Export destination and the skill premium: Evidence from Chinese manufacturing industries

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Abstract. This paper examines the relationship between average income of export destinations and the skill premium using data of Chinese manufacturing industries 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 weights, and then link it with industry-level wages and the skill premium. We find that industries that export more to high-income destinations tend to pay a higher skill premium, suggesting that, on average, skilled workers benefit more from high-income exports than unskilled workers. Our IV estimates confirm a causal relationship, and the results are robust to various specifications. Further results based on firm-level data show consistent evidence. Our paper highlights the role of high-income destination exports in shaping the uneven distributional effects of globalization for different types of workers.

Résumé. Destination d'exportation et prime de compétence : l'exemple des industries manufacturières chinoises. Grâce à des données d'entreprises manufacturières chinoises recueillies entre 1995 et 2008, nous analysons le rapport entre le revenu moyen des destinations d'exportation et la prime de compétence. À cette fin, nous déterminons

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le PIB moyen pondéré par habitant en utilisant la part des exportations vers chaque destination comme valeur pondérale pour chaque industrie, puis le corrélons aux salaires du secteur et à la prime de compétence de la main d'œuvre. Nous constatons que les industries exportant davantage vers des destinations à revenu élevé tendent à payer une prime de compétence plus importante. De tels résultats suggèrent qu'en moyenne, les travailleurs qualifiés bénéficient davantage des exportations vers les pays à haut revenu que les travailleurs non qualifiés. Nos estimations à variables instrumentales confirment cette relation de cause à effet, et les résultats sont robustes à différentes spécifications. Des résultats additionnels, fondés sur des données d'entreprises, sont autant de preuves concluantes. Notre article souligne l'importance des destinations d'exportation à haut revenu quant à la dynamique des effets distributifs inégaux de la mondialisation pour différents types de travailleurs.

JEL classification: F14, F16, F66, J24, J31

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 liberalization 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 specialized exporting services, or with technology upgrading that is complementary with skills (Matsuyama 2007, Verhoogen 2008). While existing papers focus primarily on outcome variables like skill utilization and average wages, relatively few have studied the differential wage effects for workers with different skill levels.[1]

The main aim of this paper is to investigate the relationship between export destinations and the skill premium using Chinese manufacturing industry data from 1995 to 2008. Existing papers like Brambilla and Porto (2016) present a positive association between the income level of export destinations and average wages, whereas we are more interested in examining whether the composition of export destinations affects wages of workers with different skills differently. China provides a helpful context to explore this issue. First, as a representative middle-income developing country, China has witnessed a

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.

substantial increases in the wage gap between skilled and unskilled workers (Sheng and Yang 2017), a trend that was also observed in quite a few other developing countries (Goldberg and Pavcnik 2007). Second, during our sample period, China integrated further into the world economy, especially after 2001, when it joined the WTO. China's share in total world exports almost tripled from merely 3.2% in 1995 to 9.2% in 2008, with the total value of manufacturing exports having grown from 136.5 billion USD in 1995 to 1,398.6 billion USD in 2008. Particularly, manufacturing exports to high-income destinations increased drastically, from 118.7 billion USD to 1,038.2 billion USD during the same period, as displayed in figure A1(a) in the online appendix. In the meantime, the export share to high-income destinations shows a moderately declining trend, while export shares to middle- and low-income markets increased correspondingly (online appendix figure A1(b)). This development is due mainly to the diversification of export destinations, in particular following China's accession to the WTO. Despite the overall decreasing trend in the share of exports to high-income destinations, cross-industry variations are large. This paper exploits industry-level variations in the skill premium and high-income destination exports to examine the relationship between the two.

In theory, income levels of export destination and the skill premium can be linked through three channels. One of these channels is quality upgrading, as in Verhoogen (2008), which increases an exporting firm's demand for skilled workers to satisfy the demand for high-quality goods in richer countries and to pay these workers higher wages to sustain quality production. This, in turn, induces an increase in the skill premium. Brambilla and Porto (2016) examine this idea using country–industry-level data. They find evidence supporting the quality upgrading mechanism, that is, the quality of products is higher in industries that ship products to high-income destinations, and the production of such goods is related to higher average wages. Our paper is closely related to Brambilla and Porto (2016), but rather than exploring the effects of export destination on average wages, we distinguish differential wage effects for skilled and unskilled workers within industries. This is important for developing countries like China that face high levels of income inequality in that exporting to high-income countries tends to raise average wages, but it is likely that workers with different skill levels are affected differently.

A second possible channel linking export destination and the skill premium is the required services channel proposed by Matyasuma (2007), according to which exporting to foreign markets requires export-specific knowledge and experience that are often skill-intensive. The final channel is related to export-induced technology change. The intuition is that, with the presence of fixed technology investment costs, increased revenues from exports may motivate firms to invest more in skill-intensive technologies (Yeaple 2005, Bustos 2011). Notice that these two mechanisms do not depend on the income level of export destinations. However, if exporting to high-income destinations requires additional skills or 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 investigate whether there is a causal link between export destination and the skill premium. To this end, we calculate the weighted average GDP per capita across export destinations using the share of exports to each destination as 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. Data for the analysis are taken from the World Input−Output Database, or WIOD (Timmer et al. 2015), which provides primarily input−output tables for a sample of countries, including China. It reports industry-level data on employment, labour compensation and working hour shares for different skill levels. One identification issue of this paper is that our main explanatory variable might be endogenous if there are unobservable factors that affect both the within-industry export structure to each destination and the skill premium simultaneously. For identification, we rely on exogeneous variations in foreign import demand in the spirit of Hummels et al. (2014). The idea is that positive demand shocks in foreign markets create increased import demand for products from other countries, including those from China. This introduces exogeneous variation in export shares to different markets for Chinese firms, which we can exploit to compute the weighted average destination income as an instrument for the actual average income across destinations.

Our results show a positive correlation between average destination income and the skill premium. Such a positive correlation is stronger after China's WTO accession in 2001 than the pre-WTO accession period. Processing trade takes a sizable proportion in total trade in China (Koopman et al. 2012, Dai et al. 2016) and processing exports may affect the skill premium differently from ordinary exports. We disaggregate total exports, therefore, into ordinary and processing exports and calculate the weighted average GDP per capita across destinations using ordinary and processing export shares as weights separately. Existing studies document that processing exporters have a higher relative demand for low-skilled workers (Wang and Yu 2012, Dai et al. 2016) while at the same time exporting a large fraction to high-income markets (Koopman et al. 2012). One would expect, as a result, that processing exports to high-income destinations may not increase but rather reduce the skill premium. In line with such an expectation, our empirical results show that the strong positive association between average destination income and the skill premium holds only for ordinary exports. In contrast, industries with more processing exports to high-income destinations tend to have lower skill premia.

Using predicted export-share weighted average GDP per capita across destinations as an instrument, our IV estimation identifies a positive causal 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. By distinguishing wage for high- and low-skilled workers, we find that the positive effects on the skill premium are driven by a larger positive impact on average wages of high-skilled workers than those of low-skilled workers. Our results are robust to alternative measures of average destination income and the skill premium as well as the inclusion of important control variables like the income level of import sources and geographical distances to trade partners.

Although exporting to high-income destinations could affect the skill premium through the various channels discussed above, they all lead to an increased relative demand for skills. In this paper, we find supportive evidence of this hypothesis that high-income exports increase the relative demand for high-skilled workers without identifying the channel or channels inducing the increase.

One limitation of the WIOD is that it has a relatively broad industry classification and generates a relatively small sample. To cross-check our findings, we use firm-level data of the 2004 economic survey and match them with transaction-level customs data as an alternative, complementary data source. While the cross-sectional firm-level data do not allow us to explore time variations in exports to different destinations, the more disaggregated four-digit industry codes allow us to verify the robustness of our main findings. With rich information on firm characteristics, we are able to control for additional factors that are important in the Chinese context, such as regional differences in labour market conditions, ownership of firms, gender composition of the workforce, etc. We find consistent, robust evidence that exports to richer markets widen the wage gap between skill-intensive and low skill-intensive firms, which confirms our main findings based on industry-level data.

The contribution of this paper is threefold. First, our paper contributes to the emerging literature that documents the role of export destinations in affecting labour market outcomes. Verhoogen (2008) and Bekkers et al. (2016) propose the theoretical hypothesis that export-induced quality upgrading might lead to wage inequality. Existing empirical studies focus primarily on outcome variables such as the demand for skills (Brambilla et al. 2012, Pellandra 2015, Brambilla et al. 2019) and average wages (Brambilla and Porto 2016). By contrast, this paper adds to this set of literature by directly examining the differential wage effects of exporting destinations for skilled and unskilled workers and by providing empirical evidence of the effects of export destinations on wage inequality. Second, the existing literature discusses various potential explanations for the increasing skill premium in the developing world, such as trade in intermediate products and capital goods, skill-biased technological change and export-induced quality upgrading (Goldberg and Pavcnik 2007). While our findings in this paper are in line with these studies, we highlight the role of the composition of export markets and especially the income levels of export destinations as a new explanation to the rising skill premium. An additional novelty of this paper is the differential effects of ordinary versus processing exports on the skill premium. Existing papers find that processing exporters have lower productivity, lower average wages and a lower skill intensity (Wang and Yu 2012, Dai et al. 2016). The current paper follows this strand of the literature but focuses on a different outcome variable, namely the skill premium. Our results suggest that, while exports to high-income countries in general widen the skill premium, such effects are mitigated for industries with a higher share of processing exports.

The remainder of this paper is organized 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, the skill premium and export-weighted average GDP per capita across destinations. In section 5, we report the main regression results as well as robustness checks. Section 6 presents additional evidence based on firm-level data, and section 7 concludes.

2. Theoretical mechanisms and empirical evidence

In neoclassical trade theories with a perfect labour mobility assumption (like the Heckscher−Ohlin model), wages for workers with the same skill level should be equalized across industries and there should be an aggregate skill premium in the whole economy. As such, changes in the skill premium are determined in general equilibrium by the interplay between aggregate relative demand and supply for skills. However, with a relaxation of the perfect labour mobility assumption and allowing imperfect mobility of skilled and/or unskilled workers, the wage equalization prediction does not follow and differential skill premia could exist at the industry level. This is true particularly for developing countries, where labour mobility across industries is often costly (Artuç et al. 2010, 2015). In the China context, it is evident that there are barriers to labour mobility across sectors (Brandt et al. 2013).[2] We, therefore, allow a skill premium to exist at the industry level.[3]

The relationship between export destination and the skill premium in developing countries has received a great deal of attention in recent years.

2 One example is that access to high-skilled occupations, particularly positions in state-owned enterprises (SOEs), is restricted in China, which prohibits labour movement across sectors.

3 Galiani and Porto (2010) propose a model in which a non-competitive wage setting in the import competing sector due to the presence of unions may induce differential skill premia across industries despite perfect labour mobility. A union that aims to protect unskilled workers bargains for a fraction of industrial rents from trade protection. Then heavily protected industries are more likely to pay higher average wages for unskilled workers. With the assumption that skilled workers are paid equally across industries, it follows that a skill premium exists at the industry level.

One important channel through which variations in export destinations may affect the skill premium is quality upgrading. The idea is that firms export higher-quality products to richer markets than they sell in domestic or export to 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. In a model where firms are heterogeneous in productivity, products are differentiated in quality and consumer preferences are non-homothetic such that consumers in rich countries value the quality of products more, Verhoogen (2008) documents that exchange rate devaluations induce the most productive firms to increase their exports, upgrade quality, raise employment of high-skilled workers and pay higher wages compared with less productive firms. As a consequence, the wage gap between skilled and unskilled workers within industries widens. The author finds consistent empirical evidence that supports the theoretical predictions using Mexican manufacturing firm-level data. In a model with non-homothetic input bundles where high-quality products are skill-intensive, Bekkers et al. (2016) document that products being shipped to farther markets are of higher quality, which is in line with the shipping-the-good-apples-out or the Washington apples effect as proposed by Hummels and Skiba (2004). The production of higher-quality products requires more skilled workers and hence increases the skill premium. Demand-side effects due to non-homothetic preferences of consumers as in Verhoogen (2008) reinforce the impact on the skill premium.

A number of other papers also document the quality valuation and quality provision mechanisms. 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. Based on Portuguese firm-level data, Bastos and Silva (2010) find that the unit value, as a proxy measure of product quality, 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. Using firms' innovation activities to proxy 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.

An alternative mechanism that links export destination and the skill premium is the required services channel as in Matsuyama (2007). Reaching consumers in foreign markets requires additional services compared with selling in the domestic market, such as marketing research and communicating with foreign clients, which induces a greater use of skilled workers who are specialized in international business, foreign languages, etc. These required services could differ by export destination because countries are differentiated by geographic location, culture, business models, etc. Employing firm and customs data for Argentinean manufacturing firms, Brambilla et al. (2012) directly relate variations in export destinations with the utilization of skills and examine both the quality upgrading and the required services channels. 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 services mechanisms. Similar findings are present using Chilean firm-level data (Brambilla et al. 2019). These results suggest that the skill premium may rise if wage growth for skilled workers is higher than for low-skilled ones because required services induced an increase in the demand of skilled workers.

Export-induced technology upgrading is another channel that could explain the relationship between high-income destination exports and the skill premium. This channel is built on the idea that firms make higher revenues from expanded exports, which in turn incentivises them to upgrade their technology in favour of high-skilled workers (Yeaple 2005, Bustos 2011). For Argentinean manufacturing firms, Bustos (2011) finds that firms were more likely to enter the export market and to upgrade technology in response to the reduction in Brazil's tariffs. Notice that this channel emphasises the importance of export per se other than variations in exporting destinations. If exporting to richer countries is more profitable because firms charge higher prices in those markets as in Manova and Zhang (2012), the income level of export destination matters. In other words, firms that export to high-income destinations have stronger incentives to invest in skill-intensive technologies due to higher profits, which increases the demand for skilled labour and hence the skill premium.

Empirical evidence that supports the association between export destination and the skill premium is also provided by a few other papers. Using a matched employer−employee data set of South Africa, Rankin and Schöer (2013) examine the relationship between export destinations and average wages for workers with different skill levels. Empirical results show that firms that export to Southern African Development Community (SADC) countries that are poorer than South Africa pay relatively lower average wages and skill premia, whereas firms exporting to EU and NAFTA destinations pay higher average wages and skill premia than non-exporters, which is consistent with the findings of Verhoogen (2008) and Brambilla et al. (2012). Pellandra (2015) explores the wage effects of exporting to high-income destinations 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. Brambilla and Porto (2016) use manufacturing industry-level data of 82 countries and examine the relationship between exporting to high-income destinations and average industrial wages. They find a positive link between the two and find evidence that supports the quality evaluation and quality provision mechanism, as in Verhoogen (2008). These existing studies focus primarily on either the effects of high-income exports on other labour market outcomes such as the use of skills and average wages or the effects of exports per se on the skill premium. This paper, however, can be distinguished from them because it explicitly investigates the differential effects of exports to high-income countries on wages for skilled and unskilled workers.

Our paper is related to several studies that document the effects of trade openness on the demand for skills and skill premium in China. Sheng and Yang (2017) propose that FDI offshoring is more skill-intensive than arm's length offshoring. Using household survey data and customs data, they exploit China's ownership liberalization that relaxed entry barriers to foreign investment and find that one third of the rise in the college wage premium in China's manufacturing industries could be explained by FDI offshoring. Li (2018) studies export expansion and skill accumulation in China using a local labour market approach. She finds that cities initially specializing in high skill-intensive production experienced an increase in both college and high school enrolments with export expansion relative to the initially less skill-intensive cities. Chen et al. (2017) explain the skill premium from the perspective of input trade liberalization. Without information on wages for high- and low-skilled workers within firms, they first estimate the skill premium and then link it to tariff rate reductions following China's accession to the WTO. They find robust evidence that a decrease in input tariffs increases the skill premium within firms. Li et al. (2020) and Li (2020) highlight the importance of capital goods imports in shaping the demand for skills. Based on the assumption of the capital−skill complementarity, they both find that regions exposed to more capital goods imports tend to have a higher demand for skills and thereby pay higher skill premia. While these papers try to explain the rising skill premium in China from various perspectives of international trade, none of them discusses the role of export destination. This paper contributes to this strand of literature by examining a new channel through which trade openness induces the rise in skill premium.

3. Empirical strategy

3.1. 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 this relationship and then discuss potential identification issues.

Our main estimation approach takes the following form:

$$sp_{it} = \alpha + \beta wagdppc_{it} + \boldsymbol{X}_{it}\boldsymbol{\Gamma} + \theta_i + \theta_t + \varepsilon_{it}, \tag{1}$$

where i indexes industry and t indexes year. The dependent variable sp_{it} is the skill premium defined as the log 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_i and θ_t are industry and year fixed effects that control respectively for time-invariant industry specific factors and for the potential effects of common shocks to all industries across years. ε_{it} is a mean-zero error term. We compute Huber−White robust standard errors to account for possible heteroscedasticity. The main coefficient of interest, β, captures the extent to which the skill premium varies according to changes in average income in export destinations.

Following Brambilla and Porto (2016), we define export destination income as weighted average GDP per capita across export markets using within-industry export shares to each destination as weights:

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

where i, d and t denote industry, destination market and year, respectively. $gdppc_{d,1995}$ is real GDP per capita of destination d in 1995, the first year of our sample, and $expsh_{idt}$ is the export share to destination d in total industrial exports in year t, which captures the composition effects of exports within industries. To avoid possible endogeneity issues with contemporaneous income (Brambilla and Porto 2016, Bastos et al. 2018), we use GDP per capita in the initial year, allowing us to treat GDP per capita as a predetermined characteristic. As such, variations in weighted average GDP per capita across time are attributed primarily 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.

3.2. Identification issues

Equation (1) attempts to establish a link between the industrial skill premium and the income level of export destinations. Although the export-share weighted average GDP per capita is constructed in a manner that seeks to avoid or reduce possible endogeneity by using initial income levels, export shares to different destinations may still not be exogenously determined even after controlling for various covariates. If there are unobserved factors that affect both the destination composition of exports within industries and the skill premium simultaneously, failing to control for them would create omitted variable bias. Unobserved positive productivity shocks due to, for instance, technology upgrading could raise the probability of exporting to high-income destinations as well as the skill premium and could therefore create upward biases. There are many unobserved factors that are specific to the Chinese context, which may, however, lead to a downward bias over our sample period. One of these factors is that a large fraction of Chinese exports can be classified as processing exports, which require low levels of skills and involve simple assembly of imported parts into final goods (Wang and Yu 2012, Dai et al. 2016). The increasing proportion of processing exports during our sample period contributed to a rising demand for unskilled labour, which imposed upward pressure on their wages. Moreover, processing exports are more likely to be shipped to richer markets (Wang and Yu 2012, Koopman et al. 2012), which means that a failure to account for different levels of processing trade in an industry for the whole sample period will downward bias the OLS−FE results.[4] Institutions and reforms in China could also bias the OLS estimates downwards. Since the end of the 1990s, China underwent large-scale privatization reforms, which resulted in a continuous decline in state-owned enterprises (SOEs) and generated significant variations in the SOE share across industries. SOEs often receive production subsidies and enjoy policy benefits including export-promoting ones, such that industries with a higher proportion of SOEs are likely to export more (Eckaus 2006, Girma et al. 2009) and to outperform other firms in terms of both export volumes and the number of export destinations (Manova and Zhang 2009). In addition, the SOE sector often pays lower skill premia than the private sector (Démurger et al. 2012, Whalley and Xing 2016). As such, omitting the ownership structure within industries is likely to create downward biases in the OLS−FE estimate.

An additional source of endogeneity is the potential measurement errors in the export share across destinations that could create the typical attenuation bias. For example, changes in export shares could be driven by variations in exchange rates since export values are expressed in local currency and are subsequently transformed to renminbi at the annual average, official exchange rate of the foreign currency. Actual export transactions may not be at the official exchange rate (especially when exports are invoiced in a variety of currencies). Further, exchange rates may well vary over each year, as may the amount of exporting by each industry to a specific market. The annual, average exchange rate across all transactions may not be the same as that experienced by a specific industry. A final source of endogeneity is reverse causality in that firms that pay a higher wage premium and that employ a higher share of skilled workers may produce better quality products and therefore have an increased probability to export to high-income destinations.

To deal with the endogeneity of export shares across destinations and to explore the causal relationship between export destinations and the skill premium, we estimate equation (1) using an instrumental variables (IV) approach. An ideal instrumental variable would explain variations in average income levels of export destinations but would not be correlated with the unobserved confounding factors as discussed above nor with the skill premium directly. Our strategy is to use an instrument that can explain exogeneous changes in the industry's export shares to high-income destinations

4 Our data allow for a distinction between processing and ordinary exports only from 2001 onwards.

and hence is able to explain patterns in trade. In the spirit of Hummels et al. (2014), we construct an instrument from exogenous variations in import demand across foreign markets and use it to predict China's export share to each destination.[5] The intuition is that if country d demands more products from other markets following positive demand shocks, import demand from China should also rise. As such, variations in the predicted export share to destination d are not driven by China's export supply growth but are rather due to global import demand, which is exogenous to Chinese industries as well as the skill premium. In addition, exogeneous demand/income shocks could affect demand for quality. The predicted export shares from exogeneous demand shocks can thereby explain the skill premium well.

To compute predicted export shares, we first calculate world total import demand of products in sector i minus imports from China and the import share of each country within total imports aggregated from the bilateral trade data at the HS6 level obtained from the World Integrated Trade Solution (WITS) database (World Bank 2016b). We then predict China's export share to each destination using the import share of each country from the world other than China. The predicted export share to each destination is estimated by the following equation for each industry separately:

$$expsh_{idt}^{C\rightarrow d} = \alpha_0 + \delta\, impsh_{idt}^{d\leftarrow world} + \varphi_d + \varphi_t + v_{idt}, \tag{3}$$

where $expsh_{idt}^{C\rightarrow d}$ denotes China's export share to destination d in total exports of industry i in year t and $impsh_{idt}^{d\leftarrow world}$ denotes country d's import share in world total imports of products belonging to industry i minus imports from China. φ_d and φ_t are respectively destination and year fixed effects capturing time-invariant destination-specific effects and common shocks to all destinations across years. v_{idt} is the error term. An increase in country d's import share suggests a relative rise in import demand and is expected to lead to a higher share of Chinese products being shipped to that destination. We therefore expect δ to be positive.

Using the predicted export share to each destination, $\widehat{expsh}_{idt}$, we then calculate the instrument for $wagdppc$ as follows:

$$\widehat{wagdppc}_{it} = ln\left(\sum_d \widehat{expsh}_{idt} \times gdppc_{d,1995}\right) \tag{4}$$

Finally, we estimate equation (1) using $\widehat{wagdppc}_{it}$ as the instrument for $wagdppc_{it}$.[6]

5 Hummels et al. (2014) explore the effects of offshoring and exporting on wages using Danish matched employer-employee data set. The authors use world import demand minus imports from Denmark as an instrument for firm's exports.

6 We also consider an alternative instrumental variable that uses bilateral exchange rates to predict the export share to each destination, which has been

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 primary data source on wages and the skill premium in this study is the Socio Economic Accounts (SEA) from WIOD. WIOD is a database that provides input–output tables from 1995 to 2011 for 40 countries based on various sources of officially released data, and China is one of those countries.[7] As one part of the WIOD, SEA provides industry-level data on employment, capital stock, 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, the shares of labour compensation and working hours for high-skilled, medium-skilled and low-skilled workers, which makes it possible to calculate average hourly labour compensation for each type of worker and to calculate the wage gap between high- and low-skilled workers accordingly.

Strictly speaking, precise measures of the skill premium require detailed individual-level data that allow one to estimate the wage difference between high- and low-skilled workers controlling for other worker characteristics. With such data not being readily available, we rely on industry-level information on labour compensation by skill level provided by the SEA database and approximate the skill premium with the average wage gap between high- and low-skilled workers within industries. The skill premium measure in this paper could be interpreted as an unconditional measure of wage differentials between workers with different skill levels. For China, industry-level data on employment, labour compensation, working hours, etc. are available from 1995 to 2009 from this source.[8] 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 Statistical Yearbook and China Labour Statistical Yearbook, and census data like industrial censuses and economic censuses as

used in the literature (e.g., Brambilla and Porto 2016, Bastos et al. 2018). The 2SLS estimates are similar to our main results but are imprecisely estimated due to weak instrument problems.

7 All WIOD data sets are available from `www.wiod.org`. An updated version of the data set expands the coverage to year 2014 and to 43 countries. However, the updated data set does not report data on shares of labour compensation and total working hours by skill level, which are the main data that we use to measure skill premium. We therefore stick to the earlier version of the data set. A user guide of this database is available from Timmer et al. (2015).

8 The industrial skill premium in 2009 is the same as in 2008, which is assumed by the data source, so that we restrict our sample to the years 1995 to 2008 in the main discussion.

well as individual-level data from China Household Income Project surveys.[9] The skill classification is based on the individual's educational attainment, that is, low-skilled workers are those with a middle school education or below, medium-skilled workers are those with a high school education and/or a technical secondary school education and high-skilled workers are those with a college education or above. In the later stage of the discussion, we translate these three skill groups into skilled and unskilled workers. In particular, skilled workers include high-skilled and medium-skilled ones and unskilled workers are low-skilled ones. Average hourly wages for skilled and unskilled workers are computed as the ratio of total labour compensation over total working hours for these two groups, respectively. The skill premium is thus defined as the log 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 of goods are excluded from this study. Note that the main mechanism linking export destinations 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 as agriculture, mining and quarrying and water, electricity and gas supply—the main exporting products of which are raw materials and natural resources. Therefore, we constrain our discussion to manufacturing industries throughout the paper, with a sample of 14 industries spanning 1995 to 2008. Table A1 in the online appendix shows details of the 14 industries.

Information on other industry-level characteristics is also taken from WIOD. Those data include industrial exports, gross output, gross fixed capital formation 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 are required. These data are obtained from the WITS database at the three-digit level of the International Standard Industrial Classification (ISIC) Rev. 3. To combine this source with wage data, we aggregate the three-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 taken from the World Bank Indicator Database (World Bank 2016a).[10]

9 For more details, see the WIOD SEA documents from `www.wiod.org/publications/source_docs/SEA_Sources.pdf`.

10 `http://databank.worldbank.org/data`. Taiwan is an important export destination of mainland Chinese firms, whereas its data are not available from the World Bank Indicator Database. For the purpose of completeness, data on

One important feature of China's exports is the high proportion of processing exports, which accounts for over 50% in total exports (Koopman et al. 2012). In particular, industries with a high proportion of processing exports are those that are often considered as relatively technologically sophisticated, such as machinery and equipment (Amiti and Freund 2010, Koopman et al. 2012). However, processing production is the 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 effects as strong as exports of ordinary goods on the skill premium. Moreover, Chinese firms that are engaged purely in processing exports tend to be less productive and less skill-intensive, which may further exert downward pressure on the skill premium compared with firms engaged in non-processing exports (Dai et al. 2016). To distinguish potentially different effects of ordinary and processing exports, we calculate the within-industry processing and ordinary export shares to various destinations, which are then utilized as weights to compute weighted average GDP per capita separately. Data on processing and ordinary exports are available at the four-digit HS level between 2001 and 2008 from the DRCNET Statistical Database (DRC 2016), an official database of Development Research Center of the State Council of China.[11]

Table A1 in the online appendix provides summary statistics on the skill premium and export-weighted average GDP per capita from 1995 to 2008, i.e., the entire period of this study. It shows that the average skill premium (in natural logarithm) for manufacturing industries increased continuously from 0.088 in 1995 to 0.198 in 2008. Export-weighted average GDP per capita, however, fluctuated between 194,700 and 200,900 RMB before 2001 and decreased afterwards from 197,100 in 2001 to 136,000 in 2008. Such a reduction is due mainly to the diversification of China's exporting destinations following WTO accession: Chinese products were shipped to relatively fewer markets before 2002, whereas after its accession to the WTO, the portfolio of export destinations was expanded with many of the new destinations being middle- or low-income ones.[12] As such, the share of exports shipped to middle- and low-income destinations gradually increased, as shown in figure A1 in the online appendix.

Taiwan are collected from various issues of Taiwan Statistical Data Book (NS 2016).

11 To calculate processing/ordinary export shares to each destination within industries, we classify four-digit HS level data into industry level combining six-digit HS level export data from WITS database and relevant concordance tables.

12 China exported to an average of 180.9 destinations between 1995–2001 and 186.6 destinations between 2002–2008.

TABLE 1

Descriptive statistics of high-income destination exports by industry: 1995−2008

	Panel A: Share of high-income destinations (%)			Panel B: Export share to high-income destinations (%)		
Industry	1995−2008	1995−2001	2002−2008	1995−2008	1995−2001	2002−2008
3	25.6	26.3	24.9	84.4	85.6	83.2
4	25.2	25.4	25.1	80.2	86.3	74.1
5	25.3	25.6	25.1	83.2	88.0	78.4
6	26.9	28.6	25.3	93.9	97.2	90.5
7	25.4	26.0	24.7	86.0	88.6	83.4
8	29.2	30.7	27.8	64.1	64.9	63.2
9	24.9	25.2	24.7	72.8	76.9	68.6
10	25.1	25.3	25.0	84.2	89.3	79.1
11	25.1	25.5	24.7	77.9	81.6	74.2
12	25.2	25.3	25.0	80.9	84.1	77.7
13	25.0	25.0	25.1	76.0	77.4	74.5
14	25.1	25.0	25.1	88.6	90.5	86.6
15	25.4	26.0	24.8	75.4	77.5	73.4
16	25.4	25.6	25.1	92.4	94.2	90.6
Average	25.6	26.1	25.2	81.4	84.4	78.4

NOTES: Panel A shows the share of high-income destinations in total number of exporting destinations. Panel B shows the export share to high-income destinations in total export value. Both statistics are calculated based on data obtained from the WITS database. A country is identified as a high-income destination if the 1995 per capita GDP is above the 75th percentile.

Table 1 presents additional descriptive statistics about high-income destination exports by industry. Panel A shows that the average share of high-income destinations in the total number of exporting markets decreased from 26.1% pre-WTO accession to 25.2% post-WTO accession, with 12 out of 14 industries experiencing a reduction in the share. This suggests that a diversification of exporting markets took place after WTO accession. Meanwhile, the average export share to high-income markets decreased from 84.4% to 78.4% during the same periods, as shown in panel B. However, variations across industries are large: skill-intensive industries such as industry 13 ("Machinery, not elsewhere classified") and 15 ("Transport equipment") experienced a relatively smaller reduction. The different patterns of high-income exports and weighted average GDP per capita before and after 2001 motivate us to explore the possible differences in the pre- and post-WTO accession periods.

The time series of the average skill premium and export-weighted GDP per capita in table A1 of the online appendix do not seem to be systematically related. This could be because simple averages across industries hide variations in relative wages and in weighted average GDP per capita across industries. As shown in table 1, there are large variations in high-income market exports across industries. In figure 1, we display changes in the industrial skill premium against changes in weighted average GDP per capita across export destinations by industry between 1995 and 2008. All industries

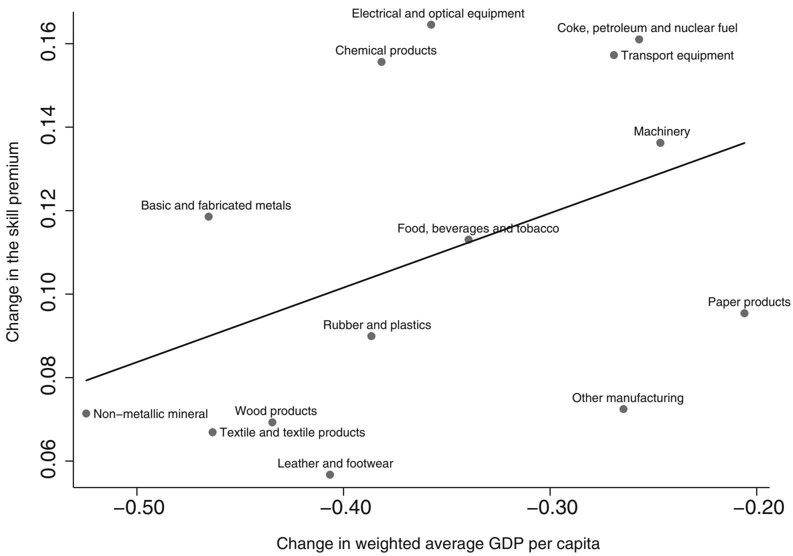

FIGURE 1 Changes in skill premium and in weighted average destination GDP per capita in manufacturing industries between 1995 and 2008

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

observed a reduction in weighted average GDP per capita across export destinations, the same as the overall trend in online appendix table A1. More importantly, industries with lower reductions in weighted average GDP per capita, such as machinery, transport equipment and coke, petroleum and nuclear fuel, 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 supportive evidence of a potential positive relationship between average destination income and the skill premium. Distinguishing between the two periods pre- and post-WTO accession, we observe a similar positive correlation only post-WTO accession, as shown in figure A2 in the online appendix. This provides suggestive evidence that the positive relationship between average destination income and the skill premium may be driven mainly by the post-WTO accession period. We formally explore this possibility in the next section.

5. Skill premium and average export destination income: Empirical results

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

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)
Average destination GDP per capita	0.107***	0.109***	0.115***	0.116***	0.075***	0.081***
	(0.027)	(0.028)	(0.028)	(0.029)	(0.021)	(0.021)
Export share		−0.008		−0.005	−0.064**	−0.058**
		(0.029)		(0.029)	(0.025)	(0.024)
Gross fixed capital formation (log)			0.042***	0.042***	−0.022**	
			(0.010)	(0.010)	(0.010)	
Productivity					0.044***	0.040***
					(0.004)	(0.004)
Constant	−1.215***	−1.243***	−1.552***	−1.569***	−1.177***	−1.340***
	(0.327)	(0.338)	(0.354)	(0.361)	(0.266)	(0.241)
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 results of OLS–FE regressions of the 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; all others are identified as unskilled workers. The export share denotes the share of total exports in gross output in each industry. Gross fixed capital formation is in log form. Productivity is labour productivity, calculated as the log of real output per worker. Robust standard errors are in parentheses. $^{*}p<0.1$. $^{**}p<0.05$. $^{***}p<0.01$.

the endogeneity issues, check the robustness of the relationship and, finally, provide empirical evidence on the main theoretical mechanism.

5.1. Baseline results

Table 2 reports the baseline fixed effects regression results. In column (1), we present the relationship between the 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 the Asian financial crisis in 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 that changed its mix of export destinations such that the average income of their export destinations was raised by 10% is found on average to have 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 and in non-exporting firms. Wage adjustments in non-exporting firms must be indirect via the effects on exporting firms. However, the export share used to calculate the weighted average GDP per capita captures only the composition of export destinations within industries but does not account for scale effects, that is, differences in the degree of exposure to exports across industries. For example, an industry with a high share of exports to the US but a low total export value would observe a high level of average destination income; but we would not expect strong effects on wages due to the relatively low exposure to exports. To control for 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 liberalization and the industrial wage premium in Colombia and India, respectively, we include industry-level capital as an additional control variable, measured as the log of real gross fixed capital formation.

Regression results for the extended specifications are shown in columns (2) to (4) of table 2. 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 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 with the basic result in column (1) and stay highly significant, indicating that the association between the skill premium and weighted average income is robust to the inclusion of these two controls.

Another 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 log of 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 log of gross fixed capital formation that changes from positive to negative. Given that more capital-intensive industries are often more productive ones, we leave out gross fixed capital formation in column (6), but the main result does not vary much. In later discussions, we report results of our preferred specification as in column (4).[13] Results based on the alternative specification as in column (6) are quite similar.

China joined the WTO in December 2001, following which export destinations expanded and export values increased substantially. As shown in table 1 and figure A2, variations in the export destination composition and in weighted average destination income tend to be larger across

13 The choice of the specification in column (4) as our preferred one is also due to the concern that the specification in column (6) has a weak instrument problem as we will show later.

TABLE 3

Skill premium and weighted average GDP per capita across export destinations in manufacturing industries: Heterogeneity of the results

	1995–2001 (1)	2002–2008 (2)	Ordinary exports (3)	Processing exports (4)
Average destination GDP per capita	0.021	0.024**	0.012*	−0.004
	(0.046)	(0.011)	(0.007)	(0.006)
Export share	0.036	0.053***	0.060***	0.055***
	(0.076)	(0.016)	(0.017)	(0.017)
Gross fixed capital formation (log)	0.104***	0.009**	0.009**	0.008**
	(0.012)	(0.004)	(0.004)	(0.004)
Constant	−0.775	−0.166	−0.024	0.177**
	(0.522)	(0.140)	(0.090)	(0.082)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	98	98	98	98
R^2	0.820	0.980	0.980	0.979

NOTES: This table shows regression results that distinguish between periods before and after the WTO accession (columns (1) and (2)) and between ordinary exports and processing exports (columns (3) and (4)). Average destination GDP per capita in columns (3) and (4) is calculated using the share of ordinary exports and processing exports to each destination within industries as weights, respectively. Regressions in columns (3) and (4) are based on the sample from 2002 to 2008 because of data constraints. Robust standard errors are in parentheses. $^{*}p<0.1$. $^{**}p<0.05$. $^{***}p<0.01$.

industries post-WTO accession. One may expect the impact of high-income destination exports on the skill premium to be stronger in the post-WTO accession period. To examine such a possibility, we split the sample into two subperiods—pre- and post-WTO accession—and run regressions separately. The regression results are presented in columns (1) and (2) of table 3.

The regression results show that the estimated coefficients on weighted average GDP per capita remain positive for both subperiods but are significant only in the post-WTO accession period. These results show that the positive relationship between high-income exports and the skill premium documented in table 2 is driven mainly by the period after China's accession to the WTO, a period that witnessed more diversification of its exports by destination.

A distinctive feature of China's exports is the high share of processing exports. 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. Wang and Yu (2012) and Dai et al. (2016) find that Chinese processing firms tend to be less skill-intensive. Hence, we do not expect processing exports to have a sizeable impact on the demand for skilled labour, but rather contribute to a rising demand for unskilled workers and consequently to a reduction in the skill premium. This does not comply with the quality provision channel discussed earlier. However, notice that processing exports still require certain export-specific services as in Matsuyama (2007). If exporting to high-income destinations involves a higher demand for workers with certain skills (e.g., foreign language skills, knowledge of foreign business models, etc.), destination income levels could still affect the skill premium through the required services channel.

Carefully looking into the industrial structure of processing production shows that industries with a high share of processing imports and exports are those that are often regarded as relatively skill-intensive and more technologically sophisticated, like machinery and equipment. We would expect a more rapid upgrading of technology in these industries and a higher utilization of skills (Amiti and Freund 2010, Koopman et al. 2012). Indeed, those imported intermediate inputs generally come from high-income economies like the US and Japan, and, accordingly, processing exports are transported back mostly to those destinations. With the presence of processing exports, the total export-weighted average destination income may not capture well the quality upgrading or technology effects since a large share of processing exports to high-income countries contributes much to the weighted average income but does not really have a sizeable impact on skill utilization and on the skill premium. To address this issue, we collect data on ordinary exports and processing exports, 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 available to us only for the years between 2001 and 2008. According to the results in columns (1) and (2), we constrain our sample to the post-WTO period (2002−2008), but our results are rather similar when 2001 is included.

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, and the results are reported in columns (3) and (4) in table 3. The estimate of the ordinary export-weighted destination GDP per capita is positive and significant at the 10% level, whereas processing exports to high-income countries appear to be negatively correlated with the skill premium, albeit with an insignificant coefficient. The differential results based on ordinary and processing exports suggest that an industry with more exports of ordinary goods to high-income destinations tends to have a higher skill premium, whereas a rise in the exports of processing goods to high-income destinations tends to be associated with a lower skill premium. Such differential results, especially the absence of an effect of processing exports on the skill premium, also provide suggestive evidence that is consistent with the quality provision channel rather than the required services channel.

Overall, our baseline results show that industries exporting more to high-income destinations tend to pay a higher skill premium. Such a positive relationship is driven mainly by the post-WTO accession period and by ordinary exports.

5.2. IV estimates

Due to the potential endogeneity of the weighted average destination income, we need to consider whether we should interpret the results in table 2 as correlations rather than causal effects. To check whether the positive relationship between weighted average destination income and the skill premium is a causal one, we estimate equation (1) with an instrumental variable approach. 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 foreign import demand. Specifically, we run regressions for each industry separately, and the regression results are reported in table A3 in the online appendix. Conditional on year fixed effects and destination fixed effects, the estimated coefficient on foreign import demand is positive and highly significant for 12 out of 14 industries. This implies that an increase in foreign import demand from the world other than China is associated with a rise in the share of China's exports to that destination. This significant correlation between the instrument and the export share is important in that it provides support for the statistical validity of our instrumental variable. Using the predicted export share to each destination, we then recalculate the predicted weighted average GDP per capita for each industry and use it as an instrument for our main regressor to estimate equation (1) utilizing the two-stage least squares (2SLS) approach.

Table 4 reports the 2SLS estimation results. Specifically, columns (1) to (6) correspond to various specifications controlling for alternative sets of additional variables as in table 2. The first-stage regression results, as shown in panel A, present a consistent and significantly positive correlation between our instrument and the endogenous regressor across specifications. To check formally on the strength of the instrument, we report at the bottom of table 4 the effective first-stage F-statistic of Montiel Olea and Pflueger (2013). It tests the null hypothesis of weak instruments for 2SLS regressions with one single endogenous variable, as in our case, and is valid with heteroscedasticity, autocorrelation, and clustered standard errors. The first-stage F-statistic is above 10 in most cases except columns (5) and (6) where the F-statistic is slightly lower than 10, indicating that our instrumental variable is generally reliable to precisely estimate the causal effects of high-income destination exports on the skill premium.

The second-stage regression, as shown in panel B, shows that the coefficient of the weighted average destination GDP per capita is significantly positive and is robust to the inclusion of various control variables. Since the first-stage F-statistic in columns (5) and (6) is lower than 10, we also report

TABLE 4

Skill premium and weighted average GDP per capita across export destinations in manufacturing industries: 2SLS regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First-stage results						
Predicted average GDP per capita	0.329***	0.337***	0.328***	0.336***	0.302***	0.322***
	(0.098)	(0.099)	(0.097)	(0.098)	(0.107)	(0.105)
Panel B: Second-stage results						
Average destination GDP per capita	0.348***	0.342***	0.352***	0.347***	0.219***	0.222***
	(0.120)	(0.118)	(0.117)	(0.116)	(0.084)	(0.079)
Export share		−0.061		−0.056	−0.086***	−0.085***
		(0.038)		(0.038)	(0.027)	(0.028)
Gross fixed capital formation (log)			0.057***	0.054***	−0.005	
			(0.015)	(0.014)	(0.014)	
Productivity					0.037***	0.036***
					(0.006)	(0.004)
Constant	−4.205***	−4.126***	−4.637***	−4.540***	−2.990***	−3.061***
	(1.476)	(1.456)	(1.495)	(1.469)	(1.065)	(0.955)
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	0.845	0.853	0.852	0.859	0.923	0.922
Montiel−Pflueger effective F-statistics	11.363	11.717	11.335	11.676	7.941	9.393
Anderson−Rubin Wald test F-statistics	20.054	20.843	22.180	23.385	12.714	14.688
Anderson−Rubin Wald test p-values	0.000	0.000	0.000	0.000	0.000	0.000

NOTES: This table shows the 2SLS regression results using predicted average GDP per capita as the instrumental variable. Predicted average GDP per capita is calculated using world import demand predicted export share as weights. Panel A shows the first-stage regression results and panel B shows the second-stage regression results. The first-stage regressions control for the same control variables as in panel B. The instrument for weighted average GDP per capita is defined as in equation (4). All other variables are defined the same as in table 2. All specifications control for year and industry fixed effects. Robust standard errors are in parentheses. $^{*}p < 0.1$. $^{**}p < 0.05$. $^{***}p < 0.01$.

an Anderson−Rubin Wald test that is robust to weak instruments in table 4 (Anderson and Rubin 1949). It tests the null hypothesis that the coefficient of our endogenous variable, the export-weighted average GDP per capita, in the structural equation is zero. It is equivalent to estimating the reduced form of equation (1) with the predicted export-weighted destination GDP per capita as regressor and testing whether the coefficient of this variable is equal to zero. The F-statistic and p-value show that the null hypothesis is rejected at a 1% significance level, suggesting that the IV estimates are significantly different from zero. We therefore believe that the results confirm a causal relationship and suggest that an increase in exports to high-income destinations widens the wage gap between skilled and unskilled workers within industries. Given that specifications in columns (5) and (6) have potential weak instrument issues, we thereby treat column (4) as our preferred specification. The estimated coefficient in column (4) indicates that a 10% increase in average destination income raises the skill premium by 3.47%.

The estimated IV coefficients are larger than the OLS−FE results in table 2, indicating that our OLS−FE estimates are downward biased. As discussed in section 3.2, such a downward bias could originate from various reasons, including omitted variables (e.g., the differential effects of the share of processing exports or the share of SOEs across industries), simultaneity between exporting to high-income markets and the skill premium as well as possible measurement errors of the weighted average GDP per capita across exporting destinations.

The above results show a positive relationship between weighted average destination income and the skill premium. However, an increase in the skill premium could be either the result of a higher wage growth for skilled than for unskilled workers, or from a wage rise for skilled workers combined with a wage decline for unskilled workers. To clarify these alternative possibilities, we run regressions with average hourly wages for skilled and for unskilled workers as the dependent variable separately, and the results are reported in columns (1) and (2) in table A4 in the online appendix. It is evident that export-weighted average GDP per capita raised average wages for both types of workers, which is consistent with Brambilla and Porto (2016) who find a positive effect on average industrial wages. However, the coefficient is larger in magnitude for skilled workers, which accounts for the rising skill premium. This pattern is robust to the inclusion of various control variables.[14]

5.3. Robustness checks

In this section, we check the robustness of our main results by considering various specifications. These robustness checks include accounting for the precision of predicting export shares to each destination by using weights, using alternative measures of the dependent variable or of the main regressor, and controlling for additional variables.

As discussed earlier, the export share to each destination that is used when constructing our instrumental variable is predicted from a set of

14 As mentioned earlier, we leave out 2009 from our sample given that skill premium in 2009 is the same as in 2008 due to assumptions imposed by the data source. However, we also find that this does not affect our main findings when we repeat the above regressions including 2009 (results are reported in table A5 in the online appendix).

separate regressions for each industry. The precision of predicting export shares may affect the strength of our instrumental variable in the first stage of the 2SLS estimations when export shares are not precisely predicted. As shown in table A3 of the online appendix, foreign import demand is not significantly correlated with export shares in industries 7 ("Pulp, paper, printing and publishing") and 8 ("Coke, refined petroleum and nuclear fuel"). To alleviate this concern, we follow Goldberg and Pavcnik (2005) and Dix-Carneiro and Kovak (2017) and weigh regressions using the inverse of the standard error of the estimated coefficient on import demand share (as shown in online appendix table A3). This places a smaller weight on industries whose export shares are not precisely predicted. Column (1) in table 5 reports the results. The coefficient of the average destination GDP per capita remains highly significant and is slightly larger.[15]

In column (2), we allow destination income to vary across years and use the time-variant GDP per capita to calculate industry-level weighted average incomes. 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. The estimated effect of weighted average destination income on the skill premium stays positive and highly significant. The size of the coefficient is comparable to our baseline results as shown in table 2. This confirms that our main results are not sensitive to changes in destination income over time. However, variations in trade partners' incomes could be affected by contemporary shocks that are correlated to wages in the Chinese market. Allowing trade partners' incomes to vary over time may also introduce additional measurement errors of the main regressor that create further biases. Therefore, we use the initial value of destination income as our preferred specification (Brambilla and Porto 2016, Bastos et al. 2018).

In all earlier results, the skill premium is defined as the ratio of the wages of skilled and unskilled workers, where skilled workers are those with a high school education or above. Taking advantage that our main data source, the WIOD, reports wage data for high-, medium- and low-skilled workers, we consider an alternative classification of skills. Specifically, we shift the medium-skilled workers from the skilled group to the unskilled group. As such, skilled workers are those with a college education or above and all others are now identified as unskilled workers. The skill premium, therefore, measures the wage gap between college or above diploma holders

15 In an alternative robustness check, we cluster the standard errors at the industry level to allow for potential serial correlation across time within industries and we get similar results with slightly lower significance. However, due to the small number of industries in our data, clustering the standard errors at the industry level may cause biased inference (Angrist and Pischke 2009, Cameron and Miller 2015). We therefore stick to the heteroskedasticity-robust standard errors.

TABLE 5

Skill premium and weighted average GDP per capita across export destinations in manufacturing industries: Robustness checks, 1995–2008

	Including weights (1)	Time-variant GDP (2)	Alternative skill premium (3)	Controlling for import (4)	Controlling for distance (5)
Average destination GDP per capita	0.389***	0.272***	0.073**	0.392***	0.353***
	(0.135)	(0.099)	(0.032)	(0.135)	(0.129)
Export share	−0.090**	−0.046	−0.010	−0.093**	−0.091**
	(0.040)	(0.037)	(0.010)	(0.047)	(0.044)
Gross fixed capital formation (log)	0.051***	0.046***	0.011***	0.057***	0.049***
	(0.017)	(0.012)	(0.003)	(0.016)	(0.017)
Import-weighted average GDP per capita				−0.027**	−0.025**
				(0.013)	(0.013)
Weighted average distance					−0.023
					(0.017)
Constant	−5.052***	−3.546***	−0.678*	−4.803***	−4.112**
	(1.684)	(1.239)	(0.410)	(1.685)	(1.666)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	196	196	196	196	196
R^2	0.844	0.854	0.992	0.843	0.862
First-stage F-statistics	10.307	9.873	11.676	10.995	10.381

NOTES: This table shows the 2SLS results of various robustness checks. Column (1): using the inverse of the standard error of the estimated coefficient on import demand share as weights. Column (2): allowing GDP per capita of destinations to vary across years when calculating the export-weighted average destination GDP per capita and the instrumental variable. Column (3): alternative definition of skilled workers; skilled workers are those with a college education or above (high-skilled) and unskilled workers include all others who have a technical school education, a high school education or below (medium skilled and low skilled). Column (4): controlling for import-weighted average GDP per capita defined as weighted average GDP per capita across import source economies using the share of imports from each economy in total industrial imports as weights. Column (5): controlling for weighted average distance across trade partners using export share to each destination as weights. All specifications include the industrial export share, the log of gross fixed capital formation, year fixed effects and industry fixed effects. Robust standard errors are in parentheses. $^{*}p < 0.1$. $^{**}p < 0.05$. $^{***}p < 0.01$.

(high-skilled workers) and others (medium- and low-skilled workers). Column (3) presents results using the revised skill premium definition as dependent variable. The estimated coefficient of average destination GDP per capita stays significantly positive, indicating that exporting to rich markets increases the wages of college graduates relative to other workers. However, compared with the results in table 2, the magnitude of the effects is markedly smaller. This implies that medium-skilled workers may not earn significantly different wages from the high-skilled during our sample period. One reason could be that the pool of college graduates was quite small in the early 2000s in China. Given the rising demand for skills, medium-skilled workers may have had to take up more skilled jobs, leading to an increase in wage premium relative to low-skilled workers but a reduction in the wage disparity with high-skilled workers. Thus, our earlier definition of skilled workers could capture changes in skill premium more precisely.

Along with rapidly growing exports following the WTO accession, another prominent feature of China's trade is the rapid increase in its imports, due to factors such as tariff rate reductions, rising incomes and the input requirements of exports. As documented in Li et al. (2020) 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 an 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 relatively small proportion (Koopman et al. 2012). To account for the role of imports from high-income economies, we generate an import-weighted average GDP per capita across import sources using import share as weight analogously to the export-weighted average GDP per capita measure used in the analysis so far. Notice that a higher value of this variable indicates that industries tend to import more from high-income economies.

Interestingly, the estimated coefficient of import-weighted average GDP per capita is significantly negative, as shown in columns (4), 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) is for processing production (Amiti and Freund 2010, Koopman et al. 2012).[16] Even if imports from high-income economies are embodied with advanced technology, processing production is only involved with a simple assembly of imported parts into final goods and does not require much in terms of labour 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.

An additional concern is that exporting destinations may affect the quality of products and subsequently the demand for skills and the skill premium through the shipping-the-good-apples-out mechanism (Bekkers et al. 2016), which suggests that exporters tend to ship good-quality products to geographically distant markets (Hummels and Skiba 2004). Considering that many of China's major high-income trade partners are also located at a far

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

distance, such as the US and the EU, it is likely that it is not exporting to high-income destinations but rather exporting to distant destinations that causes increases in the skill premium. To check this possibility, we construct a measure of weighted average distance across exporting destinations in a way analogous to equation (2) and add it as an additional control variable, similar to Brambilla and Porto (2016). Data on distances to each trade partner are taken from the CEPII GeoDist database (Mayer and Zignago 2011). The 2SLS results are set out in column (5). The negative but insignificant coefficient on the weighted average distance rules out the Washington apples effect in the Chinese context and the coefficient on the weighted average GDP per capita stays virtually unchanged, supporting our main findings that exporting to high-income countries, rather than geographically distant ones, drives up the skill premium.

5.4. Examining channels: The impact on relative demand for skills

As discussed in section 2, exporting to rich countries could affect the skill premium through various channels, including the quality upgrading channel (Verhoogen 2008), the required services channel (Matsuyama 2007) and the export-induced technology upgrading channel (Yeaple 2005, Bustos 2011). These three channels, however, all work through raising relative demand for skills: production of high-quality goods requiring skilled workers; exporting to foreign markets requiring additional services that involve a greater use of skilled worker; and technical changes being skill biased. In this section, we do not examine the three channels separately, rather we focus on their effects on the demand for skills, in a manner that incorporates all three channels.

We measure the relative demand for skills using the ratio of total hours worked by high-skilled relative to low-skilled workers. Data on total working hours by different skill levels at the industry level are taken from the WIOD SEA database. The 2SLS results are reported in table 6. The coefficient on average destination GDP per capita is significantly positive and robust to controlling for export share and gross fixed capital formation. This suggests that exporting to high-income destination induces industries to utilize more skills. The coefficient in column (3) indicates that a 10% increase in average income across destinations raises the ratio of total hours worked by high-skilled relative to low-skilled workers by 0.09. Relative to the average ratio of 0.80, this effect is equivalent to a 11.6% growth. Overall, the results in table 6 support the argument that high-income destination exports induce a widening of the skill premium through raising the relative demand for skills.

6. Export destinations and skill premium: Firm-level evidence

Our empirical results based on the WIOD industry-level data find robust evidence that industries exporting more to high-income destinations tend to pay a higher skill premium. Despite the advantage of allowing for a direct measure of the skill premium, one limitation of the WIOD is that the industry

TABLE 6
Relative demand for skills and weighted average GDP per capita across export destinations: 2SLS estimation results

Dependent variable: Relative demand for skills	(1)	(2)	(3)
Average destination GDP per capita	0.935***	0.915***	0.924***
	(0.346)	(0.341)	(0.338)
Export share		−0.194*	−0.185*
		(0.100)	(0.099)
Gross fixed capital formation (log)			0.105***
			(0.036)
Constant	−10.852**	−10.597**	−11.405***
	(4.270)	(4.210)	(4.281)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	196	196	196
R^2	0.986	0.987	0.987
First-stage F-statistics	11.363	11.717	11.676

NOTES: This table reports the 2SLS estimation results using relative demand for skills as the dependent variable. Relative demand for skills is measured as the ratio of total working hours by high-skilled workers over those by low-skilled workers. Robust standard errors are in parentheses. $^{*}p < 0.1$. $^{**}p < 0.05$. $^{***}p < 0.01$.

classification is relatively broad. It also constrains us from controlling for additional characteristics that may affect the skill premium, for instance, the ownership structure, gender composition, etc. To address these concerns, we undertake additional firm-level analysis.

We rely on data from the 2004 National Economic Census (NBS 2016), conducted by the National Bureau of Statistics (NBS) of China. The economic census provides complete firm-level information on accounting statements. Compared with the annual survey of industrial firms, the census additionally reports information on the number of workers by education level and by gender, allowing us to consider the skill structure and the gender composition of firms. Unfortunately, the economic census data do not report wages by education groups but only the total wage bill. To measure the within-industry skill premium, we take advantage of the explicit measure of the skill intensity within firms and compare average wages of skill-intensive firms and less skill-intensive ones, assuming that more skill-intensive firms pay higher wages (Brambilla et al. 2012). For consistency with the industry-level discussion we constrain our sample to manufacturing firms. In contrast to the broad classification of the WIOD, the economic census reports 479 four-digit industries.

To uncover variations in firm's export destinations, we use detailed transaction-level customs data from the General Administration of Customs of China (GACC 2016). It records firm exports of each HS eight-digit product to different markets. In order to examine the relationship between a firm's export structure and its skill utilization and wages, we match the customs data with the 2004 economic census data using firm names, which is commonly used in the literature (e.g., Wang and Yu 2012, Yu 2015).

Based on the matched firm and customs data set, we are able to calculate the weighted average export market GDP per capita at the firm level for 2004. Specifically, we follow equation (2) but replace the industry-level export share to each destination with a firm-level share. Our firm-level econometric specification is as follows:

$$lnwage_{ijc} = \alpha + \beta_1 wagdppc_{ijc} + \beta_2 skillsh_{ijc} + \beta_3 wagdppc_{ijc} \times skillsh_{ijc} + \gamma \boldsymbol{X}_{ijc} + \theta_j + \theta_c + \varepsilon_{ijc}, \tag{5}$$

where the dependent variable $lnwage_{ijc}$ is the logarithm of average wages for firm i that belongs to industry j and is located in city c. $wagdppc_{ijc}$ is firm-level weighted average GDP per capita. $skillsh_{ijc}$ is the share of skilled workers. We interact $wagdppc_{ijc}$ with a firm's skill share to capture the differential impact of high-income destination exports on firms with different skill intensity.

We control for a set of firm-level characteristics that may affect wages ($\boldsymbol{X}_{ijc}$), including the share of exports over total sales, the log of sales per capita, the share of female workers, ownership type dummies and six firm age categories. We include four-digit industry dummies, θ_j, to account for differences across industries. Conditional on industry dummies, the coefficient on the interaction term, β_3, measures whether exporting to high-income destinations affects wages of firms with a high as opposed to a low share of skilled workers differently within industries, thereby implicitly capturing the effects of high-income exports on the within-industry skill premium and making our firm-level analysis comparable to the industry-level analysis. We additionally include city dummies, θ_c, to capture systematic wage differences across regions. In the context of the Chinese labour market with limited migration across regions due to the household registration (*hukou*) system, the inclusion of city indicators particularly addresses differential labour market conditions that may affect a firm's wage setting (Wang et al. 2021). ε_{ijc} is the error term. We cluster standard errors at the industry level to allow for potential correlations within industries.

As before, we consider two alternative measures of skilled workers based on the education level, i.e., those with a high school education or above, and those with a college education or above.[17] In addition, the economic census also reports the number of workers with professional skill titles for each firm. Our third measure of skilled workers corresponds to those with a skill title. Accordingly, we measure a firm's skill intensity as the share of skilled workers.

17 For each firm, the economic census classifies workers into five education categories: middle school or below, high school, college, university, and master or above.

Additionally, we classify firms as skill-intensive and low skill-intensive ones depending on whether the share of skilled workers is above the median level.

As defined above, our main measure of high-income market exports is the export-weighted average GDP per capita across destinations. Taking advantage of the rich information on firms' exports to each destination, we use an alternative measure, defined as the share of a firm's exports to high-income markets relative to its total exports. High-income economies are those with a per capita income level higher than the 75th percentile in 2004.

Although we control for a rich set of firm features, a firm's export share to different destinations could be endogenous if unobserved factors affect its choice of export markets and wages simultaneously. We alleviate this concern by exploring past export experience of firms. Specifically, we calculate export shares using the average exports to each destination between 2000 and 2003.[18] In addition, we use the income level of each economy in 2000 to calculate the weighted average GDP per capita to avoid contemporary shocks to domestic and export markets. The export share to high-income destinations is also calculated based on the exports between 2000 and 2003. Summary statistics of firm-level variables are present in table A6 in the online appendix.

Table 7 reports the results using weighted average GDP per capita as the measure of a firm's high-income destination exports. Columns (1) to (3) correspond to the three alternative measures of skills, and column (4) uses the dummy variable indicating skill-intensive firms.

In all specifications, firms with a higher share of skilled workers pay strictly higher average wages. Similarly, firms exporting more to high-income destinations tend to pay higher average wages, as shown in columns (2) to (4). This is in line with the findings of Brambilla and Porto (2016) using cross-country data. Different to their work, our focus is the coefficient of the interaction term, which is positive and highly significant across all specifications. This implies that conditional on skill intensity, firms that export to richer economies pay higher average wages. The coefficients in column (4) suggests that skill-intensive firms pay 7.7% higher average wages than low skill-intensive ones. However, such a difference increases further by 0.7% with each one percent rise in the average destination income. Since we control for industry dummies, our results indicate that high-income destination exports increase the skill premium within industries, which supports our main results based on industry-level data.

The coefficients of our control variables are generally consistent with expectations. The positive coefficients of the export share indicate a weak export premium, but it is only significant in column (2). Other factors constant, less female-intensive firms and more productive ones pay higher wages. Compared with SOEs, collective-owned enterprises and domestic private firms pay lower average wages, while workers employed in foreign-invested

18 We exclude firms that exported in 2004 but did not export during 2000 to 2003.

TABLE 7

Average wages and average destination GDP per capita: Evidence from firm-level data

	Skill share 1 ≥ High school (1)	Skill share 2 ≥ College (2)	Skill share 3 With skill title (3)	Skill-intensive firm (4)
Skill × Average destination GDP per capita	0.014***	0.032***	0.026***	0.007***
	(0.002)	(0.003)	(0.004)	(0.001)
Skill	0.189***	0.522***	0.275***	0.077***
	(0.009)	(0.016)	(0.016)	(0.004)
Average destination GDP per capita	−0.001	0.002***	0.004***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Export share	0.158	0.200*	0.092	0.118
	(0.116)	(0.104)	(0.120)	(0.120)
Female share	−1.105***	−1.092***	−1.111***	−1.116***
	(0.021)	(0.019)	(0.022)	(0.022)
Sales per worker (log)	0.228***	0.218***	0.234***	0.233***
	(0.004)	(0.004)	(0.004)	(0.004)
Ownership (reference: SOEs)				
Collective	−0.187***	−0.167***	−0.203***	−0.203***
	(0.011)	(0.010)	(0.011)	(0.011)
Domestic private	−0.156***	−0.143***	−0.168***	−0.169***
	(0.010)	(0.010)	(0.011)	(0.010)
Foreign	0.044***	0.049***	0.049***	0.038***
	(0.011)	(0.011)	(0.012)	(0.011)
Firm age (reference: 1−15)				
16−30	0.048***	0.053***	0.042***	0.045***
	(0.004)	(0.004)	(0.004)	(0.004)
31−45	0.068***	0.078***	0.063***	0.066***
	(0.009)	(0.009)	(0.009)	(0.009)
46−60	0.118***	0.127***	0.115***	0.116***
	(0.014)	(0.013)	(0.013)	(0.013)
60+	0.309***	0.316***	0.298***	0.304***
	(0.029)	(0.028)	(0.028)	(0.028)
City dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	232,037	232,037	232,037	232,037
R^2	0.427	0.436	0.424	0.424

NOTES: The dependent variable is the log of firm-level average wages. Export-weighted destination GDP per capita is calculated using a firm's average export share to each destination during the period of 2000−2003 as weight and the value of GDP per capita in 2000. In column (1), the skill share is defined as the share of workers with at least high school education; in column (2), the skill share is defined as the share of workers with college education or above; in column (3), the skill share is defined as the share of workers with professional skill titles. Skill in column (4) indicates skill-intensive firms with a higher than median share of workers who received at least high-school education. Export share is the share of exports in total sales. Female share is the share of female workers. Robust standard errors clustered at the industry level are in parentheses. SOEs = state-owned enterprises. $^{*}p < 0.1$. $^{**}p < 0.05$. $^{***}p < 0.01$.

TABLE 8
Average wages and high-income destination exports: Evidence from firm-level data

	Skill share 1 (1)	Skill share 2 (2)	Skill share 3 (3)	Skill-intensive firm (4)
Skill × High-income export share	0.142***	0.338***	0.282***	0.073***
	(0.020)	(0.035)	(0.049)	(0.010)
Skill	0.194***	0.532***	0.281***	0.079***
	(0.009)	(0.016)	(0.016)	(0.004)
High-income export share	0.006	0.026***	0.047***	0.034***
	(0.007)	(0.007)	(0.007)	(0.006)
City dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes
Observations	232,037	232,037	232,037	232,037
R^2	0.427	0.436	0.424	0.424

NOTES: The dependent variable is the log of firm-level average wages. The definition of skill shares in columns (1) to (3) and the skill dummy in column (4) are the same as in table 7. High-income export share denotes the share of exports to high-income markets in a firm's total exports between 2000 and 2003. All specifications include the export share over sales, female share, the log of sales per worker, ownership, firm age groups, city dummies, four-digit industry dummies and a constant. Robust standard errors clustered at the industry level are in parentheses. $^{*}p < 0.1$. $^{**}p < 0.05$. $^{***}p < 0.01$.

firms are paid better. The latter is consistent with the findings of Sheng and Yang (2017). Our results also indicate that wages increase monotonically with firm age.

In table 8, we present results of firms' export share to high-income destinations. In line with the results presented in table 7, average wages increase with the share of skilled workers for all measures of skills. Firms with a higher share of its exports to high-income markets pay higher average wages. The coefficients of the interaction term are positive and highly significant in all specifications. To allow for a comparison with the results of table 7, the results in column (4) suggest that a 10 percentage point increase in the high-income export share is associated with a 0.73% rise in the skill premium. Overall, our results based on firm-level data support our earlier findings that exports to rich markets increase the skill premium.

7. Conclusions

Rising wage inequality between skilled and unskilled workers in developing countries has drawn wide attention in the literature. Recent studies have emphasized the importance of export destination in affecting the utilization of skilled workers and average wages, which implies that it could be a potential factor driving 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 contributes to a widening wage gap between skilled and unskilled workers.

We first calculate the weighted average GDP per capita across destinations for each industry using the within-industry export share to each destination as weights, and empirically model its relationship with the skill premium. To address the potential endogeneity of the export share measure, we explore exogenous variations in foreign import demand, based on which we predict the export shares and use them as weights to construct an instrument for the observed average destination income. We find that exporting more products to high-income destinations increases skill premia, resulting from higher average wages for high-skilled than for low-skilled workers. This implies that workers in developing countries with higher skill levels may benefit more from an expansion of exports to rich countries. Our main results are robust to the inclusion of additional control variables, including import-share weighted average source country income and geographical distances to export destinations. In particular, a lack of significant effects of geographical distances rules out the shipping-the-good-apples-out channel.

Considering the high importance of processing trade in China, we distinguish ordinary exports from processing exports 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 weights. The empirical results present a positive relationship between ordinary export-weighted average destination income and the skill premium, whereas there is a negative albeit insignificant impact of processing exports, that is, industries that experience an increase in exports of processing products to high-income destinations do not experience an increase in the skill premium. This is perhaps not surprising given that processing production is actually simple assembly work that requires mainly low-skilled workers; an expansion of processing exports leads to an increase in the demand for low-skilled workers. This finding is important because 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. Considering that processing exports to foreign countries also require certain skill-intensive services, the insignificant effects of processing exports on the skill premium suggest that the required services channel as in Matsuyama (2007) did not play a role during our sample period. 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.

Instead of examining each possible mechanism separately, we investigate whether exporting to rich markets raises the relative demand of skilled workers. Our results imply that industries that shipped more products to high-income destinations tend to require more skills.

We further validate our results using matched firm-level data from the 2004 economic census and transaction-level customs data. Using four alternative measures of skills and two measures of high-income destination exports, we find consistent and robust evidence that firms with a higher share of skilled workers tend to pay higher average wages, with those exporting more to richer economies paying even higher wages. This confirms our main results based on industry-level data that high-income destination exports widen the skill premium within industries.

Supporting information

Supplementary material accompanies the online version of this article. The data and code that support the findings of this study are available in the Canadian Journal of Economics Dataverse at `https://doi.org/10.5683/SP3/OQFXYO`.

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