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Export destinations and skill premium: Evidence from chinese manufacturing industries

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Export Destinations and Skill Premium: Evidence from Chinese Manufacturing Industries

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Abstract

This paper examines the relationship between average income of export destinations and skill premium 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 weight, and then link it with industry-level wages and 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. Our paper contributes to the understanding of the influence of export destinations on the uneven distributional effects of globalisation for different types of workers.

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

JEL Classification: F14; F16; F66; J24; J31

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1 Introduction

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

The main purpose of this paper is to investigate the relationship between export destinations and skill premium using Chinese manufacturing industry data from 1995 to 2008. In particular, given that existing papers like Brambilla and Porto (2016) present a positive association between the income level of export destinations and average wages, we are more interested in whether the composition of export destinations differently affects wages of workers with different skills. China provides a helpful context to explore this issue. First, as a representative middle-income developing country, China has observed a substantial increases in the wage gap between skilled and unskilled workers (Sheng and Yang, 2016), which has also been witnessed in quite a few other developing countries (Goldberg and Pavcnik, 2007). Second, during our sample period, China has integrated further into the world economy, especially after 2001 when China joined the WTO. China's share in world total exports almost tripled from merely 3.18% in 1995 to 9.15% in 2008, with the total value of manufacturing exports grew from 136.80 billion USD in 1995 to 1.40 trillion in 2008. Particularly, manufacturing exports to high-income destinations increased drastically from 111.67 billion USD to 947.00 billion during the same period.

In theory, export destinations and skill premium can be linked through two channels. One is quality upgrading: given that consumers in richer countries have a greater demand for high-quality goods, thus firms that export to these markets have to upgrade the quality of their products. Quality upgrading requires more skilled workers and firms need to pay higher wages to skilled workers to sustain quality production, which in turn induces an increase in the skill premium (Verhoogen, 2008). This idea requires that consumers have non-homothetic preferences in the exporting market, and on the supply side that the production of quality products and skills are complementary. Brambilla et al. (2012) examine this idea using data of Argentinean manufacturing firms and find that exporters to high-income destinations hire more skilled workers than other exporters and non-exporters. Our paper is closely related to Brambilla and Porto (2016), who explore the effects of export destination on average wages. Based on country-industry-level data, they find that average wages tend to be higher in industries exporting more to rich countries. In addition, they find evidence that supports the quality upgrading mechanism, that is,

[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.

the quality of products is higher in industries that ship products to high-income destinations, and the production of high-quality goods is related to higher average wages. By contrast, this paper distinguishes differential wage effects for skilled and unskilled workers within industries. This is important for developing countries like China with high income inequality since even if exporting to high-income countries tends to raise average wages, it is likely that workers with different skill levels are affected unevenly.

An alternative, possible channel linking export destinations and the skill premium is 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 on skill-intensive technologies (Yeaple, 2005; Bustos, 2011a,b). Notice that this mechanism does not depend on the characteristics of export destinations. However, if exporting to high-income destinations is more profitable, firms or industries that export more to those markets are expected to hire more skilled workers and to observe an increase in the skill premium.

Based on these theories, the current paper aims to investigate whether there is a causal link between export destination and skill premium. To this end, we calculate the weighted average GDP per capita across export destinations using the share of export to each destination as 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 is taken from the World Input-Output database (WIOD) which primarily provides 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. Although this database does not directly provide data on the skill premium, it is possible to compute this using data on labour compensation and working hour shares. One identification issue of this paper is that our main explanatory variable might be endogenous if there are unobservable factors that affect the within-industry export structure to each destination and the skill premium simultaneously. Our strategy is to use predicted export shares based on bilateral exchange rates to calculate the weighted average destination income as an instrument for the actual average income across destinations (Park et al., 2010; Brambilla and Porto, 2016; Bastos et al., 2018).

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

The remainder of this paper is organised as follows. In the next section, we briefly present potential mechanisms that link export destination and the skill premium and relevant empirical evidence. Section 3 shows our empirical strategy. Section 4 describes data sources and the construction of our main variables, skill premium and export-weighted average GDP per capita across destinations. In Section 5, we report the main regression results as well as robustness checks and Section 6 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 equalised 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 equalisation predictions do 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 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. One important channel through which variations in export destinations may affect the skill premium is quality upgrading. The basic idea is that firms export higher-quality products to richer markets than they sell in domestic 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. Verhoogen (2008) is among the first that documents the quality upgrading mechanism. His model is built on three crucial assumptions. First, as in Melitz (2003), firms are heterogeneous in productivity and only the most productive firms are able to export due to the presence of fixed costs to enter foreign markets. Second, products are differentiated in quality and consumer preferences are non-homothetic, such that consumers with higher incomes value product quality more than those with lower incomes. Third, on the production side, producing high-quality goods requires skilled workers, and firms need to pay high enough wages to those workers to motivate effort. On top of these assumptions, exchange rate devaluations induce the most productive firms to increase exports, upgrade quality, raise employment of high-skilled workers and pay higher

[2] One example is that access to higher skilled occupations, particularly positions in SOEs, is restricted in China, which prohibits labour movement across sectors.

[3] Galiani and Porto (2010) propose a model in which non-competitive wage setting in the import competing sector due to the presence of unions may induce differential skill premia across industries despite of 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 skill premium exists at the industry level.

wages compared to less productive firms, which widens the wage gap between skilled and unskilled workers within industries. Based on Mexican manufacturing firm-level data, Verhoogen (2008) investigates differences in exports, quality of goods and wages of white-collar workers versus blue-collar workers for firms that are heterogeneous in initial productivity when facing the 1994 peso crisis. The empirical findings are consistent with the theoretical predictions.

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

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

A number of other papers also document the quality valuation and quality provision mechanisms. On the demand side, using data on bilateral industry-level trade flows between 60 countries, Hallak (2006) identifies a positive relationship between income per capita and demand for quality. On the supply side, and based on Portuguese firm-level data, Bastos and Silva (2010) find that unit value, as a 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. However, unit values not only reflect product quality but also reflect mark-ups. Input quality may be relatively unaffected by mark-ups. Bastos et al. (2018) re-visit the income-based quality choice using detailed Portuguese firm-product-level data by focusing on the quality of inputs. Empirical results reveal a significant and positive association between average destination income and input prices, indicating that firms export higher-quality products to rich countries and in doing so require high-quality inputs. Using firms' innovation activities as proxy for quality, Crinò and Epifani (2012) uncover a strong negative correlation between R&D intensity and the share of exports to low-income destinations using Italian manufacturing firm-level data, which is consistent with the hypothesis that export quality is positively correlated with destination income.

The export-induced technology upgrading channel has been investigated by a number of researchers. In a general equilibrium model, Yeaple (2005) assumes that firms can choose technologies and workers with various skill levels. A reduction in trade costs increases firms' incentives to expand exports, adopt new technologies that favour high-skilled workers, and pay higher wages to skilled workers. Building on Yeaple's model, Bustos (2011b) argues that increases in revenue from rising exports induce firms to upgrade technology. In a related paper, Bustos (2011a) documents that a reduction in trade partners' tariff rates encourages the most productive firms to shift their production technology to be more skill-intensive. As a result, trade-induced reallocation of market share towards more productive firms induces an increase in the relative demand for skilled workers and in the skill premium. For Argentinean manufacturing firms, Bustos (2011a) finds that the reduction in Brazil's tariffs led the most productive firms to upgrade skills but other firms to downgrade. Notice that this channel emphasises the importance of export *per se* other than variations in exporting destinations. If exporting to richer countries is more profitable due to the fact that firms charge higher prices in those markets as in Manova and Zhang (2012), the income level of export destination matters. In other words, firms that export to high-income destinations have stronger incentives to invest on skill-intensive technologies due to higher profits and therefore increase the demand for skilled labour and the skill premium.

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

3. Empirical Strategy

3.1 Econometric specification

The main objective of this paper is to identify the effects of export destinations 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 model 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 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 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. Notice that our main interest is the measure of average destination income $wagdppc_{it}$. Its coefficient 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:

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

where i, d, and t denote industry, destination market, and year, respectively. $gdppc_{d,1995}$ is GDP per capita of destination d in real terms in 1995, the first year of our sample, and $exsh_{idt}$ is the export share to destination d in total industrial exports in year t, which captures the composition effects of exports within industries. To avoid possible endogeneity issues with contemporaneous income (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 primarily attributed to changes in the exposure to different export destinations. In the later discussion, we allow destination GDP per capita to vary across time and our results do not change much.

3.2 Identification issues

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

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

$$exsh_{idt} = \alpha_0 + \delta exchr_{dt} + \varphi_d + \varphi_t + v_{idt} \tag{3}$$

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

We estimate Equation (3) separately for each industry and predict the export share to each destination $\widehat{exsh}_{idt}$ accordingly. Then we calculate the instrument for $wagdppc$ as follows:

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

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

4. Data

4.1 Industry-level data on wages and other characteristics

Industry-level data on wages for workers with different skill levels are relatively scarce in China. The primary data source on wages and the skill premium in this study is the Socio Economic Accounts (SEA) from World Input-Output Database (WIOD).[4] WIOD is a new database that provides time series of input-output tables from 1995 to 2011 for 40 countries based on various sources of officially released

[4] All WIOD datasets are available from http://www.wiod.org. A user guide of this database is available from Timmer et al. (2015).

data, and China is one of those countries. 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, labour compensation share and working hour share 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 skill premium accordingly.[5]

For China, industry-level data on employment, labour compensation, working hours, etc., are available from 1995 to 2009 from this source.[6] Note that data for workers with different skill levels at the industry level are not readily available from other sources. To generate consistent and comparable industry-level relative wage series, SEA combines comprehensive data from various officially released data sources, including various issues of China Statistical Yearbook, China Industrial Economic Statistical Yearbook, China Labour Statistical Yearbook, census data like Industrial Censuses and Economic Censuses, as well as individual-level data from China Household Income Project surveys.[7] 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 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 groups. 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 are excluded from this study.[8] 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 natural sources. Therefore, we constrain our discussion to manufacturing industries throughout the paper, with a sample of 14 industries spanning 1995 to 2008.

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

4.2 Export-weighted average GDP per capita across export destinations

To calculate the export share to each destination, data on exports to each destination at the industry level is required. These data are obtained from the World Integrated Trade Solution (WITS) database at the

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

[6] Due to the fact that industrial skill premium in 2009 is completely the same as in 2008, which is assumed by the data source, we restrict our sample from 1995 to 2008 in the main discussion.

[7] For more details, see the WIOD SEA documents from http://www.wiod.org/publications/source docs/ SEA Sources.pdf.

[8] Here exports specifically denote exports in goods.

3-digit level of the International Standard Industrial Classification (ISIC) Revision 3. To combine with wage data, we aggregate the 3-digit ISIC Rev.3 industry codes into WIOD broad industry classifications. Time series on GDP per capita, GDP deflator, Consumer Price Index (CPI), and exchange rates are from the World Bank Indicator Database.[9]

One important feature of China's exports is the high proportion of processing exports, which account for over 50% in total exports (Koopman et al., 2012). In particular, industries with 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. To distinguish potential different effects of ordinary and processing exports, we calculate the within-industry processing and ordinary export shares to various destinations, which are utilised as weights to compute weighted average GDP per capita separately. Data on processing and ordinary exports are available at the 4-digit HS level between 2001 and 2008 from the DRCNET Statistical Database, an official database of Development Research Center of the State Council of China.[10]

Table 1 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 194.70 thousand and 200.89 thousand RMB before 2001 and decreased afterwards from 197.11 thousand in 2001 to 135.96 thousand in 2008. This reduction is mainly attributed to the decline of the share of exports going to Hong Kong and Japan, both of which ranked in the top of China's export destinations in terms of real GDP per capita. China exported more than 40% of its total exports to these two markets in 1995 and this share fell to around 20% in 2008.The time-series of the average skill premium and export-weighted GDP per capita do not seem to be systematically related. This could be the case since simple averages across industries hide industrial variations in relative wages and in weighted average GDP per capita. However, the different patterns of weighted average GDP per capita before and after 2001 motivate us to explore the possible differences in the relationship between the two in the pre- and post-WTO accession periods.

Recall that the primary data used in this paper is at the industry level. In Figure 1, we show changes in the industrial skill premium against changes in weighted average GDP per capita across export destinations by industry between 1995 and 2008. It shows that all industries observed a reduction in weighted average GDP per capita across export destinations, the same as the overall trend in Table 1. More importantly, industries with lower reductions in weighted average GDP per capita, such as machinery, not elsewhere classified (13) and transport equipment (15), experienced a relatively higher rise in the skill premium. The estimated correlation coefficient between the two is positive and significant at the 10% level, which provides supportive evidence of a potential positive relationship between average destination income and the skill premium.

[9] http://databank.worldbank.org/data. Taiwan is an important export destination of mainland Chinese firms whereas its data is not available from the World Bank Indicator Database. For the purpose of completeness, data on Taiwan are collected from various issues of Taiwan Statistical Data Book.
[10] To calculate processing/ordinary export shares to each destination within industries, we classify 4-digit HS level data into industry level combining 6-digit HS level export data from WITS database and relevant concordance tables.

Table 1: Summary statistics of the industrial skill premium and weighted average GDP per capita (1000 RMB) across export destinations in manufacturing industries: 1995-2008

	Skill premium		Weighted average GDP per capita	
	Mean	Standard deviation	Mean	Standard deviation
1995	0.088	0.025	194.705	26.214
1996	0.096	0.020	198.428	26.590
1997	0.105	0.015	196.270	22.887
1998	0.114	0.010	195.555	23.052
1999	0.123	0.005	200.893	23.998
2000	0.133	0.001	198.096	23.893
2001	0.143	0.005	197.112	25.768
2002	0.154	0.011	193.362	24.159
2003	0.156	0.007	189.868	24.538
2004	0.169	0.010	187.160	21.342
2005	0.178	0.012	179.852	21.857
2006	0.188	0.014	168.580	19.624
2007	0.189	0.009	154.764	18.222
2008	0.198	0.016	135.960	16.336

Notes: This table shows summary statistics of industrial skill premia and export-weighed average GDP per capita across export destinations in manufacturing industries. The industrial skill premium is defined as the log of the average hourly wage ratio of skilled to unskilled workers for each manufacturing industry. Export-weighted GDP per capita across export destinations is defined by Equation (2).

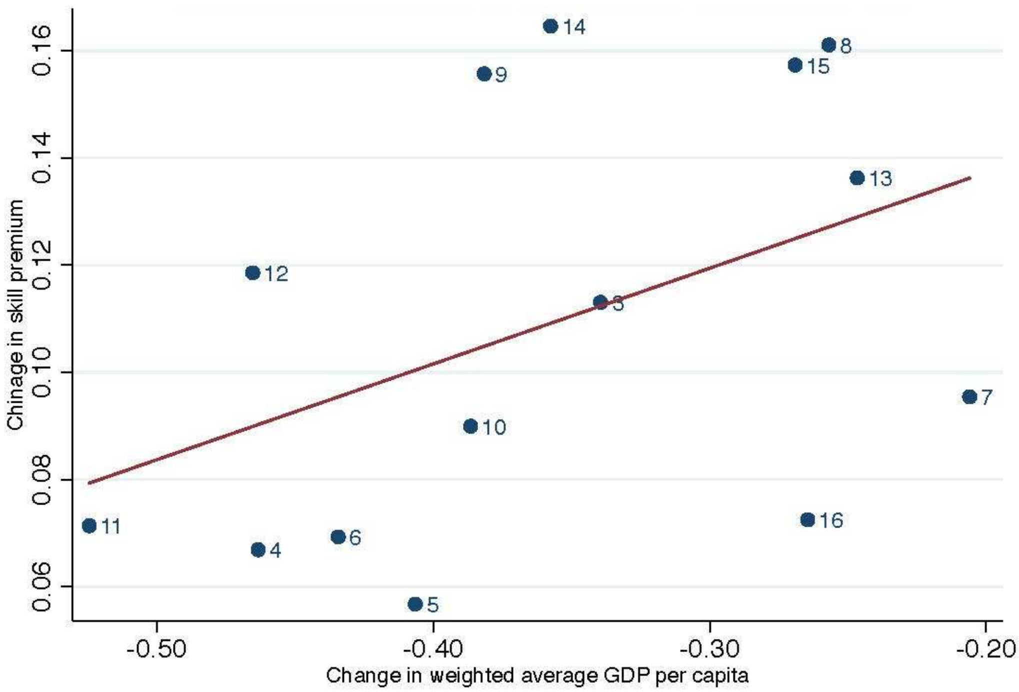

Figure 1: Changes in skill premium and in weighted average destination GDP per capita in manufacturing industries between 1995 and 2008

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 coefficient of $\Delta wagdppc_{i,2008-1995}$, β, is 0.18 with robust standard error being 0.09 (p = 0.08) and the partial R^2 being 0.19. Concordance of industry code and industry name is shown in Table A.4 in the Appendix.

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

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

5.1 Main results

Table 2 reports the baseline fixed effects (FE) regression results. In Column (1), we present the relationship between skill premium and average income across export destinations conditional only on year fixed effects and industry fixed effects. Note that year fixed effects control for common shocks to all industries in each year, such as 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 with a 10% higher average income across export destinations is found on average to have a 1.07% higher skill premium.

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

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

Notes: This table shows results of 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 a high school education or above. Others are identified as unskilled workers. Export share denotes the share of total exports in gross output in each industry. GFCF denotes gross fixed capital formation. Productivity is labour productivity, calculated as the log of real output per worker. Robust standard errors are computed in all specifications. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Absolute *t*-values in parentheses.

Note that the skill premium is calculated based on wage data of all workers, including those working in exporting firms and those in non-exporting firms. Wage adjustments in non-exporting firms must be indirect via the effects on exporting firms. However, the export share used to calculate weighted average GDP per capita only captures the composition of export destinations within industries, but does not account for the scale effects, that is, differences in the degree of exposure to exports across industries. For example, an industry with a high share of export to the U.S. but a low total export value would observe a high level of average destination income but we would not expect strong effects on wages due to the relatively low exposure to export. To control for the scale effects, we include the share of exports in industrial output as a control variable. Following Goldberg and Pavcnik (2005) and Kumar and Mishra

(2008), who study trade liberalisation and the industrial wage premium in Columbia and India respectively, we include industry-level capital as an additional control variable, measured as the log of real gross fixed capital formation (GFCF).

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

Another important factor that affects wages is productivity. The argument is that more productive firms are more likely to pay higher wages through rent sharing. Following Brambilla and Porto (2016), we add labour productivity, calculated as the 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 GFCF that changes from positive to negative. Given that more capital-intensive industries are often more productive ones, we leave out GFCF in Column (6) but the main result does not vary much.

The baseline results show a positive relationship between weighted average destination income and the skill premium. However, an increase in the skill premium could be either from 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 wages for skilled and for unskilled workers as the dependent variable separately, and the results are reported in Appendix Table A.1. It is evident that export-weighted average GDP per capita is positively correlated with average wages for both skilled and unskilled workers, which is consistent with Brambilla and Porto (2016) who find a positive correlation with average industrial wages. However, the coefficient is larger in magnitude for skilled than for unskilled workers, which accounts for the rising skill premium. This pattern is robust to the inclusion of various control variables.[11]

Due to the potential endogeneity of the weighted average destination income, we cautiously interpret the results in Table 2 as correlation or association instead of causality. To identify whether the positive correlation between weighted average destination income and the skill premium is a causal relationship, we estimate Equation (1) with instrumental variables. As discussed earlier, to construct an instrument for the weighted average destination income, we first estimate Equation (3) to predict the export share to each destination that is attributed to the exogenous changes in exchange rates. Specifically, we run regressions for each industry separately following Brambilla and Porto (2016) and the regression results are reported in Appendix Table A.2. Conditional on year fixed effects and destination fixed effects, the estimated coefficient on bilateral exchange rate is positive and statistically significant for 12 out of 14

[11] As mentioned earlier, we leave out 2009 from our sample considering that skill premium in 2009 is the same as in 2008 due to assumptions imposed by the data source. However, we also check that this does not affect our main findings by repeating the above regressions with inclusion of 2009 (results available from the authors upon request).

industries. This implies that an appreciation of foreign currency is associated with a rise in the share of China's exports to that destination. In addition, the R^2 is over 0.90 for 10 industries, suggesting that the overall fit of the model is good. Using the predicted export share to each destination, we calculate the weighted average GDP per capita for each industry and use it as the instrument for our main regressor to estimate Equation (1) utilising the two-stage least squares (2SLS) approach.

In Table 3, we report the 2SLS estimation results. Specifically, Columns (1) to (6) correspond to various specifications controlling for alternative additional variables as in Table 2. The first-stage regression results, as shown in Panel A, present a positive correlation between our instrument and the endogenous regressor, ranging between 0.436-0.519 across specifications. This correlation is statistically significant and robust throughout all specifications. We also report a number of diagnostic statistics to check the quality of our instrument in Table 3. Since there is no particular reason to assume that the errors are homoscedastic, we report the heteroscedasticity-robust Kleibergen and Paap (2006) LM statistics to test for under-identification. This test checks whether the excluded instrumental variable is correlated with the endogenous regressor. The Kleibergen and Paap LM statistics indicates that we can reject the null hypothesis that the model is under-identified. However, it is still possible that the instrument is only weakly correlated with the endogenous regressor. Concerning this issue, we further report the effective first-stage F-statistic of Montiel Olea and Plueger (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 errors. Comparing the *F*-statistic with the critical values implies that we cannot reject the null hypothesis that our instrument is weak. With this issue in mind, we follow Bastos et al. (2018) who use similar instruments to examine the relationship between export destination income and input prices for Portuguese firms, and report weak-instrument-robust inference below.

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. Due to the presence of a weak instrument, these results should be interpreted with caution. In Table 3, we also report an Anderson-Rubin (1949) Wald test that is robust to weak instruments. 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 across all specifications, 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. However, Angrist and Pischke (2009) document that the IV estimates are biased towards the OLS estimates with the presence of weak instrumental variables. Compared with the FE results in Table 2, the estimated IV coefficients are larger. This indicates that our IV estimates are likely to underestimate the true relationship between average destination income and the skill premium. We keep this caveat in mind in all following discussions.

Alternatively, we use the wage bill share of skilled workers as dependent variable following Feenstra and Hanson (1999) and replicate the above regressions. The results are reported in Table A.3. Both FE and 2SLS regressions show positive and statistically significant coefficients of the average destination income, suggesting that the wage bill share of skilled workers increases with a rise in exports to high-income destinations within industries. In other words, high-income exports are positively associated with skill premia at the industry level, which is consistent with our main results. In later discussions, we use our preferred measure as the dependent variable, i.e. the industry-specific skill premium, because this measure is more straightforward.[12]

Table 3: Skill premium and weighted average GDP per capita across export destinations in manufacturing industries: 2SLS regressions, 1995-2008

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First-stage results						
Predicted average GDP p/c	0.436**	0.504**	0.456**	0.519**	0.482**	0.480**
	(2.359)	(2.542)	(2.412)	(2.570)	(2.275)	(2.320)
Observations	196	196	196	196	196	196
Panel B: Second-stage results						
Average destination GDP p/c	0.371**	0.336**	0.338**	0.312**	0.242**	0.242**
	(2.243)	(2.444)	(2.270)	(2.455)	(2.440)	(2.426)
Export share		-0.059		-0.048	-0.090***	-0.089***
		(1.419)		(1.224)	(3.160)	(2.979)
ln(GFCF)			0.056***	0.052***	-0.003	
			(3.769)	(3.954)	(0.176)	
Productivity					0.036***	0.036***
					(5.600)	(7.491)
Constant	-4.491**	-4.052**	-4.457**	-4.101**	-3.283***	-3.295***
	(2.198)	(2.390)	(2.349)	(2.551)	(2.637)	(2.752)
Observations	196	196	196	196	196	196
R^2	0.833	0.855	0.858	0.872	0.917	0.917
Kleibergen-Paap LM-statistic	5.477	6.518	5.696	6.656	5.853	5.824
Kleibergen-Paap LM *p*-value	0.019	0.011	0.017	0.010	0.016	0.016
Montiel-Pflueger effective *F*-statistic	5.564	6.461	5.819	6.604	5.177	5.385
Anderson-Rubin Wald test *F*-statistic	21.456	23.844	20.123	22.784	13.700	13.354
Anderson-Rubin Wald test *p*-value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: This table shows the 2SLS regression results of skill premium on export-weighted average GDP per capita across export destinations in manufacturing industries. Panel A shows the second-stage regression results and Panel B shows the first-stage regression results. The instrument for weighted average GDP per capita is defined as in Equation (4). All other variables are defined the same as in earlier tables. All specifications control for year and industry fixed effects. Specifications (1)-(6) in Panel B include the same controls as Columns (1)-(6) in Panel A. Robust standard errors are computed in all specifications.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Absolute *z*-values in parentheses.

5.2 Robustness checks

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

[12] We also experiment using the wage bill share of skilled workers as the dependent variable in all following regressions and our main findings remain robust.

Time-variant GDP per capita

In all above regressions, we use GDP per capita in 1995 to calculate the weighted average destination income to avoid potential endogeneity problems. In this section, we allow destination income to vary across years and use this time-variant GDP per capita to calculate industry-level weighted average income. As such, this variable captures not only variations in the exposure to different export destinations but also changes in income levels at each destination over the years. Using the revised weighted average income across destinations as the main regressor, we repeat the above regressions.

In Table 4, we report both FE and 2SLS regression results. The estimated correlation between skill premium and weighted average destination income is positive and highly significant across specifications. Accounting for the endogeneity of the weighted average GDP per capita, the positive relationship remains significant. One may notice that the estimated coefficients are similar to those in our baseline results as shown in Table 2. This confirms that our main results are not sensitive to the changes in destination income over time. However, variations in trade partners' incomes could potentially affect exports and wages in the Chinese market, which introduces an additional endogeneity problem. Therefore, using the initial value of destination income is our preferred specification (Brambilla and Porto, 2016; Bastos et al., 2018).

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

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: FE estimation						
Average destination GDP p/c	0.073***	0.073***	0.077***	0.076***	0.051***	0.055***
	(3.036)	(3.042)	(3.161)	(3.132)	(2.749)	(2.974)
R^2	0.897	0.897	0.902	0.902	0.939	0.938
Panel B: 2SLS estimation						
Average destination GDP p/c	0.285*	0.261**	0.264*	0.245**	0.182**	0.182**
	(1.928)	(2.104)	(1.945)	(2.110)	(2.163)	(2.140)
R^2	0.837	0.853	0.855	0.866	0.918	0.918
Observations	196	196	196	196	196	196
Kleibergen-Paap LM statistic	4.883	5.824	4.990	5.859	5.329	5.320
Kleibergen-Paap LM *p*-value	0.027	0.016	0.026	0.016	0.021	0.021
Montiel-Pflueger effective *F*-statistic	4.371	5.094	4.490	5.133	4.482	4.575
Anderson-Rubin Wald test *F*-statistic	16.667	18.567	15.502	17.595	11.291	10.898
Anderson-Rubin Wald test *p*-value	0.000	0.000	0.000	0.000	0.001	0.001

Notes: This table shows the robustness of the main findings by allowing GDP per capita of destinations to vary across time. Panel A shows the FE regression results and Panel B shows the 2SLS regression results. Specifications (1)-(6) include the same controls as Columns (1)-(6) in Table 2 and all specifications control for year and industry fixed effects. Robust standard errors are computed in all specifications. * p <0.1, ** p <0.05, *** p <0.01. Absolute *t*-values in parentheses. Absolute *z*-values in parentheses in 2SLS regressions.

Alternative skill measures

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

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

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: FE estimation						
Average destination GDP p/c	0.017**	0.017*	0.019**	0.018**	0.008	0.010
	(2.076)	(1.969)	(2.224)	(2.098)	(1.102)	(1.391)
R^2	0.994	0.994	0.994	0.994	0.995	0.995
Panel B: 2SLS estimation						
Average destination GDP p/c	0.062	0.058	0.056	0.053	0.035	0.035
	(1.500)	(1.620)	(1.463)	(1.580)	(1.235)	(1.218)
R^2	0.993	0.993	0.993	0.994	0.995	0.995
Observations	196	196	196	196	196	196
Kleibergen-Paap LM statistic	5.477	6.518	5.696	6.656	5.853	5.824
Kleibergen-Paap LM *p*-value	0.019	0.011	0.017	0.010	0.016	0.016
Montiel-Pflueger effective *F*-statistic	5.564	6.461	5.819	6.604	5.177	5.385
Anderson-Rubin Wald test *F*-statistic	4.803	5.639	4.232	5.063	2.079	2.020
Anderson-Rubin Wald test *p*-value	0.030	0.019	0.041	0.026	0.151	0.157

Notes: This table checks an alternative definition of skills. 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). Panel A reports the FE regression results and Panel B report the 2SLS regression results. The instrument for average destination GDP per capita is defined as in Equation (4). Specifications (1)-(6) include the same controls as Columns (1)-(6) in Table 2 and all specifications control for year and industry fixed effects. Robust standard errors are computed in all specifications. * p <0.1, ** p <0.05, *** p <0.01. Absolute t-values in parentheses. Absolute z-values in parentheses in 2SLS regressions.

Table 5 presents the results. In panel A, we show the FE regression results. It is evident that the revised skill premium and the export-weighted average GDP per capita across destinations are still positively correlated, though the estimated coefficient is less significant. The IV estimates, as shown in panel B, remain positive across specifications but insignificant. Notice that with the presence of weak instruments, the Anderson-Rubin Wald test reported at the bottom of the table suggests that the IV estimates are indeed significantly different from zero in Columns (1)-(4). Compared with the results in Table 2 and in Table 3, the estimated coefficients are markedly smaller in magnitudes in all specifications. This means that the high to medium and low skills wage gap resulted from exposure to high-income exports is smaller than high and medium to low skill wage gap, which implies that medium-skilled workers are less disadvantaged than low-skilled workers relative to the high skilled workers. Overall, the results in Table 3 provide supportive evidence for our main argument.

Relative supply of skilled labour

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

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

Columns (1) and (4) in Table 6 report the FE and IV estimation results with relative skill supply as an additional control variable. The coefficient on this variable is positive and highly significant, implying that industries with a greater supply of skilled labour tend to have higher skill premia. This is consistent with the *directed technology effect* proposed in Acemoglu (1998) and suggests that the positive technology effect dominates the negative substitution effect. The coefficient on export-weighted average destination income remains positive, though we lose significance in the IV estimation.

Imports from high-income economies

Along with rapidly growing exports following the WTO accession, another prominent feature of China's trade is the rapid increase in imports, due to factors such as tariff rate reductions, rising incomes and the exposure of exports. As documented in Li et al. (2014) and Raveh and Reshef (2016), imports of capital goods and intermediate goods from advanced economies, especially R&D intensive capital goods and high-quality intermediate inputs, are complementary to skills and therefore are related to 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 fairly small proportion (Koopman et al., 2012). Analogously to the construction of export-weighted average GDP per capita across export destinations, we generate weighted average GDP per capita across import sources using import share as weight, and include it in the regression to account for the role of imports from high-income economies. Notice that a higher value of this variable indicates that industries tend to import more from high-income economies.

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

	Panel A: FE estimation			Panel B: 2SLS estimation		
	(1)	(2)	(3)	(4)	(5)	(6)
Average destination GDP p/c	0.043***	0.079***	0.045***	0.035	0.313**	0.054*
	(5.323)	(3.483)	(5.384)	(1.041)	(2.324)	(1.661)
Relative skill supply	0.362***		0.357***	0.364***		0.355***
	(24.442)		(25.034)	(23.579)		(23.707)
Import-weighted average GDP p/c		-0.024***	-0.006		-0.029***	-0.006*
		(2.749)	(1.633)		(2.906)	(1.729)
Constant	-0.803***	-0.946***	-0.753***	-0.713*	-3.849**	-0.887**
	(7.196)	(3.235)	(6.659)	(1.681)	(2.328)	(2.221)
Observations	196	196	196	196	196	196
R^2	0.991	0.945	0.991	0.991	0.898	0.991
Kleibergen-Paap LM statistic				5.114	5.316	4.080
Kleibergen-Paap LM *p*-value				0.024	0.021	0.043
Montiel-Pflueger effective *F* statistic				4.655	4.753	3.887
Anderson-Rubin Wald test *F* statistic				0.575	18.897	1.271
Anderson-Rubin Wald test *p*-value				0.449	0.000	0.261

Notes: This table shows robustness checks that examine the relationship between skill premium and export-weighted average GDP per capita across export destinations. Panel A shows the FE regression results and Panel B shows the 2SLS regression results. Relative supply of skilled labour is measured as the ratio of total working hours by skilled workers over those by unskilled workers, where skilled and unskilled workers are defined the same as before. Import-weighted average GDP per capita is defined as weighted average GDP per capita across import source economies using the share of imports from each economy in total industrial imports as weight. All specifications include industrial export share, the log of gross fixed capital formation, labour productivity, year fixed effects and industry fixed effects. Robust standard errors are computed in all specifications. * p <0.1, ** p <0.05, *** p <0.01. Absolute *t*-values in parentheses. Absolute *z*-values in parentheses in 2SLS regressions.

Interestingly, the estimated coefficient of import-weighted average GDP per capita is significantly negative, as shown in Columns (2) and (5) in Table 6, suggesting that imports from high-income economies appear to benefit unskilled workers more than skilled workers. One potential reason is that a large proportion of China's imports (of both intermediate and capital goods) is for processing production (Amiti and Freund, 2010; Koopman et al., 2012).[13] Even if imports from high-income economies are embodied with advanced technology, processing production is only involved with simple assembling of imported parts into final goods and does not require much in terms of 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.

In Columns (3) and (6), we include both relative supply of skills and the import-weighted average GDP per capita as control variables. It is evident from both FE and IV results that the variable of interest remains positive and significant. It is worthwhile to mention that in specifications that control for relative supply of skills, the coefficient of average destination income is much lower than that in specifications when it is not controlled for, which indicates that omitting these crucial factors may bias our main results upwards.

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

5.3 Additional supporting evidence

Distinguishing ordinary exports and processing exports

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

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

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

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

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

	Panel A: Ordinary exports		Panel B: Processing exports	
	FE	2SLS	FE	2SLS
	(1)	(2)	(3)	(4)
Average destination GDP p/c	0.019***	0.027**	-0.015***	-0.020
	(3.408)	(2.572)	(2.649)	(1.021)
Observations	98	98	98	98
R^2	0.983	0.983	0.983	0.982
Kleibergen-Paap LM statistic		3.263		1.251
Kleibergen-Paap LM *p*-value		0.071		0.263
Montiel-Pflueger effective *F*-statistic		5.519		1.590
Anderson-Rubin Wald test *F*-statistic		3.071		0.580
Anderson-Rubin Wald test *p*-value		0.084		0.449

Notes: This table shows regression results that distinguish between ordinary exports and processing exports. In panel A, average destination GDP per capita is calculated using the share of ordinary exports to each destination within industry as weight. In panel B, average destination GDP per capita is calculated using the share of processing exports to each destination within industry as weight. The instrument for average destination GDP per capita is defined as in Equation (4). All specifications control for industrial export share, the log of gross fixed capital formation, labour productivity, relative skill supply, import weighted average source income, year fixed effects and industry fixed effects. Robust standard errors are computed in all specifications. * p <0.1, ** p <0.05, *** p <0.01. Absolute t-values in parentheses. Absolute z-values in parentheses in 2SLS regressions.

Differences before and after China's WTO accession

China joined the WTO in December 2001, following which China has integrated into the world economy rapidly. Table 1 shows that the export-weighted average GDP per capita fluctuated before 2001 but declined afterwards. As explained earlier, such reduction mainly results from the substantial drop in export shares to a few developed destinations, like Hong Kong, Japan and the U.S. Complementarily, the share of exports to other high-income countries and to middle- and low-income countries increased. Despite the reduction in export shares in a few destinations, China's total exports to both high-income destinations and middle- and low-income destinations rose rapidly following China's WTO accession in 2001. One may expect that the skill premium effects in the post-WTO accession period are stronger due to the huge expansion of foreign markets. To examine possible differences before and after 2001, we split the sample into two sub-periods: pre- and post-WTO accession periods and run regressions separately.[14] The regression results are presented in Table 8.

The FE regression results in Columns (1) and (3) show that the estimated coefficients on weighted average GDP per capita remain positive. However, the coefficient is larger in magnitude in the post-WTO accession period, suggesting a stronger effect in the second period. The IV estimate, however, turns out negative but insignificant for the pre-WTO accession period. Regarding the post-WTO accession period, the estimated coefficient of the average destination income is positive and significant at 10% level. Overall, our results provide some evidence that the positive effects of high-income exports on skill premium are stronger in the period after China's accession to the WTO.

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

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

	Panel A: 1995-2001		Panel B: 2002-2008	
	FE	2SLS	FE	2SLS
	(1)	(2)	(3)	(4)
Average destination GDP p/c	0.015**	-0.226	0.034***	0.080*
	(2.414)	(0.262)	(3.632)	(1.924)
Observations	98	98	98	98
R^2	0.997	0.926	0.983	0.980
Kleibergen-Paap LM statistic		0.091		1.737
Kleibergen-Paap LM *p*-value		0.763		0.188
Montiel-Pflueger effective *F*-statistic		0.065		1.546
Anderson-Rubin Wald test *F*-statistic		2.312		2.352
Anderson-Rubin Wald test *p*-value		0.133		0.130

Notes: This table compares the differential effects of export destination income on skill premium before and after China's WTO accession in 2001. Panel A shows the FE regression results and Panel B shows the 2SLS regression results. The instrument for export-weighted average GDP per capita is defined as in Equation (4). All specifications control for industrial export share, the log of gross fixed capital formation, labour productivity, relative skill supply, import-weighted average source country income, year fixed effects and industry fixed effects. Robust standard errors are computed in all specifications. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Absolute t–values in parentheses. Absolute z-values in parentheses in 2SLS regressions.

6 Conclusions

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

We first calculated 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 the relationship between that and the skill premium. To address the potential endogeneity of the export share measure, we follow Brambilla and Porto (2016) and Bastos et al. (2018) to explore the exogenous variations in exchange rates in destination countries, based on which we predict the export shares and use them as weights to construct an instrument for the observed average destination income. The baseline results reveal a positive relationship between average wages and average destination income, which is consistent with the findings in Brambilla and Porto (2016). More importantly, we find that industries that export more products to high-income destinations tend to have higher skill premium, resulting from higher wages for skilled than for unskilled workers. This implies that workers in developing countries with 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 the relative supply of skilled workers and import share weighted average source country income. Our IV estimations indicate a causal link between high-income destination exports and the skill premium.

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 (though insignificant) effect for 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 mainly requires low-skilled workers; an expansion of processing exports leads to an increase in the demand for low-skilled workers. This finding is important since it highlights that skilled workers benefit more from the growth of ordinary exports whereas unskilled workers may benefit more from processing exports. This may have implications for the design of industrial policies, given that ordinary and processing exports have different impacts on the relative wages of skilled and unskilled workers. Additionally, we find that the positive relationship is stronger during the post-WTO accession period when both Chinese total exports and exports to high-income destinations grew substantially.

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Appendix

Table A.1: Wages and weighted average GDP per capita across export destinations in manufacturing industries, 1995-2008

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

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

Table A.2: Export share and bilateral exchange rate

Industry	3	4	5	6	7	8	9
Real exchange rates	0.00024**	0.00017	0.00023**	0.00064***	0.00032**	-0.00024	0.00017***
	(2.110)	(1.333)	(2.545)	(2.625)	(2.303)	(0.741)	(2.906)
Observations	2,172	2,289	2,274	2,092	2,159	1,644	2,259
R^2	0.952	0.891	0.977	0.897	0.931	0.736	0.958
Industry	10	11	12	13	14	15	16
Real exchange rates	0.00049***	0.00128***	0.00084***	0.00058***	0.00016**	0.00146***	0.00018**
	(4.046)	(4.479)	(3.418)	(5.508)	(2.549)	(6.786)	(2.349)
Observations	2,267	2,254	2,272	2,267	2,274	2,226	2,279
R^2	0.958	0.923	0.926	0.966	0.980	0.891	0.979

Notes: This table shows the FE regression results of Equation (3) that regresses within-industry export share to each destination on bilateral real exchange rates (RER) by industry. The title for each column is the industry code that is used in this paper. Industry names can be found in Table A.4. Year fixed effects and destination fixed effects are included. Robust standard errors are computed in all specifications. * p <0.1, ** p <0.05, *** p <0.01. Absolute t-values in parentheses.

Table A.3: Wage bill share of skilled workers and weighted average GDP per capita across export destinations in Chinese manufacturing industries: 1995-2008

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: FE estimation						
Average destination GDP p/c	0.055***	0.057***	0.059***	0.060***	0.042***	0.044***
	(4.752)	(4.811)	(4.957)	(5.008)	(4.570)	(5.025)
R^2	0.998	0.998	0.998	0.998	0.999	0.999
Panel B: 2SLS estimation						
Average destination GDP p/c	0.154**	0.140***	0.139**	0.129***	0.098***	0.098***
	(2.504)	(2.759)	(2.546)	(2.784)	(2.743)	(2.735)
R^2	0.997	0.997	0.997	0.997	0.998	0.998
Observations	196	196	196	196	196	196
Kleibergen-Paap LM statistic	5.477	6.518	5.696	6.656	5.853	5.824
Kleibergen-Paap LM p-value	0.019	0.011	0.017	0.010	0.016	0.016
Montiel-Pflueger effective F-statistic	5.564	6.461	5.819	6.604	5.177	5.385
Anderson-Rubin Wald test F-statistic	22.625	24.237	20.780	22.816	9.002	9.165
Anderson-Rubin Wald test p-value	0.000	0.000	0.000	0.000	0.003	0.003

Notes: This table uses the wage bill share of skilled workers as the dependent variable. Skilled workers are defined as those with a high school education or above. Panel A reports the FE regression results and Panel B report the 2SLS regression results. The instrument for export weighted average GDP per capita is defined as in Equation (4). Specifications (1)-(6) include the same controls as Columns (1)-(6) in Table 2 . Robust standard errors are computed in all specifications. * p <0.1, ** p <0.05, *** p <0.01. Absolute t-values in parentheses. Absolute z-values in parentheses in 2SLS regressions.

Table A.4: Industry classification used in this paper

Industry	ISIC rev.3 code	Industry name
3	15-16	Food, beverages and tobacco
4	17-18	Textiles and textile products
5	19	Leather, leather products and footwear
6	20	Wood and products of wood and cork
7	21-22	Pulp, paper, printing and publishing
8	23	Coke, refined petroleum and nuclear fuel
9	24	Chemicals and chemical products
10	25	Rubber and plastics
11	26	Other non-metallic mineral
12	27-28	Basic metals and fabricated metal
13	29	Machinery, not elsewhere classified
14	30-33	Electrical and optical equipment
15	34-35	Transport equipment
16	36-37	Manufacturing, not elsewhere classified; recycling