The effect of exports on labor share: a semiparametric approach using Chinese manufacturing panel data

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Abstract

We decompose the effects of export on labor share into a stand-alone neutral effect and indirect non-neutral effects, which alter the marginal impact of three key determinants of labor share found in the literature. While the neutral effect of export has been extensively studied, the potential non-neutral effects remain unexplored. We investigate both effects of exports using micro-level Chinese firm-level data from 1998-2007. We employ a fixed-effect varying coefficient model to reveal the potential nonlinearity of the export's effects while alleviating the risk of model mis-specification. Our model is estimated by a spline-backfitted kernel estimator, which is more efficient and computationally attractive than its alternative estimators. We find that while exports neutrally increase labor share as expected, it declines labor share non-neutrally through intensifying the negative marginal impact of firms' capital intensity, monopoly power, and capital-augmented technological progress on labor share. As a result, the net effect of exports is not beneficial to labor's share of income, and varies in magnitude across firm's characteristics, regions, and time periods.

Keywords: Labor share, export, globalization, varying coefficient model, fixed-effect semi-parametric panel model

JEL Classification: C14, F16, F66, O50.

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1 Introduction

China has been actively engaged in global economic activities in the past four decades. As of 2016, China exported 2,098 billion dollars, making it the largest export economy and the "world's factory". While international trade has contributed substantially to the employment, economic growth, and product sophistication in China (Dong and Xu, 2009; Ma et al., 2015; Upward et al., 2013), little is known about the impact of export on the labor share of income during this process.

The worldwide labor's share of national income has shrunk since the 1980s (Blanchard et al., 1997).[1] A wave of subsequent studies investigated the determinants of labor share across countries, with international trade commonly attributed to account for the declining labor share (Ortega and Rodriguez, 2001; Harrison, 2005; Guscina, 2006; Jaumotte and Tytell, 2008; Daudey and García-Peñalosa, 2007; Young and Zuleta, 2015; Young and Tackett, 2017). In the case of China, labor share declined by 12.45 percentage points during 1995-2007, despite the fast economic growth through intensive exporting (Bai and Qian, 2010). In manufacturing industries, the most tradable sector in Chinese economy, labor share dropped by three percentage points over 1998-2007 as shown in Figure 1.[2] Hence, exporting may play a key role in explaining China's labor share.

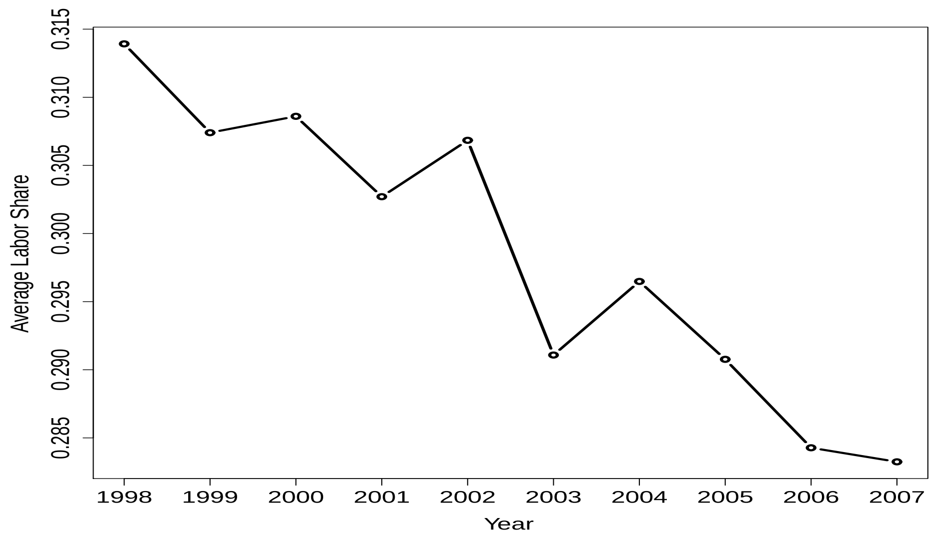
The current literature in labor share suggests that exports can directly affect the labor share, and we call this a neutral effect. The neutral effect flows from neoclassical trade theory (Ohlin, 1952; Stolper and Samuelson, 1941), which has been commonly discussed by many subsequent studies (Guerriero and Sen, 2012; Boggio et al., 2010; Zhang and Lu, 2014). The theory states that owners of capital gain higher returns in capital-abundant countries (usually developed countries) that export capital-intensive goods, whereas labor gains higher returns in labor-abundant countries (usually developing countries) that export labor-intensive products. Given the abundant labor in China, therefore, the neutral effect of exports is expected to be positive with respect to China's labor share (Huang et al., 2011).

However, exports may also affect labor share indirectly through altering the partial effects of three key determinants of labor share in the literature, namely, capital intensity, monopoly power, and capital-augmenting technologies. We call these non-neutral effects. First, a higher capital intensity (e.g., capital-labor ratio) would decline labor share given a substitutable labor-capital relationship, which is commonly observed in developing countries (Elsby et al., 2013; Tian and Wang, 2018). Since exporting firms tend to be more capital intensive than non-exporting firms (Bernard and Jensen, 1997), we expect that higher exports

[1] For the importance of studying factor shares, see an excellent discussion by Atkinson (2009).

[2] See the data description in Section 3.

Figure 1: Labor Share in Chinese Manufacturing Industries: 1998-2007

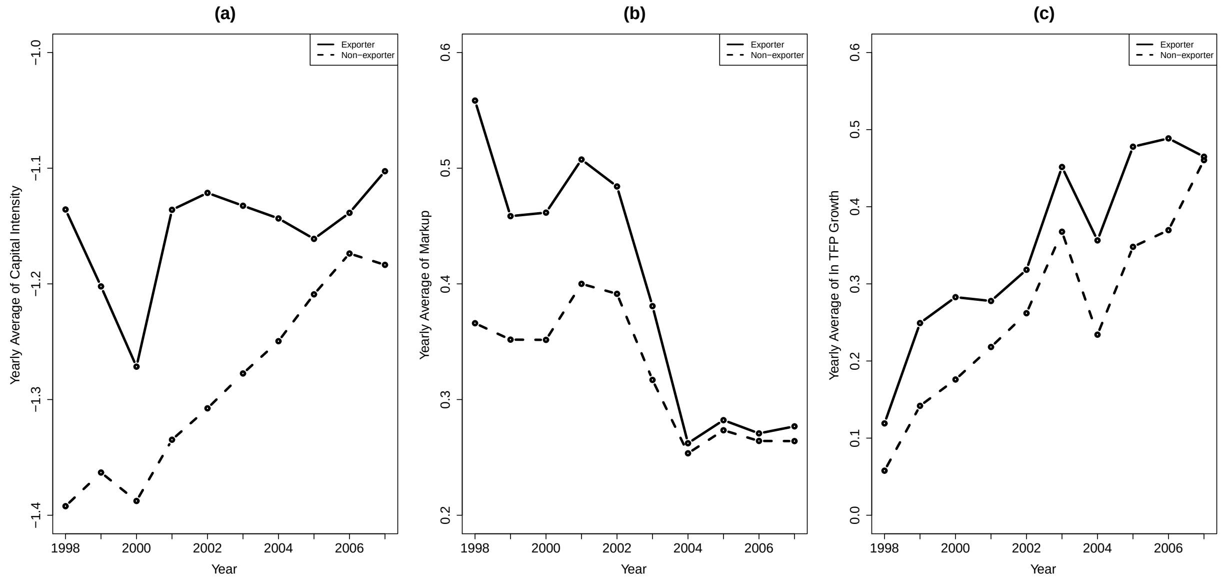


Date Source: Chinese Annual Surveys of Industrial Production.

may further intensify the negative effect of capital intensity on labor share. Second, firms with higher exports are likely to possess monopoly power, which creates incentives to charge higher markups that decline labor share by eroding labor's bargaining power (De Loecker and Warzynski, 2012; Dorn et al., 2017). In addition, Fan et al. (2017) document that exporters in Chinese manufacturing firms are induced to increase markup through trade liberalization. Hence, intensive exports may enlarge the negative effect of markup on China's labor share. Finally, Chinese industrial enterprises have extensively adopted capital-augmented technology (Fisher-Vanden and Jefferson, 2008), which is likely to lower labor share when labor and capital are substitutable (Bentolila and Saint-Paul, 2003; Karabarbounis and Neiman, 2013). Since capital-augmenting technology is commonly captured by total factor productivity (TFP) (Bentolila and Saint-Paul, 2003), and the TFP is typically higher in exporting firms (Aw et al., 2011; Bernard et al., 2003; Bernard and Jensen, 1997), we expect that a higher export intensity may amplify the negative effect of capital-augmenting technologies on China's labor share.

Given the relevance of both neutral and non-neutral effects of exports on labor share, both effects should be taken into account in an empirical study. Nonetheless, the majority of studies in the Chinese labor share literature have only paid attention to the neutral effect of exports (see, for example, Zhang and Lu (2014)), leaving the existing argument of its non-neutral effects unexplored. A few recent studies have moved into this direction by examining the underlying interactive relationship between trade and labor share from a microeconomic

Figure 2: Exporters vs Non-exporters in capital intensity, total factor productivity, and markup.



Date Source: Chinese Annual Surveys of Industrial Production.

foundation (Böckerman and Maliranta, 2011; Perugini et al., 2017), although China is not considered in their sample.

In this paper, we fill the gap by contributing to the literature in two ways. First, we decompose the total effects of export into its neutral effect and three non-neutral effects, which potentially alter the marginal impact of: 1) capital intensity (proxied by capital-labor relative ratio), 2) monopoly power in imperfect competition (proxied by markup), and 3) capital-augmented technology (proxied by TFP) on labor share. To uncover the empirical evidence from micro-level foundation, we employ firm-level data from Chinese Annual Surveys of Industrial Production during 1998 to 2007. Compiling by the National Bureau of Statistics of China, the survey is compulsory for all state-owned firms and non-state-owned firms with annual sales above five million RMB, representing about 90% of the gross industrial output of the whole nation (Jin et al., 2018). Since most Chinese firms with exporting behavior are in manufacturing industries, we focus on Chinese manufacturing firms in our study. To alleviate the measurement error problem as well as the entry-exit effect of firms, we consider a balanced panel of 4,767 Chinese manufacturing firms from 1998-2007. Figure 2 plots yearly-averaged capital-labor ratio, markup, and TFP from our sample in panel (a)-(c), respectively. Clearly, the magnitude of each variable is higher in exporters than non-exporters, supporting our conjunctures that the three variables may have heterogeneous effect on labor share conditioning on different level of exports.[3]. Our sample also covers the time period of extensive and expansive trade that includes the nation's entry to the World Trade Organization (WTO). Hence, we expand on these observation and empirically test both neutral and non-neutral effects of exports, as well as its heterogeneity across firm's ownership, regions, and time for which China joined WTO.

Second, we do not restrict the labor share regression to be a linear function of exports, which is a common choice of model specification in the literature. In the absence of a clear functional form from economic theories, however, a correct labor share regression structure is unknown in practice, thus making the linear regression subject to potential model misspecification. To alleviate the issue, we implement a semiparametric varying coefficient model with fixed effect (VCM-FE) that allows for both the neutral and non-neutral effects to be unknown functions of export. We show that the VCM-FE nests the linear OLS fixed effect regression model (OLS-FE) with interaction terms as a special case. Inspired by Wang and Yang (2009) and Sun and Malikov (2018), we estimate the unknown functions in VCM-FE by a spline-backfitted kernel estimator, with firm-specific fixed effect removed via de-mean approach. Compared with alternative estimators in the literature, our estimator is more efficient and computationally attractive. Another advantage of estimating VCM-FE is its ability to obtain observation-specific estimates of neutral and non-neutral export effects, therefore revealing the potential nonlinearity of exports effects across firms and times.

We note that understanding the economic determinants of labor share is particularly important for China with its export-led economic growth strategy, since it reveals the proportion of economic benefits that has been shared by labor along with its' participation in the global supply chain. Given China's high degree of engagement in exports, labor participation rate, and heterogeneity across firms' characteristics, the Chinese economy is an ideal laboratory to study the relationship between exports and labor's share of income. It also has policy implication for the Chinese labor market, since the magnitude of Chinese labor share decline is important to understanding income inequality in China (Zhou, 2015).

Following the introduction above, Section 2 presents a brief literature summary, with the an emphasize on how the exports potentially affect labor share through the marginal impact of capital intensity, monopoly power, and capital-augmenting technology on labor share. Section 3 details the data used in our analysis, followed by the empirical approach in Section 4. Section 5 in turn presents and discusses empirical results, and Section 6 concludes with suggestions for policy implication.

[3] The negative yearly-averaged values in panel (a) is due to the natural log value of capital-labor ratio.

2 Literature Background

2.1 Labor share and export in China

Labor's share of income is important for contemplating economic growth itself, since the extent to which the growth benefits of a nation has been enjoyed by labor and/or capital remains unclear in general. In political economics, labor share is always considered a proxy of labor's welfare, so the declining trend of labor share is often used by unions as an evidence that is against labor (Young and Zuleta, 2015). Historically, labor share – the ratio of labor compensation to domestic output – was seen as constant over time. In the late 1980s, however, a declining trend of labor share was documented by Blanchard et al. (1997). This economic phenomenon occurred in developed countries as well as in traditionally "labor-intensive" developing countries (Boggio et al., 2010).

As a labor-intensive developing country, China achieved its growth miracle partially due to its export-led growth strategy. While a number of studies have focused on the performance and determinants of China's export-led growth (Amiti and Freund, 2010; Guo and N'Diaye, 2009; Girma et al., 2009; Jiang, 2008), only a handful of studies focus on the effect of exports on labor share even though millions of workers have participated in the export sector. Bai and Qian (2010) employ a firm-level data set similar to this paper, and find that the state-owned enterprises (SOEs) reconstruction and the monopoly power enhancement significantly lower labor share in Chinese industries during 1998 to 2007. However, their study does not consider the role of exports. Luo and Zhang (2010) suggest that the increasing share of foreign firms in export industries and trade transformation towards capital-intensive products are the main reasons for the declining labor share in China. However, they did not find a significant impact of exports using provincial level data. Zhou (2015) argues that the change of industrial structure in tradable sector accounts for a part of the decline in labor share in the industrial sector. The focus of Zhou's study, however, is on the effect of import penetration in the time of export-import processing trade in Pearl River delta and export-led processing trade in Yangtze River, thus making its empirical results difficult to be generalized in China. Finally, Huang et al. (2011) using provincial level data document that technological progress, represented by TFP, significantly pulls down China's labor share. However, the dependence of TFP's effect on labor share with exports is not discussed, which may be highly relevant as we shall discuss shortly.

To our best knowledge, the underlying channels through which exports may affect labor share in China have not been explicitly explored, particularly via a micro-level foundation. In the following section, we discuss in detail how exports may influence labor share neutrally through trade effect, and non-neutrally through altering the marginal impact of three key determinants in labor share that are commonly discussed in the literature.

2.2 Links between trade and labor share

The trade and labor share literature suggests that explanatory variables of labor share can be grouped into non-trade variables and trade variables. On the one hand, non-trade variables are highly related to the production process, which mainly includes capital intensity, the degree of monopoly power in non-perfect competition, and capital-augmented technology process. First, capital intensity is argued in a theoretical model by Elsby et al. (2013), stating that labor's share of income is significantly related to the capital intensity (i.e., capital-labor ratio). Specifically, higher capital intensity would result in higher (lower) labor share given a complementary (substitutable) relationship between labor and capital. Since capital and labor are likely to be substitutable in developing countries (Young and Tackett, 2017; Tian and Wang, 2018), higher capital intensity is likely to decrease China's labor share.

Second, higher market power of firms under imperfect competition would result in higher markup that widens the gap between marginal product of labor (MPL) and real wage, which in turn exerts downward pressure on labor share through labor bargaining power reduction (Bentolila and Saint-Paul, 2003; Bai and Qian, 2010; Rodrik, 1998; Kalecki, 1938). Finally, Acemoglu (2003) argues that capital-augmenting technology may worsen labor share in the presence of trade, since labor's bargaining power against the use of capital is likely to be deteriorated in the presence of "trade-induced" capital-biased (or labor-saving) technology.

On the other hand, trade variables, particularly exports, may link to labor share through its *neutral* and *non-neutral* effect. The *neutral* effect stems from the classical Heckscher-Ohlin framework and Stoper-Samuelson Theorem (Ohlin, 1952; Stolper and Samuelson, 1941) and has been incorporated as one plausible theory to explain cross-country labor share by many subsequent studies (Guerriero and Sen, 2012; Boggio et al., 2010; Huang et al., 2011; Zhang and Lu, 2014). The theory predicts that a trade-induced change in product prices alters the real return for the factor intensively used in the production. Thus, owners of capital (labor) receive higher return (real wage) in capital-intensive (labor intensive) countries. Given that China has taken the comparative advantage of having labor-intensive technology, we expect a positive neutral effect of export on China's labor share.

More importantly, trade may also possesses *non-neutral* effects that works through changing the marginal impact of the three non-trade variables mentioned above. First, capital intensity may be positively related with export intensity as exporters are more capital intensive than non-exporters (Bernard and Jensen, 1997, 1999). We find it to be consistent with the case in China as shown in Panel (a) of Figure 2. Given that higher capital intensity is likely to decrease China's labor share given a substitutable relationship between capital and labor, the negative marginal effect of capital intensity on labor share may be intensified with an increase in export intensity. We test this mechanism as the first non-neutral effect by modeling the coefficient of a proxy for capital intensity as a function of exports.

In addition, trade may consolidate firms' monopoly power under imperfect competition. De Loecker and Warzynski (2012) find that exporters usually charge higher markups than non-exporters, which is also consistent with our finding in China as shown in panel (b) of Figure 2. Hung and Hammett (2016) further argue that globalization is likely to induce special "know-how" firms to expand firm size and charge higher markup, since their products don't have close substitutes. Their arguments are also consistent with the implication from "super-star" firm model by Dorn et al. (2017), which is used to explain the declining labor share in US industries. Hence, we conjecture that the negative marginal effect of firm's monopoly power on labor share may be enlarged with higher export intensity. We test this mechanism as the second non-neutral effect by modeling the coefficient of a proxy for monopoly power as a function of exports.

Finally, the channels through which trade affects labor share via capital-augmented technology is ambiguous. One side of the argument is that international trade relaxes production constraints and enhance productivity in general (i.e. technological spillovers), thereby resulting in a substantial increase in national income that makes workers betters off (Keller, 1998, 2002; Zhu and Jeon, 2007). In contrast, another part of the literature perceives trade-induced technological innovation and mechanization as capital-augmenting rather than labor-augmenting, which lowers labor share when capital and labor are substitutable (Bentolila and Saint-Paul, 2003; Karabarbounis and Neiman, 2013; Dinopoulos and Segerstrom, 1999). Also, exporters are usually more productive than non-exporters in terms of TFP (Aw et al., 2011; Bernard et al., 2003; Bernard and Jensen, 1997), which is consistent with our finding in panel (c) of Figure 2. Since TFP is a common proxy for capital-augmenting technology (Bentolila and Saint-Paul, 2003), we expect that the negative effect of capital-augmenting technology on China's labor share may be more severe in the presence of intensive exports. We test this mechanism as the last non-neutral effect by modeling the coefficient of a proxy for capital-augmenting technology as a function of exports.

In sum, the current labor share literature suggests the potential channels through which exports may affect labor share in China with the largest export sector in the world, which is ultimately an empirical question. Hence, this paper fills the gap by providing a thorough empirical evidence of how firms' exports influence labor share of income, therefore rendering market policy implications for how labor share can be effectively maintained in Chinese manufacturing industries.

3 Data

We employ data from Chinese Annual Surveys of Industrial Production (ASIP) during 1998-2007. Maintained by the National Bureau of Statistics of China (NBSC), the dataset provides reliable statistic measures, and has been implemented in many recent studies (Hsieh and Klenow, 2009; Song et al., 2011; Chen and Guariglia, 2013; Lai et al., 2016; Berkowitz et al., 2017; Zou et al., 2018). It contains balance-sheet information on all state-owned enterprises (SOEs) and "above-scale" enterprises with annual sales of five million Chinese yuan (RMB) (611,995 dollars).[4] Given that most firms with exporting behavior are in manufacturing industries, our sample covers 31 manufacturing industries with their corresponding 2-digit Chinese Industrial Classification (CIC) codes and names provided in Appendix 2.

Our main variable, *labor share*, is defined as labor's compensation (*wage*+*benefit*) divided by firms' value added, where *benefit* are bonus paid to labor at the end of each year. Our trade variable is *export intensity*, defined as the ratio of firms' export to total output. Our non-trade variables include *capital intensity*, the natural logarithm of real capital per worker; *total factor productivity* (TFP), calculated based on Levinsohn and Petrin (2003) and Petrin et al. (2004) that measures technological progress;[5] and *markup*, the difference between firms' sales and cost divided by cost that captures the degree of monopoly power in the product market. In order to avoid the impact of firm entry and exit on labor share, we curtail the sample to be a balanced panel with incumbent firms from 1998 to 2007. To mitigate outliers effect as well as measurement error problems, we drop firms with missing values, negative labor share, and the highest and lowest one percentile of all variables. The final data contains a balanced panel of 4,767 firms from 1998 to 2007, resulting in 47,670 firm-year observations.

Table 1 reports the sample mean and standard deviation (in parentheses) for the whole firm-year observations and other dimensions. We observe that when the sample is split based on whether a firm has non-zero export intensity, exporters have higher labor share than whole firm-year observations and non-exporters by nearly three and five percentage points, respectively. Also, exporters are more capital-intensive and productive than non-exporters as argued by (Bernard and Jensen, 1997, 1999). The fact that they have lower markup and thus lower monopoly power is also consistent with Lu (2010).

In addition, the difference between these two groups is found when the whole sample is divided in terms of nationality. We follow the literature to define a firm as foreign if more than 50% of the firms' paid-in capital is from foreign countries. We found foreign firms engaging intensively in the export sector, with 70% of observations of foreigner firms are

[4]The exchange rate of 8.17 RMB per USD is taken as the average nominal exchange rate between 1998 and 2007 from the Federal Reserve Bank.

[5]All price deflators used in the TFP calculation are taken from NBSC.

Table 1: Descriptive Data Summary

Variables	Whole	Exporters	Non-exporters	Foreign firms	Domestic firms	East	Inland	Before 2002	After 2002
Labor share	0.293	0.321	0.272	0.297	0.291	0.301	0.268	0.296	0.291
	(0.195)	(0.201)	(0.187)	(0.200)	(0.193)	(0.193)	(0.196)	(0.194)	(0.195)
Export intensity	0.227	0.539	0.000	0.447	0.158	0.256	0.141	0.218	0.233
	(0.442)	(0.544)	(0.000)	(0.489)	(0.402)	(0.474)	(0.321)	(0.357)	(0.490)
Capital intensity	0.435	0.468	0.413	0.643	0.370	0.431	0.448	0.424	0.443
	(0.482)	(0.516)	(0.454)	(0.624)	(0.406)	(0.483)	(0.480)	(0.500)	(0.469)
Markup	0.348	0.314	0.373	0.351	0.347	0.328	0.409	0.413	0.305
	(0.628)	(0.445)	(0.732)	(0.553)	(0.650)	(0.533)	(0.848)	(0.759)	(0.520)
TFP	2.328	2.472	2.224	2.541	2.262	2.301	2.408	2.160	2.441
	(0.822)	(0.824)	(0.804)	(0.829)	(0.809)	(0.809)	(0.855)	(0.767)	(0.838)
Observations	47,670	20,061	27,609	11,366	36,304	35,639	12,031	19,068	28,602
(% in whole sample)	(100%)	(42)%	(58)%	(24%)	(76%)	(54%)	(46%)	(41%)	(59%)

Source: Chinese Annual Surveys of Industrial Production 1998-2007. *Note*: the average of each variable is reported under each sample, with its standard deviation listed in parenthesis.

exporters.[6] Domestic firms are defined similarly and classified into three types of ownership: state-owned enterprises (SOEs), private, and collective. A comparison between foreign and domestic firms reveals that the former are two times higher than the latter in export intensity and capital intensity. Foreign firms also exhibit slightly higher (lower) markup (TFP) than domestic firms.

Furthermore, splitting the sample into the eastern (coastal) and inland regions shows that eastern regions have higher labor share and export intensity, but lower capital intensity, markup and TFP than the inland.[7] The results should not be surprising, given that "heavy industries", such as vehicle and electronic manufacturing/equipment industries, that are usually capital intensive and productive, have moved into inland regions in recent years. In contrast, most "light industries", such as textile and leather manufacturing industries, are located in the eastern area (Ma, 2018). Finally, since China joined the World Trade Organization in November of 2001, we split the sample before and after 2002. There are no obvious differences in our main variables, except that the after-2002 sample shows slightly higher (lower) export intensity, capital intensity and TFP (labor share and markup).[8]

In sum, the statistics indicate that exporters and non-exporters exhibit different patterns in labor share conditioning o capital intensity, firms' markup, and TFP. This is also the case with foreign and domestic firms and firms in different regions. We now turn to investigate how those differences due to export intensity can help to explain labor share movement in China by empirically testing its neutral and non-neutral effects.

4 Empirical Methodologies

One common empirical model to estimate the neutral and non-neutral effect of exports on Chinese labor share is a fixed-effect linear regression model (OLS-FE) with interaction terms between exports and the three non-trade variables:

$$LS_{it} = exint_{it}\alpha_0 + k_{it}(\alpha_1 + exint_{it}\alpha_4) + markup_{it}(\alpha_2 + exint_{it}\alpha_5) + TFP_{it}(\alpha_3 + exint_{it}\alpha_6) + \mu_i + v_{it} \quad (1)$$

where for $i = 1, ..., n$ and $t = 1, ..., T$ being the index of firms and time, respectively, LS is labor share, $exint$, k, $markup$ and TFP are export intensity, capital intensity, markup, and TFP, respectively. Variable μ_i is the firm-specific unobserved heterogeneity that is potentially correlated with covariates, and v_{it} is a zero-mean additive error term independent

[6] See Tian (2018) for more detailed discussions about firm ownership in China.

[7] Classification of eastern and inland regions are based on region classification code from National Bureau of Statistics of China and is given in Appendix 3.

[8] This can be due to that we only consider incumbent firms, excluding the effect of firm entry and exit.

with regressors. Here, exports in (1) affects labor share *neutrally* through its own function $exint\alpha_0$, and *non-neutrally* through the coefficient function of k (i.e., $\alpha_1 + exint_{it}\alpha_4$), $markup$ (i.e., $\alpha_2 + exint_{it}\alpha_5$), and TFP (i.e., $\alpha_3 + exint_{it}\alpha_6$). In our study, we employ a fixed effect (FE) empirical model because firm-specific fixed effect may exist over time and correlated with regressors in our study. For instance, firms locating closer to coastline may be more inclined to engage in export than inland firms. Also, the FE model is commonly specified in the literature that may meaningfully decrease the potential endogeneity issue. Finally, it is well known that a FE estimator is unbiased and consistent in both FE and random effect model, except with some efficiency loss when the RE model is true. However, RE model is inconsistent if the fixed effect is correlated with regressors.

Nonetheless, the effect of *exint* in (1) may be inconsistent, since our pre-specified linear functional form of export's effects may be potential mis-specified. To alleviate such risk, we generalize (1) by estimating the following semiparametric fixed-effect varying coefficient model (VCM-FE):

$$LS_{it} = m_0(exint_{it}) + k_{it}m_1(exint_{it}) + markup_{it}m_2(exint_{it}) + TFP_{it}m_3(exint_{it}) + \mu_i + v_{it} \quad (2)$$

where the neutral effect of export now works through $m_0(\cdot)$ and non-neutral effect through $m_s(\cdot)$, $s = 1, 2, 3$, and all functions $m_j(\cdot)$ are potentially nonlinear with respect to *exint* for $j = 0, ..., 3$. In other words, the partial effect of capital intensity, markup, or TFP growth on labor share is allowed to nonlinearly vary with the magnitude of export intensity. Clearly, model (2) nests model (1) as a special case when $\{m_j(\cdot)\}_{j=0}^3$ are all linear functions of *exint*.[9].

The varying coefficient model in (2) has gained its increasing popularity in various empirical works due to its flexibility of interactive effect estimation, efficiency of estimators, and easiness of result interpretation (see Park et al. (2015) for a survey). Recently, Sun et al. (2009) estimate (2) by constructing a kernel-smoothed version of orthogonal projection matrix to consistently estimate $m_j(\cdot)$ by concentrating out the fixed effect. However, their estimator is computational demanding, which is inappropriate in our large sample. Estimator in Sun and Malikov (2018) involves estimation of (2) by a series estimator that reduces computational cost but increase estimation inefficiency. Wang and Yang (2009) consider estimating an cross-section additive model via a combination of both kernel and series estimator, called spline-backfitted kernel estimator (SBK). Comparing with alternative estimator in the literature, the SBK is computationally efficient and substantially reduces

[9]One concern may be the potential endogeneity of export intensity in our model. We address this problem by testing the null hypothesis where export intensity is exogenous and discuss the testing procedure in Appendix 1. We find no evidence to reject the null, indicating that export intensity is not likely to be endogenous in our model, therefore justifying the use of VCM-FE.

finite-sample inefficiency and bias of estimates. In this paper, we extend their SBK to estimate function $m_j(\cdot)$ as well as its derivative $m_j^{'}(\cdot)$ in (2) due to its appealing theoretical properties, which makes its empirical application fairly practical.

For notation simplicity, we let $y_{it} \equiv LS_{it}$, $z_{it} \equiv exint_{it}$, and $x_{it} = [x_{1,it}, x_{2,it}, x_{3,it}]^{\intercal} \equiv [k_{it}, markup_{it}, TFP_{it}]^{\intercal}$. Hence, model (2) is equivalent to

$$y_{it} = X_{it}^{\intercal} m(z_{it}) + \mu_i + v_{it} \tag{3}$$

where $X_{it} = [1, x_{1,it}, x_{2,it}, x_{3,it}]^{\intercal}$, and $m(z_{it}) = [m_0(z_{it}), m_1(z_{it}), m_2(z_{it}), m_3(z_{it})]^{\intercal}$.

We consistently estimate $m(\cdot)$ and its derivative $m^{'}(\cdot)$ via two steps. First, we estimate functions $m(\cdot)$ by its series estimator. Let $\{\phi_k(\cdot)\}_{k=1}^{L_n}$ be a sequence of B-spline basis functions. For a point of $z \in Z$ with $Z = \{z_{it}\}_{i=1,t=1}^{n,T}$, we approximate the unknown function $m_j(z)$ by its series estimator $\tilde{m}_j(z)$ from

$$\tilde{m}_j(z) = \sum_{k=1}^{L_n} \phi_k(z)\beta_k,\ j = 0, ..., 3$$

where $L_n = J_n + m$ is the number of basis function, with J_n the interior knots evenly placed on the range of Z, and m is the polynomial order of the basis function. In other words, we split the function $m_s(\cdot)$ into a total of $J_n + 1$ subintervals defined on the support of Z, and fit functions in each subinterval by a polynomial function of order m. In other words, we estimate $m_s(\cdot)$ using piece-wise polynomial function. The use of $J_n + m$ subintervals is necessary due to the recursive nature of B-spline function.[10] Finally, we follow the literature to choose $m = 3$ in our study and choose J_n such that $J_n \to \infty$ and $J_n/n \to 0$ as $n \to \infty$.

In matrix form, we rewrite (3) as

$$Y = Q(X, \Phi_n(z))\boldsymbol{\eta} + D\boldsymbol{\mu} + V \tag{4}$$

where X_{it} and $\Phi_n(z_{it}) = [\phi_1(z_{it}), ..., \phi_{L_n}(z_{it})]$ is denoted as the it^{th} row of X and $\Phi_n(z)$, respectively, $\boldsymbol{\eta} = [\boldsymbol{\beta}_{0,L_n}^{\intercal}, ..., \boldsymbol{\beta}_{3,L_n}^{\intercal}]^{\intercal}$ is a $(4L_n \times 1)$ vector with $\boldsymbol{\beta}_{j,L_n} = [\beta_{j,1}, ..., \beta_{j,L_n}]^{\intercal}$, and the it^{th} row of $Q(X, \Phi_n(z))$ is given by $Q(X_{it}, \Phi_n(z_{it})) = [\Phi_n(z_{it}), x_{1,it} \otimes \Phi_n(z_{it}), x_{2,it} \otimes \Phi_n(z_{it}), x_{3,it} \otimes \Phi_n(z_{it})]$, where $\otimes$ refers to Kronecker product. Finally, we follow Sun et al. (2009) to assume $\sum_{i=1}^{n} \mu_i = 0$ so that $D = [-\iota_{n-1}, I_{n-1}]^{\intercal} \otimes \iota_T$, where I_e is a $(e \times e)$ identity matrix, and ι_e is a $(e \times 1)$ vector of ones for a constant e.

Define $M_D = I_{nT} - D(D^{\intercal}D)^{-1}D^{\intercal}$ and let $W \equiv Q(X, \Phi_n(z))$, we "swipe out" the fixed effect in (4) by pre-multiplying M_D on its both sides to have $M_D Y = M_D W\boldsymbol{\eta} + M_D V$, so

[10]We refer readers to see Eubank (1999) for an extensive review of series estimation.

we obtain our first stage series estimator $\tilde{\boldsymbol{\eta}}$ from

$$\tilde{\boldsymbol{\eta}} = \underset{\{\boldsymbol{\eta}\}}{argmin}\,(Y - W\boldsymbol{\eta})^\top M_D(Y - W\boldsymbol{\eta}) \tag{5}$$

and we approximate function $m_j(z)$ by $\tilde{m}_j(z) = \Phi_n(z)\tilde{\boldsymbol{\beta}}_{j,L_n}$.

However, $\tilde{m}_j(z)$ is not efficient, since functions in each subinterval are fitted with relatively small observation. Hence, in the second step we improve the estimation efficiency via a one-step kernel smoothing backfitting. For $s = 1, 2, 3$, let $\tilde{m}_{-0s}(z)$ ($\tilde{m}_{0s}(z)$) be a vector of $\tilde{m}(z) = [\tilde{m}_0(z), \tilde{m}_1(z), \tilde{m}_2(z), \tilde{m}_3(z)]^\top$ with elements $[\tilde{m}_0(z), \tilde{m}_s(z)]$ removed (maintained). Also, let $X_{-0s,it}$ and $X_{0s,it}$ defined similarly. We efficiently estimate the function $m_0(z)$ and $m_s(z)$ with their derivate $m_0^{'}(z)$ and $m_s^{'}(z)$ by their corresponding local linear estimator $\hat{\delta}_{0s}(z) = [\hat{m}_0(z), \hat{m}_s(z)]^\top \equiv [\hat{a}_0, \hat{a}_1]^\top \equiv \hat{\boldsymbol{a}}^\top$ and $\hat{\delta}_{0s}^{'}(z) = [\hat{m}_0^{'}(z), \hat{m}_s^{'}(z)]^\top \equiv [\hat{b}_0, \hat{b}_1]^\top \equiv \hat{\boldsymbol{b}}^\top$ from

$$(\hat{\boldsymbol{a}}^\top, \hat{\boldsymbol{b}}^\top) = \underset{\{\boldsymbol{a}^\top, \boldsymbol{b}^\top\}}{argmin} \sum_{i=1}^{n}\sum_{t=1}^{T}\left[\tilde{y}_{it} - \tilde{\mu}_i - X_{0s,it}^\top\boldsymbol{a} - X_{0s,it}^\top \otimes (z_{it} - z)\boldsymbol{b}\right]^2 K_h(z_{it}, z) \tag{6}$$

where $\tilde{y}_{it} = y_{it} - X_{-0s,it}^\top\tilde{m}_{-0s}(z_{it})$, $\tilde{\mu}_i$ is the i^{th} observation in $\tilde{\boldsymbol{\mu}} = [-\iota_{n-1}^\top\tilde{\boldsymbol{\mu}}_{-1}, \tilde{\boldsymbol{\mu}}_{-1}^\top]^\top$ with $\tilde{\boldsymbol{\mu}}_{-1} = (D^\top D)^{-1}D^\top(Y - W\tilde{\boldsymbol{\eta}})$, and $K_h(z_{it}, z) = K(\frac{z_{it}-z}{h})$ is the univariate kernel function. We choose Gaussian kernel in our study and calculate the asymptotic standard error of our estimator in (6) based on Theorem 2 in Cai et al. (2000). Notice that our VCM-FE estimates $(\hat{\boldsymbol{a}}^\top, \hat{\boldsymbol{b}}^\top)$ depend on a particular level of $exint \equiv z$, thus illustrating the potential heterogeneous effects of the export intensity on the labor share through its neutral and non-neutral channels.

The intuition behind our two-step estimator is the following. In the first step, we "hammer down" the entire function $m_s(\cdot)$ into many pieces, and within each piece we fit data using a polynomial function (i.e., the series estimator). However, doing so results in higher variance of the function estimates, which are estimated using the data information from only a small interval. Thus, in the second step, we improve the estimation efficiency by "smoothing" over the function's shape from the first step using kernel function (i.e., the kernel estimator). We do so by first constructing a new dependent variable $\tilde{y}$ that can be only explained by x_s and z. We then estimate $[m_0(\cdot), m_s(\cdot)]^\top$ by a local linear estimator in (6). It is termed "local linear" because for each evaluation point $z \in Z$, we "locally" fit a "linear" line through z based on the its neighbor observation near to z. The nearness is controlled by the bandwidth h in the kernel function $k_h(z_{it}, z)$, which assigns higher (lower) weight for points closer to (further away from) z. Therefore, a larger bandwidth implies more equal weight assigned to the neighbor points of z, and vice versa. Finally, we connect each of these linear lines to obtain the estimated function as well as its derivative $[m_0'(\cdot), m_s'(\cdot)]^{\intercal}$. Note that local linear estimator includes OLS estimator as a special case, since if $m_j(\cdot)$ is truly linear, the local linear estimator fits data using all sample points as neighbor points of z, which indicates that $h \to \infty$. Hence, our two-step estimator allows the estimated function $m_j(\cdot)$ to be properly splitted and smoothed in a sense that the finite-sample mean squared error (MSE) of estimates can be considerably minimized.

We note that the most crucial factors in our estimators are J_n and h, which not only control for the range for which data we locally fit, but also for the finite sample bias and variance the estimator possesses: a higher J_n (lower h) will increase the variance but decrease the bias of series (local linear) estimator, and vice versa. This is a well-known bias-variance trade-off in nonparametric regression estimator. Hence, the selection of J_n and h must rely on sound statistical theories in practice. In the first step, we follow Craven and Wahba (1978) to choose J_{gcv} for $\tilde{m}_j(\cdot)$ in (5) based on generalized cross-validation:

$$J_{gcv} = \underset{\{J_n\}}{argmin} \frac{\frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}\left[y_{it} - X_{it}^{\intercal}\tilde{m}(z_{it}) - \tilde{\mu}_i\right]^2}{(1 - J_n/nT)^2}, \tag{7}$$

and in the second step, we choose h_{cvls} for $\hat{m}_{0s}(\cdot)$ based on least-square cross validation:

$$h_{cvls} = \underset{\{h\}}{argmin} \sum_{i=1}^{n}\sum_{t=1}^{T}\left[\tilde{y}_{it} - \tilde{\mu}_i - \hat{m}_{0,-i}(z_{it}) - X_{s,it}^{\intercal}\hat{m}_{s,-i}(z_{it})\right]^2 \tag{8}$$

where $\hat{m}_{0s,-i}(\cdot) = [\hat{m}_{0,-i}(\cdot), \hat{m}_{s,-i}(\cdot)]$ is "leave-one-firm-out" local linear estimators that assign $k_h(z_{it}, z_{mg}) = 0$ in (6) whenever $i = m$.[11] We now turn to present and discuss the estimation result.[12]

5 Results

To facilitate our discussion on the impact of export intensity in (2), we define the following terms that are of our interest. For a particular point *exint*, we first define its *neutral effect* as the function value of $m_0(exint)$, and its *neutrally partial effect* (NP) $\frac{\partial m_0(exint)}{\partial exint} \equiv m_0'(exint)$. Intuitively, the NP is the partial effect of *exint* on labor share by assuming that the non-neutral mechanisms through k, *markup*, and TFP do not play a role in determining labor share. Second, we define *non-neutral effect* (NN) of export inten-

[11] The essential reason of using leave-one-firm-out cross validation is to ensure that a firm i with its observations $z_{i1}, ..., z_{iT}$ as outliers can be entirely removed so as to prevent h from not being too small. See Chapter 11 in Henderson and Parmeter (2015) for the related discussion.

[12] The programming code of this study is available upon the request from the second author.

sity as functions $m_j(\cdot)$, which are the partial effect of k (NN(k)), $markup$ (NN($markup$)), and TFP (NN(TFP)) on labor share. Finally, we define *totally partial effect* (TP) as $\frac{\partial LS}{\partial exint} = \frac{\partial m_0(exint)}{\partial exint} + k_{it}\frac{\partial m_1(exint)}{\partial exint} + markup_{it}\frac{\partial m_2(exint)}{\partial exint} + TFP_{it}\frac{\partial m_3(exint)}{\partial exint}$, which consists of both *neutrally partial effect* (i.e., $\frac{\partial m_0(exint)}{\partial exint}$) and *non-neutral effect* through the term $k_{it}\frac{\partial m_1(exint)}{\partial exint} + markup_{it}\frac{\partial m_2(exint)}{\partial exint} + TFP_{it}\frac{\partial m_3(exint)}{\partial exint}$. Therefore, the variation of labor share is explained by the joint impact of export intensity that works neurally through $m_0(\cdot)$ and non-neutrally through the other three channels $m_s(\cdot)$.

5.1 Whole sample

We first report the results for whole sample in Table 3 by VCM-FE, and report the percentage of exporters in the sample on the top. Since the partial effects are of our primary interest, we report the NP (i.e., $\hat{m}_0'(z)$), and NN(k), NN($markup$), and NN(TFP) (i.e., $\hat{m}_s(z)$) in each column, conditioning on the level of export intensity at three quantile (0.25, 0.5, 0.75) and two percentiles near to the boundary (0.1, 0.9). The NP of export intensity is significant at almost 1% except when *exint* exceeds 75%. Also, it exhibits a diminishing return, as it declines by 66% as *exint* rises from 0.1 to 0.9, with its mean of 0.1009. It indicates that when the effect of *capital intensity*, *TFP*, and *markup* are *irreverent* in the regression (i.e., non-neutral effects of *exint* are zero), one-percentage point increase in export intensity on average leads to a 0.1 of a percentage-point increase in labor share. The results in general support the Stolper-Samuelson theorem behind its neutral effect, predicting that exports increase labor share in China with labor-abundant production function, but assuming that its potential non-neutral effects is absent. A similar finding has also been documented in (Huang et al., 2011).

However, all non-neutral effects are highly significant and uniformly negative at 1% level over the observations of *exint*. We found that the negative non-neutral effect through capital intensity ($\hat{m}_1(z)$) significantly lowers labor share with its mean effect of -0.0373. This is in line with our hypothesis regarding the non-neutral effect through capital intensity, suggesting that the negative impact of capital intensity on labor share (due to the substitutable relationship between capital and labor) is further intensified by higher export intensity in Chinese manufacturing industries. The negative non-neutral effect through markup ($\hat{m}_2(z)$) with a mean of -0.0109 meets our expectation, and its magnitude slightly decreasing as export intensity rises. It implies that "know-how" exporting firms are likely to have higher market power in imperfect competition, thus charge higher markup that weakens labor share through widening the marginal product of labor and real wage difference. Finally, the negative non-neutral effect $\hat{m}_3(z)$ indicates that export intensity amplifies the effect of TFP

Table 2: Neutrally Partial and Non-neutrally Effects from OLS-FE Estimation

Variable	Coef	Whole	Domestic	Foreign	East	Inland	Before 2002	After 2002
expint	$\hat{\alpha}_0$ (*NP*)	0.030***	0.092***	0.032***	0.025***	0.066***	0.071**	0.033***
		(0.005)	(0.009)	(0.010)	(0.005)	(0.014)	(0.035)	(0.006)
k	$\hat{\alpha}_1$	-0.034***	-0.027***	−0.065***	−0.038***	−0.023***	−0.131***	−0.045***
		(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.006)	(0.001)
markup	$\hat{\alpha}_2$	−0.006***	−0.004***	−0.015***	−0.010***	0.0005	−0.008**	0.001
		(0.001)	(0.001)	(0.005)	(0.001)	(0.001)	(0.004)	(0.002)
TFP	$\hat{\alpha}_3$	−0.190***	−0.186***	−0.204***	−0.197***	−0.174***	−0.939***	−0.213***
		(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.006)	(0.001)
$exint \times k$	$\hat{\alpha}_4$	−0.011***	−0.010***	−0.008**	−0.009***	−0.030***	0.013	−0.009***
		(0.002)	(0.002)	(0.004)	(0.002)	(0.005)	(0.011)	(0.002)
$exint \times markup$	$\hat{\alpha}_5$	-0.014***	−0.024***	−0.009	−0.013***	−0.010**	0.012	−0.014***
		(0.003)	(0.007)	(0.007)	(0.004)	(0.004)	(0.012)	(0.004)
$exint \times TFP$	$\hat{\alpha}_6$	−0.025***	−0.039***	−0.023***	−0.020***	−0.041***	−0.002	−0.030***
		(0.002)	(0.003)	(0.004)	(0.002)	(0.005)	(0.013)	(0.002)
Mean of NN(k)		-0.036	-0.029	-0.068	-0.128	-0.047	-0.040	-0.026
Mean of NN($markup$)		-0.008	-0.007	-0.019	-0.006	-0.002	-0.013	-0.001
Mean of NN(TFP)		-0.195	-0.190	-0.213	-0.940	-0.218	-0.201	-0.179
Fixed Effect		Y	Y	Y	Y	Y	Y	Y
Firms obs (n)		4,767	3,356	887	4,767	4,767	3,762	1,196
Total obs (nT)		47,670	33,560	8,870	19,068	28,602	37,620	11,960
Adjusted R^2		0.474	0.475	0.493	0.621	0.492	0.482	0.466
F Statistic		6,828.26***	4,819.61***	1,358.82***	5,141.76***	4,640.12***	5,546.05***	1,662.30***

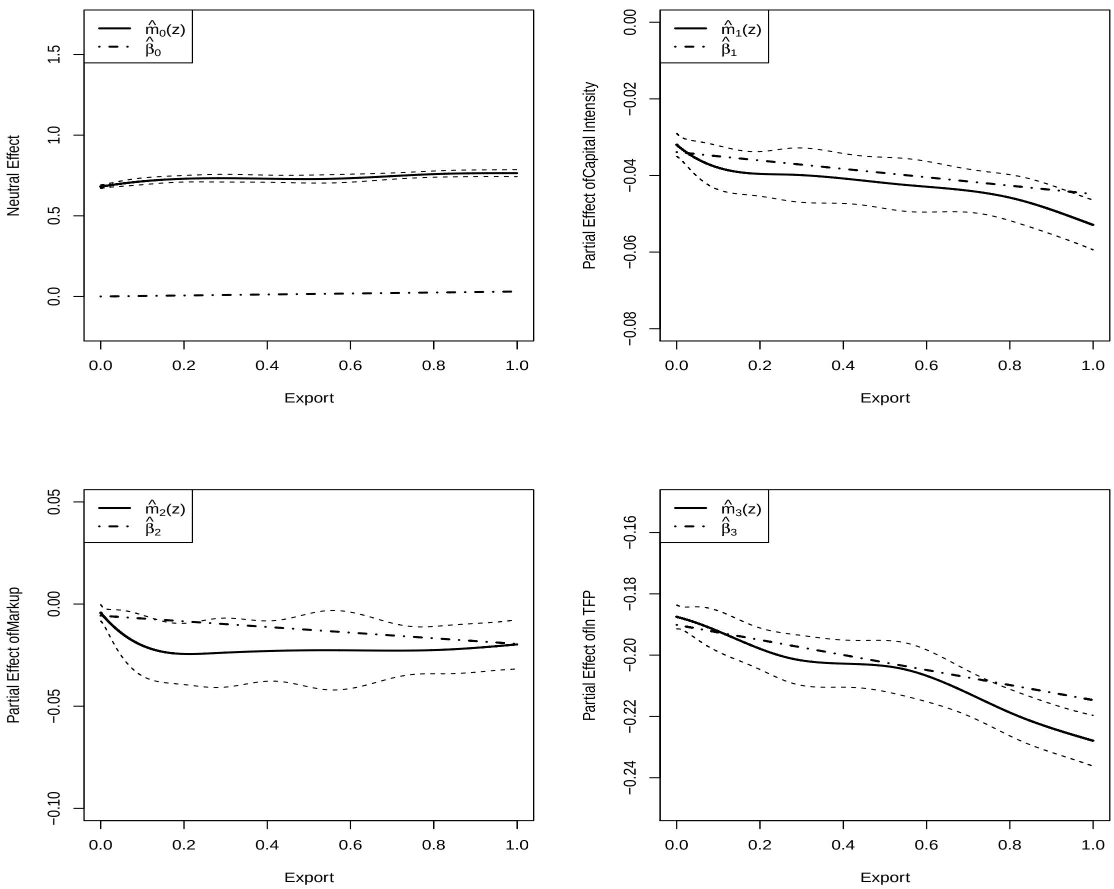
Note: Results are estimate of OLS-FE from regression (1). NP is short for neutrally partial effect of export intensity. Mean of NN(k), NN(k), and NN(k) stands for the non-neutral effect of export through k, *markup*, and TFP, respectively. *p<0.1; **p<0.05; ***p<0.01

Table 3: Neutrally Partial and Non-neutrally Effects from VCM-FE Estimation

	Whole sample (exp: 42.08%)			
exint	NP $\hat{m}_0'(z)$	NN(k) $\hat{m}_1(z)$	NN($markup$) $\hat{m}_2(z)$	NN(TFP) $\hat{m}_3(z)$
0.1	0.1822***	-0.0380***	-0.0203***	-0.1922***
	(0.038)	(0.003)	(0.008)	(0.003)
0.25	0.1619***	-0.0397***	-0.0243***	-0.2002***
	(0.038)	(0.003)	(0.008)	(0.004)
0.5	0.1214***	-0.0419***	-0.0226***	-0.2035***
	(0.038)	(0.003)	(0.009)	(0.004)
0.75	0.0833***	-0.0447***	-0.0227***	-0.2157***
	(0.039)	(0.003)	(0.006)	(0.004)
0.9	0.0617	-0.0490***	-0.0214***	-0.2238***
	(0.039)	(0.003)	(0.006)	(0.004)
Mean of NP/NN	0.1009	-0.0373	-0.0109	-0.1965
Mean of TP				
VCM-FE	-0.0108			
OLS-FE	-0.0714			
Firm obs (n)	4,767			
Total obs (nT):	47,670			
R^2:	0.3545			
h_{cvls}	0.2617			
J_{gcv}:	4			
Knots space	0.2712			

Note: Results are estimate of VCM-FE from regression (2). Mean of NP is the average of neutrally partial effect of export. Mean of NN(k), NN(k), and NN(k) stands for the non-neutral effect of export through k, *markup*, and TFP, respectively. TP represents the *totally partial effect* of export intensity. The first and second stage estimators are cubic B-spline series estimator and local linear kernel estimator, with their corresponding optimal knots J_{gcv} and bandwidth h_{cvls} reported on the lower panel. *exp* refers to the percentage of exporters in our whole sample. *p<0.1; **p<0.05; ***p<0.01

Figure 3: Neutral and Non-neutral effects plot: whole sample



on labor's share of income with its mean effect of -0.1965. Given the ambiguous effect of capital-augmented technology (proxied by TFP) on labor share discussed in Section 2, our results suggests that higher export intensity may amplify the negative effect of capital-biased technological progress on labor share, which erodes labor's bargaining power and thus shrinks their slice of pie of national income (Acemoglu, 2003; Karabarbounis and Neiman, 2013).

As discussed in Section 4, the impact of exports is jointly explained by its neutrally partial and non-neutral effects. We thus report TP of export intensity ($\frac{\partial LS}{\partial exint}$) by VCM-FE and OLS-FE in the middle panel of Table 3 for comparison purpose. The estimated TP by VCM-FE and by OLS-FE are -0.011 and -0.072, respectively, implying that the positive neutral effect of export is dominated by its non-neutral effect through the channels of capital intensity, markup, and technological progress. While the difference between the two estimated TP seems large, it is likely due to the linear model mis-specification in (1). To visualize this point, we plot in Figure 3 the neutral effect in VCM-FE by $\hat{m}_0(z)$ against that in OLS-FE by $exint_{it}\alpha_0$, and plot the non-neutral effects in VCM-FE by $\{\hat{m}_s(z)\}_{s=1}^3$ against that in

Table 4: Neutrally Partial and Non-neutrally Effects from VCM-FE Estimation

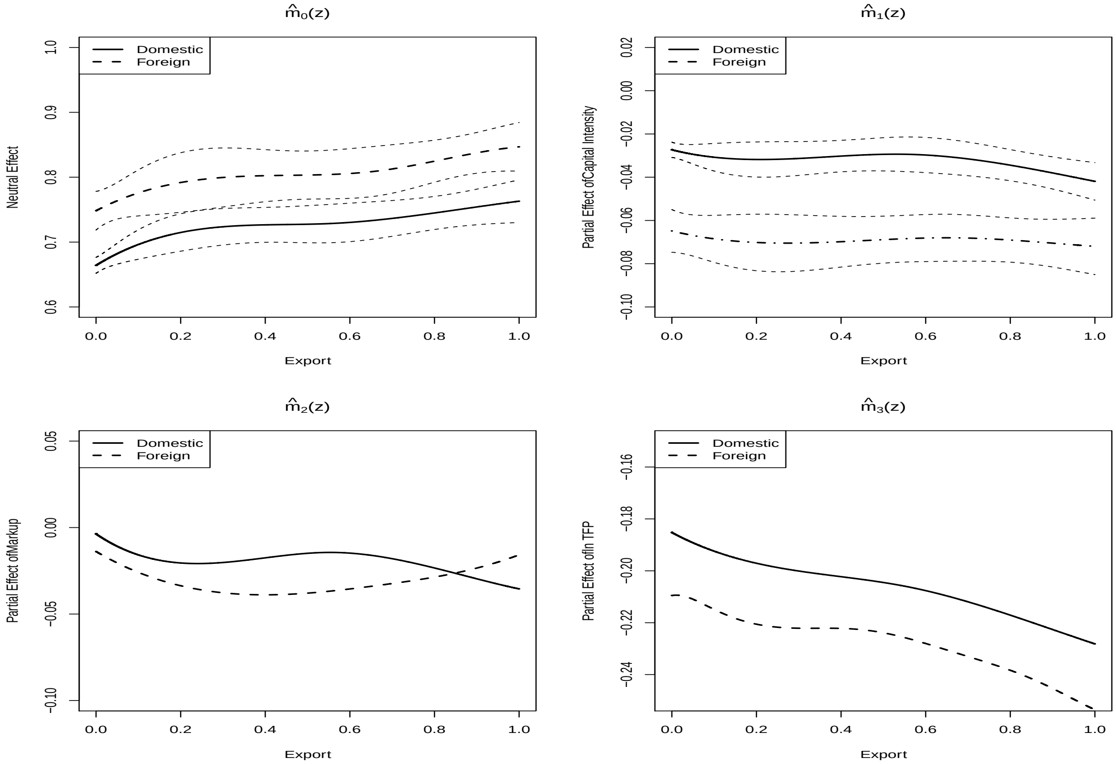
	Domestic firms (exp: 31.4%)				Foreign firms (exp: 72.16%)			
	NP	NN(k)	NN($markup$)	NN(TFP)	NP	NN(k)	NN($markup$)	NN(TFP)
exint	$\hat{m}_0^{'}(z)$	$\hat{m}_1(z)$	$\hat{m}_2(z)$	$\hat{m}_3(z)$	$\hat{m}_0^{'}(z)$	$\hat{m}_1(z)$	$\hat{m}_2(z)$	$\hat{m}_3(z)$
0.1	0.1375***	-0.0308***	-0.0158**	-0.1924***	0.1356***	-0.0652***	-0.0193	-0.2009***
	(0.024)	(0.003)	(0.007)	(0.004)	(0.017)	(0.004)	(0.015)	(0.006)
0.25	0.0986***	-0.0317***	-0.0208**	-0.1987***	0.1073***	-0.0705***	-0.0361*	-0.2061***
	(0.025)	(0.004)	(0.009)	(0.005)	(0.019)	(0.007)	(0.020)	(0.008)
0.5	0.0741***	-0.0294***	-0.0149*	-0.2045***	0.0851***	-0.0689***	-0.0379***	-0.2105***
	(0.027)	(0.004)	(0.009)	(0.005)	(0.019)	(0.006)	(0.014)	(0.007)
0.75	0.0322	-0.0329***	-0.0205**	-0.2144***	0.0836***	-0.0685***	-0.0306***	-0.2223***
	(0.029)	(0.004)	(0.009)	(0.005)	(0.022)	(0.006)	(0.013)	(0.006)
0.9	0.0548*	-0.038***	-0.0296***	-0.2226***	0.0835***	-0.0705***	-0.0234***	-0.2331***
	(0.032)	(0.004)	(0.011)	(0.005)	(0.037)	(0.006)	(0.007)	(0.006)
Mean of NP/NN	0.0834	-0.0312	-0.0201	-0.2041	0.0988	-0.0687	-0.0295	-0.2146
Mean of TP								
VCM-FE	-0.0192				0.0101			
OLS-FE	-0.2960				-0.4588			
Firm obs (n)	3,356				1,260			
Total obs (nT):	33,560				8,870			
R^2	0.3519				0.4975			
h_{cvls}	0.4711				0.5982			
J_{gcv}	2				2			
Knots space	0.5563				0.6677			

OLS-FE by $\hat{\beta}_1 = \hat{\alpha}_1 + exint_{it}\hat{\alpha}_4$, $\hat{\beta}_2 = \hat{\alpha}_2 + exint_{it}\hat{\alpha}_5$, and $\hat{\beta}_3 = \hat{\alpha}_3 + exint_{it}\hat{\alpha}_6$ obtained correspondingly in Table 2. We notice that the source of potential model-misspecification mainly stems from the estimation of the neutral effect, with OLS-FE estimates (with the mean of 0.0056) deviating from its VCM-FE counterpart and fairly close to zero. Hence, the neutral effect in OLS-FE is likely to be underestimated. This is also consistent with Huang et al. (2011), who find that while exports neutrally and positively impact labor share in China, the effect is insignificant under OLS-FE model. With a more flexible functional form considered by VCM-FE, we find that the neutral effect of exports is uniformly positive and significant. Finally, the non-neutral effects are slightly underestimated by OLS-FE but reasonably close to the VCM-FE results in terms of the mean of non-neutrally effects (i.e., mean of NN) reported in Table 2 and 3. Our results indicate that the presence of the non-neutral effects of exports, particularly through TFP, significantly pull down labor's potential gain from international trade in manufacturing industries.

5.2 Domestic vs foreign firms

It is known that foreign firms are more likely to engage in exporting behavior. In our sample, more than 70% of observations in foreign firms are exporters. We thus control for the heterogeneity of nationality by splitting the sample into foreign and domestic firms

Figure 4: Neutral and Non-neutral effects plot: domestic and foreign firms



according to the share of paid-in capital, and report the result in Table 4. For the purpose of comparison, we plot the estimated neutral effect $\hat{m}_0(z)$ and non-neutral $\hat{m}_s(z)$ against export intensity for both groups in Figure 4. One obvious difference lies on NP, which is uniformly higher in foreign firms with its mean of 0.0988 compared to 0.0834 in domestic firms. This fact can be seen from the function of neutral effect $\hat{m}_0(z)$ plotted in the first panel of Figure 4. Hence, exports directly tilts relatively higher income share toward labor in foreign than in domestic firms. Another significant difference shows up in the non-neutral effect through capital intensity $\hat{m}_1(z)$, which can be visualized from the upper-right panel of Figure 4. The mean of which is -0.0687 in foreign firms, but is shrunk by half to -0.0312 in domestic firms.

Given that foreign firms are more capital intensive (see Table 1), labor in foreign firms are easier to be substitutable in the face of surging capital. In fact, the most common industry type in foreign firms in our sample are high-end assembly line industries that have less dependence on labor.[13] The TFP and markup in domestic firms generate a slightly negative impact on labor share through export intensity than foreign firms, with the average given by (-0.0201, -0.2041) in domestic and (-0.0295, -0.2146) in foreign, respectively. As a result, we

[13] The mode of foreign firms industry type is CICC code 40 available in Appendix 2.

Table 5: Neutrally Partial and Non-neutrally Effects from VCM-FE Estimation

	East (exp: 46.61%)				Inland (exp: 30.53%)			
	NP	NN(k)	NN($markup$)	NN(TFP)	NP	NN(k)	NN($markup$)	NN(TFP)
exint	$\hat{m}_0^{'}(z)$	$\hat{m}_1(z)$	$\hat{m}_2(z)$	$\hat{m}_3(z)$	$\hat{m}_0^{'}(z)$	$\hat{m}_1(z)$	$\hat{m}_2(z)$	$\hat{m}_3(z)$
0.1	0.2916***	-0.0370***	-0.0276***	-0.2010***	0.0930***	-0.0365***	-0.0048	-0.1765***
	(0.034)	(0.003)	(0.008)	(0.004)	(0.023)	(0.005)	(0.010)	(0.006)
0.25	0.2044***	-0.0396***	-0.0324***	-0.2041***	0.0144	-0.043***	-0.0069	-0.1817***
	(0.035)	(0.003)	(0.008)	(0.004)	(0.025)	(0.006)	(0.013)	(0.008)
0.5	0.1764***	-0.0435***	-0.0275***	-0.2068***	0.0856***	-0.0400***	-0.005	-0.1934***
	(0.035)	(0.004)	(0.010)	(0.005)	(0.029)	(0.007)	(0.020)	(0.010)
0.75	0.1351***	-0.0449***	-0.0369***	-0.2185***	-0.1425***	-0.0483***	-0.0082	-0.2025***
	(0.042)	(0.003)	(0.009)	(0.004)	(0.032)	(0.007)	(0.006)	(0.010)
0.9	0.1009*	-0.0489***	-0.0381***	-0.2252***	0.2507***	-0.0519***	-0.0101	-0.2112***
	(0.058)	(0.003)	(0.010)	(0.004)	(0.048)	(0.007)	(0.009)	(0.009)
Mean of NP/NN	0.1703	-0.0415	-0.0306	-0.2111	0.0864	-0.0439	-0.007	-0.1931
Mean of TP								
VCM-FE	0.0720				0.0419			
OLS-FE	-0.3890				-0.3899			
Firm obs (n)	4,767				4,767			
Total obs (nT):	35,480				11,960			
R^2	0.3650				0.3212			
J_{gcv}	3				5			
h_{cvls}	0.3420				0.3784			
Knots space	0.412				0.4795			

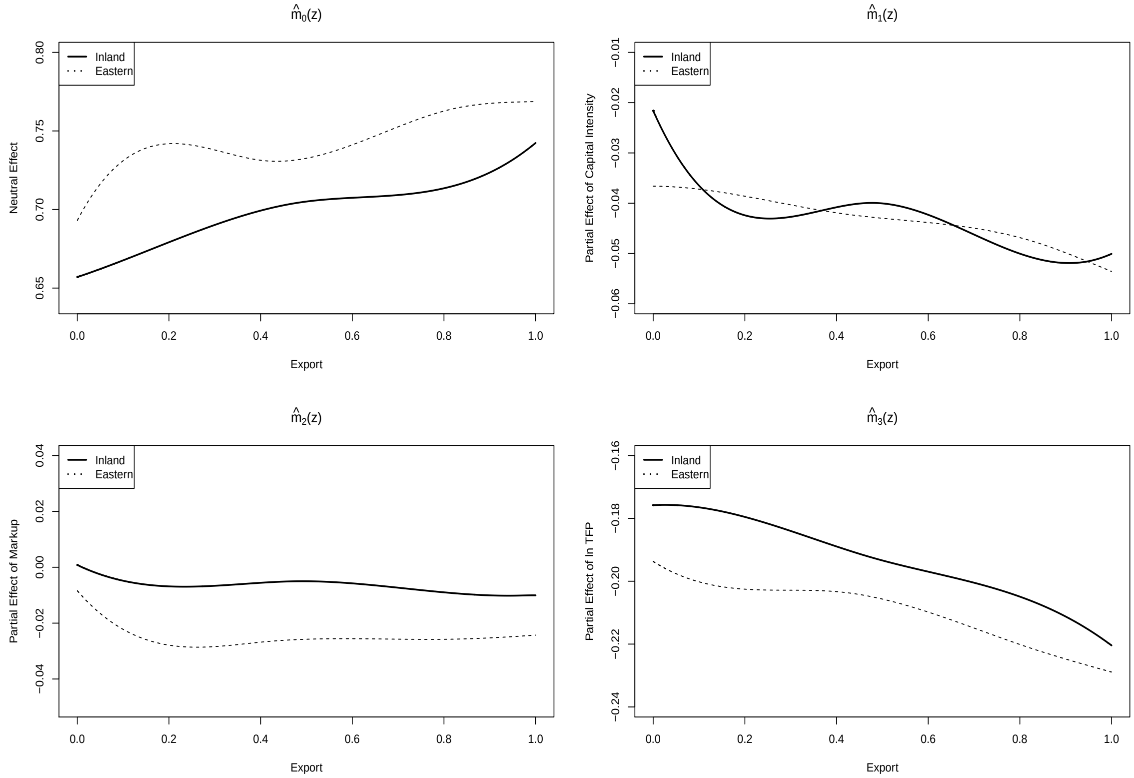
do not find distinguished differences for the non-neutral effect of TFP and markup between the two types of firms. Lastly, the neutral effect of exports that are highly significant and positive is largely offset by its corresponding negative non-neutral effects, lowering down the total partial effect to 0.0101 in foreign firms and -0.0192 in domestic firms.

5.3 Eastern and inland Region

We further account for regional heterogeneity in this subsection. In China, most exporters in *light* manufacturing firms, such as textile and leather industries (See CICC code 17 and 19 in Appendix 2), are labor-dependent. Labor-intensive industries have a strong preference to reside in the eastern (coastal) region due to the convenience of water transportation. By contrast, *heavy* industries, such as metal product industries (CICC 34) and car manufacturing industry (CICC 37) are typically located inland with less population density and wide ground for construction. We therefore split the sample into eastern and inland region on the basis of regional code by National Bureau of Statistics of China (NBSC) (reported in Appendix 2). Results are reported in Table 5 with its corresponding function plot on Figure 5.

The neutral effect of export moderately benefits laborers in manufacturing firms in the eastern region, with its mean of 0.1703 compared to that of 0.0864 inland. Unlike our

Figure 5: Neutral and non-neutral effects plot: Eastern and inland region



previous findings, exports do not lower labor share through markup as its partial effect $\hat{m}_2(z)$ is indistinguishable from zero. In contrast, firms residing in the eastern area have the markup effects significantly negative, decreasing labor share on average by a percentage point of 0.306 for every one unit it increases. The fact that markup plays no roles in inland is not surprising, given that inland region in our sample has SOEs firms two times higher than in eastern region. Since SOEs in China are known to be "iron-bowl" companies that provide fairly stable salary and benefits over time for their employees, labor' share of income in SOEs are less likely to be affected by markup.[14]

Labor in the inland region are also less affected by exports through capital intensity, as $\hat{m}_1(z)$ in inland is uniformly more negative than that in eastern area, suggesting different labor-capital elasticity of substitution across firms in inland area and coastal line. Finally, the difference of the impact of technological progress through trade $\hat{m}_3(z)$ is subtle between the two regions, implying that the negative impact of capital-biased technology on labor share is independent with regions.

[14]The words "iron-bowl" is a translated metaphor from Chinese, where *iron* means safe and endure, and "bowl" refers to having meals. Hence, it initially describes an fact that people working in SOEs are paid persistently well so that they never worry about being starving. Nowadays it refers to companies with very stable employment and income.

5.4 Before vs after 2002

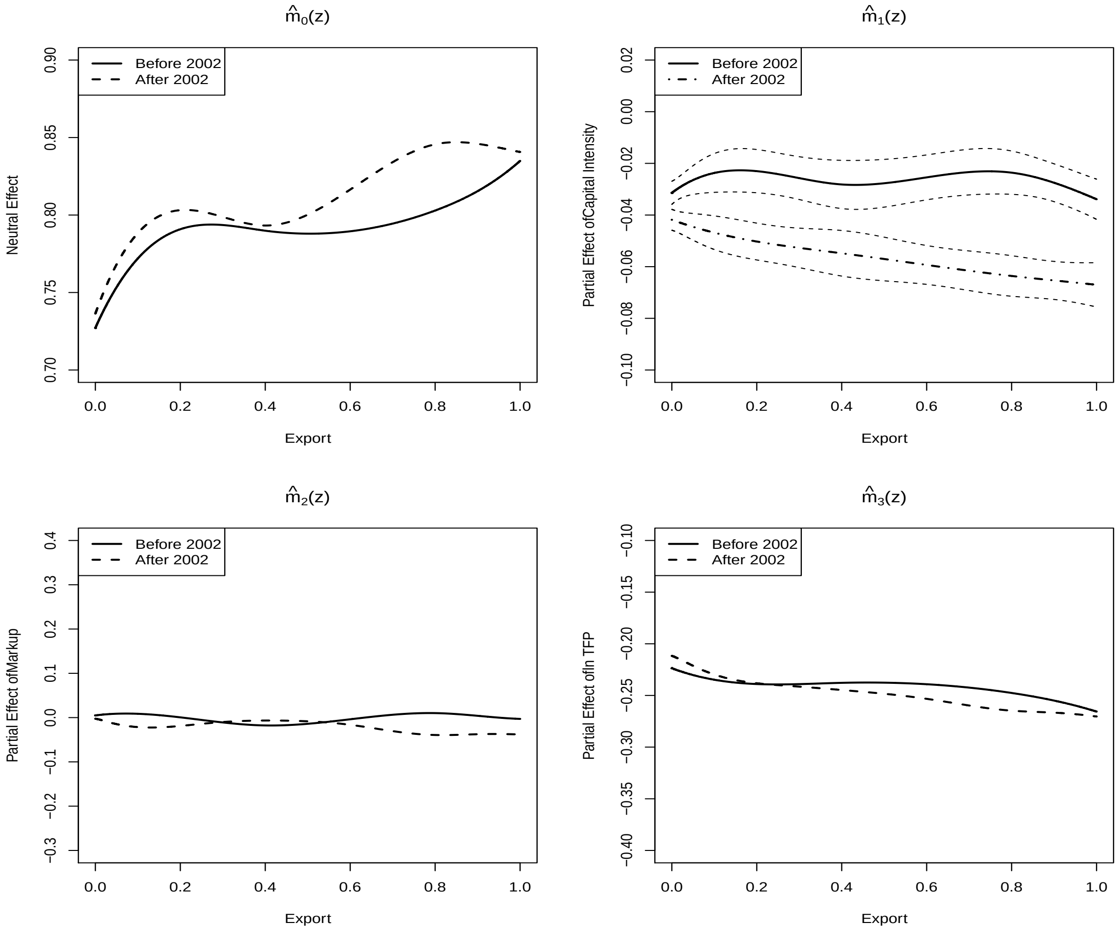
Table 6: Neutrally Partial and Non-neutrally Effects from VCM-FE Estimation

	Before 2002 (exp: 40.19%)				After 2002 (exp: 43.35%)			
	NP	NN(k)	NN($markup$)	NN(TFP)	NP	NN(k)	NN($markup$)	NN(TFP)
$exint$	$\hat{m}_0'(z)$	$\hat{m}_1(z)$	$\hat{m}_2(z)$	$\hat{m}_3(z)$	$\hat{m}_0'(z)$	$\hat{m}_1(z)$	$\hat{m}_2(z)$	$\hat{m}_3(z)$
0.1	0.1881***	-0.0237***	0.0086	-0.2348***	0.2050***	-0.0468***	-0.0072	-0.2223***
	(0.025)	(0.004)	(0.009)	(0.006)	(0.021)	(0.003)	(0.007)	(0.004)
0.25	0.1404***	-0.0242***	-0.0053	-0.2393***	0.1589***	-0.0516***	0.0004	-0.2314***
	(0.025)	(0.004)	(0.010)	(0.006)	(0.022)	(0.004)	(0.007)	(0.004)
0.5	0.0923***	-0.0277***	-0.014	-0.2376***	0.1162***	-0.057***	0.0051	-0.2383***
	(0.026)	(0.005)	(0.010)	(0.007)	(0.025)	(0.004)	(0.007)	(0.005)
0.75	0.0778***	-0.0231***	0.0095	-0.2447***	0.0940***	-0.0626***	-0.0196***	-0.2523***
	(0.027)	(0.005)	(0.013)	(0.007)	(0.030)	(0.004)	(0.009)	(0.005)
0.9	0.0872***	-0.0275***	0.0041	-0.2550***	0.0738***	-0.0653***	-0.0216***	-0.2576***
	(0.036)	(0.004)	(0.007)	(0.006)	(0.046)	(0.004)	(0.008)	(0.005)
Mean of NP/NN	0.1174	-0.0299	0.0033	-0.2319	0.1293	-0.0535	-0.0068	-0.2355
Mean of TP								
VCM-FE	0.0248				0.0035			
OLS-FE	-1.8411				-0.4400			
Firm obs (n)	4,767				4,767			
Total obs (nT):	19,068				28,602			
R^2	0.3282				0.3738			
J_{gcv}	3				4			
h_{cvls}	0.3142				0.3766			
Knots space	0.4001				0.4335			

China's membership of the World Trade Organization (WTO) in November, 2001 motives many studies to examine the effect of its entry on its financial market construction and economic growth (Allen et al., 2005; Drysdale et al., 2000; Blancher and Rumbaugh, 2004). In the context of Chinese labor share, however, the effect of its entry is void but non-trivial. The fact that Chinese labor is substitutable from capital and that capital-biased technologies are largely implemented during trade are highly likely to exert downward pressure on the share of labor's income. Thus, an interesting and important question surface as to whether exports shrink labor's share of income at a higher magnitude due to China's entry into the WTO.

We seek to the answer by splitting the sample based on the year 2002, and report the estimation results in Table 6. Results show that while the neutral effect of exports after 2002 slightly increases as the neoclassical trade theory suggests, the most (and perhaps the only one) notable difference lies on the non-neutral effect through capital intensity $\hat{m}_1(z)$, which can be seen from the upper-right panel of Figure 6. Prior to China's WTO membership, our results show that exports affect labor share negatively through capital intensity, since the effect of capital intensity is fairly stable and not changing significantly across the level of export intensity.

Figure 6: Neutral and Non-neutral effects plot: before and after the year of 2002



In the years after 2002, the effect of capital intensity through exports not only turns to be significantly negative, but also diverge away from its level before 2002; that is, the effects in two time periods do not overlap within their 95% confidence intervals. Conditioning on 10% of export intensity, for instance, a one percentage increase in capital relative to labor after 2002 would decrease labor share through exports by 0.023% higher than that in the year before 2002. This difference rises up to 0.027%, 0.029%, and 0.071% as export intensity is conditional on 25%, 50% and 75%, respectively. Evidently, China's participation in international trade since 2002 has unintentionally shifted the share of national income owned by labor toward the owners of capital by making Chinese workers in manufacturing industry to be more substitutable in the presence of cheaper capital price.

6 Conclusion

In this paper, we decompose the effects of exports on altering labor's share of income through its neutral effect and non-neutral effects. On one hand, exports affect labor share neutrally as implied from neoclassical trade theory (i.e., the neutral effect of exports). On the other hand, capital intensity, the degree of monopoly power, and capital-augmenting technology are three key determinants of labor share in the literature. We highlight how the marginal effect of the three factors on labor share can be intensified by higher export intensity (i.e., non-neutral effects of exports). Given China's intensively engagement in trade and millions of labor participation, we empirically investigate both effects of export using firm-level data from Chinese manufacturing industries during 1998-2007. To alleviate the issue of model mis-specification from a linear regression, we estimate a semiparametic varying coefficient model with fixed effects by a spline-backfitted kernel estimator, which significantly improves estimation performance and computational efficiency.

Our results are fairly consistent with our hypotheses. We find a high and positive neutral effect of exports on Chinese labor share in the absence of non-neutral effects. However, non-neutral effects are significantly negative, with the channel through TFP the most severe one, followed by capital intensity and markup. Since the totally partial effect of exports depends on both neutral and non-neutral effect, our results show that the positive neutral effect is outweighed by its non-neutral impacts. One of its underlying reasons may be partially due to China's membership of WTO since 2002, which greatly eases the elasticity of substitution between labor and capital that declines the overall effect of export on labor share.

We found that it is the capital-augmented technology and capital intensity that mostly erode labor's gain from the *growth pie* by making labor to be easily substitutable in the face of the surging capital. Most importantly, we show that the negative non-neutral effects through TFP and capital intensity continuously increase, rather than diminish, in the presence of higher export intensity. This should be of an important concern for policy makers, as the labor's overall income share is worsened with intensive exporting behavior. Effectively maintaining labor share in Chinese manufacturing industries may require the establishment of strong labor unions or related institutions that are in favor of labor's benefits. Therefore, a careful set of policies are needed, particularly in manufacturing industries, to prevent labor's share of income from being shifted away substantially.

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Appendix 1 Testing for the endogeneity of export intensity

The presence of endogeneity clearly violates the identification condition in estimating labor share regression both parametrically and nonparametrically. In this paper, we assume that firms make decisions of using labor in reaction to exporting behavior. However, there are cases where firms are inclined to export due to cheaper labor cost. That is, a reverse causality may exist in our regression that bring about endogeneity. To justify the use of our empirical methodology, we test the null hypothesis where export is endogenous. Given the fact that the semiparametric varying coefficient model is a general case of a linear model, we test the exogeneity of export intensity under the null from model 1 due to its computational ease. Recall that

$$LS_{it} = exint_{it}\alpha_0 + k_{it}(\alpha_1 + exint_{it}\alpha_4) + markup_{it}(\alpha_2 + exint_{it}\alpha_5) + TFP_{it}(\alpha_3 + exint_{it}\alpha_6) + \mu_i + v_{it} \tag{9}$$

One of the traditional ways to test for exogeneity is to use a control function (Amsler et al. (2016)), which is equivalent to two-stage least square estimation (2SLS). In principle, we first regress a reduced-form regression of the (potential) endogenous variable (i.e. *exint*) on instrumental variables and other exogenous variables in the original structural model (9). We then plug the residuals, denoted as $\hat{v}$, back to model (9). Hence, the significance (insignificance) of coefficient associated with $\hat{v}$ based on t-test indicates the endogeneity (exogeneity) of *exint*. In the absence of valid external instrumental variables from our dataset, we employ one-year and two-year lags of export as instruments. When using one-year lag as instrument, the coefficient of $\hat{v}$ is -0.079 with standard error of 0.185. When both one-year and two-year lags are employed, the coefficient of $\hat{v}$ is -0.225 with standard error of 0.044. The insignificance of both coefficients under two instrumental sets indicates that we fail to reject the null where export is exogenous.

Appendix 2 Chinese Industrial Classification Codes in Manufacturing Industry

CICC	**Industry Name**
13	Agriculture and food processing industry
14	Foodstuff manufacturing industry
15	Soft drink manufacturing industry
16	Tobacco manufacturing industry
17	Textile industry
18	Waving costume, shoes and cap manufacturing industry
19	Leather, fur and feather manufacturing industry
20	Wood working, and wood, bamboo, bush rope, palm, and straw manufacturing industry
21	Furniture manufacturing industry
22	Paper making and paper products industry
23	Print and copy of record vehicle industry
24	Stationary and sporting goods manufacturing industry
25	Oil processing, coking and nuclear manufacturing industry
26	Chemical material and chemical product manufacturing industry
27	Medicine manufacturing industry
28	Chemical fiber manufacturing industry
29	Rubber product industry
30	Plastics product industry
31	Nonmetallic mineral product industry
32	Ferrous metal refining and calendaring processing industry
33	Non-ferrous metal refining and calendaring processing industry
34	Metal product industry
35	Universal equipment manufacturing industry
36	Task equipment manufacturing industry
37	Transport and communication facilities manufacturing industry
39	Electric machine and fittings manufacturing industry
40	Communication apparatus ,computer and other electric installation manufacturing industry
41	Instrument and meter, stationery machine manufacturing industry
42	Handicraft and other manufacturing industry
43	Removal and processing of obsolete resource and material industry

Source: National Bureau of Statistics of China

Appendix 3 Provinces Classification Based on Geography

Eastern Region	Beijing	Tianjin	Hebei	Shanghai	Jiangsu
	Zhejiang	Shandong	Fujian	Guangdong	Hainan
	Liaoning				
Inland	Liaoning	Jilin	Heilongjiang	Shanxi	Anhui
	Jiangxi	Henan	Hubei	Hunan	Neimenggu
	Neimenggu	Guangxi	Chongqing	Sichuan	Guizhou
	Yunnan	Tibet	Shanxi	Gansu	Qinghai
	Ningxia	Xinjiang			