distinguishing ordinary export and processing export

As discussed earlier, imports for processing production cover a fairly high share in China's total imports. On the export side, according to Amiti and Freund (2010) and Koopman et al. (2012), the share of processing exports in China's total exports remained over 50% between 1995 and 2007. Processing production involves importing materials or parts from foreign markets, assembling those imported intermediate inputs into final goods and then exporting to foreign markets, which can be carried out by relatively low-skilled workers. Hence, processed exports may not necessarily increase the demand for skilled labour, but rather may contribute to rising demand for unskilled workers and to a reduction in the skill premium.

Carefully looking into the industrial structure of processing production, industries with high share of processing imports and exports are those that are often regarded as relatively more skill-intensive and more technologically sophisticated ones, like machinery and equipment, which we would expect more rapid upgrading of technology and higher utilisation of skills (Amiti and Freund, 2010; Koopman et al., 2012). Indeed, those imported intermediate inputs are generally from high-income economies like the U.S. and Japan, and accordingly processing exports are mostly transported back to those destinations. With the presence of processing exports, the total export weighted average destination income may not capture the quality upgrading or technology effects well since a large share of processing exports to high-income countries contributes much to the weighted average income but does not really have sizeable impact on skill utilisation and on the skill premium. To formally address this issue, we collect data on ordinary export and processing export and calculate within-industry export shares to each destination under these two regimes separately and compute weighted average GDP per capita across destinations respectively. Notice that data on exports that distinguish ordinary from processing export are only available for the post-WTO accession period (2002-2008).

We run regressions using the ordinary export share weighted average GDP per capita and the processing export share weighted average GDP per capita as the main regressor separately. In Table 7, we report results based on ordinary exports in Panel A and results based on processing exports in Panel B, with Panel C reporting OLS-FE regression results and Panel D reporting IV regression results. The estimated coefficients on ordinary export weighted average GDP per capita are all positive and significant, as shown in Panel C. By contrast, processing exports to high-income countries appear to be negatively correlated with the skill premium. This is in line with Li et al. (2014) who find positive effects of ordinary exports and negative effects of processing exports in China using a different dataset. IV estimation results confirm a positive causal relationship between ordinary export weighted average destination income and skill premium and a negative causal relationship between processing export share weighted average destination income and skill premium, though the latter, negative relationship is insignificant.

The differential results based on ordinary and processing exports suggest that one industry with more exports of ordinary goods to high-income destinations tends to be associated with a higher skill premium whereas a rise in the exports of processing goods to high-income destinations tends not to and may even reduce the skill premium. Overall, we find a positive effect of total exports.

Differences before and after China's WTO accession

China joined the WTO in December 2001, following which China has integrated into the world economy rapidly. Table 1 shows that the exported weighted average GDP per capita fluctuated before 2001, but declined afterwards. As explained earlier, such reduction mainly results from the substantial drop in export shares to a few developed destinations, like Hong Kong, Japan and the U.S. Complementarily, share of exports to other high-income countries and to middle- and low-income countries increased. Despite the reduction in export shares in a few destinations, China's total exports to both high-income destinations

Table 7: Skill premium and weighted average GDP per capita across export destinations in manufacturing industries: Ordinary and processing exports, 2002-2008

	Panel A: Ordinary exports			Panel B: Processing exports		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: OLS-FE estimation						
Export weighted average GDP p/c	0.013*	0.020***	0.019***	-0.004	-0.014**	-0.015***
	(1.849)	(3.913)	(3.408)	(0.673)	(2.541)	(2.649)
Export share	0.059***	0.063***	0.061***	0.055***	0.058***	0.055***
	(3.569)	(3.640)	(3.379)	(3.244)	(3.283)	(3.329)
Ln(GFCF)	0.005	0.002	0.002	0.004	-0.001	0.000
	(0.964)	(0.315)	(0.361)	(0.808)	(0.136)	(0.068)
Productivity	0.004	0.007**	0.007**	0.003	0.007*	0.007*
	(0.915)	(2.175)	(2.046)	(0.779)	(1.915)	(1.884)
Relative skill supply		0.112***	0.109***		0.114***	0.111***
		(4.743)	(4.473)		(4.136)	(4.106)
Import weighted average GDP p/c			-0.004			-0.010
			(0.350)			(1.003)
Constant	-0.086	-0.293***	-0.240	0.130	0.143**	0.273**
	(0.936)	(3.387)	(1.410)	(1.645)	(2.317)	(2.092)
R^2	0.980	0.983	0.983	0.979	0.982	0.983
Panel D: IV estimation						
Export weighted average GDP p/c	-0.000	0.028**	0.027**	0.004	-0.032	-0.020
	(0.004)	(2.567)	(2.572)	(0.270)	(1.240)	(1.021)
Export share	0.053***	0.067***	0.066***	0.052***	0.065***	0.056***
	(3.339)	(4.273)	(3.906)	(3.017)	(3.178)	(3.271)
Ln(GFCF)	0.005	0.001	0.002	0.005	-0.004	-0.000
	(1.080)	(0.298)	(0.311)	(1.077)	(0.639)	(0.067)
Productivity	0.003	0.008***	0.008**	0.003	0.008**	0.007**
	(0.876)	(2.686)	(2.505)	(0.847)	(2.260)	(1.993)
Relative skill supply		0.124***	0.122***		0.153**	0.122**
		(4.439)	(4.276)		(2.436)	(2.385)
Import weighted average GDP p/c			-0.002			-0.011
			(0.182)			(1.265)
Constant	0.080	-0.414**	-0.380*	0.028	0.342	0.334
	(0.614)	(2.461)	(1.838)	(0.147)	(1.241)	(1.463)
R^2	0.979	0.983	0.983	0.979	0.980	0.982
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	196	196	196	196	196	196

Notes: This table shows regression results that distinguish ordinary exports and processing exports. Panel A (Columns (1)-(3)) calculates export weighted average GDP per capita using the share of ordinary exports to each destination within industry as weight. Panel B (Columns (4)-(6)) calculates export weighted average GDP per capita using the share of processing exports to each destination within industry as weight. Panel C shows OLS-FE regression results and Panel D shows IV regression results. Instrument for export weighted average GDP per capita is defined as in Equation 4. All other variables are defined the same as in earlier tables. Robust standard errors are computed in all specifications.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Absolute t values in parentheses.

and middle- and low-income destinations rose rapidly following China's WTO accession in 2001, as shown in Figure A.2. One may expect that the skill premium effects in the post-WTO accession period are stronger due to the huge expansion of foreign markets. To examine possible differences before and after 2001, we split the whole sample into two sub-periods: pre- and post-WTO accession periods and run regressions separately.[12]

Table 8 shows the results. The estimated coefficients on weighted average GDP per capita are positive in all specifications in Panel C, which shows the OLS results. However, the coefficients are larger in magnitudes in the post-WTO accession period, suggesting a stronger effect in the second period than in the first period. In Panel D, the IV estimation results show that the coefficient of interest turns out insignificant for the pre-WTO accession period and even changes the sign in specifications that control for relative skill supply and imports. Regarding the post-WTO accession period, the coefficient appears negative and insignificant in Column (4), which reveals that the stronger correlation as suggested by the OLS regression might be not robust. However, controlling for the relative supply of skills and imports as in Columns (5) and (6) in Panel D, the coefficient of average destination income is positive and significant. Overall, our results provide some evidence that effects of high-income exports on skill premium are stronger in the period after China's accession to the WTO.

6 Conclusions

Rising wage inequality between skilled and unskilled workers in developing countries has drawn wide attention in the literature. Recent studies have emphasised the importance of export destination in affecting the utilisation of skilled workers and average wages, which implies that it could be a potential factor that drives up the skill premium in developing countries. Using Chinese manufacturing industry-level data on skill premia and exports combined with country-level data on per capita income, this paper examines the relationship between average export destination income and the skill premium, aiming to identify whether exporting to high-income countries causes the widening wage gap between skilled and unskilled workers.

[12] We include 2001 in the pre-WTO accession period provided that China joined the WTO in December 2001.

Table 8: Skill premium and weighted average GDP per capita across export destinations in manufacturing industries: Differences before and after 2001

	Panel A: 1995-2001			Panel B: 2002-2008		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: OLS-FE estimation						
Export weighted average GDP p/c	0.007	0.014**	0.015**	0.024**	0.034***	0.034***
	(0.192)	(2.337)	(2.414)	(2.082)	(3.492)	(3.632)
Export share	-0.044	-0.000	-0.002	0.052***	0.052***	0.051***
	(0.717)	(0.020)	(0.286)	(3.213)	(3.168)	(3.032)
Ln(GFCF)	0.052***	-0.025***	-0.025***	0.006	0.003	0.003
	(4.385)	(8.997)	(8.663)	(1.134)	(0.593)	(0.543)
Productivity	0.043***	-0.001	-0.001	0.003	0.006*	0.006*
	(6.341)	(0.676)	(0.607)	(0.657)	(1.784)	(1.746)
Relative skill supply		0.350***	0.349***		0.110***	0.109***
		(47.829)	(45.652)		(4.340)	(4.309)
Import weighted average GDP p/c			-0.001			-0.000
			(0.500)			(0.049)
Constant	-0.764*	-0.166**	-0.157**	-0.173	-0.401***	-0.392**
	(1.918)	(2.287)	(2.063)	(1.237)	(2.921)	(2.188)
R^2	0.878	0.997	0.997	0.981	0.983	0.983
Panel D: IV estimation						
Export weighted average GDP p/c	0.738	-0.129	-0.226	-0.001	0.065**	0.080*
	(0.462)	(0.438)	(0.262)	(0.031)	(2.419)	(1.924)
Export share	-0.146	0.019	0.040	0.053***	0.050***	0.054***
	(0.628)	(0.467)	(0.269)	(3.646)	(3.578)	(3.236)
Ln(GFCF)	-0.095	-0.064***	-0.057	0.005	0.004	0.003
	(1.211)	(4.106)	(1.107)	(1.048)	(0.773)	(0.510)
Productivity	0.033	0.002	0.003	0.003	0.006**	0.006*
	(1.292)	(0.248)	(0.186)	(0.889)	(1.988)	(1.945)
Relative skill supply		0.346***	0.348***		0.134***	0.152***
		(15.526)	(10.955)		(3.979)	(3.098)
Import weighted average GDP p/c			0.006			0.010
			(0.221)			(0.799)
Constant	-8.737	1.848	2.914	0.124	-0.794**	-1.108*
	(0.460)	(0.530)	(0.296)	(0.448)	(2.259)	(1.712)
R^2	0.214	0.972	0.926	0.979	0.982	0.980
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	98	98	98	98	98	98

Notes: This table compares the differential effects of export weighted average destination income on skill premium before and after China's WTO accession in 2001. Panel A (Columns (1)-(3)) reports regression results based on a subsample from 1995 to 2001 and Panel B (Columns (4)-(6)) reports regression results based on a subsample from 2002 to 2008. Panel C shows the OLS-FE regression results and Panel D shows the IV regression results. Instrument for export weighted average GDP per capita is defined as in Equation 4. Other variables are defined the same as in earlier tables. Robust standard errors are computed in all specifications.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Absolute t values in parentheses.

To proceed, we first calculate weighted average GDP per capita across destinations for each industry using the within-industry export share to each destination as the weight, and empirically model the relationship between that and the skill premium. To address the potential endogeneity of the export share measure, we follow Brambilla and Porto (2016) and Bastos et al. (2016) to explore the exogenous variations in exchange rates in destination countries, based on which we predict the export shares and use them as the weight to construct an instrument for the observed average destination income. The preliminary results reveal a positive relationship between average wages and average destination income, which is consistent with the findings in Brambilla and Porto (2016). More importantly, we find that industries that export more products to high-income destinations tend to have higher skill premium, resulting from higher wages for skilled than for unskilled workers. This implies that workers in developing countries with different skill levels may benefit differently from an expansion of exports to rich countries. Our main results are robust to the inclusion of additional control variables, including the relative supply of skilled workers and import share weighted average source country income. IV estimations indicate a causal link between high-income export destination and the skill premium.

Considering the high importance of processing trade in China, we distinguish ordinary export from processing export with an expectation that the positive skill premium effects of high-income exports are stronger for ordinary exports. Specifically, we calculate weighted average GDP per capita across destinations using separately ordinary export share to each destination and processing export share to each destination as the weight. The empirical results present a positive relationship between ordinary export weighted average destination income and the skill premium whereas there is a negative (though insignificant) effect for processing exports. That is, industries with an increase in the exports of processing products to high-income destinations reduce or leave unaffected the skill premium. This is perhaps not surprising given that processing production is actually simple assembly work that mainly requires low-skilled workers; an expansion of processing exports leads to an increase in the demand for low-skilled workers. This finding is important since it highlights that skilled workers benefit more from the growth of ordinary exports whereas unskilled workers may benefit more from processing exports. This may have implications for the design of industrial policies, given that ordinary and processing exports have different impacts on the relative wages of skilled and unskilled workers. Additionally, we find that the positive relationship is stronger during the post-WTO accession period when both Chinese total exports and exports to high-income destinations grew substantially.

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Appendix

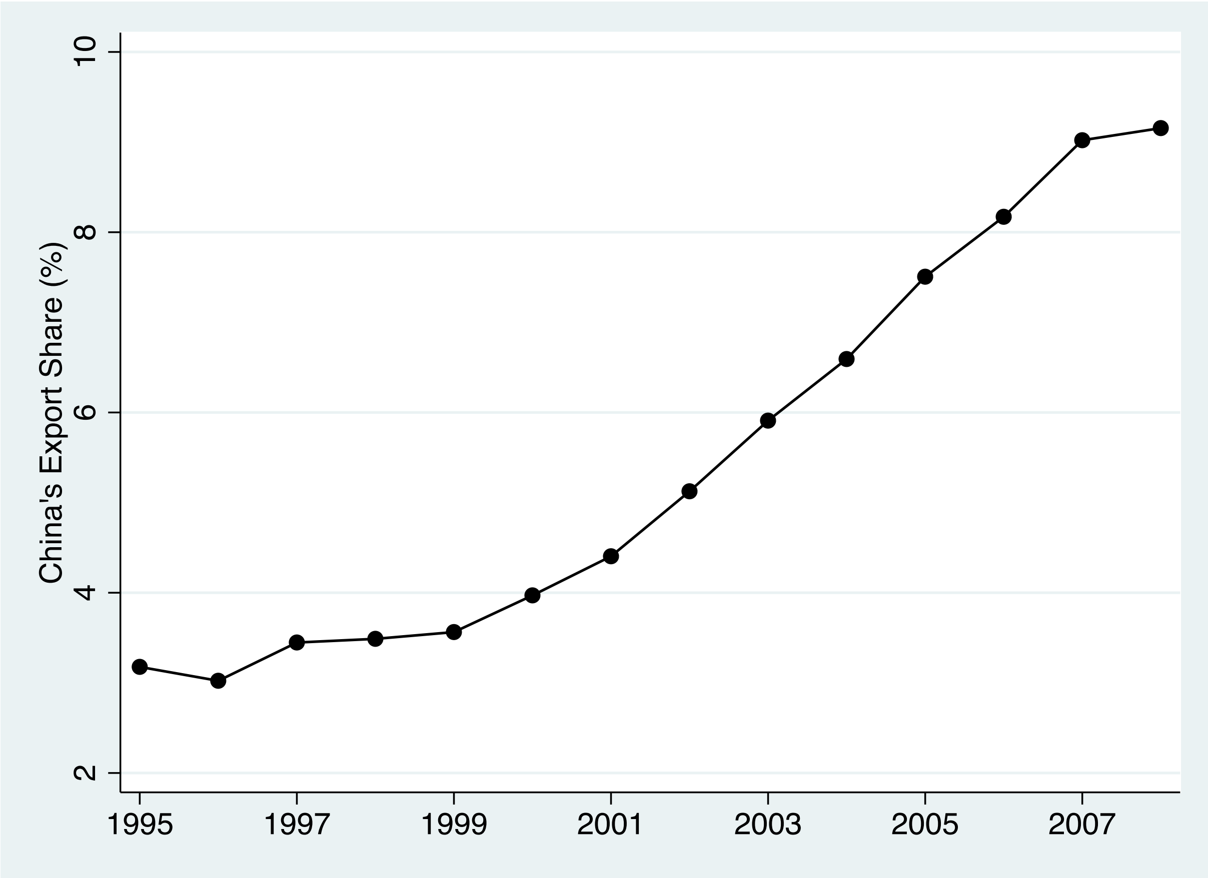

Figure A.1: Share of China's exports in world total exports (%): 1995-2008

Notes: Export data are from WITS database.

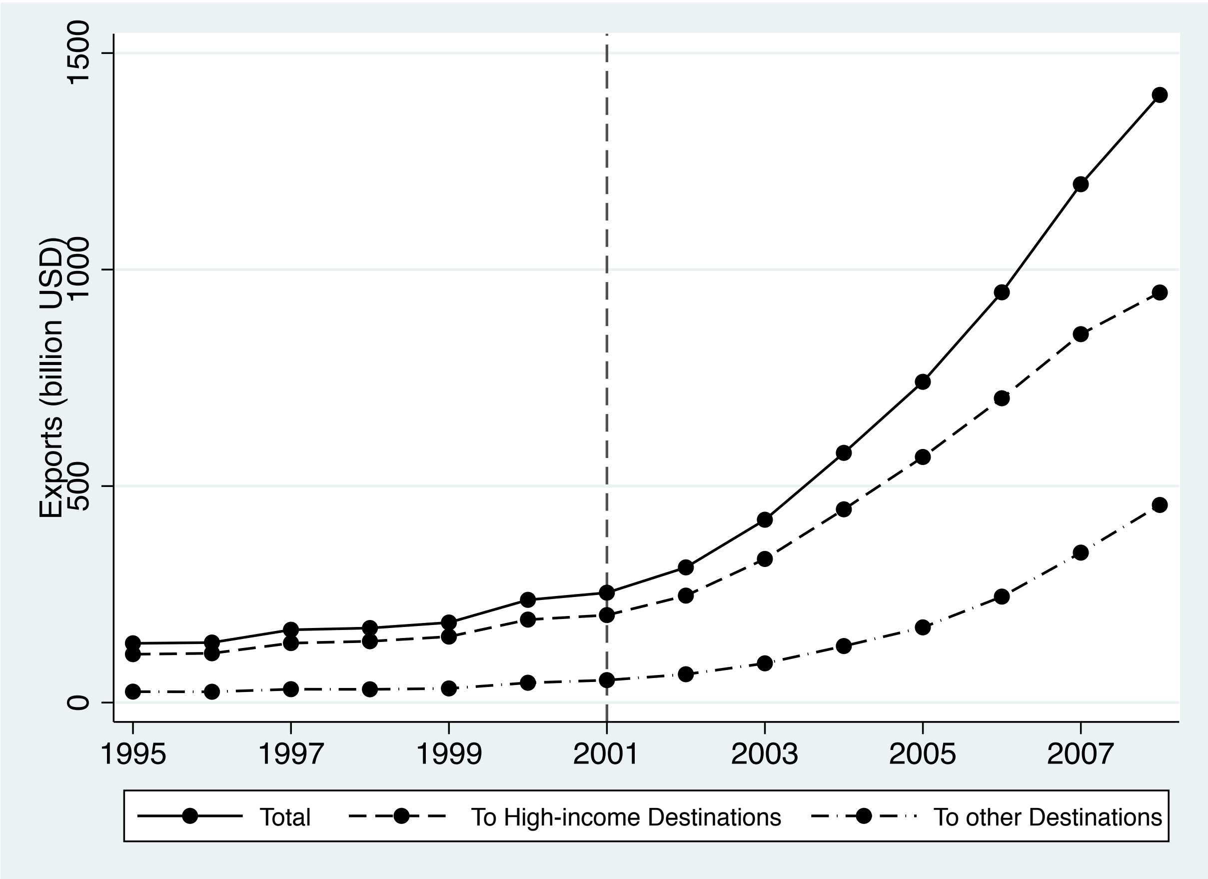

Figure A.2: China's total exports of manufacturing goods across years: 1995-2008

Notes: High-income destinations are economies that were classified as high-income ones for all years between 1995 and 2008. Exports data are from WITS database.

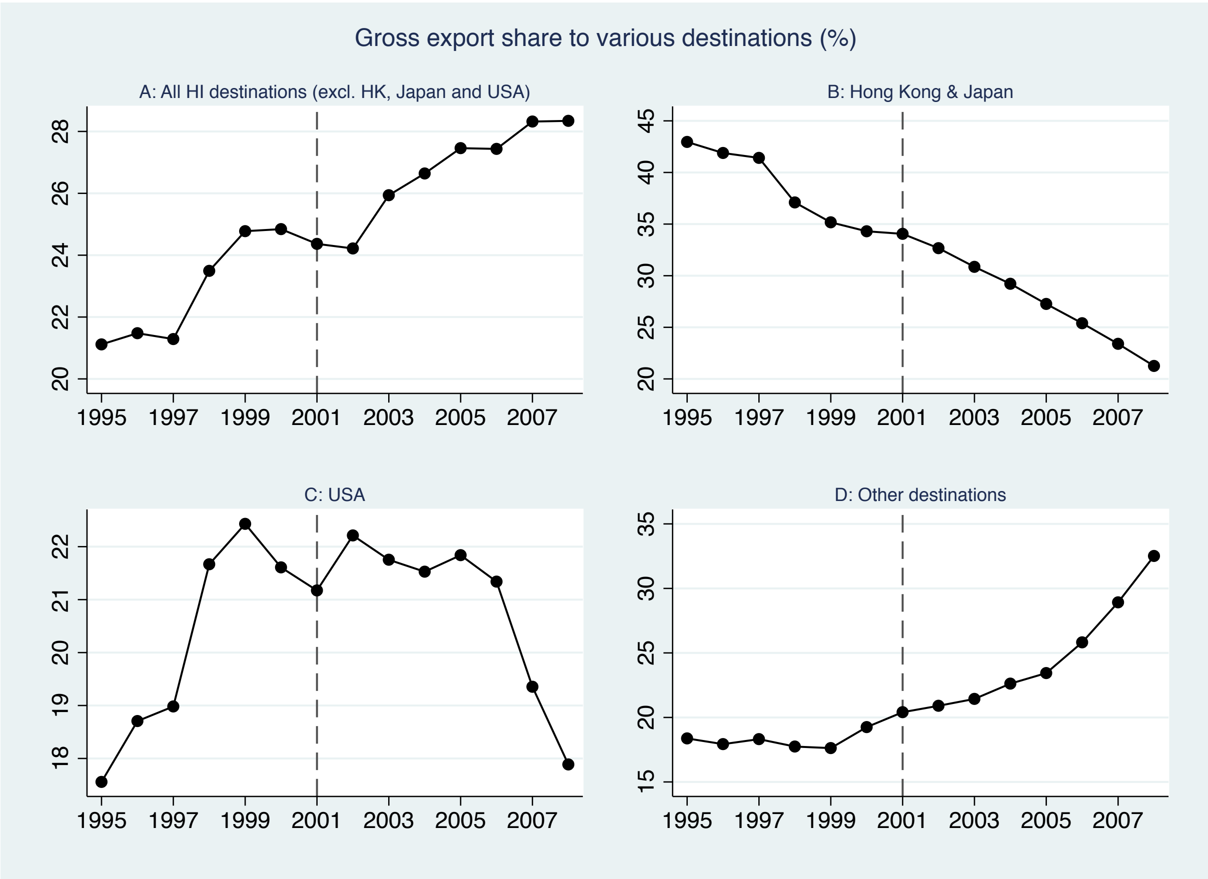

Figure A.3: Share of China's manufacturing exports to various destinations in total exports (%): 1995-2008

Notes: Figure A: Share of exports to all high-income destinations excluding Hong Kong, Japan and United States. Figure B: Share of exports to Hong Kong and Japan. Figure C: Share of exports to the U.S.A. Figure D: Share of exports to all other destinations. High-income destinations are categorised according to World Bank income group classification. Economies that were classified as high-income ones through out the sample period (1995-2008) are treated as high-income destinations.

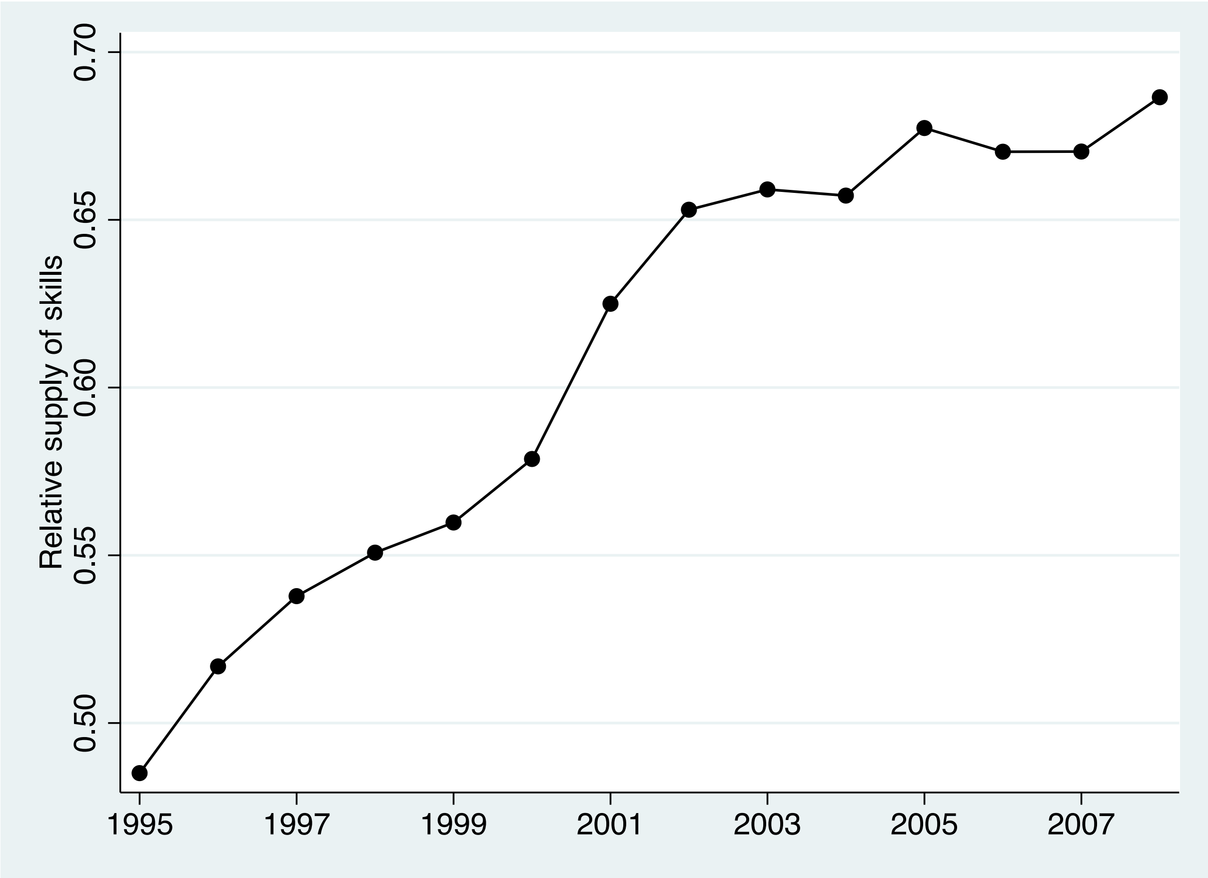

Figure A.4: Relative supply of skills: 1995-2008

Notes: Relative supply of skills is defined as the ratio of total working hours for skilled workers over total working hours for unskilled workers. Skilled workers are those with high school education or above and others are unskilled workers. Data on working hours by skill levels are from WIOD SEA database.

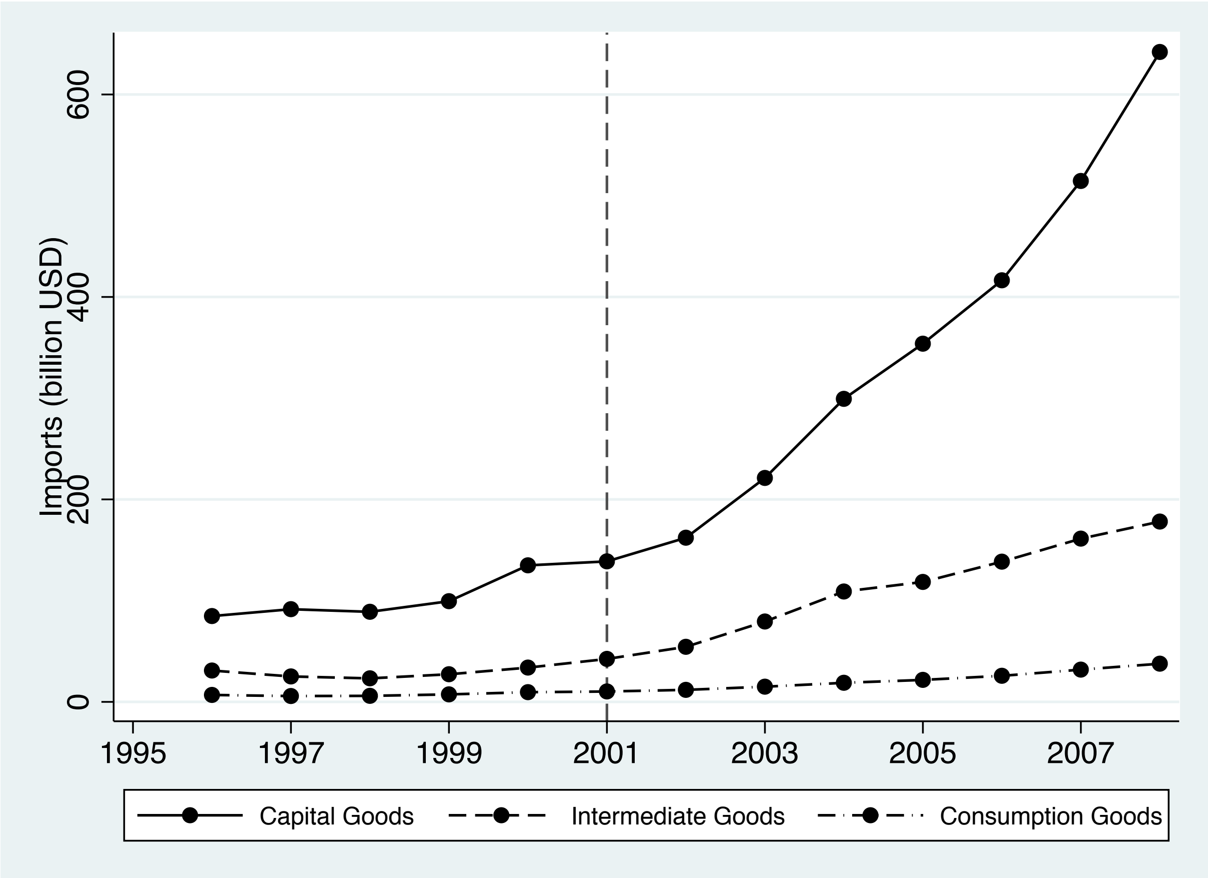

Figure A.5: China's imports of capital goods, intermediate goods and consumption goods across years: 1995-2008

Notes: Identification of capital goods, intermediate goods and consumption goods is according to United Nation Broad Economic Categories (UNBEC) classification scheme. Imports data are from WITS database.

Table A.1: Skill premium and weighted average GDP per capita across export destinations in manufacturing industries: OLS-FE regressions, 1995-2009

	(1)	(2)	(3)	(4)	(5)	(6)
Export weighted average GDP p/c	0.091***	0.091***	0.104***	0.103***	0.071***	0.078***
	(3.693)	(3.626)	(4.110)	(4.054)	(3.515)	(4.085)
Export share		0.001		0.002	-0.063**	-0.057**
		(0.029)		(0.056)	(2.495)	(2.299)
Ln(GFCF)			0.043***	0.043***	-0.021**	
			(4.639)	(4.620)	(2.204)	
Productivity					0.044***	0.040***
					(10.320)	(11.251)
Constant	-1.025***	-1.022***	-1.422***	-1.417***	-1.135***	-1.303***
	(3.409)	(3.359)	(4.368)	(4.347)	(4.435)	(5.762)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	210	210	210	210	210	210
R^2	0.904	0.904	0.909	0.909	0.942	0.941

Notes: This table shows the OLS-FE regression results of skill premium on weighted average GDP per capita across export destinations in manufacturing industries for the whole period from 1995 to 2009. Skilled workers are defined as those with high school education or above. Others are identified as unskilled workers. Export share denotes the share of total exports in gross output in each industry. GFCF denotes gross fixed capital formation. Productivity is labour productivity, calculated as real output per worker. Robust standard errors are computed in all specifications.

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Absolute t values in parentheses.

Table A.2: Wages and weighted average GDP per capita across export destinations in manufacturing industries, 1995-2008

	Dependent variable: log of average wages											
	skilled	unskilled	skilled	unskilled	skilled	unskilled	skilled	unskilled	skilled	unskilled	skilled	unskilled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Export weighted average GDP p/c	1.622***	1.515***	1.466**	1.357**	1.839***	1.724***	1.662***	1.546***	0.580**	0.505*	0.719**	0.638**
	(2.855)	(2.748)	(2.461)	(2.354)	(3.165)	(3.057)	(2.738)	(2.632)	(2.030)	(1.793)	(2.374)	(2.147)
Export share			0.501	0.508			0.579*	0.584*	-0.970***	-0.906***	-0.833***	-0.775***
			(1.269)	(1.305)			(1.723)	(1.743)	(3.868)	(3.385)	(3.288)	(2.893)
Ln(GFCF)					1.166***	1.124***	1.183***	1.141***	-0.483**	-0.461**		
					(3.790)	(3.712)	(3.787)	(3.709)	(2.138)	(2.040)		
Productivity									1.141***	1.098***	1.058***	1.018***
									(18.163)	(17.471)	(15.855)	(15.334)
Constant	-18.381***	-17.167**	-16.567**	-15.324**	-27.743***	-26.190***	-25.778***	-24.209***	-15.570***	-14.393***	-19.131***	-17.791***
	(2.652)	(2.552)	(2.287)	(2.187)	(3.577)	(3.472)	(3.217)	(3.116)	(4.067)	(3.796)	(5.498)	(5.205)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	196	196	196	196	196	196	196	196	196	196	196	196
R^2	0.885	0.886	0.886	0.887	0.896	0.898	0.897	0.899	0.967	0.966	0.965	0.964

Notes: This table shows the OLS-FE regression results of wages on export weighted average GDP per capita across export destinations in manufacturing industries. The dependent variable is the logarithm of average wages for skilled workers and for unskilled workers separately. Skilled workers are those with high school education or above and others are unskilled workers. Other variables are defined the same as in earlier tables. Robust standard errors are computed in all specifications.
* p <0.1, ** p <0.05, *** p <0.01. Absolute t values in parentheses.

Table A.3: Export share and bilateral exchange rate

Industry	3	4	5	6	7	8	9
RER	2.35e-07**	1.65e-07	2.28e-07**	6.44e-07***	3.16e-07**	-2.35e-07	1.69e-07***
	(2.110)	(1.333)	(2.545)	(2.625)	(2.303)	(0.741)	(2.906)
Obs.	2172	2289	2274	2092	2159	1644	2259
R^2	0.952	0.891	0.977	0.897	0.931	0.736	0.958
Industry	**10**	**11**	**12**	**13**	**14**	**15**	**16**
RER	4.84e-07***	1.27e-06***	8.36e-07***	5.84e-07***	1.56e-07**	1.46e-06***	1.84e-07**
	(4.046)	(4.479)	(3.418)	(5.508)	(2.549)	(6.786)	(2.349)
Obs.	2267	2254	2272	2267	2274	2226	2279
R^2	0.958	0.923	0.926	0.966	0.980	0.891	0.979

Notes: This table shows the OLS-FE regression results of Equation (3) that regresses within-industry export share to each destination on bilateral real exchange rates (RER) by industry. The title for each column is the industry code that is used in this paper. Industry names can be found in Table A.4. Year fixed effects and destination fixed effects are included and robust standard errors are computed in all specifications.

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Absolute t values in parentheses.

Table A.4: Industry classification used in this paper

Industry	ISIC rev.3 code	Industry name
3	15t16	Food, beverages and tobacco
4	17t18	Textiles and textile products
5	19	Leather, leather products and footwear
6	20	Wood and products of wood and cork
7	21t22	Pulp, paper, printing and publishing
8	23	Coke, refined petroleum and nuclear fuel
9	24	Chemicals and chemical products
10	25	Rubber and plastics
11	26	Other non-metallic mineral
12	27t28	Basic metals and fabricated metal
13	29	Machinery, not elsewhere classified
14	30t33	Electrical and optical equipment
15	34t35	Transport equipment
16	36t37	Manufacturing, not elsewhere classified; recycling