The Impact of Product Differentiation on Productivity

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(Work in progress. Please do not cite.)

Abstract

This paper develop a theoretical framework to estimate production function of firms producing more than one product across multiple industries. Our method is based on Ackerberg, Caves, and Frazer (2015), which is improved version of Olley and Pakes (1996) and Levinsohn and Petrin (2003) ,but we extend ACF further to allows firms producing multi-industries and endogenous entry and exit. We examine the impact of export product switching (i.e. simultaneously dropping and adding distinct products) on firm productivity. Using the Propensity Score Matching (PSM) method to account for endogeneity problems due to reverse causality, self-selection, and omitted variables and detailed firm-level custom and financial data of Chinese manufacturing firms, we find a positive impact of export product churning on firm productivity but smaller than we ignore endogeneity problem by factor of two. The magnitude of the impact on productivity depends on (i) the share of processing trade, (ii) firm ownership types, and (iii) industry types. The effect is strongest when the share of processing trade is low; when firms are state- and foreign-owned; and when firms produce in high technology industries. We find that resources reallocation at the intra-firm "extensive margin" through product churning contributes to raising firm productivity. This confirms the same result from advanced countries but is new evidence from a developing country, China.

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Keywords:
JEL Classifications:

1 Introduction

To be written for production estimation part. [Discussion To be added]

There has been a large literature on the impact of resource reallocation on productivity (Davis and Haltiwanger, 1999; Foster, Haltiwanger, and Syverson, 2008; Jones, 2013; Melitz and Polanec, 2015) and some studies (Restuccia and Rogerson 2008; Caselli and Gennaioli, 2003; Buera and Shin 2008; Jones 2009; Hsieh and Klenow 2009, 2010, Kali et al. 2013) argue that resource allocation across industries induced by trade liberalization is an important mechanism for economic development and growth. In particular, China's growth speedup since late 1990s can be attributed to its rapid expansion in manufacturing sectors (Young, 2003; and Bosworth and Collins, 2008), which has seen more efficient new private enterprises replacing inefficient state-owned old enterprises (Brandt et al., 2009; and Hsieh and Klenow, 2009).

Previous studies in this literature are conducted almost exclusively at the *inter*-industry or *inter*-firm level (Davis, Haltiwanger, and Schuh, 1996; Baldwin and Gu, 2006; Du, Liu, and Zhou, 2014; Sandleris and Wright, 2014; Collard-Wexler and De Loecker, 2015; Sheng, Jackson, and Gooday, 2017), examining how resource reallaction improves the efficiency of economies. The basic premise is that aggregate productivity arises when resources are reallocated from less productive industries (firms) to more productive industries (firms), and the marginalized firms or industries vanish and exit markets eventually. However, better resources allocation may also occur at the *intra-firm* level as firms transforms and evolves themselves by producing different products – the extensive margin along the product dimension. In the model of Mayer, Melitz, and Ottaviano (2014), each firm has a core competence in producing a particular product variety, and products that farther away from the core product are less profitable. In response to increased competition, firms shift resources from non-core products to core products. Likewise, Eckel and Neary (2010) argue that trade liberalization has a "cannibalization effect" that leads firms to become "leaner and meaner" by focusing on their core products.

Empirically, multi-product firms and their product switching activities are found to be commonplace in Chilean (Navarro, 2012; Alvarez, Bravo-Ortega, and Navarro, 2016). Using Chilean manufacturing firms data over the period of 1996-2003, Navarro (2012) also shows that Chilean manufacturing firms experienced a growth in sales of 43%, for which 8% were attributed to net entry of firms, and 16% and 19% to the growth of continuing firm at the intensive margin (i.e. sale expansion or decline of existing products) and the extensive margin (i.e. adding new or dropping old products), respectively. Furthermore, evidence from the U.S. (Bernard, Redding, and S. J., 2010), Slovenia (Damijan, Konings, and Polanec, 2014) and Belgium (Adalet et al., 2009) consistently shows that multi-product firms are prevalent and major exporters in developed economies and they exhibit frequent product switching activities in export markets. Bernard, Redding, and S. J. (2010) and Adalet et al. (2009) also establish several stylized facts about multi-product firms as major palyers of product switching.

Despite increasing evidence on intra-firm resource reallocation through product churning/switching[1] (i.e. products adding and dropping), research on its productivity impact from this reallocation has been relatively scant, as compared to that of inter-firm or inter-industry resource allocation. One exception is Damijan, Konings, and Polanec (2014), who show that *import* product churning contributes more to Slovenian firms' productivity growth than declining import prices or tariff reduction. Our paper differs in its focuses on *export* product churning instead import product churning. Furthermore, few previous studies on product churning look at *developing* countries. Goldberg, Khandelwal, Pavcnik, and Topalova (2010) and Bollard et al. (2013), both focusing on India, are exceptions. Interestingly, although Goldberg, Khandelwal, Pavcnik, and Topalova (2010) find that product churning is much less common in India than in the U.S., Bollard et al. (2013) show that rapid productivity growth at the early 1990s in Indian manufacturing industries can be attributed to reallocation *within* large firms. Our paper focuses on another developing but even larger country – China using recently developed frontier methods of estimating productivity as in Ackerberg, Caves, and Frazer (2015).

The main objective of this paper is to quantify the impact of intra-firm product churn-

[1] We use the terms churning and switching interchangeably.

ing to the productivity of Chinese manufacturing exporters.Our analysis focuses on Chinese manufacturing exporters over the years 2001-06 when they enjoy rapid economic growth in trade and GDP. Chinese manufacturing firms deserve special attention in this field of research because they has become a global export powerhouse. There are numerous studies on the impact of exporting (or even importing) on firm productivity (Bernard and Jensen, 1999, 2004; Melitz, 2003; Arnold and Hussinger, 2005; Kasahara and Rodrigue, 2008; Wagner, 2012; Yu, 2015). However, much less has been done on mechanism for improving their productivity: wthether (i) it is improved technology within industry, (ii) reallocation across industry, (iii) reallocation across firms within industry, or (iv) reallocation within firms across industry.[2] Among these potential four channels, we focus on the channel of reallocation within firms across industry. There are recent papers studying the product scope and trade dynamics of Chinese multi-product firms (Yu and Tian, 2012; Qiu and Yu, 2014; Fernandes and Tang, 2015), but none of them have looked at the relationship between export product churning and productivity while controlling for other channels explicitly.

To address endogeneity problems due to the self-selection of switching, simultaneity, and other potential problems, we employ the Propensity Score Matching method (PSM hereinafter). There are two obvious bias sources. Firstly, more productive firms are in a better position to adjust in the face of external shocks. Thus, ignoring self-selection bias leads to an overestimation of the impact of product churning. Second, unobserved confounding factors can induce correlation between product churning and productivity enhancement. For instance, a firm with better human or financial capitalare able to seize opportunities in new sectors as well as to improve productivity, leading to an overestimation of the impact of product churning. Thus, to make a causal statement on the effect of product churning on productivity, it is important to account for endogeneity problems from many potential sources of bias. In this paper, we also estimate the effect of product churning on productivity without accounting for endogeneity to shed light on the direction and magnitude of resulting bias. [Sensitivity analysis to be added – Synthetic control, synthetic control with penalty function from supervised learning.]

Bollard et al. (2013) contribute China's rapid economic growth in recent years to rapid

[2]Obviously, there could be other channels. Ma et al. (2014) show that, among Chinese manufacturing firms, those exhibit a larger decline in capital intensity after exporting experience higher growth in revenue-based measures of total factor productivity.

growth in manufacturing sectors as well as the displacement of inefficient state-owned enterprises (Brandt et al., 2009; and Hsieh and Klenow, 2009). Thus, we examine the heterogeneity of the product churning effects across firms according to their ownership types.[3] Furthermore, we also examine the effects across firms with different shares of processing trade and non-processing trade. Many developing countries begin their integration into the global value chain (GVC) by conducting processing trade, including China, Mexico and Vietnam (Fernandes and Tang, 2015). Thus, we can test whether exporters of processing products are major contributors to better resource reallocation of the manufacturing sector. In China, processing trade accounts for nearly a half proportion of trade (Bergin et al.,2009). Distinct from non-processing traders, processing traders first obtain intermediate inputs or raw materials from abroad and then re-export the final goods after processing (Feenstra and Hanson, 2005). Thus, these firms are more likely dependent upon external conditions and less discretion in their activities. Our dataset also reveal that firms with processing trade also have distinct firm characteristics, such as lower productivity level, lower wages and higher credit constraints in China (Wang and Yu, 2012; Dai, Harris, Lu, and Liu, 2016a; Manova and Yu, 2016). These facts imply that firms with processing trade could more vulnerable to external shock due to intermediary inputs.

Also, following the proposition of Bernard, Redding, and Schott (2011) that firms drop low-attribute products and add high-attribute products in face of trade liberalization, we examine how product attributes in terms of the technology level affect productivity improvement after churning. Finally, we examine whether productivity improvement depends upon the duration of export market participation. More productive firms may enter into export market and survive longer. Thus, we want to examine whether the positive effects of churning are exclusive to experienced firms.

To the best of our knowledge, this paper is the first study exploring product switching activities of Chinese exporters and their impact on firm productivity. Moreover, we consider the impact heterogeneity due to processing traders and state ownership, which are prominent

[3]A legacy of China's socialist system is the large presence of state-owned firms, as well as the differential treatments of state, foreign and private firms in terms of, for instance, subsidies and access to capital (Eckaus, 2006; Khandelwal, Schott, and Wei, 2013). Firm ownership is found to a key factor of Chinese firms' decision making processes (Jefferson, Rawski, Li, and Yuxin, 2000; Ding, Guariglia, and Harris, 2016) and productivity (Hu and Tan, 2016; Ding, Guariglia, and Harris, 2016). Therefore, in this paper we also distinguish firms of different types of ownership.

features of many developing countries, as well as the duration of export market participation and product technology level.

The rest of the paper is organized as follows. Section 2 introduces production function estimation. Section 3 describes the data and the PSM methodology. Section 4 reports the main empirical findings. Section 5 provides results of a number of extensions. The last section 6 concludes.

2 Production function estimation

We develop a theoretical framework that allows firms to produce more than one product across multiple industries.[4]

2.1 Industry and Product Classfication

We use two industry classifications – one broad and the other refined. The use of broad industry specification is mainly for the ease of exposition. On the other hand, we use refined classfication as we assume homogeneity among products within industry. Our broad industry classification (denote as chapter hereafter) is based on 2-digit industry indicator and includes 40 chapters. We also use more refined industry classfication (denote as industry hereafter) that includes 500 industries to make quantity data more comparable within industry. We define product based on HS 6-digit classification which includes about 5,500 products so, therefore, in our dataset each industry by broad classfication on average has about 24 products.

2.2 Muti-product firms producing in single industry

2.2.1 Model

Let L_{it} and K_{it} be the number of employees and the capital stock that firm i hires at time t. Let J_{it} be the set of products that firm i produces and R_{it} be the total sales of firm i at t. For firm i at time t, we observe $(L_{it}, K_{it}, R_{it}, J_{it})$. Let Q^e_{ijt} be the quantity of good j

[4]We use both good and product interchangeably.

that firm i produces to export at time t and P^e_{ijt} be the price of good j in the foreign market. Whenever firm i exports good j, we observe both quantity and price at the product level, but, for domestic sales as well as input uses we only have information at the firm level. For this reason, we consider goods for export as products distinct from the same goods for domestic markets (e.g. we define cloth sold in domestic market as different product from the same cloth that sold abroad). That is, even for the same kind of product, which we index by j when it is exported, we index it by $k \neq j$ for the portion that is not exported.

Each firm could produce more than one product. We consider a standard Cobb-Douglas production function with Hick's neutral technology. If firm i at time t produces and exports good j, by employing labor L_{ijt} and capital stock K_{ijt}, then its output Q_{ijt} is determined by

$$Q_{ijt} = L_{ijt}^{\alpha_\ell} K_{ijt}^{\alpha_k} \exp(\omega_{it} + u_{it}) \tag{1}$$

where α_ℓ and α_k are the output elasticities of labor and capital of the production technology and ω_{it} denotes firm-specific productivity shock that firm i observes before it maximizes its profit and u_{it} represents additional shocks that are unknown when firm i makes input decision. Note that since we consider firms export in one industry, we suppress the industry labels in (1), but $(\alpha_\ell, \alpha_k, \omega_{it}, u_{it})$ are industry specific, i.e., $(\alpha^s_\ell, \alpha^s_k, \omega^s_{it}, u^s_{it})$ for some industry s.

We write firm i's profit function as

$$\max_{\{L_{ijt}, K_{ijt}\}_{j \in J_{it}}} \sum_{j \in J_{it}} P_{ijt} Q_{ijt} - P_\ell \sum_{j \in J_{it}} L_{ijt} - P_k \sum_{j \in J_{it}} K_{ijt},$$

where P_ℓ and P_k are input prices.

We assume that the factor inputs L_{it} or K_{it} have been chosen at time $t-1$, so the firm optimally allocates these inputs across its products in J_{it} at time t. Then, P_ℓ should be interpreted as the original input price plus shadow price associated with the constraint $L_{it} = \sum_{j \in J_{it}} L_{ijt}$. In order to compute the proportion of each factor input that is used for production of product j, we consider the first order necessary conditions of the firm's profit maximization problem. In particular, by taking a derivative of the profit function with respect to L_{ijt}, we have

$$\alpha_\ell P_{ijt} Q_{ijt} = P_\ell L_{ijt} \Longleftrightarrow \alpha_\ell R_{ijt} = P_\ell L_{ijt},$$

as long as $L_{ijt} > 0$. Then, by summing over J_{it}, we have $\sum_{k \in J_{it}} \alpha_\ell R_{ikt} = P_\ell L_{it}$ where $L_{it} = \sum_{k \in J_{it}} L_{ikt}$. Hence, we have the factor ratio,

$$C_{ijt} := \frac{L_{ijt}}{L_{it}} = \frac{\alpha_\ell R_{ijt}}{\sum_{k \in J_{it}} \alpha_\ell R_{ikt}} = \frac{R_{ijt}}{R_{it}} \tag{2}$$

which also equals K_{ijt}/K_{it}. This is equivalent to assume that proportion of input used to product j among all products is the same for both labor and capital.

Note that we observe R_{it} for all (i, t) but we can construct $R_{ijt} = P_{ijt} Q_{ijt}$ only when the product j is exported. For such a good j, we rewrite (1) as

$$\begin{aligned} q_{ijt} &= \alpha_\ell \ell_{ijt} + \alpha_k k_{ijt} + \omega_{it} + u_{it} \\ &= (\alpha_\ell + \alpha_k) c_{ijt} + \alpha_\ell \ell_{it} + \alpha_k k_{it} + \omega_{it} + u_{it} \end{aligned} \tag{3}$$

where $q_{ijt} := \log Q_{ijt}$, $\ell_{ijt} := \log L_{ijt}$, $k_{ijt} = \log K_{ijt}$, and $c_{ijt} = \log C_{ijt}$.

For identification purpose, we consider the standard assumptions as below following ACF.

Assumption 1. The firm's information set at t denoted by I_{it} which includes current and past productivity shocks $\{\omega_{i\tau}\}_{\tau \leq t}$ but does not include future productivity shocks $\{\omega_{i\tau}\}_{\tau > t}$. The transitory shcoks u_{it} satisfy $E[u_{it}|I_{it}] = 0$. $\square$

Assumption 2. Productivity shocks evolve according to the distribution

$$\pi(\omega_{it+1}|I_{it}) = \pi(\omega_{it+1}|\omega_{it})$$

This distribution is known to firms and stochastically increasing in ω_{it} for all (i, t).

Assumption 3. Firms accumulate capital according to

$$k_{it} = \kappa(k_{it-1}, i_{it-1})$$

where investment i_{it-1} is chosen at period $t-1$ and therefore $k_{it} := \prod_{j \in J_{it}} k_{ijt}$ is also determined at $t-1$. Labor input ℓ_{it} has potential dynamic implications and is chosen at period t, period $t-1$, or period $t-b$ (with $0 < b < 1$). $\square$

Assumption 3 allows the choice of ℓ_{it} to affect future profits as well as current profits, which implies that ℓ_{it} can be part of the state space of the firm's dynamic profit maximization problem. This assumption is more general than the corresponding conditions of OP/LP that the choice of labor affects only current profits.

Assumption 4. Firms' intermediate input demand is given by

$$m_{it} = f_t(k_{it}, \ell_{it}, \omega_{it})$$

where m_{it} is the intermediate inputs. $\square$

Assumption 4 suggests that the intermediate inputs used for production in industry s is proportional to the output level. Moreover, we assume that each firm selects m_{it} for production conditional on $(k_{it}, \ell_{it}, \omega_{it})$.

Assumption 5. f_t is strictly increasing in ω_{it}. $\square$

Assumption 5 is required to use m_{it} as a proxy variable to control for the unobserved productivity shock, ω_{it}. Since m_{it} does not affect firm's future profits, we can follow the argument of LP to provide lower level conditions under which the monotonicity of f_t follows. Under Assumptions 3, 4, and 5, we can write an estimable equation (3) as

$$\begin{aligned} q_{ijt} &= (\alpha_\ell + \alpha_k)c_{ijt} + \alpha_\ell \ell_{it} + \alpha_k k_{it} + f_t^{-1}(k_{it}, \ell_{it}, m_{it}) + u_{it} \\ &= \gamma c_{ijt} + \phi_t(k_{it}, \ell_{it}, m_{it}) + u_{it} \end{aligned} \tag{4}$$

where we have following restrictions $\gamma = \alpha_\ell + \alpha_k$ and $\phi_t(k_{it}, \ell_{it}, m_{it}) := \alpha_\ell \ell_{it} + \alpha_k k_{it} + f_t^{-1}(k_{it}, \ell_{it}, m_{it})$. Then, we can construct the moment restriction based on Assumption 1 as

$$E[u_{it}|I_{it}] = E[q_{ijt} - \gamma c_{ijt} - \Phi_t(k_{it}, \ell_{it}, m_{it})|I_{it}] = 0 \tag{5}$$

from which we identify the returns to scale γ and Φ_t.

For the time being, we consider the firms' entry and exit decision is exogenously given. By Assumption 2, then, we have $E[\omega_{it}|I_{it-1}] = E[\omega_{it}|\omega_{it-1}] = g(\omega_{it-1}) + \varepsilon_{it}$. Then,

$E[\varepsilon_{it}|I_{it-1}] = 0$. Hence, the second stage moment restriction is given as

$$\begin{aligned} 0 &= E[u_{it} + \varepsilon_{it}|I_{it-1}] \\ &= E[q_{ijt} - \gamma c_{ijt} - \alpha_\ell \ell_{it} - \alpha_k k_{it} + g(\omega_{it-1})|I_{it-1}] \end{aligned} \tag{6}$$

where $\omega_{it-1} = \Phi_t(k_{it-1}, \ell_{it-1}, m_{it-1}) - \alpha_\ell \ell_{it-1} - \alpha_k k_{it-1}$ under the restriction of $\gamma = \alpha_\ell + \alpha_k$. The moment restriction (6) identifies (α_ℓ, α_k). Note that we could use a simple specification for $g(\cdot)$ such as $g(\omega_{it-1}) = \rho\omega_{it-1}$ for estimation.

2.2.2 Entry and Exit

Our dataset contains 111,238 firms from 2000 to 2006. However, we have firm information only for those firms with positive export flows and therefore, following OP, weconsider endogenous entry/exit. The occurences of entry and exit are non-trivial as 70% of observations firm do not export. In other words, during sample periods, for many years firms do not export.

Following OP, we assume firms maximize the expected discounted value of future net cash flows and derive a condition for the firms to stay in business or to liquidate the asset and go out of business. OP solved the dynamic optimization problem to derive an exit rule, which is represented by

$$\chi_{it} = \mathbb{1}(\omega_{it} \geq \underline{\omega}_t(k_{it})) \tag{7}$$

where $\chi_t = 0$ indicates that firm i exits in the beginning of time t. OP also showed that

$$\begin{aligned} \Pr(\chi_{it} = 1|\underline{\omega}_t(k_{it}), I_{it-1}) &= \Pr(\omega_{it} \geq \underline{\omega}_t(k_{it})|\underline{\omega}_t(k_{it}), \omega_{it-1}) \\ &= \zeta\left\{\underline{\omega}_t[\kappa(k_{it-1}, i_{it-1})], f_{t-1}^{-1}(k_{it-1}, \ell_{it-1}, m_{it-1})\right\} \end{aligned}$$

where the first equality holds by Assumption 2 and the second by Assumptions 3 to 5 for some function ζ. That is, $\Pr(\chi_{it} = 1|\underline{\omega}_t(k_{it}), I_{it-1})$ is determined by $(k_{it-1}, i_{it-1}, \ell_{it-1}, m_{it-1})$ and, therefore, we denote this probability by Ψ_{it-1}. We estimate Ψ_{it} by using a polynomial series in $(k_{it}, i_{it}, \ell_{it}, m_{it})$ as regressors in a probit estimation or by a kernel estimation.[5] Numerous studies show exclusion restriction is important in non-parametric identification of entry and exit decision. $(k_{it-1}, \ell_{it-1}, m_{it-1})$ are also used in estimation of the outcome equation so the excluded variables are i_{it-1}.

By Assumption 2, we have $E[\omega_{it}|I_{it-1}, \chi_t = 1] = E[\omega_{it}|\omega_{it-1}, \Psi_{it-1}] = g(\omega_{it-1}, \Psi_{it-1}) + \varepsilon_{it}$. Then, $E[\varepsilon_{it}|I_{it-1}, \chi_t = 1] = 0$. Hence, the moment restriction (6) is modified to

$$\begin{aligned} 0 &= E[u_{it} + \varepsilon_{it}|I_{it-1}, \chi_t = 1] \\ &= E[q_{ijt} - \gamma c_{ijt} - \alpha_\ell \ell_{it} - \alpha_k k_{it} + g(\omega_{it-1}, \Psi_{it-1})|I_{it-1}, \chi_t = 1]. \end{aligned} \tag{8}$$

The moment restriction (8) identifies (α_ℓ, α_k) as before. Following OP, we approxime $g(\cdot)$ by a polynomial series of $(\omega_{it-1}, \Psi_{it-1})$ for estimation and this is a departure from ACF's AR(1) treatment for productivity over time process (e.g. $g(\omega_{it-1}) = \rho\omega_{it-1}$).

Since we identify $(\alpha_\ell, \alpha_k, \Phi_t)$ and observe $(k_{it}, \ell_{it}, m_{it})$ for all firms, we obtain the productivity index;

$$\omega_{it} = \Phi_t(k_{it}, \ell_{it}, m_{it}) - \alpha_\ell \ell_{it} - \alpha_k k_{it}. \tag{9}$$

for all firms operating only in the industry under consideration. We apply industry-by-industry estimations for all industries in our data to identify $(\alpha_\ell^s, \alpha_k^s, \phi_t^s)$ with the industry label s being added to the notation. Thus, we can as above compute the productivity index ω_{it}^s for all the firms operating only in industry s for all the industries in the data.

2.2.3 Measurement error in capital

To Be Added

2.3 Muti-product firms producing in multiple industries

Until now, we have restricted the sample to all the firms that operate in one industry. Now, we consider firms that serve more than one industry.

[5] OP found that the kernel method gives a better fit for their data.

2.3.1 Exports

Let $s(j)$ map each good j to the industry, s that good j belongs to. For each j, there can be one $k \neq j$ such that $s(j) \neq s(k)$, i.e., for an industry that product j belongs are different from the industry that product k belongs to. Firm i that produces more than one industry[6], we modify (2) as

$$C_{ijt}^{s(j)} = \frac{L_{ijt}}{L_{it}} = \frac{\alpha_\ell^{s(j)} R_{ijt}}{\sum_{\tilde{j}\in J_{it}^{S_1}} \alpha_\ell^{s(\tilde{j})} R_{i\tilde{j}t} + \sum_{\tilde{j}\in J_{it}^{S_2}} \alpha_\ell^{s(\tilde{j})} R_{i\tilde{j}t}} \tag{10}$$

$$D_{ijt}^{s(j)} = \frac{K_{ijt}}{K_{it}} = \frac{\alpha_k^{s(j)} R_{ijt}}{\sum_{\tilde{j}\in J_{it}^{S_1}} \alpha_k^{s(\tilde{j})} R_{i\tilde{j}t} + \sum_{\tilde{j}\in J_{it}^{S_2}} \alpha_k^{s(\tilde{j})} R_{i\tilde{j}t}} \tag{11}$$

where $J_{it}^{S_1}$ and $J_{it}^{S_1}$ are the sets of goods that firm i exports in industry S_1 and S_2, respectively.

If $J_{it}^{S_2}$ is singleton, we can still construct $R_{ikt} = R_{it} - \sum_{\tilde{j}\in J_{it}^{S_1}} R_{i\tilde{j}t}$ for $\tilde{j} \in J_{it}^{S_1}$. However, unlike in one industry case, $C_{ijt}^{s(j)}$ cannot be obtained from revenue data as $\alpha_\ell^{s(j)}$ in denominator and numerator cannot be cancel out. We cannot express $C_{ijt}^{s(j)}$ using the proportion of revenues as shown in eq. (2). Thus, we obtain $\alpha_\ell^{s(\tilde{j})}$ by using the estimations in previous section and firms that produce only in one industry. We can also iteratre the procedure until $\alpha_\ell^{s(\tilde{j})}$ converges. In the first step, we only use firms that produce products only in one industry but, from second step and onward, we use all firms including firms that produce in multiple industries. Once we have the ratio from the first stage estimation, we can compute ω_{it}^s using the method in the previous section. Now ω_{it}^s vary not just in firm but also in industry because we can compute $(C_{ijt}^s,\ D_{ijt}^s)$ for all the industries where firm i operates at time t.

2.3.2 Domestic sales

We separated out domestic sales aspect from the model above because, unlike export data from custom data, domestic sales data are only available at the firm level. Thus, domestic sales and related information are aggregated over firm. With domestic sales data for each product j, the same domestic product is denoted as $k \neq j$ such that $s(j) = s(k)$, i.e., for the same good, j indicates product exported and k indicates product sold for domestic markets.

[6]For the sake of simplicity, we consider a firm produce products over two industries.

For firm i with domestic sales, we modify (2) as

$$C_{ijt}^{s(j)} = \frac{L_{ijt}}{L_{it}} = \frac{\alpha_\ell^{s(j)} R_{ijt}}{\sum_{\tilde{j} \in J_{it}^e} \alpha_\ell^{s(\tilde{j})} R_{i\tilde{j}t} + \sum_{\tilde{j} \in J_{it}^d} \alpha_\ell^{s(\tilde{j})} R_{i\tilde{j}t}} \tag{12}$$

$$D_{ijt}^{s(j)} = \frac{K_{ijt}}{K_{it}} = \frac{\alpha_k^{s(j)} R_{ijt}}{\sum_{\tilde{j} \in J_{it}^e} \alpha_k^{s(\tilde{j})} R_{i\tilde{j}t} + \sum_{\tilde{j} \in J_{it}^d} \alpha_k^{s(\tilde{j})} R_{i\tilde{j}t}} \tag{13}$$

where J_{it}^e and J_{it}^d are the sets of goods that firm i exports and domestically supplies, respectively.

If J_{it}^d is singleton, we can still construct $R_{ijt} = R_{it} - \sum_{\tilde{j} \in J_{it}^e} R_{i\tilde{j}t}$ for $j \in J_{it}^d$. Then, we can compute ω_{it}^s as above because we can compute (C_{ijt}^s, D_{ijt}^s) for all the industries where firm i operates at time t. However, if J_{it}^d contains more than one product, we can determine neither (12) nor (13) because $\alpha_\ell^{s(\tilde{j})}$ for . For all $j \in J_{it}^e$, however, we can compute the numerators but we cannot compute $\sum_{\tilde{j} \in J_{it}^d} \alpha_\ell^{s(\tilde{j})} R_{i\tilde{j}t}$ in denominator.

Under the following assumption, we can identify (C_{ijt}^s, D_{ijt}^s) by including firms sell in domestic market.

Assumption 6. For the same product, both export (j) and domestic sale (k) have the same $\alpha_\ell^{s(j)} = \alpha_\ell^{s(k)}$ and $\frac{R_{ijt}}{\sum_{\tilde{j} \in J_{it}^e} R_{i\tilde{j}t}} = \frac{R_{ikt}}{\sum_{\tilde{j} \in J_{it}^d} R_{i\tilde{j}t}}$. $\square$

This assmuption basically impose that firm's share of product among all production in both domestic and foreign markets are the same so that this assumption is violated if a firm concentrates on one product for domestic market but the other product for foreign market,

2.3.3 Weak assumption

Moreover, if J_{it}^d contains more than one product, we can determine neither (12) nor (13). For all $j \in J_{it}^e$, however, we can compute the numerators. Let $\overline{C}_{ijt}^{s(j)} := \alpha_\ell^{s(j)} R_{ijt}$ and $\overline{D}_{ijt}^{s(j)} := \alpha_k^{s(j)} R_{ijt}$ for $j \in J_{it}^e$. Then, we have $C_{ijt}^{s(j)} = \kappa_{it}^\ell \overline{C}_{ijt}^{s(j)}$ and $D_{ijt}^{s(j)} = \kappa_{it}^k \overline{D}_{ijt}^{s(j)}$ for some unknown $\kappa_{it}^\ell > 0$ and $\kappa_{it}^k > 0$ for all firm is under consideration and for all t. Then, we can calculate (12) and (13) up to the normalizing constants $(\kappa_{it}^\ell, \kappa_{it}^k)$. Thus, we have $L_{it}^s(\kappa_{it}^\ell)$ and $K_{it}^s(\kappa_{it}^k)$. Then, using the moment conditions, we can identify $(\kappa_{it}^\ell, \kappa_{it}^k)$. For example, we may revise (5) as

$$E[q_{ijt} - \alpha_\ell^s c_{ijt}^s(\kappa_{it}^\ell) - \alpha_k^s d_{ijt}^s(\kappa_{it}^k) - \phi_t^s(k_{it}^s(\kappa_{it}^k), \ell_{it}^s(\kappa_{it}^\ell), m_{it}^s(\kappa_{it}^\ell))|I_{it}] = 0 \tag{14}$$

with $s = s(j)$ for all $j \in J_{it}^e$. Note that here $(\alpha_\ell^s, \alpha_k^s, \phi_t^s)$ are already identified and regarded as knowns, but we have two unknowns $(\kappa_{it}^\ell, \kappa_{it}^k)$. Notice that we have as many restrictions as $|J_{it}^e|$, one for each $j \in J_{it}^e$, Hence, as long as $|J_{it}^e| > 1$, we can solve the restrictions for the two unknowns $(\kappa_{it}^\ell, \kappa_{it}^k)$. Therefore, we can construct ω_{it}^s for all s such that there is $j \in J_{it}^e$ with $s(j) = s$ if $|J_{it}^e| > 1$ for all firm i with $|J_{it}^d| > 1$. However, for industry s such that there is no j such that $j \in J_{it}^e$, we cannot obtain ω_{it}^s for firm i with $|J_{it}^d| > 1$. As a corollary, if firm i serves only domestic markets (no export) across more than one industry, we cannot obtain ω_{it}^s for any of industry s in which firm i operates in time t. (I suspect that large firms with more than one industry must export in all their industries. So, the discussion in this paragraph may not be relevant, hopefully.)

2.4 Identification

Our baseline equation is

$$\begin{aligned} q_{ijt} &= \alpha_\ell \ell_{ijt} + \alpha_k k_{ijt} + \omega_{it} + u_{it} \\ &= (\alpha_\ell + \alpha_k) c_{ijt} + \alpha_\ell \ell_{it} + \alpha_k k_{it} + \omega_{it} + u_{it} \end{aligned} \tag{15}$$

In the estimation of eq. 15, there are at least four well known econometric issues. Our method explicitly account for them.

- Simultaneity between input uses and unobserved productivity. We overcome this by using control function approach in ACF and we extend to multi-industry production by using firm's profit maximization conditions under homogeneity within industry while allowing heterogeneity across industry.
- Selection bias. Our treatment of selection bias follows OP method but extend to work in the framework of ACF to overcome multicollinearity between productivity and labor inputs.

- Omitted variable bias. Most studies use value added or sales data for output. However, in this case, product level price is not available and this is a major source of OVB. Our export data has information on both quantity and price at the product level so we can direct use quantity data for output to avoid this well know bias.

- Measurement error especially on capital input. Capital depreciation is notably hard to estimate. Even for highest quality data like US sensus, depending upon which method of estimating capital used, the value can be differ by 20%. Following De Locker (2017), we treat measurement of capital using more precisely estimated investment as instruments.

Production function in this paper is estimated in three steps. And each step involves non-parametric estimations (i.e. kernel estimaion and sieve approximation) which is quite demanding computationally. Parameters should be estimated by industry and year as we have to allow heterogeneity across industry and across year.

Compared to ACF, OP, and LP, our method makes progress in the following aspects:

- We use firm's profit maximization condition for each factor input as in 2 which requires to get distinct factor contribution α_ℓ to describe firm's input contribution to each product and product-mix decision. This estimation is possible through iterative estimations where initial estimates of factor contribution for each industry is obtained by using firms producing only one industry. This is an extension to multi-industry production function estimation.

- We explicitly allow firms divide factor inputs into different industry arbtrarily. However, this aspect has not been explictly addressed in the previous literature.

[More details to be added later.]

3 Data and matching method

3.1 Data

Our analysis covers Chinese manufacturing exporting firms only. We employ a merged dataset of Chinese Customs Trade Statistics (CCTS) and Chinese Annual Survey of Industrial Firms (CASIF), over the period 2001-2006.

CCTS dataset is collected by the General Administration of Customs of China. It provides comprehensive information on each trade transaction for Chinese exporting firms on product code,[7] trade flow, trade value, means of transportation and so forth. Transaction data of the CCTS dataset is reported monthly and we aggregate it up into yearly data.

The CASIF dataset provides firm-level financial information for the estimation of firm productivity. The dataset includes all state-owned enterprises (SOEs) and none-SOEs whose annual sales is above RMB 5 million yuan (equivalent to about 770,000 US dollars). In the original dataset, these firms account for 95% of total industrial output, cover about 40 industries in the HS2 classification, and locate across 31 provinces and municipalities in mainland China. The CASIF dataset had been cleaned before it was merged with the CCTS dataset[8]. After the cleaning and merging process,29 manufacturing industries at the HS2 level remained in the sample.[9] As we only have information on product churning for firms that survived in export markets, we only use the observations of firms that export continuously for at least two consecutive years. As such, 29% of firm observations are further excluded.

The two datasets were merged using firm names, following previous studies including (Wang and Yu, 2012; Upward, Wang, and Zheng, 2013; Yu, 2015). Our merged dataset includes 37.8%-54.6% of total Chinese exports and 32.1%-41.2% of firms in the CCTS dataset, and 14.6%-21.4% of firms in the CASIF dataset.[10] Our dataset has a similar profile to the merged datasets of Wang and Yu (2012) and Yu (2015).

3.2 Descriptive analysis

This paper uses the HS2, HS4 and HS6 classifications as the definitions of “chapters”, “groups” and “products”, respectively. We split exporters into four groups as shown in Table

[7]CCTS product data is classified at the Harmonized System 8-digit (HS8 hereafter) level. We aggregate the data to the HS6 level for the sake of stability of data.

[8]Following Ding, Guariglia, and Knight (2013) and Ma, Tang, and Zhang (2014), we drop observations with negative total assets minus total fixed assets, with negative total assets minus liquid assets, with negative accumulated depreciation minus current depreciation, with less than 10 employees, or with missing or misreported information for the calculation of firm productivity.

[9]Following Upward, Wang, and Zheng (2013), observations in the tobacco industry are excluded because the industry was highly regulated in China over the sample period.

[10]Upward, Wang, and Zheng (2013) explain why the two datasets cannot be completely merged.

Table 1: Distribution of single- and multi-product Chinese manufacturing exporters, 2001-06

Type	Share of export firms (%)	Share of exports value (%)	Average exporting products, groups or chapters per exporter
Single-product	23.3	7.2	1.0 products
Multi-product	76.7	92.8	7.8 products
Multi-group	68.5	88.9	5.6 groups
Multi-chapter	54.0	78.3	3.6 chapters

1: single-product firms that export a single HS6 product; multiple-product firms that export at least two HS6 products; multiple-group firms that export at least two HS4 groups; and multiple-chapter firms that export at least two HS2 chapters.[11]

Multiple-product exporters were the main driving force of China's manufacturing exports over the period 2001-06. On average, they account for 76.7% of total exporters and represent as high as 92.8% of export value.[12] The prevalence of multi-product firms in China resembles the observations in other countries such as New Zealand (Adalet et al., 2009), Slovenian (Damijan, Konings, and Polanec, 2014), Belgium (Bernard, Redding, and S. J., 2010) and Chilean (Navarro, 2012). In our sample, an average multi-product Chinese firm exports 7.8 products, more than twice of the 3.7 products per Chilean firm (Navarro, 2012). Also, Chinese firms export their products across multiple chapters as well as multiple groupings. Nearly 80% (54%) of exporting firms exported across multiple HS4 groups (HS2 chapters), accounting for close to 90% (80%) of the total export value of our sample firms.

Table 2 further examines the distributions of single- and multi-product firms based on their participation in processing trade, their ownerships and industry categories, respectively.[13]

In panel A, firms are classified into six groups based on the share of processing trade in their exports. Exporters who fully engaged in processing trade (i.e. 100% share) are defined as processing exporters (PEs); while those who did not engage in processing trade at all (i.e. 0% share) are defined as non-processing exporters (NPEs). Exporters that engaged in both processing and non-processing trade in a given year are defined as partly-processing exporters (PPEs). In our sample, NPEs account for the majority of firms (52.5%) but the

[11]By definition, a multi-product exporter must also be a single-group and a single-chapter exporter.
[12]Our figures are very closed to those of Qian and Yu (2014): 79% and 91.4%, respectively.
[13]More information about the distribution of firms is provided in the Appendix Table 1.

smallest trade value (13.3%). PPEs have the largest contribution to China's manufacturing exports. A clear message from the panel is that, across all PEs, NPEs, and PPEs, multi-product firms overwhelmingly dominate single-product firms. But among the three types of firms, PPEs exhibit a stronger tendency of having multi-products than the other two.

Panel B shows the share of single- and multi-product firms based on ownership. In our sample, state, foreign, and private firms together account for 64.1%[14] of exporting firms and 68% of export value over the sample period. Among them, foreign firms have the strongest tendency to export multi-products. This is in line with the expectation that foreign firms are more capable of bearing the higher fixed costs of spanning product varieties and have more advanced technology to introduce new products.

In panel C, firms are classified under three industry categories based on the classification used by Chen and Xu (2012). In our sample, 32.3%, 25.7% and 37.3% of the exporters operating in labour-, capital-, and technology-intensive manufacturing industries, respectively.[15] Multi-product exporters are more prominent in labour-intensive industries in terms of number of firms, but equally prominent in labour- and technology-intensive industries in terms of export value.

For any two consecutive years, we divide exporters into four exhaustive and mutually exclusive groups: those do not change export product mix (referred as the "no change" group hereafter); those only add at least one export product from one year to another ("adding"); those drop at least one existing products ("dropping"); and exporters who both add and drop products in the export market ("churning"). In this research, an export product is added if it is exported in year *t* but not in year *t-1*. Similarly, an export product is dropped if it was exported in year *t-1* but not in year *t*. Table 3 show the average share of these four groups of exporters over 2001-06.

On average over the period, nearly 80% of the manufacturing exporters altered their export product mix between two consecutive years. Export churning firms are the dominating group. Naturally, altering product mix is a more pronounced phenomenon among multi-product exporters. These statistics provide strong evidence on a hitherto neglected feature of

[14]The remaining 35.9% of exporting firms include collectively-owned firms, Sino-foreign cooperative businesses, Sino-foreign joint ventures, missing values and other types of ownership.

[15]The remaining 4.7% are in the industry of comprehensive utilization of waste resources (HS2 code 42) and metal products, machinery and equipment repair (HS2 code 43), which are excluded in Chen and Xu (2012).

Table 2: Shares of single-product and multi-product Chinese manufacturing exporters by the share of processing trade, firm ownerships and industry categories, 2001-06

Panel A: Share of processing trade	0%	(0%, 25%]	(25%, 50%]	(50%, 75%]	(75%, 100%)	100%
Single-product	29.1 (13.6)	7.9 (4.3)	10.1 (5.6)	10.4 (4.7)	11.0 (2.7)	30.5 (12.1)
Multi-product	70.9 (86.4)	92.1 (95.7)	89.9 (94.4)	89.6 (95.3)	89.0 (97.3)	69.5 (87.9)
Multi-group	62.3 (79.3)	85.8 (91.9)	82.2 (89.7)	82.9 (91.6)	82.9 (95.4)	59.1 (82.3)
Multi-chapter	48.4 (65.3)	73.4 (83.8)	69.5 (80.4)	70.0 (81.9)	69.0 (88.4)	40.2 (67.0)

Panel B: Ownership	State	Foreign	Private
Single-product	27.7 (8.5)	19.1 (5.1)	28.4 (12.6)
Multi-product	72.3 (91.5)	80.9 (94.9)	71.6 (87.4)
Multi-group	63.9 (85.0)	73.3 (92.0)	62.6 (80.4)
Multi-chapter	49.5 (73.7)	59.6 (82.8)	47.8 (65.0)

Panel C: Industry Category	Labour-intensive	Capital-intensive	Technology-intensive
Single-product	18.2 (6.5)	26.2 (13.7)	26.0 (5.7)
Multi-product	81.8 (93.5)	73.8 (86.3)	74.0 (94.3)
Multi-group	74.5 (88.9)	65.7 (78.8)	64.9 (91.5)
Multi-chapter	56.0 (70.5)	53.9 (67.4)	51.3 (83.2)

Note: Shares of firm and trade value are reported outside and inside the parentheses, respectively.

Table 3: Average product switching percentage by Chinese manufacturing exporters, 2001-06

Activity	All exporters	Single-product exporters	Multi-product exporters
No change	20.9	59.2	10.4
Adding	18.7	35.5	14.1
Dropping	14.6	NA	18.6
Churning	45.8	5.3	56.9

Note: Single-product exporters cannot only drop export products based on our definition.

Chinese manufacturing exporters, namely the existence of intra-firm resources reallocation.

Table 4 shows the shares of Chinese manufacturing exporters that switch products by their characteristics regarding processing trade, ownership, and industry category as in Table 2.

Panel A shows that, amongst the NPEs (i.e. 0% processing trade), 78.3% altered at least one export product and 42.6% added and dropped export products in the same year. For the remaining firms, there seems to be a negative relationship between the prominence of product alternation or churning and the share of processing trade. The share of "no change" firms increases from 9.7% to 37.8% as the share of processing trade rises, while the share of "churning" firms decreases from 63.9% to 26.2%. The statistics suggest that trade composition may play a role in the decision of product mix. One possible explanation is that processing trade is by nature part of some global supply chains, over which participating Chinese firms may have little decision power. As such, the more a firm engages in processing trade, the less autonomy it has in changing its product mix. Accordingly, we expect a weaker impact of export product churning on the productivity of firms that have a higher proportion of processing trade.

Panel B shows that, although foreign firms are more likely to export multi-products as indicated in Table 2, they do not have a stronger tendency to alter their product mix, as compared to state and private firms. Lastly, panel C shows that, exporters operating in labour-intensive industries are more prone to churn export products as compared to technology- and capital-intensive industries.

Table 4: Shares of Chinese manufacturing exporter switching product by the shares of processing trade, firm ownership and industry categories, 2001-06

Panel A: Share of processing trade	0%	(0%, 25%]	(25%, 50%]	(50%, 75%]	(75%, 100%]	100%
No change	21.7 (9.1)	9.7 (5.2)	11.8 (6.9)	12.2 (6.5)	13.2 (6.6)	37.8 (25.4)
Adding	20.2 (14.2)	16.1 (9.8)	17.1 (12.0)	16.4 (10.6)	18.8 (12.7)	17.1 (17.8)
Dropping	15.5 (21.1)	10.3 (10.7)	11.4 (11.3)	12.5 (14.2)	12.0 (13.4)	18.9 (22.7)
Churning	42.6 (55.6)	63.9 (74.3)	59.7 (69.8)	58.9 (68.7)	56.0 (67.3)	26.2 (34.1)
Panel B: Ownership	**State**		**Foreign**		**Private**	
No change	20.6 (8.9)		20.9 (11.9)		20.1 (8.4)	
Adding	16.7 (11.6)		18.0 (14.7)		23.6 (15.9)	
Dropping	15.7 (20.7)		14.4 (17.5)		13.2 (18.3)	
Churning	47.0 (58.8)		46.7 (55.9)		43.1 (57.4)	
Panel C: Industry category	**Labour-intensive**		**Capital-intensive**		**Technology-intensive**	
No change	15.8 (10.1)		24.1 (17.9)		22.8 (8.7)	
Adding	16.1 (14.4)		20.0 (18.1)		20.3 (13.0)	
Dropping	13.7 (10.7)		15.5 (11.4)		14.7 (7.6)	
Churning	54.4 (64.8)		40.4 (52.6)		42.2 (70.7)	

Note: Shares of firm and trade value are reported outside and inside the parentheses, respectively.

3.3 Matching

To examine the impact of product churning on firm productivity, three issues need to be addressed. First, selection bias can be caused by inherent differences between firms that churn their export products and those that do not. For instance, firms of a larger scale tend to have more product varieties (Bernard, Redding, and S. J., 2010) and as well as higher productivity (Ding, Guariglia, and Harris, 2016). Second, there could be a bias due to reverse causality from productivity to product churning. For example, Bernard, Van Beveren, and Vandenbussche (2010b); Bernard, Redding, and S. J. (2010) and Qiu and Yu (2014) demonstrate that more productive firms are prone to expand their product scope. Finally, there could be a bias due to omitted variables that affect both productivity and product churning. For instance, a firm with better human capital may be better equipped to expand their product scope and to take advantage of opportunities in other markets.

To address these issues, we employ the Propensity Score Matching method. The method was first introduced by Rosenbaum and Rubin (1983)and then further developed by Heckman, Ichimura, and Todd (1997, 1998). It has been widely used for policy evaluation (Abadie, Drukker, Herr, and Imbens, 2004; Imbens and Wooldridge, 2009). In what follow we briefly explain the how the PSM method can be adapted to estimating the productivity impact of product churning.

Firstly, we define the treatment variable as C_i^N, where i is a firm indicator and N is a indicator of treatment, no-churning. C_i^N takes the value one if firm i does not churn products and zero otherwise.[16]

For each year, the mean difference in productivity between the treatment and control groups can then be represented as follows:

$$ATT = E[Y_{i1}|C_i^N = 1] - E[Y_{i0}|C_i^N = 1] \tag{16}$$

where ATT is the average effect of the treatment on the treated, $E[Y_{i1}|C_i^N = 1]$ is the outcome value (i.e. productivity) of firm i in the case of treatment, and $E[Y_{i0}|C_i^N = 1]$ is the outcome value for the same firm in the case of no treatment. If ATT is negative, it implies that firms that do not churn products has a lower productivity than those that churn or, in

[16]Naturally people will prefer to define C_i^N such that it takes the value of one if the firm churn products and zero otherwise. The reason why we it the other way around will become clear later.

other words, a positive impact of product churning on firm productivity. However, without further assumptions we cannot estimate eq. (16) because we cannot observe $E[Y_{i0}|C_i^N = 1]$, instead we only observe $E[Y_{i0}|C_i^N = 0]$. Here we call $E[Y_{i0}|C_i^N = 1]$ the counterfactual mean outcome for the treated. Therefore, using the PSM method, we need to obtain a counterfactual set such that what would have happened to firms that did not churn products in reality if they had churned.

Here two assumptions are needed to producethe counterfactual from the control group. The first one is the conditional independence assumption (CIA) or "ignorability", which can be written as following:

$$(Y_{i0}, Y_{i1}) \perp C_i^N | X_i \tag{17}$$

where $\perp$ denotes independence, and eq. (17) expresses conditional independence such that outcome Y_i and treatment status C_i^N are independent conditioning on a set of firm characteristics, X_i. With the propensity score maching, we can rewrite the CIA as follows:

$$(Y_{i0}, Y_{i1}) \perp C_i^N | P(X_i) \tag{18}$$

where $P(X_i)$ is propensity score. The CIA in eq. 18 is a great progress over eq. 17 as it reduces multidimensional matching into one-dimensional matching.

This assumption means that the decision for the treatment is independent of the outcome after accounting for firm characteristics and it implies the following:

$$E[Y_{i0}|C_i^N = 0, P(X_i)] = E[Y_{i0}|C_i^N = 1, P(X_i)]$$

As such, the endogeneity problems due to selection, simultaneity and other sources can be addressed using assumption (18) and we can obtain ATT as:

$$ATT = E[Y_{i1}|C_i^N = 1, P(X_i)] - E[Y_{i0}|C_i^N = 1, P(X_i)] = E[Y_{i1}|C_i^N = 1, P(X_i)] - E[Y_{i0}|C_i^N = 0, P(X_i)] \tag{19}$$

Another key assumption is the common support or "overlap". This means that the probability of getting treatment for the treatment and control groups should lie in the same domain. This assumption ensures that the distributions of propensity scores for firms that churn products and firms that do not, respectively, are the same. All firms have a positive probability of the 'treatment' effect, that is $0 < P(C_i^N = 1 \Big| X_i) < 1$. Hence, ATT can be estimated as following under this assumption:

$$ATT = E[Y_{i1}|C_i^N = 1, P(X_i)] - E[Y_{i0}|C_i^N = 0, P(X_i)] \tag{20}$$

3.3.1 Implementation

Under these two assumptions, we can implement the PSM method as follows. Firstly, we estimate the probabilities of firms not churning products using a probit or logit model:

$$P(C_i^N = 1) = F(X_i\gamma + u_i > 0) \tag{21}$$

where F is a cdf and u_i is error term which is normal for the probit model and logistic for the logit model. The predicted probability of not churning for each firm i, $\hat{P}(X_i)$, obtained from eq.(21), is the firm's propensity score.

Second, we match firms that do not churn products (i.e. the treatment group) with those that churn (i.e. the control group) using the estimated propensity scores. That is, for each firm in the treatment group, firms in the control group with the same propensity score are served as the unobserved counterfactual set. The method allows an adequate "like-for-like" matching and a comparison of firm productivity between these two groups.[17]

Various algorithms can be used to match firms in the treatment and control groups on the basis of their propensity scores. In this paper, the three most commonly used algorithms are deployed: nearest neighbor matching, radius matching, and kernel matching[18]. The advantages and limitations of each of these algorithms are well documented in Diaz and Handa

[17] Note that we use churning firms as the control group rather than the treatment group. This is because the majority of Chinese exporting firms are churning (57% for multi-product firms) so, if we use churning firms as the treatment group, it is difficult to satisfy the support overlap assumption. Thereby, setting them as the control group enhances the chance of finding a good match for any given exporter in the treatment group. However, only those churning firms that are matched with non-churning firms are used in the estimation, that is, churning firms that cannot find a match are not used in the estimation. Thus, we have to interpret the effect as the average treatment effect for treated where the treatment is "not churning". As discussed above, the counterfactual is what would have happened to firms that did not churn products in reality if they had churned.

[18] In this research, we set n=1 for nearest neighbour matching estimation and r=0.1 or 0.2 for radius matching estimation.

(2006), Wamser (2014), Abadie and Imbens (2006), and Caliendo and Kopeinig (2008).

We also include an array of covariates to control for firm characteristics to better meet the conditional independency assumption. The balancing property between treatment and control groups is tested by calculating the standardized differences of all available firm characteristics variables. To fulfill the common support assumption, we drop all treated firms with a propensity score smaller than the minimum or larger than the maximum in the control group.

Of note, although most studies employ the t-statistics and a bootstrap procedure for inference with matching estimators, problems of getting standard errors with these methods were extensively discussed by Abadie and Imbens (2006). For instance, the standard t-statistic is straightforward but theoretical justifications are not available in most cases while bootstrapping is computationally demanding. Therefore, we additionally employ the permutation test as a robustness check to obtain the p-value and the corresponding confidence interval (CI) based on the matched firm observations. The permutation test was used with the PSM method in an application of estimating the impact of trade liberalization through WTO membership (Chang and Lee, 2011) and it has been used in other social science applications (Pesarin, 2001; Ho and Imai, 2006). Eq.(22) describes the exact p-value of D in the permutation test:

$$P(D' \geq D) \cong P\{N(0,1) \geq \frac{D}{\{\Sigma_{m=1}^{M}(y_{m1}-y_{m2})^2/M^2\}^{1/2}}\} \tag{22}$$

where $D \equiv (\frac{1}{m})\Sigma_{m=1}^{M} s_m(y_{m1}-y_{m2})$, $D' \equiv (\frac{1}{m})\Sigma_{m=1}^{M} w_m s_m(y_{m1}-y_{m2})$, $s_m = 1$ if the first subject in pair m is treated and −1 otherwise, and w_m is a iid random variable such that $P(w_m = 1) = P(w_m = -1) = 0.5$, where the treatment labels of the two responses in pair m are exchanged if $w_m = -1$, and no exchange otherwise. Under the null hypothesis which indicates the same distribution and no effect for the matched observations, we can test the zero mean effect and estimate its confidence interval.

3.3.2 Variables

(1) Treatment variable

As discussed previously, the treatment variable is a dummy variable which takes value one for firms that do not churn products (i.e. they add or drop products or make no changes) and zero for those that churn. Later on we separate the exporters in the treatment group into those that add products over two consecutive years ("Adding"), that drop products ("Dropping"), and that do not change products ("Static"), and compare the productivity difference between each of them with the control group – the exporters that churn products ("Churning").

(2) Outcome variable

Firm total factor productivity (TFP) is the outcome variable. Estimating TFP using ordinary least squares (OLS) may suffer from bias due to selection, simultaneity and other endogeneity problems. Alternative methods employed to estimate TFP at the micro-firm level include the fixed effects, the generalized method of moments (GMM), the OP method proposed by Olley and Pakes (1996) and the LP method suggested by Levinsohn and Petrin (2003). The last two methods are most widely used and arguably the best ones for annual panel data (Foster, Haltiwanger, and Syverson, 2008). However, the OP method can result in a significant loss in efficiency. Moreover, whether the monotonicity condition for the OP method is met is questionable (Van Beveren, 2012) given about two-thirds of the observations in our data sample report negative or missing proxy variable for investment. Therefore, the LP method is used to compute TFP. The firm production function is assumed to be of the Cobb-Douglas form. We use the annual average balance of net value of fixed assets as a proxy for capital and the number of employee for labour. Firm value-added is used as a measure of output. Details of the LP method estimation process can be found in Van Beveren (2012).

(3) Covariates

To mitigate the endogeneity problem from self-selection, omitted variables, simultaneity, and reverse causality, we use rich set of predictors in the propensity score model. We include lagged dependent variable and observed firm characteristics variables as well as fixed effects as predictors in the estimation of the probit model as in eq.(21).[19] Using various fixed effects including industry and region, we only compare firms between the treatment and control groups in the same region and industry. The inclusion of these fixed effects would prevent

[19]The choice of covariates are very important because, once we account for differences in these observed covariates using propensity scores for matched firms, we should be able to attribute outcome differences for the matched firms (each treated and untreated firms) to the treatment.

endogeneity problems due to heterogeneity across regions and across industries, where bias from the cases that treatments are disproportionally given to certain regions and certain industries. First, the lagged value of the outcome variable, i.e.TFP$_{t-1}$, is included as a covariate to mitigate the endogeneity issue. Second, we include measures of firm size and age and their squared terms in the model, as they have been found to be positively associated with product adjustment (Bernard, Redding, and S. J., 2010). However, their association with firm productivity is not clear. On the one hand, larger firms benefit from the economies of scale and are expected to be more productive (Harris and Moffat, 2015). On the other hand, they could be burdened by their complex organizational structure (Dhawan, 2001), resulting in lower productivity levels. Likewise, younger firms can be more efficient than older firms that dragged down by vintage capital (Ding, Guariglia, and Harris, 2016), but the latter are compensated with having more experience and knowledge accumulated through 'learning-by-doing' (Jovanovic and Nyarko, 1996). Third, we include measures of profit and capital intensity, respectively. Firms that have higher profits and capital intensity are in a better position to expand their product scopes. Fourth, we include a subsidy variable measured by the ration of obtained subsidy divided by firm sale. Firms receiving government subsidies may be able to afford investing more on research and development (R&D) and technology upgrading, which can affect both product adjustment and productivity. However, government subsidies may also be a result of rent-seeking activities. Lastly, industry, region and time dummies are included to control for unobserved, industry-, region- and time-specific heterogeneity of Chinese manufacturing exporters. Table 5 provide a detailed description of all the covariates in the model.

4. Empirical results

In order to preliminarily investigate how export product churning impacts firm TFP before PSM estimation, we regress firm TFP on product churning manner as shown in Table 6, Table 7 and Table 8. Separately, we compare firm TFP between product churning and static (Table 6), adding (Table 7) or dropping (Table 8) manner. In addition, we introduce covariates as discussed in previous section step by step. Results show that the coefficients of Static, Adder

Table 5: Definition and measurements of covariates

Variables	Measurement
TFP_{t-1}	Lagged total factor productivity
Size	No. employees
$Size^2$	Quadratic value of Size
Age	No. years since firm started exporting
Age^2	Quadratic value of Age
Profit	Profit per currency unit of sales
Capital	Fixed assets per employee
Subsidy	Subsidy per currency unit of sales
Industry dummies	Defined at the 2-digit GB/T industry level
Region dummies	Three regions in total (eastern, middle and western regions)
Time dummies	Yearly

(a) GB/T is the Chinese equivalent of the Standard Industrial Classification (SIC) classification. There are 29 industries at the 2-digit GB/T level. “Manufacture of plastics” is the baseline industry.

and Dropper variables are all negative and statistically significant. This keeps consistent with our expectation indicating that export product churning firms have TFP advantage over those non-churning counterparts. When we introduce all the covariates gradually as control variables as shown in the (2)-(5) columns, the adjustment R-2 improves slightly. This also verifies the rationality and necessity of introduction of covariates.

4.2 Estimation of the propensity score and the balancing properties

The propensity score is estimated using a probit model. The treatment variable, an indicator of “not churning” for firm is the dependent variable and covariates and fixed effects introduced in the previous section are used as predictors. As an example, Table 9 reports the estimation results using the nearest neighbor matching method and the treatment effect is set to be ‘adding products’ so firms with “dropping product” and “static” are not used in the estimation. Therefore, a negative coefficient for a covariate implies that the covariate increases

Table 6: *OLS estimation of firm TFP and export product churning, in comparison of product static manner*

Variables	(1)	(2)	(3)	(4)	(5)
Static	-0.238***	-0.054***	-0.061***	-0.0592***	-0.092***
	(-37.73)	(-14.18)	(-15.90)	(-22.98)	(-23.13)
TFP_{t-1}		0.677***	0.676***	0.662***	0.658***
		(379.47)	(378.94)	(366.28)	(364.62)
Size		0.163***	0.162***	0.162***	0.167***
		(77.26)	(76.46)	(76.25)	(78.76)
Size^2		-0.002***	-0.002***	-0.002***	-0.002***
		(-40.77)	(-40.32)	(-40.72)	(-42.28)
Age		-0.028***	-0.031***	-0.032***	-0.025***
		(-6.88)	(-7.70)	(-7.99)	(-6.13)
Age^2		0.003***	0.003***	0.002***	0.002***
		(4.55)	(4.69)	(3.98)	(3.24)
Profit		1.647***	1.652***	1.626***	1.617***
		(96.62)	(96.91)	(95.38)	(95.31)
Capital		0.470***	0.470***	0.408***	0.416***
		(53.58)	(53.62)	(44.88)	(45.96)
Subsidy		-2.441***	-2.570***	-2.655***	-2.624***
		(-18.09)	(-19.02)	(-19.73)	(-19.59)
Region dummies	No	No	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes
Time dummies	No	No	No	No	Yes
Adj R-2	0.0086	0.6413	0.6418	0.6454	0.6486
No. observations	163,295	163,295	163,295	163,295	163,295

Note: *** indicates a significance level of 1%.

Table 7: *OLS estimation of firm TFP and export product churning, in comparison of product adding manner*

Variables	(1)	(2)	(3)	(4)	(5)
Static	-0.142***	-0.016***	-0.018***	-0.040***	-0.039***
	(-21.82)	(-3.99)	(-4.71)	(-10.00)	(-9.92)
TFP_{t-1}		0.665***	0.664***	0.651***	0.647***
		(370.99)	(370.70)	(358.57)	(356.98)
Size		0.157***	0.155***	0.156***	0.161***
		(76.27)	(75.43)	(75.35)	(77.73)
$Size^2$		-0.002***	-0.002***	-0.002***	-0.002***
		(-40.42)	(-39.99)	(-40.48)	(-41.97)
Age		-0.033***	-0.036***	-0.038***	-0.031***
		(-8.05)	(-8.83)	(-9.34)	(-7.56)
Age^2		0.004***	0.004***	0.004***	0.003***
		(6.10)	(6.24)	(5.86)	(5.14)
Profit		1.666***	1.670***	1.639***	1.636***
		(94.44)	(94.71)	(92.96)	(93.17)
Capital		0.491***	0.490***	0.429***	0.436***
		(51.50)	(51.44)	(43.68)	(44.62)
Subsidy		-1.977***	-2.095***	-2.219***	-2.177***
		(-13.09)	(-13.85)	(-14.73)	(-14.51)
Region dummies	No	No	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes
Time dummies	No	No	No	No	Yes
Adj R-2	0.0030	0.6398	0.6402	0.6439	0.6468
No. observations	157,043	157,043	157,043	157,043	157,043

Note: *** indicates a significance level of 1%.

Table 8: *OLS estimation of firm TFP and export product churning, in comparison of product dropping manner*

Variables	(1)	(2)	(3)	(4)	(5)
Static	-0.187***	-0.066***	-0.069***	-0.089***	-0.088***
	(-25.72)	(-15.02)	(-15.74)	(-20.04)	(-19.91)
TFP_{t-1}		0.686***	0.686***	0.672***	0.658***
		(363.59)	(363.27)	(351.31)	(364.42)
Size		0.156***	0.154***	0.155***	0.160***
		(73.09)	(72.25)	(72.38)	(74.87)
$Size^2$		-0.001***	-0.001***	-0.001***	-0.002***
		(-38.50)	(-38.07)	(-38.65)	(-40.20)
Age		-0.025***	-0.029***	-0.031***	-0.025***
		(-5.82)	(-6.54)	(-7.13)	(-5.65)
Age^2		0.003***	0.003***	0.003***	0.002***
		(4.72)	(4.82)	(4.25)	(3.76)
Profit		1.672***	1.677***	1.646***	1.638***
		(94.34)	(94.60)	(92.87)	(92.82)
Capital		0.480***	0.478***	0.409***	0.418***
		(47.76)	(47.54)	(39.65)	(40.67)
Subsidy		-2.079***	-2.195***	-2.337***	-2.259***
		(-13.53)	(-14.26)	(-15.24)	(-14.80)
Region dummies	No	No	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes
Time dummies	No	No	No	No	Yes
Adj R-2	0.0045	0.6454	0.6458	0.6495	0.6525
No. observations	147,089	147,089	147,089	147,089	147,089

Note: *** indicates a significance level of 1%.

Table 9: Estimation of the propensity score (probit model) using the nearest neighbor matching method for adding product exporters

Variables	Coefficient	Z-statistics
TFP_{t-1}	-0.105***	-23.78
Size	-0.037***	-6.76
$Size^2$	3.031e-4***	3.30
Age	-0.092***	-9.08
Age^2	0.008***	5.64
Profit	0.130***	3.07
Capital	0.039*	1.69
Subsidy	-0.828**	-2.20
Industry dummies	Yes	
Region dummies	Yes	
Time dummies	Yes	
No. of observations	98,006	
Prob>chi2	0.0000	

Note: ***, ** and * indicates a significance level of 1%, 5% and 10%, respectively.

the chance of a firm shift from adding products to churning products. The estimated coefficients are all significant at the standard levels. The results indicate that firms with a lower profit margin and capital intensity are more likely to shift from adding product/products to churning products, i.e. they become more likely to drop and add products from their export catalogues. On the contrary, more productive (in the last period) and subsidized firms are more like to shift from adding products to churning products. Furthermore, both firm size and age have a non-linear, U-shape relationship with the probability of shifting. The turning point for the size is 61 employers. That is, for firms below (above) this size, those that are relatively bigger will be more (less) likely to be churning rather than adding products. Likewise, the turning point for the age is 5.75 years. That is, for firms below (above) this age, those that are relatively more experienced will be more (less) likely to be churning rather than adding products.

Two methods are used to assess the quality of the matching. First, we perform the balancing test by calculating and comparing the differences in means for all covariates to examine how similar the treatment and control groups are. As shown in the “Unmatched” sample in Table 10, except for the covariates Profit and Subsidy, the means between the treated and controls are statistically significant before matching. This implies that those firms not churn-

Table 10: Balancing Tests

Variable	Sample	Mean		Bias(%)	Reduction in bias(%)	t-test	
		Treated	Controls			t	P>|t|
TFP_{t-1}	Unmatched	7.128	7.317	-16.1	98.5	-22.69	0
	Matched	7.128	7.131	-0.2		-0.29	0.774
Size	Unmatched	0.433	0.568	-11.1	97.5	-14.66	0
	Matched	0.433	0.436	-0.3		-0.44	0.663
$Size^2$	Unmatched	1.105	2.365	-2.2	86	-2.61	0.009
	Matched	1.105	0.929	0.3		1.3	0.194
Age	Unmatched	0.85	0.922	-8.4	98.1	-11.71	0
	Matched	0.85	0.851	-0.2		-0.2	0.845
Age^2	Unmatched	1.398	1.673	-4.8	94.4	-6.62	0
	Matched	1.398	1.414	-0.3		-0.32	0.751
Profit	Unmatched	0.035	0.034	0.9	90.4	1.3	0.195
	Matched	0.035	0.035	-0.1		-0.1	0.919
Capital ratio	Unmatched	0.101	0.092	4.7	97.4	6.86	0
	Matched	0.1	0.101	0.1		0.14	0.891
Subsidy	Unmatched	0.002	0.001	-0.6	32.4	-0.82	0.413
	Matched	0.002	0.002	-0.4		-0.48	0.629

ing are not random and selection bias comes from many sources. On the contrary, in the "Matched" sample, the differences for all covariates are statistically insignificant. The reduction in bias ranges from 86% to 98.5%, with the except of the covariate Subsidy, which has a reduction of 32.4%. These results provide strong evidence on the satisfaction of the balancing properties for the matched sample.

4.3 Comparison of productivity

For all the estimations done in this and subsequent sections, the conclusions based on all three different matching procedures are consistent with each other. Therefore, to avoid repetition, we report only the results from the nearest neighbor matching algorithm here and provide the results from the kernel and radius matching algorithms in the Appendix..

The estimated average treatment effects on treated (ATT) after matching are reported in Table 11. The control group in each subsample is the same: the product churning exporters. The ATT values are negative and statistically significant in all estimations, indicating a TFP advantage for product churning firms over the other types of firms. The ATT estimates for the unmatched subsamples are much larger that their match counterparts, indicating that the treatment effect can be severely overestimated without the matching. This reflects the

Table 11: Average treatment effect of product switching on Chinese manufacturing exporters' TFP

	PSM		No. firm			
Static	ATT	t-value	Treated	Off-support	Untreated	Off-support
Matched	-0.118***	-8.46	31,760	5	69,578	0
Unmatched	-0.238***	-22.50	31,765		69,578	
	PSM		No. firm			
Adding	ATT	t-value	Treated	Off-support	Untreated	Off-support
Matched	-0.070***	-5.39	28,426	2	69,578	0
Unmatched	-0.142***	-13.89	28,428		69,578	
	PSM		No. firm			
Dropping	ATT	t-value	Treated	Off-support	Untreated	Off-support
Matched	-0.103***	-6.62	22,236	1	69,578	0
Unmatched	-0.187***	-15.25	22,237		69,578	

Note: *** indicates significance at the 1% level. Results are based on the nearest neighbor matching algorithm.*No. firm represents number of exoprt firm in the treatment and control groups of PSM estimation.*

existence of other factors that impact both product churning and firm productivity and the necessity of controlling these factors using PSM. For instance, in the case of comparing "product churning" and "static" firms, the effect is overestimated by 101.69% $(= (0.238 - 0.118)/0.118)$.

Compared to product churning exporters, exporters that keep their product mix unchanged are associated with a 6.9% shortfall in TFP, and the corresponding shortfalls for product adding and dropping exporters are 3.7% and 8.5%, respectively.[20]

Table 11 also reports significantly negative effects under the permutation estimation for all three comparisons. The evidence is strong enough – at the 1% level – to reject the null hypothesis that there is no effect of the treatment. . Therefore, this finding reinforces the previous conclusion that product churning has a positive impact on firm productivity.

[20]The qualitative results are robust to the other two matching algorithms, while the shortfall estimates are noticeably larger when the Radius matching algorithm is used.

5. Extension

In this section, we extend the baseline estimations in a number of directions. First, we do the estimation using a subsample of firms that export throughout the entire sample period to exclude any potential influence of firm enter and exit. Second, we examine the impact of processing trade on the linkage between product churning and productivity. Third, we explore the role of firm ownership in the churning-productivity annex. Lastly, we investigate the effect of industry heterogeneity on the churning-productivity relationship. We focus on the PSM estimations based on matched sample in this section.

5.1 Ongoing exporters

Although our sample period of 2001-06 is not long, there are still new firm entering and old firm exiting during the period. Market entrance and exit dynamics could potentially interact with both firm productivity and product mix (Foster, Haltiwanger, and Krizan, 2001; Brandt, Van Biesebroeck, and Zhang, 2012; Bernard, Redding, and S. J., 2010; Bernard, Redding, and Schott, 2011; Mayer, Melitz, and Ottaviano, 2014). To test if the previous baseline estimation results are not driven by enter or exiting firms, in this sub-section we re-do the estimation using only firms that operate in the export markets for the entire sample period. The subsample has 42,960 observations, equivalent to 28.3% of the full sample used in the baseline estimations. The estimation results are reported in Table 12. Like the baseline case, all the coefficients on ATT are negative and statistically significant, irrespective of which of the three matching algorithms is used. Besides, the estimated effects of the permutation test are significantly negative at the 1% level. In fact, the quantitative results of Tables 11 and 12 are largely comparable. Therefore, the positive impact of export product churning on firm TFP as evidenced in Table 11 is not driven by entering or exiting firms.

Table 12: *Results for ongoing exporters 2001-06*

	PSM		No. firm			
Static	ATT	t-value	Treated	Off-support	Untreated	Off-support
Matched	-0.124***	-4.71	7,931	1	21,888	0
Unmatched	-0.334***	-14.97	7,932		21,888	
	PSM		No. firm			
Adding	ATT	t-value	Treated	Off-support	Untreated	Off-support
Matched	-0.074**	-3.21	7,006	0	21,888	0
Unmatched	-0.194***	-10.88	7,006		21,888	
	PSM		No. firm			
Dropping	ATT	t-value	Treated	Off-support	Untreated	Off-support
Matched	-0.110***	-4.33	6,132	2	21,888	0
Unmatched	-0.230***	-11.68	6,134		21,888	

Note: *** indicates significance at the 1% level. Results are based on the nearest neighbor matching algorithm.

5.2 Processing trade

A key feature of Chinese manufacturing exports is the important role of processing trade. In year 2006, processing trade accounts for 52.6% of Chinese exports based on the CCTS database. There are at least three reasons why the previously stated product churning-productivity relationship may not hold for processing traders. First, Chinese processing traders receive special policy treatments from the government (Yu, 2015; Dai, Maitra, and Yu, 2016b) and face much lower fixed costs to export (Fernandes and Tang, 2015). As such, they have less incentive to diversify their product range as well as to alter them to seek productivity gains. Second, processing traders do not have much control over their product mix when they are not the coordinator of the associated global supply chain. Third, even when processing traders churn their products, it is more like to be done to meet their foreign partners' requirement rather than to boot their own productivity. This is because processing trade is order-oriented as much as profit-oriented (Dai, Maitra, and Yu, 2016b).

In accordance with the descriptive analysis in Section 2, exporters are classified into five groups based on their intra-firm share of processing trade. The estimation results are shown in Table 13. *A comparison of the result of NPEs (processing trade = 0%) and PEs (processing trade= 100%) seem to confirm that processing traders do not exhibit strong churning-productivity relationship as other firms. Specifically, product churning NPEs have TFP advantage over their counterparts, while product churning PEs do not over those add new products. Moreover, when we look at PPEs (100% > processing trade > 0%), the*

Table 13: *Results for exporters with various intra-firm shares of processing trade*

Static	PSM		No. firm			
	ATT	t-value	Treated	Off-support	Untreated	Off-support
0%	-0.093***	-4.67	15,704	4	30,784	0
(0%, 25%]	-0.116**	-2.37	1,401	1	9,203	0
(25%, 50%]	-0.199**	-3.10	924	0	4,680	0
(50%, 75%]	-0.162***	-2.68	953	1	4,573	0
(75%, 100%)	-0.101***	-3.03	3,194	9	13,663	0
100%	-0.078***	-2.92	9,560	12	6,666	0
Adding	PSM		No. firm			
	ATT	t-value	Treated	Off-support	Untreated	Off-support
0%	-0.074***	-3.91	14,585	1	30,784	0
(0%,2 5%]	-0.115***	-2.98	2,302	0	9,210	0
(25%, 50%]	-0.140*	-1.82	1,336	0	4,680	0
(50%, 75%]	-0.051	-0.95	1,265	3	4,575	0
(75%, 100%)	-0.033	-1.05	4,583	3	13,663	0
100%	-0.021	-0.65	4,346	2	6,666	0
Dropping	PSM		No. firm			
	ATT	t-value	Treated	Off-support	Untreated	Off-support
0%	-0.054***	-2.45	11,179	1	30,784	0
(0%, 25%]	-0.116**	-2.21	1,481	0	9,203	0
(25%, 50%]	-0.108	-0.83	892	2	4,680	0
(50%,7 5%]	-0.173***	-2.82	971	2	4,573	0
(75%, 100%)	-0.071*	-1.78	2,917	0	13,663	0
100%	-0.083***	-2.93	4,786	6	6,666	0

Note: ***, ** and * indicates significance at the 1%, 5% and 10% level, respectively. Results are based on the nearest neighbor matching algorithm.

picture becomes more complex. For instance, PPEs that churn products seem to have a TFP advantage over PPEs that maintain a stable product mix or drop products, but not over those that add products. However, in Table 20 in the attachment, estimations based on Kernel and Radius matching are also reported. It's intriguing to find that all estimations are significant at 1% or 5% level, indicating a strong TFP of product churning exporters over their counterparts no matter what the share of processing trade is. Therefore, whether and how share of processing trade within Chinese manufacturing exporters impact product churning-firm TFP nexus deserves to be studies further in our future research.

5.3 Firm ownerships

In this sub-section, we examine if and how the churning-productivity annex may interact with the three main types of firm ownership in China. The results of the PSM estimations and permutation tests based on the Nearest Neighbour Matching method are shown in Table 14. The signs of these results are in highly consistent with that in Table 21 that are estimated based on the other two methods as reported in Table 21 in the attachment. To explain specifically, product churning exporters have a higher TFP level than their non-churning counterparts for each type of firm ownership (state, foreign and private). Moreover, the product churning is relatively bigger for state-owned firms, followed by foreign- and private-owned firms. Foreign firms usually have better access to foreign advanced technology as well as a higher absorptive capacity (Dai and Yu, 2013; Ding, Guariglia, and Harris, 2016) which may allow them to take greater advantage of resource reallocation. With regard to state-owned firms in China, the results are interesting since they are often argued to be less efficiency by previous studies. For instance, they often enjoy preferential access to credits from state-owned banks because of their political connection (Khandelwal, Schott, and Wei, 2013; Chen, Tian, and Yu, 2016), reducing their incentive to be efficient in the first place (Dougherty and Herd, 2005). Meanwhile, having political connections indicate that state-owned firms may need to conduct business in order to meet certain social objective of their political master. We hence expect a weak or even no TFP advantage of product churning state-owned firms over their non-churning counterparts. However, estimations in Table 14 and Table 21 show an obvious TFP advantage for product churning state-owned firms. We explain this by at least two reasons. On the one hand, there have been evidence demonstrating that the efficiency and productivity of Chinese state-owned enterprises (SOEs) has exhibited obvious improvements since the systemic reform in China (Fu, Vijverberg, and Chen, 2008). (Chen, Firth, and Xu, 2009)also demonstrate that China's listed SOEs affiliated to the central government perform better than listed private controlled firms in terms of the operating efficiency. On the other hand, our findings indicate that resource-reallocation within-firms provide a new channel for state-owned firms in China to obtain productivity improvement.

Table 14: *Results for exporters with various types of firm ownership*

Static	PSM		No. firm			
	ATT	t-value	Treated	Off-support	Untreated	Off-support
State	-0.173***	-2.88	1,799	10	4,105	0
Foreign	-0.134***	-7.21	11,928	5	26,625	0
Private	-0.048**	-2.14	5,472	9	11,756	0
Adding	PSM		No. firm			
	ATT	t-value	Treated	Off-support	Untreated	Off-support
State	-0.320***	-3.24	1,476	2	4,130	0
Foreign	-0.061***	-3.48	10,287	1	26,625	0
Private	-0.053***	-2.86	6,428	8	11,756	0
Dropping	PSM		No. firm			
	ATT	t-value	Treated	Off-support	Untreated	Off-support
State	-0.125*	-1.90	1,380	2	4,130	0
Foreign	-0.126***	-6.18	8,176	4	26,625	0
Private	-0.070**	-2.39	3,607	5	11,756	0

Note: ***, ** and * indicates significance at the 1%, 5% and 10% level, respectively. Results are based on the nearest neighbor matching algorithm.

5.4 Industry categories

The role of intra- and inter-industry spillovers in China's astonishing growth performance has been extensively studied (Wei and Liu, 2006; Adams, Gangnes, and Shachmurove, 2006; Caporale, Sova, and Sova, 2015). To examine whether the positive effect of export product churning on firm productivity still holds across industries in China, we now conduct the PSM and permutation estimations within various industry categories. As shown in Table 15, product churning stimulates resource reallocation for exporters in the technology-intensive industry, relative to other export product activities. More interestingly, relative to static scenario, churning has the biggest impacts for the technology-intensive industry, followed by the capital-intensive industry, and then by the labour-intensive one.

In Table 16 we divide industries into high-tech on the one hand, and low- and medium-tech on the other. The results are similar to those in Table 15 in that relative to the static scenario, churning has bigger impacts on the high-tech industry than the low- and medium-tech industry.

Technological innovation is the key for success and competition in technology-intensive industries (Practice et al.,1999), which are characterized by short product lifecycles. As such, it is not surprising to see that product churning presents a stronger impact on productivity of

Table 15: *Results for exporters with various types ofmanufacturing industries*

Static	PSM		No. firm			
	ATT	t-value	Treated	Off-support	Untreated	Off-support
Labour-intensive	-0.063***	-2.34	7,838	7	27,017	0
Capital-intensive	-0.098***	-3.55	9,482	6	15,898	0
Technology-intensive	-0.169***	-8.41	12,681	1	23,392	0
Add	PSM		No. firm			
	ATT	t-value	Treated	Off-support	Untreated	Off-support
Labour-intensive	-0.049**	-1.98	7,978	0	27,017	0
Capital-intensive	-0.046*	-1.68	7,842	0	15,898	0
Technology-intensive	-0.118***	-4.97	11,292	1	23,392	0
Drop	PSM		No. firm			
	ATT	t-value	Treated	Off-support	Untreated	Off-support
Labour-intensive	-0.095***	-3.68	6,818	3	27,017	0
Capital-intensive	-0.077**	-2.30	6,080	4	15,898	0
Technology-intensive	-0.124***	-4.78	8,189	0	23,392	0

Note: ***, ** and * indicates a significance level of 1%, 5% and 10%, respectively. Results are based on the Nearest Neighbour Matching.

Chinese exporters operate in technology-intensive industries.

Table 16: *Results for exporters with various types ofmanufacturing industries*

Static	PSM		No. firm			
	ATT	t-value	Treated	Off-support	Untreated	Off-support
High-tech	-0.143***	-2.84	2,867	6	4,936	0
Low- and Medium-tech	-0.130***	-8.81	28,885	7	64,642	0
Adding	PSM		No. firm			
	ATT	t-value	Treated	Off-support	Untreated	Off-support
High-tech	-0.084**	-2.13	2,549	3	4,936	0
Low- and Medium-tech	-0.069***	-4.69	25,874	2	64,642	0
Dropping	PSM		No. firm			
	ATT	t-value	Treated	Off-support	Untreated	Off-support
High-tech	-0.103**	-2.23	1,812	4	4,936	0
Low- and Medium-tech	-0.111***	-6.94	20,420	1	64,642	0

Note: ***, ** and * indicates a significance level of 1%, 5% and 10%, respectively. Results are based on the Nearest Neighbour Matching.

6. Conclusion

This paper aims to explore how firms can increase productivity through product churning. Our focus is Chinese manufacturing exporters, which have a strong tendency to export multi-products and alter their product mix on annual basis.

Using the Propensity Score Matching method, we find strong evidence of a positive impact of export product churning on firm TFP. Product churning exporters have TFP advantage over those exports that only add or drop products or that do not change their product mix. The finding is consistent with the hypothesis that, by changing product mix, firms can optimally allocate resources to areas where they are deployed most efficiently, which in turn raises firm productivity. Therefore, our results lend empirical support to the theoretical work of Eckel and Neary (2010), Bernard, Redding, and Schott (2011), and Mayer, Melitz, and Ottaviano (2014).

We find that the churning-productivity annex does not necessarily hold for processing traders. However, the finding is not uniform across firms that engaged in various degrees of processing trade. *Sprisingly, we find that state-owned firms can also obtain TFP improvement through product churning and resource reallocation within-firms.* The precise mechanism through which processing trade and firm ownership impact on the churning-productivity connection needs to be further explored. Nevertheless, our findings indicate that, as far as intra-firm resource reallocation is concerned, firms in developing countries may behave differently from their developed countries counterparts due to differences in economic environment (Goldberg, Khandelwal, Pavcnik, and Topalova, 2010).

References

ABADIE, A., D. M. DRUKKER, J. L. HERR, AND G. W. IMBENS (2004): "Implementing matching estimators for average treatment effects in Stata," *Stata Journal*, 4(3).

ABADIE, A., AND G. W. IMBENS (2006): "Large sample properties of matching estimators for average treatment effects," *econometrica*, 74(1), 235–267.

ADALET, M., ET AL. (2009): "Multi-product exporters and product turnover behaviour of New Zealand exporters," Discussion paper, New Zealand Treasury.

ADAMS, F. G., B. GANGNES, AND Y. SHACHMUROVE (2006): "Why is China so competitive? Measuring and explaining China's competitiveness," *The World Economy*, 29(2), 95–122.

ALVAREZ, R., C. BRAVO-ORTEGA, AND L. NAVARRO (2016): "Product Mix Changes and Performance in Chilean Plants," *Ind Corp Change*, 25 (6), 1001–1017.

ARNOLD, J. M., AND K. HUSSINGER (2005): "Export behavior and firm productivity in German manufacturing: a firm-level analysis," *Review of World Economics*, 141(2), 219–243.

BALDWIN, J. R., AND W. GU (2006): "Plant turnover and productivity growth in Canadian manufacturing," *Industrial and Corporate Change*, 15(3), 417–465.

BERNARD, A. B., AND J. B. JENSEN (1999): "Exceptional exporter performance: cause, effect, or both?," *Journal of international economics*, 47(1), 1–25.

——— (2004): "Exporting and Productivity in the USA," *Oxford Review of Economic Policy*, 20(3), 343–357.

BERNARD, A. B., REDDING, AND P. S. J., SCHOTT (2010): "Multiple-product firms and product switching," *The American Economic Review*, 100(1), 70–97.

BERNARD, A. B., S. J. REDDING, AND P. K. SCHOTT (2011): "Multiproduct firms and trade liberalization," *The Quarterly Journal of Economics*, 126(3), 1271–1318.

BERNARD, A. B., I. VAN BEVEREN, AND H. VANDENBUSSCHE (2010b): "Multi-product exporters, carry-along trade and the margins of trade," *National Bank of Belgium Working Paper*, (203).

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.

CALIENDO, M., AND S. KOPEINIG (2008): "Some practical guidance for the implementation of propensity score matching," *Journal of economic surveys*, 22(1), 31–72.

CAPORALE, G. M., A. SOVA, AND R. SOVA (2015): "Trade flows and trade specialisation: The case of China," *China Economic Review*, 34, 261–273.

CHANG, P.-L., AND M.-J. LEE (2011): "The WTO trade effect," *Journal of International Economics*, 85(1), 53–71.

CHEN, C., W. TIAN, AND M. YU (2016): "Outward FDI and domestic input distortions: Evidence from Chinese firms," *Trustees of Boston University Working Paper*.

CHEN, F., AND K. XU (2012): "Local market size and total factor productivity of Chinese manufacturing firms. s," *China Industrial Economic (a Chinese journal)*, 5, 44–56.

CHEN, G., M. FIRTH, AND L. XU (2009): "Does the type of ownership control matter? Evidence from Chinaâs listed companies," *Journal of Banking & Finance*.

COLLARD-WEXLER, A., AND J. DE LOECKER (2015): "Reallocation and technology: evidence from the US steel industry," *The American Economic Review*, 105(1), 131–171.

DAI, M., R. HARRIS, Y. LU, AND H. LIU (2016a): "Exports and firm survival: do trade regime and productivity matter?," *Applied Economics Letters*, 23(6), 457–460.

DAI, M., M. MAITRA, AND M. YU (2016b): "Unexceptional exporter performance in China? The role of processing trade," *Journal of Development Economics*, 121, 177–189.

Dai, M., and M. Yu (2013): “Firm R&D, Absorptive Capacity and Learning by Exporting: Firm-level Evidence from China,” *The World Economy*, 36(9), 1131–1145.

Damijan, J. P., J. Konings, and S. Polanec (2014): “Import Churning and Export Performance of Multi-product Firms,” *The World Economy*, 37(11), 1483–1506.

Davis, S. J., and J. Haltiwanger (1999): “Gross job flows,” *Handbook of labor economics*, 3, 2711–2805.

Davis, S. J., J. Haltiwanger, and S. Schuh (1996): “Small business and job creation: Dissecting the myth and reassessing the facts,” *Small business economics*, 8(4), 297–315.

Dhawan, R. (2001): “Firm size and productivity differential: theory and evidence from a panel of US firms,” *Journal of economic behavior & organization*, 44(3), 269–293.

Diaz, J. J., and S. Handa (2006): “An assessment of propensity score matching as a non-experimental impact estimator evidence from Mexico’s PROGRESA program,” *Journal of human resources*, 41(2), 319–345.

Ding, S., A. Guariglia, and R. Harris (2016): “The determinants of productivity in Chinese large and medium-sized industrial firms, 1998–2007,” *Journal of Productivity Analysis*, 45(2), 131–155.

Ding, S., A. Guariglia, and J. Knight (2013): “Investment and financing constraints in China: does working capital management make a difference?,” *Journal of Banking & Finance*, 37(5), 1490–1507.

Dougherty, S., and R. Herd (2005): “Fast-Falling Barriers and Growing Concentration: the emergence of a private economy in China,” *OECD Economics Department Working Paper*, (471).

Du, J., X. Liu, and Y. Zhou (2014): “State advances and private retreats?—Evidence of aggregate productivity decomposition in China,” *China Economic Review*, 31, 459–474.

Eckaus, R. S. (2006): “China’s exports, subsidies to state-owned enterprises and the WTO,” *China Economic Review*, 17(1), 1–13.

ECKEL, C., AND J. P. NEARY (2010): "Multi-product firms and flexible manufacturing in the global economy," *The Review of Economic Studies*, 77(1), 188–217.

FEENSTRA, R. C., AND G. H. HANSON (2005): "Ownership and control in outsourcing to China: Estimating the property-rights theory of the firm," *The Quarterly Journal of Economics*, 120(2), 729–761.

FERNANDES, A. P., AND H. TANG (2015): "Scale, scope, and trade dynamics of export processing plants," *Economics Letters*, 133, 68–72.

——— (2016): "Trade Patterns and Dynamics of Processing Exporters: Evidence from China," *Working Paper*.

FOSTER, L., J. HALTIWANGER, AND C. SYVERSON (2008): "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?," *American Economic Review*, 98(1), 394–425.

FOSTER, L., J. C. HALTIWANGER, AND C. J. KRIZAN (2001): "Aggregate productivity growth: lessons from microeconomic evidence," in *New developments in productivity analysis*, pp. 303–372. University of Chicago Press.

FU, F.-C., C.-P. C. VIJVERBERG, AND Y.-S. CHEN (2008): "Productivity and efficiency of state-owned enterprises in China," *Journal of Productivity Analysis*.

GOLDBERG, P. K., A. K. KHANDELWAL, N. PAVCNIK, AND P. TOPALOVA (2010): "Multiproduct firms and product turnover in the developing world: Evidence from India," *The Review of Economics and Statistics*, 92(4), 1042–1049.

HARRIS, R., AND J. MOFFAT (2015): "Plant-level determinants of total factor productivity in Great Britain, 1997–2008," *Journal of Productivity Analysis*, 44(1), 1–20.

HECKMAN, J. J., H. ICHIMURA, AND P. TODD (1998): "Matching as an econometric evaluation estimator," *The review of economic studies*, 65(2), 261–294.

HECKMAN, J. J., H. ICHIMURA, AND P. E. TODD (1997): "Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme," *The review of economic studies*, 64(4), 605–654.

HO, D. E., AND K. IMAI (2006): "Randomization inference with natural experiments: An analysis of ballot effects in the 2003 California recall election," *Journal of the American Statistical Association*, 101(475), 888–900.

HU, C., AND Y. TAN (2016): "Export spillovers and export performance in China," *China Economic Review*, 41, 75–89.

IMBENS, G. W., AND J. M. WOOLDRIDGE (2009): "Recent developments in the econometrics of program evaluation," *Journal of economic literature*, 47(1), 5–86.

JEFFERSON, G. H., T. G. RAWSKI, W. LI, AND Z. YUXIN (2000): "Ownership, productivity change, and financial performance in Chinese industry," *Journal of Comparative Economics*, 28(4), 786–813.

JONES, C. (2013): *Misallocations, Economic Growth, and Input-Output Economics, Advances in Economics and Econometrics, Vol. II*Cambridge University Press.

JOVANOVIC, B., AND Y. NYARKO (1996): "Learning by Doing and the Choice of Technology," *Econometrica*, 64(6), 1299–1310.

KASAHARA, H., AND J. RODRIGUE (2008): "Does the use of imported intermediates increase productivity? Plant-level evidence," *Journal of development economics*, 87(1), 106–118.

KHANDELWAL, A. K., P. K. SCHOTT, AND S.-J. WEI (2013): "Trade liberalization and embedded institutional reform: evidence from Chinese exporters," *The American Economic Review*, 103(6), 2169–2195.

LEVINSOHN, J., AND A. PETRIN (2003): "Estimating production functions using inputs to control for unobservables," *The Review of Economic Studies*, 70(2), 317–341.

MA, Y., H. TANG, AND Y. ZHANG (2014): "Factor intensity, product switching, and productivity: Evidence from Chinese exporters," *Journal of International Economics*, 92(2), 349–362.

Manova, K., and Z. Yu (2016): “How firms export: Processing vs. ordinary trade with financial frictions,” *Journal of International Economics*, 100, 120–137.

Mayer, T., M. J. Melitz, and G. I. Ottaviano (2014): “Market size, competition, and the product mix of exporters,” *The American Economic Review*, 104(2), 495–536.

Melitz, M. J. (2003): “The impact of trade on intra-industry reallocations and aggregate industry productivity,” *Econometrica*, 71(6), 1695–1725.

Melitz, M. J., and S. Polanec (2015): “Dynamic Olley-Pakes productivity decomposition with entry and exit,” *The Rand journal of economics*, 46(2), 362–375.

Navarro, L. (2012): “Plant level evidence on product mix changes in Chilean manufacturing,” *The Journal of International Trade & Economic Development*, 21(2), 165–195.

Olley, G. S., and A. Pakes (1996): “The dynamics of productivity in the telecommunications equipment industry,” *Econometrica*, 64(6), 1263–1297.

Park, A., D. Yang, X. Shi, and Y. Jiang (2010): “Exporting and firm performance: Chinese exporters and the Asian financial crisis,” *The Review of Economics and Statistics*, 92(4), 822–842.

Pesarin, F. (2001): *Multivariate permutation tests: with applications in biostatistics*, vol. 240. Wiley Chichester.

Qiu, L. D., and M. Yu (2014): “Multiproduct firms, export product scope, and trade liberalization: The role of managerial efficiency,” *HKIMR Working Paper*.

Rosenbaum, P. R., and D. B. Rubin (1983): “The central role of the propensity score in observational studies for causal effects,” *Biometrika*, 70(1), 41–55.

Sandleris, G., and M. L. Wright (2014): “The costs of financial crises: Resource misallocation, productivity, and welfare in the 2001 argentine crisis,” *The Scandinavian Journal of Economics*, 116(1), 87–127.

SHENG, Y., T. JACKSON, AND P. GOODAY (2017): “Resource reallocation and its contribution to productivity growth in Australian broadacre agriculture,” *Australian Journal of Agricultural and Resource Economics*, 61(1), 56–75.

UPWARD, R., Z. WANG, AND J. ZHENG (2013): “Weighing China’s export basket: The domestic content and technology intensity of Chinese exports,” *Journal of Comparative Economics*, 41(2), 527–543.

VAN BEVEREN, I. (2012): “Total factor productivity estimation: A practical review,” *Journal of Economic Surveys*, 26(1), 98–128.

WAGNER, J. (2012): “International trade and firm performance: a survey of empirical studies since 2006,” *Review of World Economics*, 148(2), 235–267.

WAMSER, G. (2014): “The Impact of Thin-Capitalization Rules on External Debt Usage–A Propensity Score Matching Approach,” *Oxford Bulletin of Economics and Statistics*, 76(5), 764–781.

WANG, Z., AND Z. YU (2012): “Trading Partners, Traded Products and Firm Performances of China’s Exporter-Importers: Does Processing Trade Make a Difference?,” *The World Economy*, 35(12), 1795–1824.

WEI, Y., AND X. LIU (2006): “Productivity spillovers from R&D, exports and FDI in China’s manufacturing sector,” *Journal of international business studies*, 37(4), 544–557.

YU, M. (2015): “Processing trade, tariff reductions and firm productivity: evidence from Chinese firms,” *The Economic Journal*, 125(585), 943–988.

YU, M., AND W. TIAN (2012): “China’s firm-level processing trade: trends, characteristics, and productivity,” *China Center for Economic Research Working Paper Series*, (E2012002).