Domestic Segment of Global Value Chains in China under State Capitalism[1]

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Abstract

This paper studies the relationship between the evolution of the domestic segment of global value chains and the return of state capitalism in China. To this end, we propose a method to estimate an extended input-output (IO) table that tracks inter-sector transactions between different types of firms in a domestic economy. The method is an application of constrained optimization, which relies on basic information from a country's national IO table, as well as sector- and firm-level data. We also discuss how to construct bootstrapped standard errors for such extended IO tables. We then apply the extended IO table to study the domestic segment of global value chains in China. We find not only that state-owned enterprises' (SOE) domestic value-added to gross exports ratio (DVAR) is much higher than those of other firms, its DVAR has also increased significantly in recent years (from 1.2 in 2007 to 1.7 in 2010). Our findings suggest that SOE still play an important role in shaping China's exports after years of privatization.

Key words: value-added trade; global value chains; quadratic optimization; intra-national trade, state capitalism

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1. Introduction

China's unprecedented economic growth in the last two decades was often attributed to its policies that promote trade and foreign direct investment (FDI) (Branstetter and Lardy, 2006). During its embrace of globalization, the country also undertook active reforms to privatize or let go many state-owned enterprises (SOE).[5] Privatization induced an active entry of the more efficient private firms, which contribute significantly to the country's productivity and economic growth (Brandt, Van Biesebroeck, Zhang, 2012; Zhu, 2012).

While the role of SOE in the Chinese economy has been diminishing in the past few decades (Lardy, 2014), recent evidence shows that SOE have become more dominant in the economy again, especially in the key upstream sectors, such as banking, electricity, petroleum and natural gas. The recent surge in SOE's profits, in part due to the 4-trillion Yuan stimulus package implemented by the Chinese central government at the dawn of the 2008 global recession, has aroused concerns about the future path of the Chinese economy.[6]

The main objective of the paper is to study the evolution of the domestic segment of global value chains (GVC) in China, and examine whether such evolution may have contributed to the rise of the so-called state capitalism. We study the issue from the perspective of international trade by analyzing SOE's contribution to the country's domestic value added (DVA) in exports. More specifically, our research answers the following questions: In which sectors did SOE still possess a dominant presence? How did the distribution and evolution of SOE across sectors along the GVC shape other firms' participation in trade? How might downstream firms' increasing exports contribute to the revived

[5] The 15th Congress of the Chinese Communist Party in 1997 marked the watershed of China's economic reforms. The Congress formally sanctioned ownership reforms of the SOE and also legalized the development of private enterprises.

[6] The phrase *guo jin min tui*, which literally means "the state advances, the private sector retreats", has become viral in social media and the academic community. For instance, China National Petroleum Corporation and China Mobile together made profits of $33 billion in 2009, more than the country's 500 most profitable private companies combined (*Economist* "The rise of state capitalism", published on Jan 21, 2012). More privatization in upstream sectors, in particular the banking sector, has been proposed, but the progress has been slow.

dominance of SOE in China?

To answer these questions, we first develop a general framework to use firm-level data to extend a standard input-output (IO) table into a more detailed account that reports inter-sector transactions between different types of firms in an economy. The method we propose belongs to the large class of quadratic optimization models,[7] which feature minimization of a quadratic penalty function with arguments equal to the values of the extended IO table, subject to a series of accounting identities and adding-up constraints based on official statistics (e.g., industry-level exports and imports). Our method requires only a minimal set of information: (1) a country's national IO table, (2) firm balance-sheet data, and (3) trade statistics by firm group and sector. New to the literature, we propose a method to compute standard errors for the estimates of an extended IO table, using samples bootstrapped from the underlying micro data.

We implement the optimization model using China's IO tables for 2007 and 2010, along with census data for both manufacturing and service firms in 2008.[8] Firms are categorized into four groups based on their equity ownership and size, namely state-owned, foreign, large private, and small and medium-sized private firms. We then estimate the value of the IO transactions between any pair of firm groups in the extended tables using our proposed constrained quadratic optimization. Based on the estimates from the extended tables, we further quantify the contributions of different domestic IO channels through which Chinese DVA in exports was generated.[9]

We find that in China, SOE's DVA in exports is significantly larger than the value of their gross exports, contrasting with the conventional view that Chinese exports are associated with a lower

[7] In mathematical terms, our method belongs to a class of methods called constraint matrix balancing. Another class of matrix balancing is bi-proportional scaling, which is based on adjusting the initial matrix by multiplying its row and column by positive constants until the matrix is balanced (Stone et al., 1963). The alternative strategy is usually referred to as RAS.

[8] Previous research has extended an IO table to take into account differences between processing and non-processing trade in China and Mexico (e.g., Koopman, Wang, and Wei, 2014).

[9] The same approach has been used to split a national IO table for China into regional IO tables (Koopman, Meng, and Wang, 2014). These regional IO tables can be used to assess the effects of trade liberalization on intra-national trade and regional income disparity. See Tombe and Zhu (2015) for such an analysis for China.

domestic value added to gross exports ratio (DVAR) (Chen et al., 2012; Koopman, et al. 2012). Specifically, the DVAR of SOE is estimated to be 1.7 in 2010, increasing by 47% from 1.2 in 2007. Among private firms, large firms' DVA ratio is around 0.7 while that of small and medium-sized enterprises is above 1 for both years (1 in 2007 and to 1.3 in 2010). Foreign firms' DVAR hovers around 0.35 for both years.[10] In sum, SOE and small and medium-sized enterprises' DVAR's are much larger than those of other types of firms, and therefore that of aggregate exports.

To address the concern that our estimates can be imprecise and sensitive to the initial conditions and constraints imposed in the optimization, we propose a way to use firm-level data to construct confidence intervals for all estimates in the extended IO tables, based on bootstrapped standard errors. The procedure involves simulating thousands of IO tables, using constraints and initial values constructed with data from randomly drawn firm samples. The bootstrapped standard errors for our estimates show that the estimation results in general are robust to the choices of initial values in the objective function and linear constraints.[11]

Equipped with the extended IO tables, we study the volume and pattern of domestic trade transactions between different types of firms in China. We find that indirect exports (i.e., exporting through other firms) accounted for about 80% of SOE's DVA in both 2007 and 2010. About 40% of their DVA was indirect exports through small-medium-sized enterprises and foreign firms, suggesting that despite their relatively small engagement in direct exports, SOE's actual participation in and therefore impact on China's exports have been much more significant. Similar to SOE, large private and small and medium-sized private firms also have a large share of indirect exports in DVA. Different from all other firm groups, foreign firms tend to have significantly lower DVA ratios, both direct and indirect.

[10] These results contrast with the findings in developed countries, such as the United States, where large firms tend to have lower DVA.

[11] The estimates can become less precise if the underlying firm observations used to construct those conditions are more dispersed. Naturally, when we reduce the number of observations in each firm category by considering more dimensions of firm characteristics, the standard errors of our estimates will increase.

We also use our extended IO tables to analyze the reasons behind the high and rising indirect export participation by both state-owned and small-medium-sized enterprises. Focusing on the sectoral composition of indirect exports by firm group, we find that SOE's indirect exports are related to their prevalence, measured by output and export shares, in upstream and mostly non-tradable sectors, such as energy and mining; metal and non-metallic mineral extraction; electricity; gas and water supply; as well as banking. The dominance of SOE in upstream sectors, unlike in other countries where large private firms tend to prevail, is an outcome of China's unique sequencing privatization across sectors. Its privatization started from the downstream, competitive sectors of the economy in the late 1990s, and ended without privatizing the upstream, monopolistic sectors.

Consistently, we find that SOE are on average more upstream in GVC *within* sectors, based on the upstreamness measures proposed by Antràs et al. (2012) and Fally (2012). Although small and medium-sized firms also have high DVA and indirect export ratios, they are on average more downstream along GVC within sectors. The reasons for their higher DVA and indirect export ratios, compared to large private firms, are probably due to their greater propensity to sell intermediate inputs and services to direct exporting firms. Such analysis of the ownership pattern of GVC inside China can offer important insights for understanding the country's past and future economic growth, and the underlying political economic factors.[12]

Despite the focus on China, our estimation framework is general enough to be applied to study a wide range of trade and economic geography topics, such as how demand or supply shocks propagate across sectors and regions in a country; how much do small and medium-sized firms benefit from an

[12] For instance, to the extent that SOE are less productive than non-state firms (e.g., Zhu, 2012), a deeper privatization of SOE or lower entry barriers in upstream industries may increase the efficiency of direct exporters in the downstream, which in turn increases the speed of upgrading of Chinese exporters' along GVC. The conventional view is that China's export growth is largely driven by the dynamic labor-intensive private sector, especially the foreign-dominated processing trade sector. Our findings add to this conventional view by showing that SOE, through their protected position in the upstream, have been playing an important role in shaping Chinese export patterns and performance.

indirect participation in GVC without exporting directly; and which region or sector of a country benefits the most from trade, both directly and indirectly.

Our paper makes several contributions to the literature. First, it adds to the growing literature on the measurement of global production fragmentation using IO tables (e.g., Hummels, Ishii, and Yi, 2001, Johnson and Noguera, 2016; Koopman, Wang, and Wei, 2014). The literature has focused on the shares of domestic versus foreign value added in international trade, paying relatively little attention on the composition and dynamics of the domestic segment of GVC. In particular, studies on how international trade affects domestic trade between firms and industries have been sparse.[13] The two notable exceptions are studies by Koopman, Wang, and Wei (2012) and Ma, Wang and Zhu (2015).[14] Our paper improves upon the existing studies on several fronts. First and foremost, on the methodological front, we show how to compute standard errors for all estimates in our extended IO table and the related estimates. Second, our firm census data set covers much more firms, including all small and medium-sized firms. Third, our research focus is very different. Koopman, Wang, and Wei (2012) focus on correcting the upward bias in the estimated domestic content in exports when processing trade are pervasive in a country. Ma, Wang and Zhu (2015) on the other hand focus on the contribution of foreign versus domestic exporters to China's GDP. This paper offers a more detailed account of the domestic segment of GVC, and specifically highlights the much higher SOE's DVAR, a unique aspect of the domestic segment of GVC in China.

Related to the literature on trade in value-added, our approach extends the IO-table based approach to take into account an important aspect emphasized by the recent trade literature – firm heterogeneity in

[13] A recent paper by Furusawa et al. (2017) studies the effects of firms' offshoring on a country's domestic production network.
[14] Both studies also employ constrained optimization to estimate the inter-sector transactions between different types of firms (processing and non-processing firms in the former while foreign and domestic firms in the latter) in China.

international trade.[15] Firms differ substantially in export intensity, import intensity, and participation in GVC. Other characteristics such as ownership structure (domestic/foreign, private/public), location, size can also directly affect the way firms respond to trade liberalization and other economic shocks. The usual method that relies on the aggregate IO tables ignores most of the underlying firm heterogeneity. The lack of information on inter-firm transactions in the micro data also restricts the construction of IO tables by firm group.[16] Relatedly, Kee and Tang (2016) show that a country's domestic content in exports computed using IO tables are generally biased downward.[17] By proposing a method to extend a typical IO table, our paper takes a first step to reduce the aggregation biases due to firm heterogeneity.

This paper also contributes to the literature on the determinants of firms' indirect exporting. Research in international trade shows that only a small fraction of firms, typically the more productive ones that expect enough export profits to overcome the fixed exporting costs, participate in international trade directly (e.g., Bernard et al., 2015). Many non-exporters may engage in international trade indirectly, through intermediaries and by providing intermediate inputs and services to exporters. While the literature on trade intermediaries has received quite some attention recently (e.g., Bernard et al., 2010 and Ahn, Khandelwal, and Wei, 2012), how much value added is generated from exporting indirectly though other firms has not received the deserved attention, partly due to the lack of data.[18]

[15] This literature started with Bernard et al. (2003) and Melitz (2003). See Bernard el al. (2015) for a comprehensive review of both the theoretical and empirical literatures on firms and trade.

[16] Moreover, a widely recognized drawback of using IO tables to measure DVA is the assumption that firms within an industry use the same technology for production. Proportionality assumptions are often made in order to distribute imports into different final uses and different source countries, as information on bilateral trade between suppliers and users is generally not available at the country-industry level. These assumptions have been shown to lead to substantial biases in the estimation of countries' value added, factor content of trade, and our general inference of the impact of trade on countries' macro-economy (e.g., Puzzello, 2012). For instance, De La Cruz et al. (2011) and Koopman, Wang and Wei (2012) show that by allowing different imported material intensities for processing and non-processing exporters, the estimated foreign value added ratio in aggregate exports from both China and Mexico increases significantly.

[17] It is because when constructing IO tables, statistical agencies rely on large firms, which tend to have higher import intensities.

[18] A notable exception is the report by the USITC (2010), who also uses the constrained optimization methodology to estimate the contribution of small and medium enterprise (SME) to US exports. The report finds that SME's total contribution to U.S. exports increased from less than 28% to 41% in 2007, when the value of intermediates supplied by SME to exporting firms is taken into account.

Our paper provides a method that combines firm-level and industry-level data to quantify the volume of indirect exports, and through which channel they are generated.

On the methodological front, our paper contributes to previous attempts to cast the estimation of unknown values in IO tables as a constrained matrix balancing problem (van der Ploeg, 1988, Nagurney and Robinson, 1989, Bartholdy, 1991). It also adds to the information theory literature on estimating inter-region transactions using regional economic statistics and input-output accounts (Batten, 1982; Batten and Martellato, 1985, Canning and Wang, 2005). In particular, our paper is closely related to Golan, Judge and Robinson (1994), who also pose the estimation as an optimization problem with a nonlinear criterion objective function and multiple linear constraints.

Finally, this paper adds to the large literature on the progress of privatization and the role of SOE in the Chinese economy (e.g., Brandt et al, 2012; Zhu, 2012; Hsieh and Song, 2015).[19] Different from existing studies, we focus on quantifying the trade pattern of SOE, and how it affects and is affected by trade of other firms.

The rest of this paper is organized as follows. Section 2 develops the conceptual framework for our estimation. Section 3 introduces the optimization model. Section 4 describes the data sources and the initial conditions of the optimization procedures. Section 5 explains how conventional bootstrapping can be combined with our method to compute standard errors for our estimates. Section 6 applies the method by studying the estimated DVA for different firm groups in China, focusing on SOE. Section 7 concludes.

2. Conceptual Framework

This section first defines the concepts of direct and indirect DVA and then introduces the structure of

[19] Research on the effects of the unique sequence of privatization across sectors has been sparse. Notable exceptions include the recent theoretical work by Song et al. (2011) and Wang et al. (2012), who both highlight and rationalize the high profitability of SOE.

an extended IO table. We will then show how to decompose indirect exports into their various domestic IO channels based on firm groups, and specify the variables that cannot be readily computed using information from standard IO tables and thus need to be estimated. Details about the estimation will be discussed in Section 3.

2.1 The definition of Domestic Value Added in Exports

The standard domestic IO table reports the value of intermediate inputs sold by one industry to another in an economy. An IO economy with N industries must satisfy the following equation:

$$\mathbf{u} = \mathbf{A_V} + \mathbf{uA^d} + \mathbf{uA^m}, \tag{1}$$

where $\mathbf{u}$ is a 1×N unit vector, $\mathbf{A_V} = \left[\frac{v_\mathrm{j}}{\mathrm{x_j}}\right]$ is a 1×N vector of each industry's ratio of value added (v) to gross output (x); $\mathbf{A^d} = \left[a_{ij}^D\right] = \left[\frac{z_{ij}^D}{x_j}\right]$ is an N×N matrix of the coefficients of direct input of domestic goods and services (z_{ij}^D); $\mathbf{A^m} = \left[\frac{z_{ij}^F}{x_j}\right]$ is an an N×N matrix of direct input of imported goods and services (z_{ij}^F).

Taking $\mathbf{uA^d}$ to the left hand side of eq. (2) and rearranging it yields

$$\mathbf{u} = \mathbf{A_V}(\mathbf{I} - \mathbf{A^d})^{-1} + \mathbf{uA^m}(\mathbf{I} - \mathbf{A^d})^{-1} = \mathbf{A_V B} + \mathbf{uA^m B}, \tag{2}$$

where $\mathbf{B} = (\mathbf{I} - \mathbf{A^d})^{-1}$ is the well-known Leontief inverse matrix.[20] which can be used to compute the total gross output needed in the domestic economy due to one dollar of exports. The value added created by the direct exporters is called *direct* DVA. To produce direct DVA, intermediate inputs have to be used, which in turn generate additional value added produced by firms further upstream. Such a process of value-added generation continues infinitely in the domestic IO network. The total DVA induced by

[20] Similar to $\mathbf{A}$, $\mathbf{B}$ is a high dimensional matrix that is composed of 6 x 6 block matrices. Each block matrix, $\mathbf{B^{g1,g2}}$, is a 42×42 matrix with elements equal to the total requirement coefficients, representing the amount of required gross output by firm group g1 for a one unit increase in domestic final demand or exports.

one dollar of exports is thus equal to the sum of direct and all rounds of indirect DVA generated.

Post-multiplying both sides of eq. (2) by the diagonal matrix with elements equal to exports from each sector $\hat{\mathbf{E}}$, yields

$$\mathbf{u}\hat{\mathbf{E}} = \mathbf{u}\hat{\mathbf{A}}_{\mathbf{V}}\mathbf{B}\hat{\mathbf{E}} + \mathbf{u}\mathbf{A}^{\mathbf{m}}\mathbf{B}\hat{\mathbf{E}}, \tag{3}$$

where $\hat{\mathbf{A}}_{\mathbf{V}}$ is a $\mathrm{N} \times \mathrm{N}$ diagonal matrix of $\mathbf{A}_{\mathbf{V}}$.

Eq. (3) states that the country's total gross exports $\mathbf{u}\hat{\mathbf{E}}$, a 1×N row vector, can be decomposed into DVA in exports $\mathbf{u}\hat{\mathbf{A}}_{\mathbf{V}}\mathbf{B}\hat{\mathbf{E}}$ (either used directly for production of exported goods and services, or indirectly by firms that supply domestic inputs that are used by exporters), and imported materials embedded in exports $\mathbf{u}\mathbf{A}^{\mathbf{m}}\mathbf{B}\hat{\mathbf{E}}$, which include imported intermediates used directly by exporters or embodied in other domestic intermediates used by them.

The first term on the right hand side of eq. (3), $\mathbf{u}\hat{\mathbf{A}}_{\mathbf{V}}\mathbf{B}\hat{\mathbf{E}}$, is the key to our quantification of DVA. Specifically, $\hat{\mathbf{A}}_{\mathbf{V}}\mathbf{B}\hat{\mathbf{E}}$ is a N×N matrix, with each element representing the source (from which sector) and the channel (indirectly through which sector) of DVA. Depending on the research question, one can aggregate $\hat{\mathbf{A}}_{\mathbf{V}}\mathbf{B}\hat{\mathbf{E}}$ vertically or horizontally to estimate DVA. If the goal is to decompose DVA into its using (downstream) sectors, we can use the forward-linkage approach by summing up the elements of $\hat{\mathbf{A}}_{\mathbf{V}}\mathbf{B}\hat{\mathbf{E}}$ horizontally across each row. If the goal is to measure DVA embodied in gross exports from different sourcing sectors, we can adopt the backward-linkage approach by summing up the elements of $\hat{\mathbf{A}}_{\mathbf{V}}\mathbf{B}\hat{\mathbf{E}}$ vertically in each column.[21]

To implement the forward-linkage approach so that we can trace the final use of value added created by the primary factors of production, we post-multiply both sides of eq. (3) by a N×1 unit vector, $\boldsymbol{\mu}$. This operation sums up horizontally the value added to obtain DVA at the sector level. Formally, the forward-linkage based DVA is

[21] See Wang, Wei and Zhu (2013) for a more detailed discussion on forward- and backward-linkage approaches to measure value-added exports.

$$\mathbf{DVA_{fw}} = \mathbf{DVA\mu} = \hat{\mathbf{A}}_{\mathbf{V}}\hat{\mathbf{E}}\boldsymbol{\mu} + \hat{\mathbf{A}}_{\mathbf{V}}(\mathbf{B}-\mathbf{I})\hat{\mathbf{E}}\boldsymbol{\mu}, \tag{4}$$

where $\mathbf{DVA_{fw}}$ is a N×1 column vector.

To implement the backward-linkage approach, we expand the N×N DVA matrix as

$$\mathbf{DVA} = \hat{\mathbf{A}}_{\mathbf{V}}\mathbf{B}\hat{\mathbf{E}} = \hat{\mathbf{A}}_{\mathbf{V}}\hat{\mathbf{E}} + \hat{\mathbf{A}}_{\mathbf{V}}(\mathbf{B}-\mathbf{I})\hat{\mathbf{E}}. \tag{5}$$

On the right hand side of eq. (5), the first term, $\hat{\mathbf{A}}_{\mathbf{V}}\hat{\mathbf{E}}$, captures direct DVA, while the second term, $\hat{\mathbf{A}}_{\mathbf{V}}(\mathbf{B}-\mathbf{I})\hat{\mathbf{E}}$, represents indirect DVA. The elements along the diagonal of $\hat{\mathbf{A}}_{\mathbf{V}}(\mathbf{B}-\mathbf{I})\hat{\mathbf{E}}$ represent indirect exports in the same sector, while its off-diagonal elements reveal indirect exports through other sectors.

2.2. Splitting a Domestic IO Table based on Firm Characteristics

Given our focus, we split the 42-sector non-competitive IO table of China into 6 sub-accounts,[22] based on 3 ownership types: State (S), Foreign (F), or Private (P); and 2 size categories: large and small-and-medium-sized. With a total of 252 firm-group-sector combinations (3 ownership types × 2 firm sizes × 42 sectors), we need to estimate 252 × 252 (including the within-firm-group transactions) unknown values of domestic transactions. From now on, matrices and vectors will be presented in boldface.

Fig. 1 illustrates the extended IO table. Matrices *Z, Y, E, X,* and *M* represent, respectively, intermediate inputs, domestic final demand, exports, total output, and imports. We use a two-alphabet superscript to denote one of the 6 firm groups. The first alphabet denotes ownership type (S, F, or P) while the second subscript denotes firm size (L or S). A combination of an ownership type and a size

[22] The non-competitive IO table assumes that imported and domestic products are not substitutable, in contrast to the standard IO table that assumes perfect substitutability between imported and domestic products. When competitive IO tables are used, only one set of IO coefficients are needed. The underlying Leontief or linear production functions assumed in either approach have their obvious drawbacks. However, we consider our approach, which permits different IO coefficients on imported and domestic inputs across sector-pairs, to be more suitable for the purpose of our study.

category gives us a firm group, $g \in$ {SL, SS, FL, FS, PL, PS}. Subscripts *i* and *j* represent supplying and using sectors.

The last three rows in Fig. 1 report imported intermediate inputs (Z^F), value added (V) and total gross output (X), respectively. The last three columns are respectively domestic final use, exports, and also total gross output. The remaining part of the extended IO table, which we aim to estimate, is a 6×6 block of square matrices, each of which is 42×42 in dimension. For example, $\mathbf{Z}^{\mathbf{SL,SL}}$ in row (1) and column (1) is a 42×42 matrix, with an element in row *i* and column *j*, $z_{ij}^{SL,SL}$, representing output produced by large SOE in sector *i* used as intermediate inputs by other large SOE in sector *j*. Moving horizontally across row (1), each matrix, $\mathbf{Z}^{\mathbf{SL,g}}$, is a 42×42 matrix with an element $z_{ij}^{SL,g}$ in row *i* and column *j* representing output that is still produced by large SOE in sector *i* but is used as intermediate inputs by group-*g* firms in sector *j*. Similarly, when moving down vertically within a column, each entry is a 42×42 matrix $\mathbf{Z}^{\mathbf{g1,g2}}$ with elements $z_{ij}^{g1,g2}$ representing output produced by group-*g1* firms in sector *i*, sold as intermediate inputs to group-*g2* firms in sector *j*.

Row (7) of Fig. 1 describes the various uses of imported goods. The first 6 entries are 42×42 matrices, $\mathbf{Z}^{\mathbf{F,g2}}$, with element, $z_{ij}^{F,g2}$, representing imported product *i* used as intermediate inputs by group-g2 firms in sector *j*. The 7th entry, $\mathbf{Y}^{\mathbf{F}}$, is a 42×1 vector of imports for final consumption and capital formation by sector. The last entry in row 7, $\mathbf{M}$, is a 42×1 vector of total imports by sector. Rows 8 and 9 contain the matrices of sectoral value added and gross output of the 6 different firm groups, respectively.[23]

[23] For example, in the first column in Row 8, $\mathbf{V}^{\mathbf{SL}}$ is a 1x42 row vector that has element *i* equal to the direct value added of large SOE in sector *i* (cost of production factors).

Figure 1: Input-Output Table with Separate Transactions by Firm Ownership Type and Size

				Intermediate use								
				SL	SS	FL	FS	PL	PS	Domestic Final Use	Exports	Gross Output
				(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			Dimension	N	N	N	N	N	N	1	1	1
Domestic Intermediates	(1)	SL	N	$Z^{SL,SL}$	$Z^{SL,SS}$	$Z^{SL,FL}$	$Z^{SL,FS}$	$Z^{SL,PL}$	$Z^{SL,PS}$	Y^{SL}	E^{SL}	X^{SL}
	(2)	SS	N	$Z^{SS,SL}$	$Z^{SS,SS}$	$Z^{SS,FL}$	$Z^{SS,FS}$	$Z^{SS,PL}$	$Z^{SS,PS}$	Y^{SS}	E^{SS}	X^{SS}
	(3)	FL	N	$Z^{FL,SL}$	$Z^{FL,SS}$	$Z^{FL,FL}$	$Z^{FL,FS}$	$Z^{FL,PL}$	$Z^{FL,PS}$	Y^{FL}	E^{FL}	X^{FL}
	(4)	FS	N	$Z^{FS,SL}$	$Z^{FS,SS}$	$Z^{FS,FL}$	$Z^{FS,FS}$	$Z^{FS,PL}$	$Z^{FS,PS}$	Y^{FS}	E^{FS}	X^{FS}
	(5)	PL	N	$Z^{PL,SL}$	$Z^{PL,SS}$	$Z^{PL,FL}$	$Z^{PL,FS}$	$Z^{PL,PL}$	$Z^{PL,PS}$	Y^{PL}	E^{PL}	X^{PL}
	(6)	PS	N	$Z^{PS,SL}$	$Z^{PS,SS}$	$Z^{PS,FL}$	$Z^{PS,FS}$	$Z^{PS,PL}$	$Z^{PS,PS}$	Y^{PS}	E^{PS}	X^{PS}
Imported Intermediates	(7)	Abroad	N	$Z^{F,SL}$	$Z^{F,SS}$	$Z^{F,FL}$	$Z^{F,FS}$	$Z^{F,PL}$	$Z^{F,PS}$	Y^{F}		M
Value-added	(8)		N	V^{SL}	V^{SS}	V^{FL}	V^{FS}	V^{PL}	V^{PS}			
Gross Output	(9)		1	$(X^{SL})^T$	$(X^{SS})^T$	$(X^{FL})^T$	$(X^{FS})^T$	$(X^{PL})^T$	$(X^{PS})^T$			

Note: SL, SS, FL, FS, PL, and PS stand for large SOE, small SOE, large foreign, small foreign, large private, and small private firms, respectively. Dimension equals to the number of elements in either the row or column of each matrix.

We can redefine the input-output matrices in the extended IO table as follows

$$\mathbf{A^{g1,g2}} = \left[a_{ij}^{g1,g2}\right] = \left[\frac{z_{ij}^{g1,g2}}{x_j^{g2}}\right]$$

$$\text{and} \quad \mathbf{A^{F,g2}} = \left[a_{ij}^{F,g2}\right] = \left[\frac{z_{ij}^{F,g2}}{x_j^{g2}}\right],$$

where *i* and *j* stand for the row and column subscripts, respectively. $\mathbf{A^{g1,g2}}$ is a 42×42 block matrix, with each element being an IO coefficient representing the amount of output produced by firms in group *g1* used as intermediate inputs in the production of one unit of output by group-*g2* firms. *g1* and *g2* can each be one of the six firm groups.

Stacking $\mathbf{A}^{\mathbf{g1,g2}}$ and $\mathbf{A}^{\mathbf{F,g2}}$ up in a mega matrix following the structure of the IO table outlined in Fig. 1 yields

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}^{\mathbf{d}} \\ --- \\ \mathbf{A}^{\mathbf{m}} \end{bmatrix},$$

where $\mathbf{A}^{\mathbf{d}} = \begin{bmatrix} \mathbf{A}^{\mathbf{SL,SL}} & \mathbf{A}^{\mathbf{SL,SS}} & \mathbf{A}^{\mathbf{SL,FL}} & \mathbf{A}^{\mathbf{SL,FS}} & \mathbf{A}^{\mathbf{SL,PL}} & \mathbf{A}^{\mathbf{SL,PS}} \\ \mathbf{A}^{\mathbf{SS,SL}} & \mathbf{A}^{\mathbf{SS,SS}} & \mathbf{A}^{\mathbf{SS,FL}} & \mathbf{A}^{\mathbf{SS,FS}} & \mathbf{A}^{\mathbf{SS,PL}} & \mathbf{A}^{\mathbf{SS,PS}} \\ \mathbf{A}^{\mathbf{FL,SL}} & \mathbf{A}^{\mathbf{FL,SS}} & \mathbf{A}^{\mathbf{FL,FL}} & \mathbf{A}^{\mathbf{FL,FS}} & \mathbf{A}^{\mathbf{FL,PL}} & \mathbf{A}^{\mathbf{FL,PS}} \\ \mathbf{A}^{\mathbf{FS,SL}} & \mathbf{A}^{\mathbf{FS,SS}} & \mathbf{A}^{\mathbf{FS,FL}} & \mathbf{A}^{\mathbf{FS,FS}} & \mathbf{A}^{\mathbf{FS,PL}} & \mathbf{A}^{\mathbf{FS,PS}} \\ \mathbf{A}^{\mathbf{PL,SL}} & \mathbf{A}^{\mathbf{PL,SS}} & \mathbf{A}^{\mathbf{PL,FL}} & \mathbf{A}^{\mathbf{PL,FS}} & \mathbf{A}^{\mathbf{PL,PL}} & \mathbf{A}^{\mathbf{PL,PS}} \\ \mathbf{A}^{\mathbf{PS,SL}} & \mathbf{A}^{\mathbf{PS,SS}} & \mathbf{A}^{\mathbf{PS,FL}} & \mathbf{A}^{\mathbf{PS,FS}} & \mathbf{A}^{\mathbf{PS,PL}} & \mathbf{A}^{\mathbf{PS,PS}} \end{bmatrix}$, (6)

and $\mathbf{A}^{\mathbf{m}} = [\mathbf{A}^{\mathbf{F,SL}} \quad \mathbf{A}^{\mathbf{F,SS}} \quad \mathbf{A}^{\mathbf{F,FL}} \quad \mathbf{A}^{\mathbf{F,FS}} \quad \mathbf{A}^{\mathbf{F,PL}} \quad \mathbf{A}^{\mathbf{F,PS}}]$. Notice that **A** has 294 (7×42) rows and 252 (6×42) columns.

Let us also define $\mathbf{A}_{V}^{\mathbf{g1}} = \left[\frac{v_{\mathrm{j}}^{\mathbf{g1}}}{\mathbf{x}_{\mathrm{j}}^{\mathbf{g1}}}\right]$ as a 1×42 vector of direct value added coefficients for firm group *g1* where $\frac{v_{\mathrm{j}}^{\mathbf{g1}}}{\mathbf{x}_{\mathrm{j}}^{\mathbf{g1}}}$ is the ratio of value added to output by group-*g1* firms producing in sector *j*. Putting them horizontally into a vector yields $\mathbf{A_V} = \left[\mathbf{A}_{V}^{\mathbf{SL}}, \mathbf{A}_{V}^{\mathbf{SS}}, \mathbf{A}_{V}^{\mathbf{FL}}, \mathbf{A}_{V}^{\mathbf{FS}}, \mathbf{A}_{V}^{\mathbf{PL}}, \mathbf{A}_{V}^{\mathbf{PS}}\right]$, a 1×252 row vector covering all sectors and firm groups.

Eq. (6) can be further decomposed into its various channels through which DVA is created. The first row in $\widehat{\mathbf{A}}_{\mathbf{V}}\widehat{\mathbf{E}}\boldsymbol{\mu}$ represents the direct DVA from large SOE (SL). The first row of the second term, $\widehat{\mathbf{A}}_{\mathbf{V}}(\mathbf{B}-\mathbf{I})\widehat{\mathbf{E}}\boldsymbol{\mu}$,, is the sum of 6 terms as follows:

$$\widehat{\mathbf{A}}_{\mathbf{V}}^{\mathbf{SL}}(\mathbf{B}^{\mathbf{SL,SL}}-\mathbf{I})\widehat{\mathbf{E}}^{\mathbf{SL}}\widetilde{\boldsymbol{\mu}} + \widehat{\mathbf{A}}_{\mathbf{V}}^{\mathbf{SL}}\mathbf{B}^{\mathbf{SL,SS}}\widehat{\mathbf{E}}^{\mathbf{SS}}\widetilde{\boldsymbol{\mu}} + \widehat{\mathbf{A}}_{\mathbf{V}}^{\mathbf{SL}}\mathbf{B}^{\mathbf{SL,FL}}\widehat{\mathbf{E}}^{\mathbf{FL}}\widetilde{\boldsymbol{\mu}} \tag{7}$$
$$+\widehat{\mathbf{A}}_{\mathbf{V}}^{\mathbf{SL}}\mathbf{B}^{\mathbf{SL,FS}}\widehat{\mathbf{E}}^{\mathbf{FS}}\widetilde{\boldsymbol{\mu}} + \widehat{\mathbf{A}}_{\mathbf{V}}^{\mathbf{SL}}\mathbf{B}^{\mathbf{SL,PL}}\widehat{\mathbf{E}}^{\mathbf{PL}}\widetilde{\boldsymbol{\mu}} + \widehat{\mathbf{A}}_{\mathbf{V}}^{\mathbf{SL}}\mathbf{B}^{\mathbf{SL,PS}}\widehat{\mathbf{E}}^{\mathbf{PS}}\widetilde{\boldsymbol{\mu}},$$

where $\widetilde{\boldsymbol{\mu}}$ is a 42×1 column vector. $\widehat{\boldsymbol{A}}_{\mathbf{V}}^{\mathbf{SL}}(\mathbf{B}^{\mathbf{SL,SL}}-\mathbf{I})\widehat{\mathbf{E}}^{\mathbf{SL}}\widetilde{\boldsymbol{\mu}}$ is indirect DVA via large SOE, while

$\widehat{\mathbf{A}}_{\mathbf{V}}^{\mathbf{SL}}\mathbf{B}^{\mathbf{SL,SS}}\widehat{\mathbf{E}}^{\mathbf{SS}}\widetilde{\boldsymbol{\mu}}$, $\widehat{\mathbf{A}}_{\mathbf{V}}^{\mathbf{SL}}\mathbf{B}^{\mathbf{SL,FL}}\widehat{\mathbf{E}}^{\mathbf{FL}}\widetilde{\boldsymbol{\mu}}$, $\widehat{\mathbf{A}}_{\mathbf{V}}^{\mathbf{SL}}\mathbf{B}^{\mathbf{SL,FS}}\widehat{\mathbf{E}}^{\mathbf{FS}}\widetilde{\boldsymbol{\mu}}$, $\widehat{\mathbf{A}}_{\mathbf{V}}^{\mathbf{SL}}\mathbf{B}^{\mathbf{SL,PL}}\widehat{\mathbf{E}}^{\mathbf{PL}}\widetilde{\boldsymbol{\mu}}$, and $\widehat{\mathbf{A}}_{\mathbf{V}}^{\mathbf{SL}}\mathbf{B}^{\mathbf{SL,PS}}\widehat{\mathbf{E}}^{\mathbf{PS}}\widetilde{\boldsymbol{\mu}}$ represent large SOE's indirect DVA via small SOE, large foreign, small foreign, large private, and small and medium-sized enterprises' exports, respectively. Other rows in eq. (7) can be interpreted similarly for other firm groups. Eq. (7) thus provides detailed information about the volume of direct and indirect DVA, as well as the IO channels through which firm groups' indirect exports are generated.

3. Estimation Method

We now use eqs. (4), (5), and (7) to study the direct and indirect DVA by firm group at the aggregate and sector levels. Since the conventional IO table from all statistical agencies we are aware of reports only inter-sector transactions, but not the block matrices by firm group, we need to develop a method to estimate the subaccounts described in Fig. 1.

Before describing our estimation methods, let us revisit what information is available from a standard IO table. At the sector level, a standard national IO table contains the following information:

x_i: gross output of sector *i*;

z_{ij}^D: domestic goods from sector *i* used as intermediate inputs in sector *j*;

z_{ij}^F: imported goods from sector *i* used as intermediate inputs in sector *j*;

v_j: direct value added in sector *j*;

e_i: total exports of sector *i* goods;

m_i: total imports of sector *i* goods;

y_i^D: total domestic final-good demand for sector *i* goods (excluding exports);

y_i^F: total final-good demand for imported goods *i*.

This information from a national IO table will be used to construct the adding-up constraints in our optimization, which restrict the estimates of our extended IO table to add up to the values in the original

IO table. To estimate our extended IO table with 6 sub-accounts, we complement the data from the IO table with firm-level data in order to initialize the optimization and construct the linear constraints (see Section 5 below for details).

The key unknowns to be estimated are the inter-sector transaction flows between different firm groups, (i.e., $z_{ij}^{g1,g2}\ \forall i,j,g1,g2$). In addition, we need to estimate sector i's intermediate inputs imported by each firm group g in sector j (i.e., $z_{ij}^{F,g}\ \ \forall i,j,g$). We also need to estimate sector-level domestic final demand by firm group g (i.e., $y_j^g\ \forall j,g$), which can be constructed using firm-level data.

To estimate these values, we develop a quadratic optimization model that uses information from the standard national IO tables, sector-level trade statistics, and firm-level data. The optimization model has the following objective (penalty) function:

$$\min \mathrm{S} = \sum_{g1=SL}^{OS}\sum_{g2=SL}^{OS}\left\{\sum_{i=1}^{K}\sum_{j=1}^{K}\frac{\left(\widehat{z_{ij}^{g1,g2}}-z0_{ij}^{g1,g2}\right)^2}{z0_{ij}^{g,f}}\right\}$$

$$+\sum_{g=SL}^{OS}\left\{\sum_{i=1}^{K}\sum_{j=1}^{K}\frac{\left(\widehat{z_{ij}^{F,g}}-z0_{ij}^{F,g}\right)^2}{z0_{ij}^{F,g}}\right\}+\sum_{g=SL}^{OS}\left\{\sum_{j=1}^{K}\frac{\left(\widehat{y_j^g}-y0_j^g\right)^2}{y0_j^g}\right\} \qquad (8)$$

Importantly, the solutions to the above optimization need to satisfy the following six groups of linear constraints:

$$\sum_{g2=SL}^{OS}\sum_{j=1}^{K}\left(\widehat{z_{ij}^{g1,g2}}\right)+\widehat{y_i^{g1}}=\overline{x_i^{g1}}-\overline{e_i^{g1}}; \qquad (9)$$

$$\sum_{g1=SL}^{OS}\sum_{i=1}^{K}\left(\widehat{z_{ij}^{g1,g2}}\right)=\overline{x_i^{g2}}-\overline{v_i^{g2}}; \qquad (10)$$

$$\sum_{g1=SL}^{OS}\sum_{g2=SL}^{OS}\widehat{z_{ij}^{g1,g2}}=z_{ij}^D; \qquad (11)$$

$$\sum_{g=SL}^{OS}\widehat{z_{ij}^{F,g}}=z_{ij}^F; \qquad (12)$$

$$\sum_{g=SL}^{OS}\widehat{y_i^g}=y_i^D; \qquad (13)$$

$$\sum_{g=SL}^{OS} \sum_{j=1}^{K} \widehat{z_{ij}^{F,g}} + y_i^F = m_i, \quad (14)$$

and the non-negativity constraints:

$$\widehat{z_{ij}^{g1,g2}} \geq 0; \quad \widehat{z_{ij}^{F,g}} \geq 0; \quad \widehat{y_i^g} \geq 0, \quad (15)$$

as well as the adding-up constraints:

$$\sum_{g=SL}^{OS} \overline{v_i^g} = v_i \quad ; \sum_{g=SL}^{OS} \overline{x_i^g} = x_i \ ; \ \sum_{g=SL}^{OS} \overline{e_i^g} = e_i \ . \quad (16)$$

In the objective function (8), the target variables we aim to estimate are indicated with $\widehat{\ }$ while the initial values for the targets are denoted with 0. To kick-start the optimization, we set initial values for all unknown variables using various proportionality assumptions and micro data from Chinese official sources (see Section 5 for details). Sensitivity analysis, based on different initial values, reveals that our results are not sensitive to using different initial values in the objective function or linear constraints with constants computed from different randomly drawn firm samples (See Section 4 for a discussion about the computation of the standard errors and Section 6.2 for the results).

We use the inverse of the initial values as weights to reduce the "penalty" of large values and thus large deviations on the objective function.[24] Depending on the weights chosen, our optimization model covers a broad range of commonly used linear estimators. If the weights are all equal to one, the model resembles a constrained least squares estimator. If initial values are used as weights as what we do in this paper, the model resembles a weighted constrained least square estimator. If the weights are set proportional to the variances of the initial values, and if the initial values are statistically independent, the model yields unbiased linear estimates of the true unknown variables (Byron, 1978). If the weights are set exactly equal to the variances of the initial values (Stone, 1984, van der Ploeg, 1988), the model will be identical to the Generalized Least Squares estimator. Finally, as noted by Stone et al. (1942) and proven by Weale (1985), when the errors of the initial values are normally distributed, the solutions

[24] For example, basic business services tend to have a higher cost share for many sectors

satisfy the maximum likelihood criteria.

We obtain these linear constraints (eqs. (9)-(16)) from two data sources. The first data source is the firm census data, which we use to compute total gross output ($\overline{x_i^g}$), exports ($\overline{e_i^g}$), and value added ($\overline{v_i^g}$) for firm group g in sector i. These variables are indicated with $\overline{\ }$. We will compute standard errors for these constants using bootstrapped firm samples (see Section 4 below). The second data source is the IO table, from which we obtain information on domestic goods from sector i used as intermediate inputs in sector j (z_{ij}^D), imported intermediates from sector i used in sector j (z_{ij}^F), total imports in sector i (m_i), total domestic final demand for sector i goods (y_i^D), and final demand for imported goods i (y_i^F). We keep these values from IO tables constant not only throughout the optimization, but also during bootstrapping.

All constraints need to be satisfied for all i (42 of them) and j (42 of them), g (6 of them), *g1* (6 of them), and *g2* (6 of them). These constraints have straightforward economic interpretations. Eq. (9) is a set of supply-and-use balancing (row sum) constraints for the extended IO table. It states that total gross output by firm group in sector i must equal the sum of their use of intermediate inputs, exports, and supply of goods and services to final consumers. Eq. (10) is the set of production and cost balancing constraints. It defines the value of gross output by firm group in sector j as the sum of intermediate inputs and primary factors of production. Eqs. (11) to (14) are a set of adding-up constraints to ensure that the solutions from the model sum up to the aggregate statistics (i.e., domestic final demand, imports, and inter-sector transactions) in the national IO table at both the sector and sector-pair levels. Note that the initial values we set are unlikely to satisfy all of these linear restrictions of the model simultaneously.

Our estimation model is flexible enough to take into account a wide range of information in the optimization process. Additional constraints, such as upper and lower bounds imposed on unknown variables, can be added. Extra terms in the objective function to penalize solutions that deviate substantially from select linear constraints can also be added. Such flexibility is particularly important for obtaining optimal solutions when there are inconsistences in the constants in linear constraints from different data sources.

4. Data Sources and Variable Initialization

As described in Section 3, the initial values and constants in some of the linear constraints of the optimization program are computed using data from China's IO tables and firm-level census. Specifically, we implement the optimization using China's 42-sector "non-competitive" IO tables for both 2007 and 2010, along with the country's firm census for 2008. Both data sources are from China's National Bureau of Statistics (NBS). The firm census data cover over 5 million enterprises in China, including all SOE and private enterprises from all manufacturing and services sectors. Balance sheet information, such as firms' ownership type, equity share by ownership type, output, value added, four-digit industry code (about 900 categories), exports, employment, original value of fixed assets, and intermediate inputs. We define firms' ownership type based on the firm's registration type or equity share by ownership, similar to Hsieh and Song (2015). Specifically, a firm is considered state (foreign) -owned if it is registered as a state (foreign) company *or* has more than 50% equity owned by state (foreign) investors. The same criterion is used to define private firms. Estimates for both 2007 and 2010 are reported.[25]

For all sector linkages in the IO table, we aim to estimate transactions between any pair of the 6 firm groups: large SOE (SL), small and medium-sized SOE (SS), large foreign (FL), small and medium-sized foreign (SF), large private (LP), and small and medium-sized private enterprises (SP). Firm size category (large versus small-and-medium) is determined by firm employment and sales, with

[25] Notice that changes in the estimates are due to using IO tables from different years, as we only have one year of census data.

sector-specific thresholds specified by the NBS. Table A1 in the appendix reports those criteria.

The decision of putting firms into 6 groups is supported by the underlying firm distributions of export intensity and value added to sales ratios reported in the firm-level data. Fig. 2 shows that firm average export intensity differs substantially across ownership types, not so much along the firm size dimension. In particular, foreign firms are a lot more export-oriented than domestic firms. Fig. 3 shows that foreign firms also tend to have a higher value added to output ratio than domestic firms. Within domestic firms, large firms tend to have higher value added to output ratios. Among foreign firms, there is little difference in these key variables between Hong Kong SAR, China, Macau, and Taiwan, China (HKMT) firms and non-Chinese foreign firms. Based on these findings, we separate firms based on 3 ownership types and 2 sizes, and group HKMT firms with other foreign firms. Putting firms into more refined categories comes with a cost of having too few firms in each cell and thus less precise estimates.

We then use several aggregate statistics computed from firm census data to divide the aggregate numbers for each sector in the IO table across the 6 different firm groups. Specifically, we distribute each sector's gross output into the various firm groups proportional to their corresponding shares in total, according to the census data. Similarly, we also assign sectoral exports (but not imports) proportionally to each firm group's share in aggregate exports, according to the census data. We split each sector's wage and profits (operating surplus) across firm groups based on their corresponding shares in each sector's value-added. We use detailed import data disaggregated by firm ownership type for each 8-digit HS category from China's Customs Administration. We first use the United Nations Broad Economic Categories (BEC) code to separate imported intermediates from imported final goods at the HS 6-digit level. We then apply these customs-based import shares at the firm-group-sector level to distribute the sectoral imports from the IO tables across groups. These firm-group-sector statistics for output, exports, and imports are used in the linear constraints described in (9)-(16).

To initialize all $z0_{ij}$'s in the objective function (8), we need to allocate each industry's total intermediate inputs, both domestic and imported, to different firm groups and sectors. To this end, we first use the NBS firm census to compute output $x0_j^g$ and value added $v0_j^g$ for each firm group in each sector. For each firm-group-sector pair, we compute its share of total intermediate inputs, $x0_j^g - v0_j^g$. Using these shares, we distribute $z0_{ij}^D$ and $z0_{ij}^F$ from the national IO table across the 6 firm groups. Table A4 and A5 in the appendix report the shares of these variables by firm group and sector. The specific procedures to set the initial values for the target variables in the optimization model are described below.

1. It takes two steps to set the initial value for $z0_{ij}^{F,g}$ (imports by group *g* in sector *j* from sector *i*). For sectors that have zero imports of intermediate inputs according to the customs trade statistics, but positive values in the IO table (such as various service sectors), we simply use the shares of each group of firms in the sector's total intermediate inputs as weights to initialize $z0_{ij}^{F,g}$ as

   $$z0_{ij}^{F,g} = \frac{\overline{x_j^g} - \overline{v_j^g}}{\sum_{g,j}(\overline{x_j^g} - \overline{v_j^g})} z_{ij}^F, \qquad (\mathrm{g} = \mathrm{SL}, \mathrm{SS}, \mathrm{FL}, \mathrm{FS}, \mathrm{PL}, \mathrm{PS}) \tag{17}$$

   where $\overline{x_j^g}$ and $\overline{v_j^g}$ are sector *j*' output and value added by group-*j* firms.

   For sectors that have positive imported intermediate inputs according to the trade statistics, we first compute each firm group's share in the sector's imported inputs based on customs statistics to distribute imported inputs across firm groups. Using this adjusted z_{ij}^F and eq. (17), we further allocate the imported inputs by each ownership type to large and small-and-medium firm categories, respectively.

2. To set the initial value for $z0_{ij}^{g1,g2}$ (the volume of domestic intermediates supplied by group *g1* in sector *i* to group *g2* in sector *j*), we first assume that the share of intermediate inputs produced by *g1* in sector *i* equals the share of *g1*'s gross output in sector *i*. On the user side, we assume that *g2*'s

share of intermediate input absorption in sector *j* equals their share of intermediate inputs in total intermediate inputs demanded by the same sector. All information is available in the firm census data. Based on these two assumptions, we split the original z_{ij}^{D} according to the following formula:

$$z0_{ij}^{g1,g2} = \frac{\overline{x_{\iota}^{g1}}}{\bar{x}_{\iota}} \frac{(\overline{x_{J}^{g2}} - \overline{v_{J}^{g2}})}{(\overline{x_{J}} - \overline{v_{J}})} z_{ij}^{D}, \quad (g1, g2 = SL, SS, FL, FS, PL, PS), \tag{18}$$

where $\bar{x}_{\iota}$ and $\overline{\overline{v_{\iota}}}$ are sector *i*' total output and value added, respectively.

Finally, to set the initial value for $y0_{i}^{g}$ (total domestic demand for goods and services supplied by firm group *g* in sector *i*), we use the following formula:

$$y0_{i}^{g} = \overline{x_{\iota}^{g}} - \frac{\overline{x_{\iota}^{g}}}{\bar{x}_{\iota}} \sum_{j=1}^{N} z_{ij}^{D} - \overline{e_{\iota}^{g}}, \tag{19}$$

where z_{ij}^{D} and $\overline{e_{\iota}^{g}}$ are the value of sector's *i* sales to sector *j* and foreign customers, respectively.

5. Computing Standard Errors for the Estimates in the Extended IO Table

Any estimation, by definition, must be associated with measurement errors. One may be particularly concerned about how our estimates are sensitive to the set of initial values and linear constraints we impose in our optimization. In this section, we discuss how to incorporate the conventional bootstrapping procedures in our optimization model to obtain standard errors for the estimates.

Our proposed procedures of obtaining standard errors follow closely the standard bootstrapping procedure. The main idea is to create many random samples of IO tables, and use them to construct sample distributions of the estimated IO transactions.[26] Specifically, we randomly draw firm samples with replacement from the 2008 census data set. The number of draws in each firm-group-sector category (6 x 42) is set equal to the actual number of firms in that category in the census data. Using

[26] Robinson et al. (2001) develop a method to handle measurement errors in cross-entropy minimization by using an error-in-variables formulation. Estimating the error variances in a large data set using their approach is computationally challenging.

each random sample, we compute gross output (total sales), exports, wages, and operating surplus for each of the 252 firm-group-sectors.[27] We then use the data from each bootstrapped sample to reset the constants in some of the linear constraints (eq. (9)-(10) above) and all the initial values in the objective function (8) in the optimization model in order to estimate a new extended IO table. These bootstrapping and optimization exercises are repeated until we get 2000 simulated IO tables.[28]

With 2000 extended IO tables, we can now construct a distribution of each estimate in the extended IO table. Overall, the magnitudes of the standard errors of the IO coefficients, compared to the estimates, are relatively small. Most of them are within the 10% range around the coefficient estimates.[29] There are a few exceptions in which the standard errors are large. When reporting our results below, we will provide the 95% confidence intervals of the estimates, whenever applicable. We will also report the standard-error-to-mean ratios of the values used in the linear constraints for different firm groups to show how the large variance of firm values within each firm group may lower the precision of our estimates.

It is worth noting that developing a method to compute standard errors for the estimates in our IO table and the resulting estimated DVA have a wider appeal. One such application is to assess the accuracy of any national IO table. IO tables provided by statistical agencies are survey-based and thus also contain measurement errors. Some of them are due to reporting errors, while others are due to

[27] Important information to categorize firms is sometimes missing for some firm-sector groups. For those groups, we make the following data assumptions. We assume that all firms in the agricultural sectors are small and medium-sized. Moreover, since the 2008 firm census data do not cover firms from the railroad and transportation sector, we use information from the 135-sector version of IO table to extend the 2007 and 2010 IO tables. In addition, we assume that all firms in the railroad sector are large SOE, while firms in other transportation sectors are assigned based on their size according to the 2008 firm census data. For service-sector firms with zero export, we use a proportionality assumption to impose the share of exports.

[28] Note that in our bootstrapping exercise, some IO tables generated cannot be used as certain balancing conditions (i.e., eqs. (9)-(16)) are not satisfied. When initializing our quadratic optimization, we need to use aggregated firm level statistics computed from the micro data to set the right hand side values of the balancing conditions (eqs. (9)-(10)). Since these statistics are computed from random samples drawn from the firm census, sometimes they can take extreme values. Our quadratic optimization will fail to converge as one of the balancing conditions fails to hold. We discard those tables (less than 10%) and keep drawing until we have a sample of 2000 bootstrapped tables.

[29] Results are available upon request.

assumptions made by statisticians in the absence of crucial information.[30] A well-known source of measurement error is the imposition of different proportionality assumptions when information about the distribution of imported inputs across sectors is unknown.[31] Our method of constructing standard errors can be used not only to assess the precision of our estimates, but also to gauge that of the coefficients in any IO tables from statistical agencies, as long as the corresponding micro data for computing standard errors are available.

6. Empirical Findings

Based on the estimates of the model described in Sections 2 and 3, we portray the domestic segment of GVC in China. For clarity, we will report results for 4 firm groups – SOE, foreign, large private, and small and medium-sized private firms, despite our estimation over 6 firm groups. In other words, we aggregate the two SOE groups into one, and two foreign groups into one.

6.1 Contributions of Different Firm Groups

Let us first report in Table 1 the contributions of different firm groups to the macroeconomic outcomes in China. Besides DVA which we have to estimate, all numbers are computed based on the actual data from either 2007 and 2010 IO tables or the 2008 firm census. Columns 1 - 3 in Table 1 show that SOE accounted for 5% of the total number of firms, 19% of value added, and 9% of employment of China in 2008. These relatively small shares are in part an outcome of years of economic reforms by the Chinese government to privatize or let go SOE, especially the small ones in downstream sectors. SOE's contributions to gross exports and value-added in exports (DVA) in 2007 are 12% and 21%, respectively

[30] See Lenzen et al. (2010) for various reasons for why the numbers reported by a standard IO table may contain measurement errors.

[31] See Puzzello (2012) for an illustration of the potential biases in the measurement of domestic content, foreign content, and factor content in trade, due to the proportionality assumptions made about imported input usage.

(columns 4 - 5). The large difference between the two suggests that SOE have a large share of indirect exports through other firms. Even when SOE's gross export share declined significantly from 12% in 2008 to 9% in 2010 (columns 6 - 7), their share in DVA actually increased slightly from 21% to 22%. The opposite trends in gross exports versus DVA will be analyzed in greater detail below.

(Insert Table 1 here)

Table 1 also shows that small and medium-sized enterprises are numerous and employ the majority of workers in China (column 1). They accounted for 55% and 79% of China's value added and employment in 2008, respectively (columns 2 - 3). In terms of gross exports, their contribution was much smaller – only 28% (column 4). This low share of exports is consistent with the conventional view that most small firms do not export directly because of the potentially high fixed export costs.[32] In terms of DVA, small and medium-sized enterprises account for 42% (column 5). The much larger contribution of small and medium-sized enterprises to DVA implies that they have a higher share of indirect exports, through other firms. In terms of the aggregate gross exports and DVA, SOE and small and medium-sized enterprises look similar. We will reveal the key underlying differences in terms of their distributions across industries and the channels through which they achieve high DVA ratios below. Unlike SOE, the shares of small and medium-sized enterprises in both gross exports and DVA in exports declined since 2007.

As expected, foreign firms are much more export-oriented. They are small in number, similar to SOE, but account for close to half of China's gross exports. Their share in total DVA is much smaller though (only 27%). This fact is consistent with the literature that reports a low DVA ratio in Chinese exports, particularly in processing exports (Koopman, Wang, and Wei, 2012; Kee and Tang, 2016). Processing exporters take advantage of the duty-free incentives by importing more intermediates than typical exporters. Given that most of the processing exporters are foreign-owned, the finding of a low

[32] See Bernard et al. (2015) for a theoretical model and stylized facts based on US firm-level data.

DVA ratio of foreign firms' exports is not surprising.

6.2 Domestic Value Added in Exports

Next, we use our extended IO tables to decompose DVA by firm group into direct and indirect DVA, based on the forward-linkage approach described in Section 2. Results for the backward-linkage approach are reported in Appendix A.

(Insert Table 2 here)

Column 1 of Table 2 shows the estimated DVA of different firm groups. The DVA of SOE is about 1446 billion RMB in 2007, while those of foreign, large, and small and medium-sized private enterprises are respectively 1841, 718, and 2942 billion RMB.[33] The corresponding 95% confidence intervals, reported in parentheses, provide great confidence that our estimated DVA for different firm groups are statistically significant at the conventional levels. Column 2 reports the standard-error-to-mean ratio of each estimate. For 2007, the ratio ranges from only 7% for foreign firms to 32% for SOE, and similarly for 2010. The relatively lower precision for SOE's estimated DVA could be due to the larger variance in the underlying values across firms within a sector, which we will verify below.

Column 3 reports each firm group's ratio of DVA to gross exports (the DVA ratio). Both SOE and small and medium-sized enterprises have the DVA ratio above 1. In 2007, SOE's DVA ratio is 1.17 while small and medium-sized enterprises' ratio is 1.02. As a comparison, the DVA ratios of foreign and large private firms are 0.36 and 0.70, respectively. The finding of a larger-than-unity DVA ratio confirms the results in Table 1 that SOE's contribution to Chinese exports is much larger if measured in value added terms than in gross terms. Moreover, these findings contrast sharply with the evidence for advanced economies where the DVA ratio is typically smaller than 1. In sum, the low DVA ratio of Chinese aggregate exports, as reported in the literature, hides substantial heterogeneity in DVA across

[33] These numbers in US dollars are about 196, 250, 98, and 399 billion, based on 2007 USD-RMB exchange rate.

firm ownership types and sizes.

Panel B of Table 2 shows the same set of estimates using the 2010 IO table. As reported, all but foreign firms experienced an increase in DVA. The increase was particularly sharp for SOE and small and medium-sized enterprises. SOE's DVA ratio rose by about 47% to 1.73 while that of small and medium-sized enterprises grew by about 27% to 1.29 (column 4). The significant increase in the DVA ratio of SOE lends some support to the speculation that the state sector has advanced in the Chinese economy in recent years, especially after the global financial crisis in 2008 when the Chinese central government implemented macroeconomic policies to stimulate the economy. The higher-than-unity DVA ratio of SOE (and also that of small and medium-sized enterprises) implies that many non-exporters from the group produce intermediate inputs and services that are embedded in Chinese exports.

Table 3 examines the potential reasons for the pattern of DVA across firm groups, by examining a group's indirect exports (i.e., DVA generated by selling to other firm groups in the domestic production network). The share of indirect exports in a firm group's total DVA is reported in square brackets. The 95% confidence interval of each estimate is reported in parentheses, with the corresponding standard-error-to-mean ratio reported in italics.

(Insert Table 3 here)

First, we find the following pecking order: in 2007, SOE have the highest share of indirect exports in total DVA (80%), followed by large (72%) and small and medium-sized enterprises (63%), with foreign firms having the lowest share (46%). The indirect export share of SOE remained at 80% in 2010. Put it differently, in both years, 80% of SOE's DVA was embedded as inputs in other firms' exports. Total indirect DVA of SOE are estimated to be around 1.15 trillion and 1.46 trillion in 2007 and 2010, respectively. The standard-error-to-mean ratios of these estimates are about 0.3.

Small and medium-sized enterprises' share of indirect exports in total DVA increased significantly by 10 percentage-points from 63% to 73% between 2007 and 2010, consistent with the hypothesis that small exporters could be more financially constrained after the global finance crisis to engage in direct exporting. Once again, foreign firms are substantially different from domestic firms and have a much lower share of indirect exports (about 46% in 2007, which decreased to 43% in 2010). Given the prevalence of foreign firms in processing trade and of intra-firm trade associated with vertical FDI, the low indirect export ratio is expected.

In Table 4, we further decompose the estimated indirect DVA into different IO channels. Specifically, we report a group's indirect DVA through the four firm groups. First and foremost, most of SOE's indirect exports went through private enterprises. In particular, 84% (67%/80%) and 89% (71%/80%) of SOE's indirect DVA exports in 2007 and 2010, respectively, were through private firms. Foreign firms accounted for over 40% (35%/80%) and 55% (44%/80%) of SOE's indirect exports in 2007 and 2010, respectively (column 2). On the other hand, small and medium-sized enterprises accounted for about a quarter (20%/80%) of their indirect exports in 2007, and declined in importance to about 20% (17%/80%) in 2010 (column 4). Based on 2000 random samples bootstrapped from firm census, the standard errors of these estimated channels of indirect exports are largely robust.

(Insert Table 4 here)

The shares of indirect exports for both large and small and medium-sized private firms are also high, though significantly lower than that of SOE. Foreign firms play an important role in helping large firms to export indirectly than small and medium-sized enterprises, due to their high export orientation. The role of small and medium-sized enterprises in helping other firms to export declined between 2007 and 2010.

Before explaining the different patterns of DVA across ownership types, let us discuss the large standard errors of some of the estimates, especially for SOE. Notice that the precision of the estimates for each firm group is naturally affected by the underlying standard errors of the related firm-level values. When there are only a few firms operating in a sector with a large difference in major variables, bootstrapping observations with replacement implies a high likelihood that the same firm is drawn multiple times, yielding aggregates that could differ widely across bootstrapped samples for that firm group. In other words, the resulting bootstrapped standard error of an aggregate value will be large when the sample size is small.

To empirically verify this hypothesis, we report in Table 5 the standard-error-to-mean ratios of the key values, $x0_i^g$, $e0_i^g$, and $v0_i^g$, which were used to initialize the constants in the objective function and some of the linear constraints, based on different bootstrapped samples drawn from the 2008 firm census. As fully described in eq. (17)-(19), the values we use to initialize the model are computed indirectly using these three key values. They are also used to construct weights to distribute the IO table's statistics to the firm-group-sector level, which will then be used as linear constraints (9) and (10). Thus, the distributions of $x0_i^g$, $e0_i^g$, and $v0_i^g$ are the major drivers of the differences across the estimates of the extended IO tables constructed with bootstrapped samples. Constants in those adding-up constraints that are not differentiated across firm groups are obtained directly from the IO table at the sector level, and remain constant across bootstrapped samples.[34]

(Insert Table 5 here)

As reported in Table 5, the bootstrapped standard-error-to-mean ratios of the constants in the linear constraints for most firm groups are smaller than 0.05, with those for SOE's value added (0.116) and large private firms' exports (0.162) and value added (0.117) being the exceptions. These findings are

[34] These include imports in sector i (m_i in eq. (14)), domestic intermediate inputs sold among industries (z_{ij}^D in eq. (11)), imported intermediate inputs sold among industries (z_{ij}^F in eq. (12)), and the demand for final goods in sector i that are either domestic or imported (y_i^D in eq. (13) and y_i^F in eq. (14)).

consistent with the high standard-error-to-mean ratios for the estimated direct and indirect DVA for state-owned and large private firms reported in Table 3. These are the firm groups that have a small number of firms.[35]

6.3 The Prevalence of State-owned Enterprises both within and between Industries

Next we attempt to understand the reasons for the similarity in the DVA ratio between state-owned and small and medium-sized enterprises by examining the cross-industry pattern of indirect exports across firm groups. Table 6 shows a substantial heterogeneity in indirect export shares (in total DVA) across 14 broad sectors. "Upstream" sectors, such as energy and mining; metal and non-metallic mineral extraction; electricity, gas and water supply; as well as the financial sector all have very high indirect export shares (over 90%). A reason is that the sectors with high indirect export shares tend to be non-tradable, either by nature or due to protection by the government.[36] They export indirectly by providing essential intermediate inputs and services to downstream exporters. Thus, focusing only on gross exports in analyzing firms' export participation can substantially underestimate their actual participation in GVC and thus the economic impact of trade liberalization.

(Insert Table 6 here)

In addition to the cross-industry variation, within a sector we also see a non-negligible variation in the indirect export share across firm groups. For instance, in the "Light manufacturing" sector, the ratio of indirect to direct DVA in exports was 50% in 2007, one of the lowest, but the ratio for SOE was 75%. That ratio for SOE further increased to 92% in 2010. In wholesale and retail trade, while the

[35] However, it is difficult to reconcile the small standard-error ratios for small and medium-sized firms' initial values on the one hand, and larger ratios for their estimated DVA as reported in Table 3, on the other. One possibility is that small and medium-sized firms participate in GVC by selling primarily to state-owned and large private firms in the domestic economy. The less precise estimates of the latter two groups' DVA may in turn lower the precision of small and medium-sized firms' estimated DVA. Again, IO linkages matter.

[36] In the case of banking, only 5 major state-owned banks have dominated different segments of the sector due to entry restriction to private firms.

indirect-to-direct export ratio was 24% (38%) for small and medium-sized enterprises in 2007 (2010), it was 83% (61%) for foreign firms. These differences may reflect the predominance of small and medium-sized private trade intermediaries, while foreign firms are less likely to be engaged in services (possibly due to policy restrictions), they are more likely to produce goods and sell them overseas either by themselves directly or through other domestic trade intermediaries. A casual observation shows that SOE tend to have a higher indirect export share in sectors that are associated with a lower average indirect export share, such as electronic equipment; while small and medium-sized private firms tend to have a higher indirect export share in industries that have a higher average indirect export share, such as energy and mining, and the financial sector.

To analyze these channels more systemically and show that the relative upstream positions held by SOE is not only a between-sector phenomenon but also a within-sector one, we use the method proposed by Antràs et al. (2012) to compute the upstreamness indices by firm group in each sector. Briefly speaking, the upstreamness index captures the average distance between a sector and final-good consumers. Appendix B describes several important extensions we make to Antràs et al. (2012), and how we use the extended IO table to compute such indices. Table A7 in the appendix reports the 240 upstreamness indices (40 industries x 4 firm groups), along with the industry's upstreamness index computed based on the standard IO table. Table 7 reports that the top 5 most "upstream" industries (out of 40) in China were "Extraction of Petroleum and Natural Gas", "Mining of Ferrous Metal Ores", "Mining and Washing of Coal", "Production and supply of Electricity and heat", "Processing of Petroleum, Coking and Nuclear Fuel" in 2007. The values of upstreamness for these sectors range between 4 and 5, meaning that these sectors are on average 4-5 sectors away before reaching final-good consumers. The bottom 5 "upstream" sectors were "Real Estate", "Health and Social service", "Education", "Construction industry", "Public administration and social organization" in the same year.

(Insert Table 7 here)

Consistent with the high indirect export ratios, SOE tend to have the highest upstreamness index among all firms types within each sector, while small and medium-sized enterprises tend to have the lowest upstreamness index, particularly for the least upstream sectors. Fig. 4 plots the state-owned, foreign, large private, and small and medium-sized enterprises' upstreamness indices against the industry overall upstreamness indices, which are estimated using the original IO table. The upstreamness indices for SOE (blue squares) are mostly above the 45-degree line, suggesting that SOE often command a more upstream position than other firm groups along a value chain, even in the same sector. Small and medium-sized enterprises, on the other hand, are often much closer to final-good consumers.

7 Concluding Remarks

This paper proposes a method to extend a standard input-output (IO) table to incorporate firm heterogeneity when portraying the domestic segment of global value chains in a country. Using conventional IO tables, firm-level data for both manufacturing and service sectors, and quadratic optimization techniques, we estimate direct and indirect DVA for different firm groups in China. We decompose a firm group's indirect DVA into different domestic IO channels through which DVA was generated. Our approach is flexible enough to incorporate the standard bootstrapping techniques to compute standard errors and confidence intervals for the estimates in the extended IO table, as well as the associated estimates of DVA.

We find that in China, both SOE and small and medium-sized domestic private firms have much higher shares of indirect exports and DVA ratios, compared to foreign and large domestic private firms. Using China's IO tables for 2007 and 2010 respectively, we find evidence of increasing DVA ratios for all firm groups, particularly for SOE. These findings suggest that China's SOE still play an important role in shaping its domestic segment of GVCs, despite their diminishing importance in other macroeconomic outcomes.

Our findings shed light on the consequences of a unique sequence of privatization in China. Years of privatization have led to the dominance of large SOE in upstream sectors. Based on DVA, we find that Chinese firms' engagement in GVC could be a reason for the observed return to state capitalism in the country. We leave the econometric analysis about the political-economic factors behind the unique sequence of privatization and the resulting economic effects for future research.

References

Ahn, J., A. Khandelwal, S.J. Wei (2011) "The Role of Intermediaries in Facilitating Trade," December 2010, Journal of International Economics, 84(1), 73-85.

Antràs, P., D. Chor, T. Fally and R. Hillberry (2012) “Measuring the Upstreamness of Production and Trade Flows” *American Economic Review Papers and Proceedings*, Vol. 102, No. 3, pp. 412-416.

Bartholdy, K. (1991) “A Generalization of the Friedlander Algorithm for Balancing of National Accounts Matrices” *Computer Science in Economics and Management*, 2, 163-174.

Batten, D.F. (1982) “The Interregional Linkages Between National and Regional Input-Output Models” *International Regional Science Review*, 7, 53-67.

Batten, D.F. and D. Martellato (1985) “Classical Versus Modern Approaches to Interregional Input-Output Analysis” *Annals of Regional Science*, 19, 1-15.

Bernard, A., J. Eaton, J.B. Jensen, and S. Kortum (2003) “Plants and Productivity in International Trade.” *American Economic Review*, 93(4): 1268-1290

Bernard, A., B. Jensen, S. Redding, and P.K. Schott (2010) “Wholesalers and Retailers in U.S. Trade” *American Economic Review*, 100(2), 408-413.

Bernard, A., B. Jensen, S. Redding, and P.K. Schott (2015) “Global Firms” Princeton University mimeo.

Bernard, A., B. Jensen, S. Redding, and P. Schott (2015) “Global Firms”, *Journal of Economic Literature*, forthcoming.

Brandt, L., J Van Biesebroeck, and Y. Zhang (2012) “Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing” *Journal of Development Economics*, 97(2), 339-351.

Branstetter, L. and N. Lardy (2006) “China's Embrace of Globalization” NBER Working Paper, No. 12373.

Byron, R. P. (1978) “The Estimation of Large Social Account Matrix,” *Journal of Royal Statistical Society*, A, 141(Part 3), 359-367.

Canning, P. and Z. Wang (2005) “A Flexible Mathematical Programming Model to Estimate Interregional Input–Output Accounts” *Journal of Regional Science*, Volume 45, Issue 3, pages 539–563.

Chen, X., Cheng, L. K., Fung, K. C., Lau, L. J., Sung, Y. W., Zhu, K., and Duan, Y. (2012) “Domestic value added and employment generated by Chinese exports: A quantitative estimation” *China Economic Review*, Vol. 23, Issue 4, pp. 850–864.

De La Cruz, J., R. Koopman, Z. Wang, and S.J. Wei (2010) “Estimating Foreign Value-added in Mexico’s Manufacturing Exports.” USITC Working Paper.

Furusawa, T., T. Inui, K. Ito, and H. Tang (2017) “Global Sourcing and Domestic Production Networks” Johns Hopkins University Working Paper.

Golan, A., G. Judge, and S. Robinson (1994) “Recovering Information From Incomplete or Partial Multisectoral Economic Data” *Review of Economics and Statistics*, Vol. 76, No. 3, pp. 541-549.

Hsieh C-T. and Z. Song (2015) “Grasp the Large, Let Go of the Small.” *Brookings Papers in Economic Activity*, Spring 2015.

Johnson, R. and G. Noguera (2016) “A Portrait of Trade in Value Added over Four Decades” *Review of Economics and Statistics, forthcoming*.

Kee, H.L. and H. Tang (2016) “Domestic Value Added in Exports: Theory and Firm Evidence from China” *American Economic Review*, 106(6), June 2016, pp. 1402-1436.

Koopman, R., Z. Wang, and S.J. Wei (2008) “How Much of Chinese Exports is Really Made in China? Assessing the Domestic Value-Added When Processing Trade is Pervasive” NBER Working Paper No. 14109.

Koopman, R., Z. Wang, and S.J. Wei (2012) “Estimating Domestic Content in Exports When Processing Trade Is Pervasive,” *Journal of Development Economics*, 99:1, pp.178-89.

Koopman, R., Z. Wang and S.J. Wei (2014) “Tracing Value-added and Double Counting in Gross Exports,” *American Economic Review*, 104(2):459-494. Also available as NBER Working Paper No. 18579.

Koopman, R., B. Meng, and Z. Wang (2014) “How Global Value Chains are Fragmented and Extended in China's Domestic Production Networks” USITC Working Paper.

Lardy, N. R. (2014) *Markets over Mao*. Peterson Institute for International Economics.

Lenzen, M., Wood, R., & Wiedmann, T. (2010). Uncertainty analysis for multi-region input–output models– a case study of the UK's carbon footprint. *Economic Systems Research*, 22(1), 43-63. Chicago

Ma, Hong, Zhi Wang and Kunfu Zhu (2015) “Domestic Value-added in China’s Exports and Its distribution by Firm Ownership.” (With), *Journal of Comparative Economics*, 43(1):3-18.

Melitz, M. (2003) “The impact of trade on aggregate industry productivity and intra-industry reallocations.” *Econometrica*, 71, no. : 1695-1725.

Nagurney, A. and A.G. Robinson (1989) “Equilibration Operators for the Solution of Constrained Matrix Problems”*Algorithms and Model Formulations in Mathematical Programming*, pp. 165-166.

Puzzello, L. (2012) “A Proportionality Assumption and Measurement Biases in the Factor Content of Trade” *Journal of International Economics*, forthcoming.

Roberto, A. E. (2004) “Sources of export success in small- and medium-sized enterprises: the impact of public programs”, *International Business Review*, Volume 13, Issue 3, June 2004, Pages 383–400.

Robinson, S., A. Cattaneo and M. El-Said (2001) “Updating and Estimating a Social Accounting Matrix Using Cross Entropy Methods” *Economic System Research*, 13(1), 47-64.

Song, Z., K. Storesletten, and F. Zilibotti (2011) “Growing like China” *American Economic Review*, 101(1), 196-233.

Stone, R., D.G. Champernowne and J.E. Meade (1942) "The Precision of National Income Estimates." *Review of Economic Studies*, 9(2), 110-125.

Stone, R. (1984) “Balancing the national accounts. The adjustment of initial estimates: a neglected stage in measurement” in A. Ingham and A.M. Ulph (eds.), *Demand, Equilibrium and Trade*. London: Macmillan.

Tombe, T. and X. Zhu (2015) “Trade, Migration, and Productivity: A Quantitative Analysis of China” University of Toronto Working Paper.

USITC (2010) “Small and Medium-Sized Enterprises: Characteristics and Performance” Investigation No. 332-510, United States International Trade Commission Publication 4189, November 2010.

van der Ploeg, F. (1988) “Balancing Large Systems of national Accounts" *Computer Science in Economics and Management*, 1, 31-39.

Wang, Y., X. Li and X. Liu (2012) “A Model of China's State Capitalism” HKUST Working Paper.

Wang, Z., S.J. Wei and K. Zhu (2013) “Quantifying International Production Sharing at the Bilateral and Sector Level”. NBER Working Paper 19677.

Weale, M. R. (1985) “Testing Linear Hypotheses on National Account data” *Review of Economics and Statistics*, 67, 685-689.

Zhu, X. (2012) “Understanding China’s Growth: Past, Present, and Future,” *Journal of Economic Perspective*, 26 (4), 103–124.

Table 1: Contribution by Each Firm Group to China's Main Economic Activities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number of Firms (2008)	Value Added (2008)	Employment (2008)	Gross Exports (2007)	Estimated DVA (2007)	Gross Exports (2010)	Estimated DVA (2010)
A: Share (%)							
Firm Type							
State-owned	4.73	19.16	9.24	12.07	20.81	9.40	22.02
Foreign	3.01	16.34	6.49	49.47	26.50	56.65	26.67
Large Private	0.22	9.91	4.82	10.08	10.35	10.41	10.10
Small and Medium Private	92.04	54.58	79.45	28.38	42.34	23.54	41.21
B: Value (Billion for values; million for employment)							
Firm Type							
State-owned	188,829	5098	71	1231	1446	1052	1821
Foreign	120,073	4348	50	5046	1841	6340	2205
Large Private	8,836	2637	37	1028	719	1164	835
Small and Medium Private	3,674,676	14520	612	2895	2942	2635	3407
Total	3,992,414	26604	770	10200	6947	11191	8268

Note: Domestic value added in exports (DVA) is estimated using our extended IO tables for 2007 and 2010, respectively. Data on value added and employment are from China's National Bureau of Statistics (NBS) 2008 firm census. Data on gross exports are computed based on IO tables from 2007 and 2010, respectively.

Table 2: Domestic Value Added in Exports (DVA)

	(1)	(2)	(3)	(4)
A. 2007	Domestic Value Added in Exports (DVA) in Bil RMB	Standard Error/ Mean	DVA/ Gross Exp	Change relative to 2007 (%)
State-owned	1446	0.315	1.17	
	(1169, 1723)			
Foreign	1841	0.071	0.36	
	(1762, 1920)			
Large Private	719	0.217	0.70	
	(590, 848)			
Small and Medium Private	2942	0.236	1.02	
	(2309, 3574)			
Total	6947	0.005	0.68	
	(6787, 7108)			
B. 2010				
State-owned	1821	0.318	1.73	47.4%
	(952, 2690)			
Foreign	2205	0.081	0.35	-4.7%
	(1822, 2589)			
Large Private	835	0.224	0.72	2.5%
	(446, 1224)			
Small and Medium Private	3407	0.235	1.29	27.3%
	(1777, 5037)			
Total	8268	0.004	0.74	8.5%
	(8197, 8339)			

Note: Authors' estimation based on data from firm census data from 2008 and IO tables for 2007 and 2010, respectively. All data used are from China's National Bureau of Statistics. 95% confidence intervals are reported in brackets in column 1. Column 2 reports the ratios of the standard error to mean of the estimates.

Table 3: Indirect DVA (in Billion RMB)

2007	Total Indirect DVA	
State-owned	1150	(666, 1634)
	[80%]	*0.297*
Foreign	853	(648, 1057)
	[46%]	*0.078*
Large Private	520	(321, 718)
	[72%]	*0.192*
Small and Medium Private	1860	(1147, 2572)
	[63%]	*0.206*
Total	4382	(4216, 4548)
	[63%]	*0.019*
2010		
State-owned	1458	(887, 2030)
	[80%]	*0.302*
Foreign	952	(698, 1205)
	[43%]	*0.079*
Large Private	587	(343, 830)
	[70%]	*0.198*
Small and Medium Private	2496	(1611, 3381)
	[73%]	*0.216*
Total	5493	(5317, 5668)
	[66%]	*0.017*

Note: Authors' estimation based on China's firm census data from 2008 and IO tables for 2007 and 2010, respectively. All data are from China's National Bureau of Statistics. The estimated indirect DVA is reported in billion RMB. The share of indirect DVA in total DVA for each firm group is reported in square brackets. The 95% confidence interval of each estimate is reported in parentheses, with the corresponding standard-error-to-mean ratio reported in italics.

Table 4: Indirect DVA through Different Firm Group (in Billion RMB)

	(1)		(2)		(3)		(4)	
via	State-owned		Foreign		Large Private		Small and Medium Private	
2007								
State-owned	190	(47, 333)	510	(352, 668)	158	(77, 239)	292	(189, 394)
	[13%]	*0.292*	[35%]	*0.362*	[11%]	*0.329*	[20%]	*0.225*
Foreign	121	(53, 189)	430	(346, 514)	105	(60, 151)	197	(174, 219)
	[7%]	*0.088*	[23%]	*0.120*	[6%]	*0.116*	[11%]	*0.030*
Large Private	80	(20, 140)	230	(161, 299)	70	(35, 106)	139	(103, 175)
	[11%]	*0.197*	[32%]	*0.253*	[10%]	*0.229*	[19%]	*0.118*
Small and Medium Private	225	(78, 373)	785	(687, 883)	212	(149, 276)	637	(226, 1048)
	[8%]	*0.163*	[27%]	*0.121*	[7%]	*0.138*	[22%]	*0.318*
Total	616	(494, 734)	1955	(1740, 2171)	546	(445, 647)	1264	(993, 1535)
	[9%]	*0.049*	[28%]	*0.097*	[8%]	*0.081*	[18%]	*0.097*
2010								
State-owned	167	(0, 334)	795	(606, 983)	191	(99, 284)	306	(181, 430)
	[9%]	*0.303*	[44%]	*0.372*	[11%]	*0.340*	[17%]	*0.220*
Foreign	85	(-4, 174)	582	(487, 677)	114	(58, 171)	170	(145, 195)
	[4%]	*0.097*	[26%]	*0.109*	[5%]	*0.125*	[8%]	*0.026*
Large Private	58	(-14, 131)	328	(244, 413)	76	(34, 117)	125	(78, 171)
	[7%]	*0.206*	[39%]	*0.262*	[9%]	*0.238*	[15%]	*0.121*
Small and Medium Private	191	(9, 373)	1321	(1183, 1459)	274	(194, 355)	710	(220, 1200)
	[6%]	*0.177*	[39%]	*0.145*	[8%]	*0.158*	[21%]	*0.304*
Total	501	(357, 646)	3026	(2796, 3256)	655	(544, 767)	1310	(997, 1623)
	[6%]	*0.051*	[37%]	*0.087*	[8%]	*0.079*	[16%]	*0.089*

Note: Authors' estimation based on China's firm census data from 2008 and IO tables for 2007 and 2010, respectively. All data are from China's National Bureau of Statistics. The estimated indirect DVA through each firm group is reported in billion RMB. The share of each firm-group's contribution (column) to each firm group's DVA (row) is reported in square brackets. The shares add up to less than 100%, with the residual being the share of direct DVA in total DVA of the group (row). The 95% confidence interval of each estimate is reported in parentheses, with the corresponding standard-error-to-mean ratio reported in italics.

Table 5: Standard-Error-to-Mean Ratios of the Key Values from Bootstrapped Samples

2007	State-owned	Foreign	Large Private	Small and Medium Private
gross output (x^g_i)	0.019	0.013	0.029	0.005
exports (e^g_i)	0.028	0.021	0.162	0.006
value added (v^g_i)	0.116	0.042	0.117	0.037
2010				
gross output (x^g_i)	0.018	0.013	0.027	0.005
exports (e^g_i)	0.027	0.020	0.142	0.005
value added (v^g_i)	0.114	0.035	0.108	0.032

Note: Authors' estimation and calculation based on China's National Bureau of Statistics firm census data from 2008. Notice that only the statistics for the initial values *directly* computed from the firm data are reported. Initial values that are computed indirectly using such firm-based initial values, including imported intermediate inputs by firm type g ($z0^{Fg}_{ij}$), domestic inter-sector transactions between two firm types ($z0^{g1g2}_{ij}$), and domestic demand for firm type g's output in sector i ($y0^g_i$). See eq. (17)-(19) in the main text about how the initial values in the objective function are computed based on x^g_i, e^g_i and v^g_i.

Table 6: Indirect DVA/ Total DVA (4 groups, 14 sectors) (%)

Panel A: 2007

Sector	All	SOE	FE	LP	SME
Energy and mining	94.03	94.57	92.30	93.01	**94.58**
Metal and non-metallic mineral extraction	90.14	89.15	88.18	**92.17**	91.17
Light manufacturng	49.61	**74.83**	36.87	58.18	51.70
Petrochemical	74.89	**87.58**	62.67	75.69	79.79
Metal and non-metal processing	67.29	68.87	69.00	**75.37**	60.58
Machinery and equipment	47.02	**72.52**	36.86	53.35	46.90
Electronic equipment	20.75	**45.45**	16.71	34.41	36.29
Other manufacturing	76.35	59.75	29.67	36.68	**87.02**
Electricity, gas and water supply	99.41	**99.51**	**99.56**	98.85	98.95
Building industry	33.63	33.18	**35.94**	33.39	33.38
Transportation and warehousing	52.87	59.78	87.92	**90.06**	40.50
Wholesale and retail trade	42.72	72.22	**82.72**	76.36	24.26
Financial sector	98.18	97.94	97.82	97.78	**98.51**
Other Services	66.02	75.35	79.31	**80.82**	45.23
Total	63.07	**79.54**	46.31	72.24	63.23

Panel B: 2010

Sector	All	SOE	FIE	LP	SME
Energy and mining	96.55	95.95	93.34	96.64	**99.23**
Metal and non-metallic mineral extraction	94.77	97.65	81.86	**99.53**	94.27
Light manufacturng	53.61	**91.84**	32.43	61.02	68.09
Petrochemical	74.41	79.82	55.62	78.30	**87.82**
Metal and non-metal processing	73.16	76.08	56.37	79.06	**82.83**
Machinery and equipment	48.18	**72.16**	34.08	48.43	65.87
Electronic equipment	31.85	**71.90**	24.54	46.09	**71.75**
Other manufacturing	55.35	**92.84**	44.74	67.41	65.20
Electricity, gas and water supply	99.23	99.09	**99.88**	99.23	**99.69**
Building industry	17.82	28.08	**76.61**	26.66	9.65
Transportation and warehousing	69.10	71.17	74.42	**90.52**	66.08
Wholesale and retail trade	45.51	53.18	**60.98**	55.78	38.05
Financial sector	96.75	97.26	97.43	**97.90**	96.43
Other Services	70.49	71.60	77.65	**86.97**	61.10
Total	66.43	**80.10**	43.15	70.30	73.25

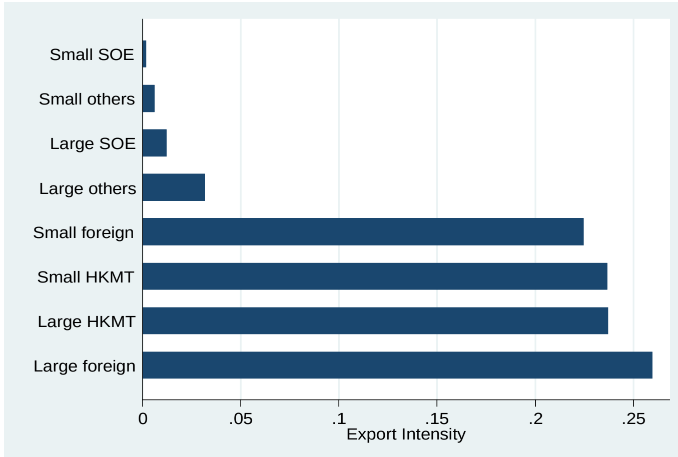
Note: SOE = state-owned enterprises; FE = foreign enterprises. LGE = large private enterprises; SME = small and medium-sized private enterprises. Authors' estimation and calculation based on data from the 2008 firm census. All data are from China's National Bureau of Statistics. Italic fonts indicate industries that have indirect export share exceeding 90%. Boldface denotes the highest among the four ownership types within the industry.

Table 7: Top and Bottom Industry Upstreamness

		All	By Type			
Code	Sector		SOE	FE	LGE	SME
		2007				
		Top 5				
3	Extraction of Petroleum and Natural Gas	5.09	6.02	5.31	4.99	4.39
4	Mining of Ferrous Metal Ores	5.03	5.80	5.79	5.27	4.30
2	Mining and Washing of Coal	4.90	5.72	5.35	4.91	3.98
23	Production and supply of Electricity and heat	4.46	5.09	4.69	4.35	3.75
11	Processing of Petroleum, Coking and Nuclear Fuel	4.27	5.22	4.77	4.04	3.59
		Bottom 5				
33	Real Estate	1.67	2.65	2.58	1.53	1.22
40	Health and Social service	1.26	1.50	1.48	1.48	1.08
39	Education	1.20	1.43	1.46	1.31	1.05
26	Construction industry	1.06	1.08	1.24	1.08	1.02
42	Public administration and social organization	1.02	1.05	1.10	1.05	1.01
		2010				
		Top 5				
3	Extraction of Petroleum and Natural Gas	5.22	6.31	4.91	5.32	4.22
2	Mining and Washing of Coal	5.04	5.66	5.84	5.24	4.68
4	Mining of Ferrous Metal Ores	5.13	5.86	5.09	5.04	4.68
23	production and supply of Electricity and heat	4.60	5.31	4.30	4.14	3.85
11	Processing of Petroleum, Coking and Nuclear Fuel	4.38	5.57	5.08	4.19	4.06
		Bottom 5				
33	Real Estate	1.60	3.41	3.00	1.46	1.22
40	Health and Social service	1.20	1.34	3.03	1.37	1.05
39	Education	1.09	1.39	1.77	1.11	1.02
26	Construction industry	1.06	1.10	2.83	1.09	1.02
42	Public administration and social organization	1.03	1.11	2.50	1.13	1.01

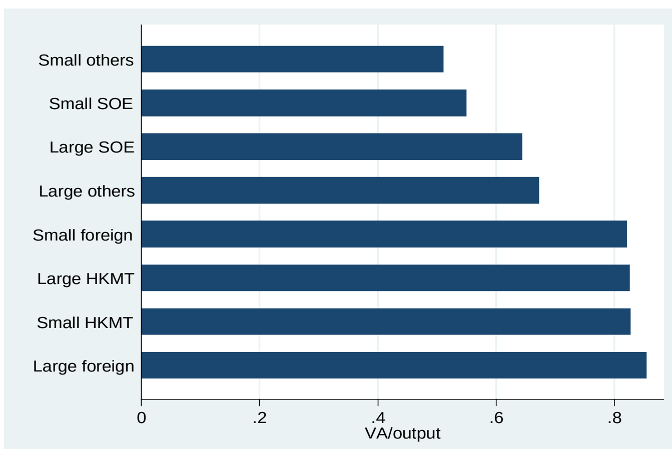
Note: Authors' estimation based on data from 2007 IO tables. SOE = state-owned enterprises; FE = foreign enterprises. LGE = large private enterprises; SME = small and medium-sized private enterprises. Bolded face denotes the highest in each row for the top 5, and the lowest in each row for the bottom 5. there are altogether 40 sectors.

Figure 2: Firm Average Export Intensity



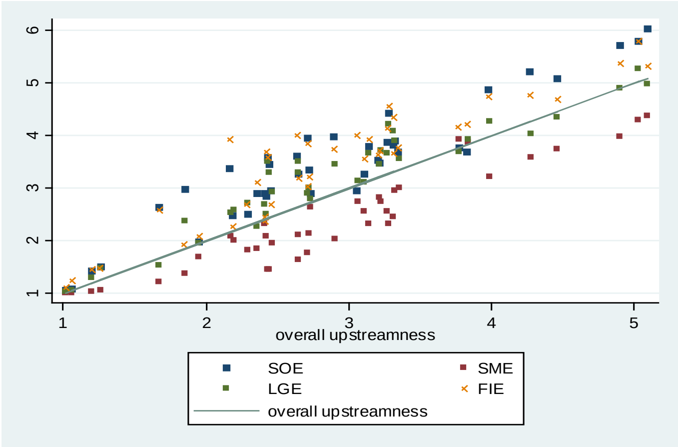
Source: China's National Bureau of Statistics Firm Census Data (2008)

Figure 3: Firm Average Value Added to Output Ratio



Source: China's National Bureau of Statistics Firm Census Data (2008)

Figure 4: Upstreamness of by Ownership Type



Source: Chinese National Bureau of Statistics (2007) IO table and industrial firm census data. SOE = state-owned enterprises; SME = small and medium-sized enterprises; LGE = large private enterprises; FIE = foreign invested enterprises.