PRODUCTIVITY DYNAMICS AND ECONOMIC TRANSITION IN CHINA

By

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DEDICATION.

I would like to dedicate this dissertation to Chunfang Hu, my deceased grandfather. I wish I had been able to complete this dissertation, so that he could have shared this experience with me.

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Product Selection and Export Growth: Evidence from Chinese Exporters

1.1 Introduction

Determining how firms grow into new markets is integral to a number of key economic questions. The industrial organization literature strongly suggests that firm turnover and product churning have been repeatedly found to play an important role in determining industry aggregates. Likewise, the international trade literature often cites the impact that trade liberalization has in reallocating resources across firms and its' influence on industry productivity. Macroeconomists often suggest that micro-level distortions can significantly affect the allocation of resources, the equilibrium set of producers and the resulting macroeconomic outcomes.

This paper uses rich data to re-examine firm-level growth, survival and performance in a context which is of global interest: the rapid growth of Chinese exports, which has had important economic impacts worldwide. Numerous developing countries have recommitted to export promotion as a key plank within their development platform so as to achieve similar success in international markets. Importing countries have concurrently struggled to determine the appropriate policy response in the face of large inflows of Chinese products. However, little is known about the microeconomic evolution of Chinese export determinants. Have rapid increases in efficiency allowed Chinese exporters to expand across markets worldwide? In contrast, was the rapid expansion of Chinese exports demand driven? Were key changes to export behavior occurring at the industry, firm, or product-level?

Unfortunately, empirically answering these questions, in any country, is generally complicated by a lack of adequate data. In particular, most firm-level data sets report total sales, but do not allow researchers to distinguish between movements in product prices and quantities. Foster, Haltiwanger and Syverson (2008) show that revenue based measures of productivity tend to conflate the influence of both physical productivity and prices on US firm-behaviour. Likewise, Gervais (2012) argues that among US manufacturers measured demand-level differences are at least as important in explaining firm-level selection and revenue growth as firm-level productivity. In our context, separately identifying idiosyncratic demand and productivity is key to characterizing the nature of firm-selection in international markets. Further, although most estimates are based on detailed manufacturing data, these data sets rarely provide any information on the location of sales or the behaviour of manufacturing firms across different export markets. Most analyses are restricted to studying one (the domestic market) or at most a few markets (e.g. domestic vs. export markets). While a number of key insights have been gained by examining firm-level behaviour within a small number of markets, these studies generally do not allow us to distinguish how market-level characteristics influence the decision to enter and maintain a presence in vastly different export markets.

We are able to shed new light on firm growth in international markets by joining two key sources of information. First, we use customs level data containing detailed information on the price, quantity and destination of the products exported by the universe of Chinese exporters. Second, the customs data is carefully matched with Chinese firm-level data describing firm-level inputs and domestic revenue. By separately observing prices and quantities in export markets we are able to disentangle the differential effects of idiosyncratic productivity and demand shocks on aggregate export growth. Further, we use these differences to characterize turnover across markets, the persistence in export demand and product selection across markets in each year between 2002 and 2005.

Our approach follows a long tradition which characterizes industries as collections of heterogeneous producers with varying levels of technological efficiency (e.g. Jovanovic (1982), Hopenhayn (1992), Ericson and Pakes (1995), Melitz (2003), and Asplund and Nocke (2006)). A key feature in each of these models is the strong link between producers' productivity levels and their performance in a given market. Further, endogenous selection mechanisms are often found to drive movements in industry aggregates as market shares are reallocated to more efficient producers. Over time less productive plants decline and exit markets entirely while more efficient plants enter and grow into new markets, encouraging selection-driven aggregate sales growth across markets. As is common in China, many exporters produce multiple products for multiple destination markets. As such, we consider a framework which closely follows the literature studying multiproduct firms and international trade (Bernard, Redding and Schott (2011), De Loecker (2011), De Loecker et al. (2012)).

There is near universal support for the notion that productivity is a key determinant of export behaviour.[1] Manova and Zhang (2011, 2012) confirm similar findings among Chinese manufacturers and further document large pricing and quality differences across Chinese exporters and destinations worldwide.[2] Our study builds on this work by measuring firm-specific differences in market-specific demand and quantifying the extent to which this dimension of firm-heterogeneity contributes to aggregate export growth.

Our results contribute to a series of recent findings which confirm that the misallocation of resources across firms can have a large impact on aggregate outcomes.[3] We show that nearly half of all aggregate export growth can be related to changes in idiosyncratic productivity or demand differences across firms, products and markets. Moreover, our results indicate that at least 73 percent of the idiosyncratic component of export growth can be attributed to growth in firm-product demand. Across all destination markets, firm-types (ordinary, processing, foreign, state-owned), and product-types (differentiated, undiffer-

[1] Leading examples include Clerides, Lach and Tybout (1998), Bernard and Jensen (1999b) and Aw, Chung and Roberts (2000), among others. Dai et al. (2011) and Lu (2010) both argue that productivity is strongly associated with firm-level exporting in China, though the two papers dispute the role of productivity on exporting.

[2] Crozet et al. (2012) document that quality or demand differences likewise contribute to differences in export behaviour among French wine producers. Specifically, they confirm that producers of high quality wines export to more markets, charge higher prices, and sell more in each market.

[3] In particular, Restuccia and Rogerson (2008), Foster, Haltiwanger, and Syverson (2008), and Hsieh and Klenow (2008) each suggest that selection and resource allocation have important effects on aggregate TFP. The results mirror findings from the trade literature which strongly indicate that trade liberalization has led to substantial resource reallocation and productivity across countries (See, for example, Bernard and Jensen (1999a) for the US, Pavcnik (2002) on Chile, Trefler (2004) on Canada).

entiated), idiosyncratic demand is always at least as important in determining aggregate export growth as productivity growth and often much more so. In this sense, our findings indicate strong differences in the margins through which aggregate exports grow. We find a number of novel findings by further decomposing demand and productivity across firms and markets. In particular, we highlight three mechanisms which contribute significantly to aggregate demand growth: the strong growth of surviving products with small initial market shares, the rapid reallocation of market shares towards products with growing demand, and high rates of product exit among low demand products.

An increasing number of papers suggest that demand may play a particularly important role in determining export decisions and outcomes. A seminal piece studying firm-level entry to export markets by Das, Roberts and Tybout (1997) argues strongly that among nearly identical exporters with very similar measures of firm-level efficiency, the set of export outcomes varies widely. Demidova, Kee and Krishna (2012) and Rho and Rodrigue (2014) recently document that export market demand shocks are key determinants of exporter behaviour in Bangledesh and Indonesia, respectively. In a paper closely related to ours, Roberts et al. (2012) structurally estimate a model of Chinese footwear exporters. They find that the implied distribution of demand varies much more than that of productivity. Consistent with this research, we find that product survival in export markets is closely related to measures of production efficiency and idiosyncratic demand shocks, though demand is found to have a much larger impact relative to productivity.

Further, we show that high rates of turnover in international markets have a large impact on the evolution of productivity and demand across Chinese exporters. We document that both new varieties and exiting varieties are strongly characterized by very small measures of idiosyncratic demand relative to incumbent varieties of the same products. These differences in demand, in combination with high rates of churning, appear to have a significant effect on firm-level pricing. We find that new entrants are typically less productive than incumbent exporters and they choose relatively high prices. Our results suggest that entrants are choosing prices which are on average 19 percent higher than incumbent exporters of the same products.

Our paper proceeds by outlining a simple model which motivates the empirical exercises that follow. Section 3 describes our data and disentangles our measures of productivity and demand across firms, products and markets. It also documents the association of productivity and demand with key product-level export outcomes. The fourth section determines how much aggregate export growth is directly attributable to productivity or demand heterogeneity. Further, we decompose the demand and productivity components of aggregate export growth to document the role of within-firm growth, reallocation and net entry on the evolution of aggregate demand and productivity among exporting firms and products. Section 5 studies the persistence of productivity and demand across varieties, the nature product selection across international markets, and investigates the role which product churning has on the distribution of these characteristics across firms and products. Section 6 concludes.

1.2 A Simple Model of Selection and Exporting

We begin by outlining a model to motivate our empirical work. The model is purposefully simple and a close variant to those used elsewhere in the trade and industrial organization literature. In particular, the framework we present below is effectively a small modification of the Bernard, Redding and Schott (2011) multi-product firm extension of the Melitz (2003) model and, as such, maintains many of the benefits of these earlier models. In particular, we will allow firms to choose to produce for I different destination markets, but will characterize their decisions as a function of both idiosyncratic productivity, φ, and demand, δ. An important distinction in our case, however, is that each firm will potentially have a different productivity level for each product and, simultaneously, they will have a different level of demand for each product in each destination market. We also allow for the presence of product-specific fixed costs associated with supplying market i with product k,

$f_{ik} > 0$. These market-and-product specific costs represent the costs of market research, advertising and conforming products to destination market standards, etc.

In each country there is an unbounded measure of potential firms who are identical prior to entry. There is a continuum of symmetric products, which we normalize to the interval [0,1], and entry into any product market requires sunk product development costs, s_k, to draw a variety-specific productivity level for product k, φ_k, and a market-and-variety-specific demand shock, δ_{ik}, for product k from the joint distribution, $G_k(\varphi_k, \delta_{1k}, ..., \delta_{Ik})$. We treat the variable δ_{ik} as a variety and market-specific taste shifter for product k (i.e. a firm-and-product-specific demand shock in each destination market). The marginal distributions of φ_k and δ_{ik} are defined over $[\varphi_k^l, \varphi_k^u]$ and $[-\delta_{ik}, \delta_{ik}]$, respectively. If the firms choose to receive draws, they then determine whether to begin production, which products to produce, which markets to serve, and earn the corresponding profits.

Each market i is populated by L_i homogeneous consumers who supply 1 unit of labor each and consume y_i units of a homogeneous numeraire good and C_{ik} units of product k. The representative consumer's utility function is $U_i = y_i^{\beta}[\int_0^1 C_{ik}^{\nu} dk]^{(1-\beta)/\nu}$ where $C_{ik} = [\sum_{i=1}^{I} \int_{\omega \in \Omega_{ijk}} [\delta_{ijk}(\omega) c_{ijk}(\omega)]^{\rho} d\omega]^{1/\rho}$, i and j index countries, ω indexes varieties of product k supplied from country i to country j, Ω_{ijk} is the endogenous set of product k varieties from j sold in country i, $\sigma = 1/(1-\rho)$ is the elasticity of substitution across varieties and $\kappa = 1/(1-\nu)$ is the elasticity of substitution across products. We make the common assumption that $\sigma > \kappa > 1$ and write the firm's residual demand function for product k in market i as

$$q_{ijk}(\omega) = Q_{ik}\left(\frac{P_{ik}}{p_{ijk}(\omega)}\right)^{\sigma} = A_{ik} p_{ijk}(\omega)^{-\sigma} \tag{1.1}$$

where Q_{ik} and P_{ik} are corresponding quantity and price indices, respectively, while p_{ijk} is the firm's optimal price.

Output is produced with a single input x_k according to the production function $q_k = \varphi_k x_k$. The input can be purchased on competitive factor markets at a price w_j which is constant across producers located in the same country j, but can vary across source countries, $j = 1,...,I$. The total cost of production of product k for a firm located in country j is then $C_{jk}(q_k) = \frac{w_j}{\varphi_k} q_k$. We assume further that accessing market i is costly. Specifically, in order to sell abroad firms incur iceberg transport costs $\tau_{ij} \geq 1$ per unit shipped from source country j to destination country i. Firm-level marginal costs of producing and selling a unit of product k for market i are $MC_{ijk} = \frac{w_j \tau_{ij}}{\varphi_k}$ which vary across firms and products located in the same source country j and exporting to the same destination country i because of firm-and-product-specific productivity.

Profit maximization implies that the producer's optimal price in market i is

$$p_{ijk} = \frac{w_j \tau_{ij}}{\rho \varphi_k \delta_{ik}} \tag{1.2}$$

The optimal price is intuitively increasing in the demand for the industry's output, product-specific demand and the transport cost between where the product is produced and the market where it is sold.

Using the equations for optimal price and quantity we can write product k's optimal profit in market i as

$$\pi_{ijk} = \frac{R_{ik}}{\sigma} \left(\frac{\rho P_{ik} \varphi_k \delta_{ik}}{w_j \tau_{ij}} \right)^{\sigma-1} - f_{ik} = \frac{R_{ik}}{\sigma} \left(\rho P_{ik} \phi_{ijk} \right)^{\sigma-1} - f_{ik}$$

Following Foster, Haltiwanger and Syverson (2008) we define a product and market-specific profitability index $\phi_{ijk} = \frac{\varphi_k \delta_{ik}}{w_j \tau_{ij}}$. Product-level profits imply a critical value of this index, ϕ_{ik}^*, where producers with $\phi_{ijk} < \phi_{ik}^*$ will not find operations profitable for product k in market i. Solving the optimal profits equation for ϕ_{ik}^* gives us

$$\phi_{ik}^* = \left(\frac{\sigma f_{ik}}{R_{ik}} \right)^{\frac{1}{\sigma-1}} \frac{1}{\rho P_{ik}}$$

A key feature of this index is that it holds for *all* firms selling product k in market i regardless of whether they reach market i through export or domestic sales. The profitability index generally captures the fact that firms which face higher transport costs are less profitable and, as such, require higher productivity or demand draws to compensate for these costs. We can then rewrite profits from any market as $\pi_{ijk} = \left[\left(\frac{\phi_{ijk}}{\phi_{ik}^*}\right)^{\sigma-1} - 1\right] f_{ik}$. This allows us to write total profits from the sale of a given product across all markets $\pi_{jk} = \sum_i \max\{0, \pi_{ijk}\}$ and total firm profits across all products as $\pi_j = \sum_k \pi_{jk}$.

1.2.1 Free Entry and Equilibrium

A product-level free-entry condition pins down the equilibrium values ϕ_{ik}^* in each destination market. Specifically, the $(\phi_{1k}^*, ..., \phi_{Ik}^*)$ must set the net expected value of entry into the product-market by firms in each country equal to zero. That is, ϕ_{ik}^* must satisfy

$$V_k^E = \int_{\omega_k} \int_{\delta_{1k}} \cdots \int_{\delta_{Ik}} \pi_{jk}(\phi_{i1k}, ...\phi_{iIk}, \phi_{1k}^*, ..., \phi_{Ik}^*) g_k(\varphi_k, \delta_{1k}, ..., \delta_{Ik}) d\delta_{Ik}, ..., d\delta_{1k} d\varphi_k - s_k = 0$$

The above expression summarizes the equilibrium in each product market. It combines the condition that producers only enter product markets where they make non-negative profits with the condition which specifies that entry occurs until the expected value of the product is zero. The equilibrium requires that successful producers receive large enough idiosyncratic productivity and demand draws to meet the profitability thresholds. As such, the model suggests that demand and productivity jointly determine product entry and survival across markets.

1.2.2 Measures of Productivity and Demand

We consider two different measures of productivity in our empirical exercise. These have a close relationship with those specified in our simple model. Our first productivity measure, often called physical productivity ($TFPQ$) is based on quantities of physical output:

$$TFPQ_k = \frac{q_k}{x_k} = \frac{\varphi_k x_k}{x_k} = \varphi_k \tag{1.3}$$

The second productivity measure, typically referred to as revenue productivity ($TFPR$), is based on producer revenue.

$$TFPR_{ijk} = \frac{p_k q_k}{x_k} = p_k \varphi_k = \frac{w_j \tau_{ij}}{\rho \delta_{ik}} \tag{1.4}$$

The key difference between these two measures of productivity is that revenue productivity captures fluctuation in efficiency and prices, while physical productivity ideally captures variation in efficiency alone.

1.2.3 Discussion

Our model, though simple, provides us with a number of key implications about the relationship between exogenous parameters and the equilibrium cutoff profitability level. These in turn provide us with a sense of how product churning and resource allocation patterns will vary across products and countries. The first result pertains to the relationship between iceberg trade costs and the equilibrium cutoff ϕ^*_{jk}. We find that a decrease in iceberg trade costs, say through trade liberalization or improvements in shipping technology, unambiguously increases the equilibrium profitability cutoff, $\frac{\partial \phi^*_{jk}}{\partial \tau_{ij}} < 0$. This implies that as trade costs fall relatively unprofitable products - products with low productivity or demand - will struggle to survive in equilibrium. Similarly, it is straightforward to show that in industries where individual varieties are stronger substitutes for each other will also be characterized by higher equilibrium cutoff values, $\frac{\partial \phi^*_{jk}}{\partial \sigma_k} > 0$. Again, this result is hardly surprising. If consumers are less able to substitute away from a given product, producers with less appealing products or higher costs are implicitly protected from being driven out of business by high-demand and/or low-cost competitors. Intuitively we expect that industries which produce more homogeneous products will typically be characterized by a higher value of σ_k and, as such, have higher equilibrium profitability cutoffs, *ceteris paribus*.[4]

[4]These results are very small extensions of those already shown in the literature. See Melitz (2003), Melitz and Ottaviano (2008), Foster, Haltiwanger and Syverson (2008) or Bernard, Redding and Schott (2011) for

Our simple results provide insight into the evolution of products across markets and time. First, the selection of products and firms into markets depends on product-specific, market-specific and trade-specific factors. The model shows that product-level outcomes will vary with product-level productivity and demand in all markets. Although revenue-based TFP measures are positively correlated with true productivity, they also confound idiosyncratic demand with efficiency. This suggests that the impact of productivity on market entry and turnover may vary substantially with measurement. Second, shifts in market and industry conditions affect the margins of adjustment across heterogeneous producers. Last, product market selection and export sales will vary directly with trade costs and the size of trading economies.

1.3 Data and Measurement

Our objective is to characterize the micro-level determinants of export growth in China. To accomplish this goal we match two key sources of information. First, we use data on the universe of Chinese firms that participate in international trade over the 2002-2005 period. These data have been collected by the Chinese Customs Office and report the f.o.b. value of firm exports in U.S. dollars across destination countries and products in the Chinese eight-digit Harmonized System. The data set also provides information about the quantities traded.[5] The level of detail in the customs data is an important feature in the construction of export prices and quantities because they are not contaminated by aggregation across products, firms or markets. Further, we will exploit this key feature in order to capture a measure of firm-product-level efficiency which will not reflect movements in export prices (as with revenue productivity) or the aggregation of different prices across markets or time.

The customs data is carefully matched with annual firm-level data from the Chinese

examples.

[5]In general, each product is recorded in a single unit of measurement. The number of distinct product codes in the Chinese eight-digit HS classification is similar to that in the 10-digit HS trade data for the United States.

manufacturing sector. Specifically, we use annual firm-level data for the period 2000-2005 on all industrial firms that are identified as being either state-owned, or non-state-owned firms with sales above 5 million RMB. These data come from annual surveys conducted by the National Bureau of Statistics (NBS).[6] The firm-level data include detailed information on firm-level revenues, export sales, intermediate materials, employment, wages, capital stock, ownership and industry classification.

1.3.1 The Matching Process

Matching the firm-level data with the corresponding customs data is a key step in our empirical exercise. Both sets of data contain firm-identifiers which allow us to track firms over time in either data set. Unfortunately, different firm-identifiers are used in each data set which prevent us from using this natural metric to match firms to export products. Instead, we match the customs data with manufacturing data by using the names of each firm which are contained in both data sets. Our matching algorithm and results are very similar to those in Manova and Yu (2011) and Wang and Yu (2012) and capture approximately two-thirds of the exporters in the manufacturing data set.[7]

We conduct a number of tests to study the composition of exports across products and firms in both the matched sample and the firm-level data. In each case we find that the two samples are very similar. For instance, Figure 1.1 presents the distribution of export revenues across firms the firm-level data and the matched sample. We observe that the distribution of exports across firms is nearly identical in the matched and full sample of firms. Likewise, Table 1.1 reports the percentage of exports for each two digit industry

[6]The unit of observation is the firm, and not the plant. Sales of 5 million RMB roughly translate to $US 600,000 over this period. During this period manufacturing prices were relatively stable. Brandt, van Biesebroeck and Zhang (2012) suggest that nearly 95 percent of all observations in a similar sample are single-plant firms.

[7]We cannot match all of the data in both data sets for a number of plausible reasons. For instance, our firm-level data only captures relatively large firms. Because of this we often cannot match small exporters in the customs data with any record in the firm-level data. Nonetheless, we are confident that our matched sample is strongly comparable to the sample of Chinese manufacturing exporters from the firm-level data set.

in both the (full) firm-level data set and our matched sample. In each case, the mean percentage of sales from exports are very close.

1.3.2 Variable Construction

In this section we briefly summarize the construction of key variables. Full details are provided in the Appendix. We first calculate the average export price for each product in each year using a revenue-weighted geometric mean. Observed export prices and revenues are converted to a common year using the average annual price as a deflator. Annual values are calculated as quantity weighted averages over each calendar year.

Real intermediate materials are constructed by deflating nominal intermediate materials with the Brandt, Van Biesebroeck and Zhang (2012) benchmark intermediate input deflators. Real capital stock is constructed using book values in 2000, nominal new investment each year and the Brandt-Rawski investment deflators for China. We employ the perpetual inventory method, under the assumption that current investment becomes productive next year, to construct an annual series of capital holdings for each firm, $k_{f,t+1} = (1-d)k_{ft} + i_{ft}$ where d is the depreciation rate, f indexes firms and t indexes years.[8]

We calculate the materials share as the average share of intermediate inputs in total revenues. The labor share is calculated analogously with the exception that we follow Hsieh and Klenow (2008) to adjust the reported wage bill to account for unreported employee compensation. Similarly, in the absence of reliable capital share information we follow Hsieh and Klenow (2008) and assume constant returns to scale so that $\alpha_k = 1 - \alpha_l - \alpha_m$. We have alternatively tried estimating the input shares, and productivity, using control function methods (De Loecker et al, 2012). Moreover, our later results are all unaffected by this change.[9]

[8] For our main results we use the total wage bill to measure the quality-adjusted labor stock for each firm. We have alternatively tried constructing productivity using the number of employees as our measure of employment. Since this difference had virtually no effect on any of our results, we omit further results and discussion from the main text.

[9] Our Supplemental Appendix describes in detail an alternative productivity estimation procedure, pro-

Last, we need to apportion inputs to account for multi-product firms. We do this as in Foster, Haltiwanger and Syverson (2008). For each firm we first calculate the percentage of total revenues from a given exported product k in each year, ρ_{fkt}. Then for any input variable (capital, intermediate materials, labor) we calculate the total amount of each input x_{fkt} allocated to the production of the exported product as $x_{fkt} = \rho_{it}\tilde{x}_{ft}$ where $\tilde{x}_{it}$ is the total amount of input used in firm f in year t.[10]

1.3.3 Measuring Productivity

Our primary measure of total factor productivity is

$$\ln TFPQ_{fkt} = \ln q_{fkt} - \alpha_k \ln k_{fkt} - \alpha_l \ln l_{fkt} - \alpha_m \ln m_{fkt}$$

where q_{fkt} is the physical units of product k produced by firm f for export in year t across all destinations. Similarly, k_{fkt}, l_{fkt} and m_{fkt} represent the firm-product-year measures of capital, labor and materials, respectively, and α_k, α_l and α_m capture each input's share parameter.

Numerous papers studying the nature of firm-level export growth have relied exclusively on revenue based measures of productivity. For purposes of comparability we also compute a measure of revenue based productivity as

$$\ln TFPR_{fkt} = \ln q_{fkt} p_{fkt} - \alpha_k \ln k_{fkt} - \alpha_l \ln l_{fkt} - \alpha_m \ln m_{fkt}$$

where p_{fkt} is the firm f's average deflated export price of product k in year t.

Variation in $TFPQ$ generally reflects differences in physical efficiency and, possibly,

vides new demand estimates and repeats all exercises in this paper on a limited sample of products for which we can estimate productivity. In general, we find very similar results to those reported in the main text.

[10]De Loecker et al. (2012) estimate the input share across product for multi-product firms. They find that input allocations across products are very similar to those calculated by allocating inputs according to product revenue shares. Note that we cannot follow their method exactly in this instance since our data does not include product-level information on domestic sales for each firm.

factor input prices. In general, it captures some measure of the producer's average unit cost. The revenue based productivity measure captures both variation in physical efficiency and log output prices. Prices, not surprisingly, vary widely in our data set since our exporting firms choose very different prices across locations and time. As such, we expect that each variable will have a similar, but not necessarily identical, impact on firm behaviour.

1.3.4 Measuring Demand

We seek to separate the influence of demand and productivity on exporter behaviour and study the impact of both on export growth. Our demand estimation methodology here follows those in Foster, Haltiwanger and Syverson (2008) and Eslava, Haltiwanger, Kugler and Kugler (2009), but accounts for the structure of our model and features which are unique to our setting. Specifically, we begin by considering the following simple product-level regression of demand,

$$\ln q_{fikt} \quad = \quad \ln A_{ikt} - \sigma_k \ln p_{fikt} + \varepsilon_{fikt} \tag{1.5}$$

where f, i, k, and t index firms, destination markets, products, and time, respectively, and ε_{fikt} is an *iid* error term. We allow for each product market in each year to receive a demand shock unique to that specific market and product. As discussed in Manova and Zhang (2012) export prices often reflect destination market differences in size, income, distance and isolation. The product-market-year fixed effects control for both time-invariant and time-varying fixed effects in each product market.[11]

Finally, we expect that if there is a positive demand shock (a large ε_{fikt}) this is likely to be reflected in higher prices, p, and sales, q. To account for possible endogeneity bias we estimate equation (1.5) by IV product-by-product. As argued in Foster, Haltiwanger and Syverson (2008), Eslava, Haltiwanger, Kugler and Kugler (2009) and Gervais (2012)

[11] Our data captures nearly 200 distinct destination countries.

a natural instrument for output prices in this context is our measure of firm-level physical productivity. As we demonstrate below, our measure of physical productivity is strongly, negatively correlated with export prices even though it was not constructed using any export price information. Moreover, our measure of physical productivity should capture shocks to firm-costs and are arguably uncorrelated with market-specific demand shocks. We proceed by using log physical productivity to instrument for log prices.

Our IV estimates imply that the average estimate of α_1 across industries is -4.12. If we were to interpret these as the elasticities in a CES demand framework, we would compute firm-level markups for the average industry in our data to be approximately 32 percent. These results are broadly in line with those found in other countries, markets and estimation methods. Further, Table 1.2 documents a number of elasticity estimates across products. In general, more differentiated products are associated with low elasticities, as we would expect.[12] We then construct a firm-specific measure of export demand, d_{fikt}, using equations (1.2) and (1.5) as

$$\hat{\sigma}_k \ln d_{fikt} \equiv \ln A_{ikt} - \hat{\sigma}_k \ln\left(\frac{w_{jkt}\tau_{ijkt}}{\rho_k}\right) + \hat{\sigma}_k \ln(\delta_{fikt}) + \varepsilon_{fikt} = \ln q_{fikt} - \hat{\sigma}_k \ln(\varphi_{fkt}) \quad (1.6)$$

1.3.5 Sample Properties

Sample Correlations

Table 1.3 collects correlations and standard deviations for each of the core variables of our study. Specifically, we document summary statistics for our two measures of firm exports (log physical units sold and log revenue), our two measures of productivity ($\ln TFPQ$ and $\ln TFPR$), our measure of product-market-year specific demand shocks ($\ln d$), log price and the log of capital. We remove product-market-year fixed effects from each variable so that product-market heterogeneity or aggregate intertemporal shocks do not drive our re-

[12] See Table 1.2 for estimation results. See Foster, Haltiwanger and Syverson (2008), Eslava, Haltiwanger, Kugler and Kugler (2009), De Loecker and Warzynski (2012) for further discussion and citations.

sults.

The first point we wish to make is that the measures of exports (physical units shipped and export revenue) are highly correlated. The correlation between physical and revenue sales reflects the wide dispersion in firm-level heterogeneity within industries as evidenced by the large standard deviations for each of these measures. Second, we also observe that our two measures of total factor productivity are also positively correlated with each other, but this correlation is smaller than that of physical and revenue sales. This is hardly surprising; heterogeneous exporters vary substantially in their location, duration and size of export sales. The positive, but weaker, correlation between physical and revenue based productivity suggests that quantitative results based on revenue-based measures of productivity have the potential to be misleading. Third, both demand and physical productivity display substantially more dispersion than revenue productivity. Below, we study whether the larger observed differences across firms and products translate into a greater impact on export growth across markets.

Product-level prices are negatively correlated with physical productivity, suggesting that more productive Chinese exporters tend to charge lower prices in export markets. Despite wide price dispersion across producers, the negative covariance between prices and physical productivity causes the dispersion of revenue productivity to be smaller than that of physical productivity. Perhaps surprisingly, prices display little unconditional correlation with our measure of product and firm-specific demand. We find that this is in part due to relatively high turnover among exported products in export markets.

Export Sales, Entry and Frequency

We observe large differences in both measures of idiosyncratic demand and productivity. What is less obvious from our preceding decomposition, however, is the extent to which these are related to export performance. We begin by studying the impact of demand and productivity on key export outcomes: export sales, export frequency and the number of active export markets. To keep our exercise simple, we normalize our measure of product-specific productivity so that each productivity distribution has a mean of 0 and standard deviation of 1. Likewise, we normalize demand shocks in each product market and then average over markets to roughly measure whether the firm's product is generally in the upper or lower part of the demand distribution across markets. We then use a flexible specification (fractional polynomials) to regress the resulting distributions of productivity and demand against the log of each firm's total export sales in the same year.[13]

Figure 1.2 plots the estimated relationship between productivity or demand and total firm-level export sales. We find that export sales are strongly increasing in both productivity and demand. Under the admittedly strong assumption that the demand shocks in each market are independent of each other, our normalization will equalize the standard deviation of both productivity and demand. The slope of each line (productivity or demand) is suggestive of each component's individual relationship with export sales. We observe that the slope of the demand curve is steeper than the productivity curve almost everywhere.

Figure 1.3 plots a similar relationship between productivity, demand and the frequency of exporting. Likewise, Figure 1.4 captures the relationship between productivity or demand and the number of active export markets. The dependent variable in this exercise is the number of distinct countries to which the firm exports in a given year. Export frequency and the number of export markets are both positively associated with productivity and demand. Again, casual observation, though hardly conclusive, would suggest that a one standard deviation increase in demand may have a substantially larger impact on entry or export frequency than a one standard deviation increase in productivity.

[13] Specifically, we normalize firm-product specific physical productivity by subtracting the product-specific average productivity from each variable and dividing the difference by standard deviation of product-specific physical productivity. We repeat this normalization exercise for demand, except, in this second case, the normalization is product-and-market specific since we observe a demand shock for each market a firm-product pair enters. To develop a measure of product-specific, rather than product-market specific demand, we take the simple average over all markets the firm entered in each year. We then renormalize our measure of firm-specific demand so that both normalized demand and productivity have a mean of zero and a standard deviation of one.

1.4 Idiosyncratic Sources of Aggregate Export Growth

It is widely reported that Chinese exports have grown dramatically over the past two decades. Even in our short sample, this pattern is striking; in many export markets we observe that aggregate exports are 4 or 5 times larger in 2005 than they were in 2002. Little is known, however, regarding the differential role demand and productivity to Chinese export growth. We proceed by first characterizing the importance of idiosyncratic changes across firms, products and markets for explaining export growth (whether demand or productivity). We then quantify the relative impact of changes in physical productivity and demand. Finally, we further decompose aggregate idiosyncratic productivity and demand growth to determine the extent to which each of these can be attributed to growth within firm-product pairs, reallocation across products or product churning in international markets.

Our model implies that the quantity sold of product k by firm f in market i can be written as

$$\ln q_{fikt} = \sigma_k \ln \varphi_{fkt} + \sigma_k \ln d_{fikt}$$

where, as before,

$$\begin{aligned} \ln d_{fikt} &= \ln A_{ikt} - \sigma_k \ln\left(\frac{w_{jkt}\tau_{ijkt}}{\rho_k}\right) + \sigma_k \ln(\delta_{fikt}) + \varepsilon_{fikt} \\ &= c_{ikt} + \sigma_k \ln(\delta_{fikt}) + \varepsilon_{fikt}. \end{aligned} \tag{1.7}$$

and the product-market-year specific effects which are constant across all firms in the same product-market and year are collected in c_{ikt}. Examining equation (1.7) we cannot separately decompose growth into productivity growth, demand growth, and product-market-year effects using data on sales, productivity and a composite demand term, d_{fikt}, because d_{fikt} contains both idiosyncratic components, δ_{fikt}, and market-specific components, c_{ikt}. This is problematic because if we were to compare the individual contributions of d_{fikt}

and φ_{fkt} to export growth, we would be loading all changes which increased the export sales of all Chinese exporters into the 'demand' component. As such, to the extent that Chinese exporters have universally experienced substantial growth in export sales due to aggregate shocks (c_{ikt}) we may potentially strongly overstate the impact of idiosyncratic demand changes relative to those of productivity.[14]

We address this by considering the sales of any given exporter relative to a reference (average) firm selling the same product in the same destination market in the same year. For convenience, let the reference firm simply be the sample average in that product-market-year. Specifically, we consider the difference between export sales for any given firm and the reference firm as

$$\begin{aligned}
\ln q^I_{fikt} &\equiv \ln q_{fikt} - \ln q^A_{ikt} \\
&= \sigma_k(\ln \varphi_{fkt} - \ln \varphi^A_{ikt}) + \sigma_k(\ln d_{fikt} - \ln d^A_{ikt}) \\
&= \sigma_k(\ln \varphi_{fkt} - \ln \varphi^A_{ikt}) + \sigma_k(\ln \delta_{fikt} - \ln \delta^A_{ikt}) \\
&= \sigma_k \ln \varphi^I_{fikt} + \sigma_k \ln \delta^I_{fikt} \qquad (1.8)
\end{aligned}$$

where $\ln q^A_{ikt} = \frac{1}{N_{ikt}} \sum_{f \in \mathscr{F}_{ikt}} \ln q_{fikt}$, $\ln \varphi^A_{ikt} = \frac{1}{N_{ikt}} \sum_{f \in \mathscr{F}_{ikt}} \ln \varphi_{fkt}$, $\ln d^A_{ikt} = \frac{1}{N_{ikt}} \sum_{f \in \mathscr{F}_{ikt}} \ln d_{fikt}$, $\ln \delta^A_{ikt} = \frac{1}{N_{ikt}} \sum_{f \in \mathscr{F}_{ikt}} \ln \delta_{fikt}$, N_{ikt} is the number of firms selling product k in destination market i in year t and $\mathscr{F}_{ikt}$ is the set of all firms which export good k to destination i in year t. In this sense, we refer an outcome (sales, productivity, demand) with an 'A' superscript as the average for a given product-market-year triplet ikt. The difference between observed outcome and the average is denoted with an I which implies that any variation in this component reflects only idiosyncratic variation relative to the average. As demonstrated in equation (1.8), a key advantage of this simple transformation is that it relates what we observe in the data (d_{fikt}) to what we want to measure in theory (δ_{fikt}). Specifically, the benefit of this approach is that it eliminates the constant c_{ikt} without eliminating trend

[14]We might expect that all Chinese exporters in a given market observe export growth due to deregulation, trade liberalization, adverse demand shocks to competitors from other countries, etc.

growth for any given firm. That said, any 'within-firm' or trend growth will be measured relative to the product market average firm in each year.[15]

We can then define aggregate exports in a given market as $Q_{ikt} \equiv \sum_{f\in\mathscr{F}_{ikt}} \theta_{fikt} \ln q_{fikt}$ where $\theta_{fikt} = \frac{q_{fikt}}{\sum_{f\in\mathscr{F}_{ikt}} q_{fikt}}$ is firm f's market share of exports in product k to destination market i in year t. Inserting the individual demand function into the aggregate export equation gives us a measure of aggregate export growth

$$\Delta Q_{ikt} = \Delta Q^A_{ikt} + \Delta Q^I_{ikt} = \Delta Q^A_{ikt} + \sigma_k \Delta \Phi^I_{ikt} + \sigma_k \Delta \mathscr{D}^I_{ikt}$$

where $Q^A_{ikt} = \sum_{f\in\mathscr{F}_{ikt}} \theta_{fikt} \ln q^A_{ikt} = \ln q^A_{ikt}$, $Q^I_{ikt} = \sum_{f\in\mathscr{F}_{ikt}} \theta_{fikt} \ln q^I_{fikt}$, $\mathscr{D}^I_{ikt} = \sum_{f\in\mathscr{F}_{ikt}} \theta_{fikt} \ln \delta^I_{fikt}$, $\Phi^I_{ikt} = \sum_{f\in\mathscr{F}_{ikt}} \theta_{fikt} \ln \varphi^I_{fikt}$ and $\Delta Q_{ikt} = Q_{ikt} - Q_{ik,t-1}$.

The first quantities of interest for the decomposition exercise correspond to the percentage of aggregate export growth ΔQ_{ikt} which can be attributed to idiosyncratic changes ΔQ^I_{ikt} and those that affect all firms equally in the same product-market and year, ΔQ^I_{ikt}.

$$\text{Idiosyncratic Growth} = \frac{\Delta Q^I_{ikt}}{\Delta Q_{ikt}}, \qquad \text{Average Growth} = \frac{\Delta Q^A_{ikt}}{\Delta Q_{ikt}}$$

Next, we are further interested in determining the extent to which changes in idiosyncratic growth ΔQ^I_{ikt} are a function of demand growth, $\mathscr{D}^I_{ikt}$, or productivity growth, Φ^I_{ikt}. That is, we want to compute

$$\text{Demand Contribution} = \frac{\sigma_k \Delta \mathscr{D}^I_{ikt}}{\Delta Q^I_{ikt}}, \qquad \text{Productivity Contribution} = \frac{\sigma_k \Delta \Phi^I_{ikt}}{\Delta Q^I_{ikt}}.$$

These ratios capture the fraction of export growth, relative to the reference firm, which are attributable to demand or productivity growth in each market. After computing the productivity and demand contributions for each market, we then take a simple average of the contributions over the nearly 200 export markets and report our results in Table 1.4.

[15] An additional subtle feature is that while $\ln \varphi_{fkt}$ is not destination-specific, $\ln \varphi^I_{fikt}$ is destination-specific since $\ln \varphi^A_{ikt}$ varies by destination i.

We find four striking results. First, we find that the idiosyncratic component accounts for 47 percent, or nearly half, of all export growth in our sample. Second, year-to-year productivity changes explain 27 percent of the idiosyncratic component. This is broadly consistent with a wide set of research which suggests that firm size and export performance are strongly, positively associated with measures of firm and/or production efficiency. Third, idiosyncratic changes in product-and-firm specific demand explain over 70 percent of the relative export growth across firms. Remarkably, the same pattern emerges in almost all markets, and across firm and product types, though there are some key patterns which emerge. In particular, our fourth striking finding is that demand growth appears to play a particularly important role for undifferentiated products where it accounts for nearly all of the idiosyncratic component of export growth. The production of homogeneous, highly standardized goods are likely be characterized by firms with nearly identical production efficiency.[16] In contrast, productivity growth is substantially more important among products produced by state-owned firms where it explains nearly 34 percent of the idiosyncratic component over the 2002-2005 period. Notably, even among state-owned firms demand growth explains almost twice as much as productivity growth.

1.4.1 Sources of Demand and Productivity Growth

To get a sense of where the gains in demand come from we further decompose our measure of idiosyncratic log demand into components capturing within-firm demand growth, the reallocation of demand across Chinese exporters and net entry. Specifically,

$$\begin{aligned}\Delta\mathscr{D}^I_{ikt} \quad = \quad & \sum_{l\in C}\theta_{fik,t-1}\Delta\ln\delta^I_{fikt} + \sum_{l\in C}(\ln\delta^I_{fik,t-1} - \mathscr{D}^I_{ik,t-1})\Delta\theta_{fikt} + \sum_{l\in C}\Delta\ln\delta^I_{fikt}\Delta\theta_{fikt} \\ & + \sum_{l\in E}\theta_{fikt}(\ln\delta^I_{fikt} - \mathscr{D}^I_{ikt}) - \sum_{l\in X}\theta_{fik,t-1}(\ln\delta^I_{fik,t-1} - \mathscr{D}^I_{ik,t-1}) \qquad (1.9)\end{aligned}$$

[16] We check that the products we describe as undifferentiated and differentiated satisfy Rauch (1999) classification of undifferentiated or differentiated products.

where $\mathscr{D}^I_{ikt}$ is our measure of aggregate demand for product k in market i and year t relative to the reference firm in that product market and year, C is the set of continuing varieties, X is the set of exiting varieties, and E is the set of entering varieties in year t.[17] Our decomposition closely follows the straightforward decomposition for "aggregate productivity" proposed by Foster, Haltiwanger and Krizan (2001) but is extended to capture the fact that for idiosyncratic demand we need to consider relative growth (rather than absolute growth) so as to eliminate product-market-year specific effects.

The first term in this decomposition captures changes relative demand growth within firm-product pairs, weighted by the initial shares in the export product market. It captures whether products with relatively large market shares in year $t-1$ tend to grow faster or slower than the average product. The second term represents a between-product component. It reflects changing market shares weighted by the deviation of initial $(t-1)$ product demand from the initial product-market index. The third term is a relative covariance-type term and captures the correlation between changes in demand and market shares. This term captures whether firms which experience relatively large changes in idiosyncratic demand simultaneously observe relatively large increases in market shares. The final two terms capture the effect of product turnover. For comparison purposes we also provide an analogous decomposition of average log productivity.[18]

The first row of Table 1.5 reports the results for our decomposition of average export demand. We find, not surprisingly, that relative within-product growth is strongly negative. This indicates that surviving products which initially had below average market shares were likely to experience stronger than average demand growth. As we expect, products with small market shares which do not grow are highly likely to dropped from export markets

[17]To be clear, we define an entering variety as a firm-product pair which was not exported to market i in year $t-1$ but is exported to market i in year t. An exiting variety is a variety which is exported to market i in year $t-1$, but was not exported to market i in year t.

[18]Note the the second, fourth and fifth terms are identical to those in Foster, Haltiwanger and Krizan (2001). The computation and interpretation of the first and third terms, in contrast, are substantially different since we are now comparing product-level changes relative to a reference (average) product rather than to a level itself.

altogether.[19] The second term indicates that there is little increase in market shares for products which had relatively high demand in the previous year. Rather, the third term indicates that firms which experience large increases in demand experience even larger contemporaneous increases in market shares. Finally, net entry increased total export demand growth across markets by 2.5 percentage points. It would be mistaken, however, to interpret this finding as small; as argued above, aggregate demand growth is the largest contributor to total export growth. Moreover, it is telling that the exit of low demand firms contributes significantly to aggregate demand growth. We investigate these features of the data further in Section 5.

The second row of Table 1.5 provides analogous results for the physical productivity of Chinese exporters. We find substantial, but much smaller changes by comparison. For instance, the within-firm results suggest that surviving small firms are likely to report higher physical productivity growth than large established exporters. However, relative productivity growth is only a fourth of that of demand. The between and cross terms suggest that relatively large productivity improvements induce contemporaneous increases in market shares, while net entry improves aggregate demand growth by 1.5 percentage points. Combined with our findings on product turnover across productivity and demand we find that product churning in export markets increased export growth by two percentage points, or, in other words, it explained approximately 7 percent of aggregate export growth alone.

Finally, the third row of Table 1.5 considers the same decomposition for revenue productivity. We find starkly different results, particularly for the within and cross findings. For revenue productivity, we observe that small surviving exporters demonstrate smaller than average revenue productivity growth and smaller market share changes for a given revenue productivity improvement. Both of these results indicate that prices confound movements in costs and revenues; increases in costs tend to be reflected in higher prices

[19] This finding mirrors that in the firm growth literature where it is well known that, without correcting for endogenous firm exit, small firms are often observed to grow faster than large firms. See Mansfield (1962), Evans (1987) or Hall (1987) for examples.

and changes in revenue productivity which are misleading relative to genuine changes in physical efficiency. The Supplemental Appendix presents a similar decomposition across regions of the world, types of firms and product differentiation (Tables A2-A4). In each case, we find qualitatively similar results.

Given the findings from our decomposition exercise we would expect that the evolution of demand over time may have a strong impact on exporter behavior over time. Similarly, if we studied entering, exiting and incumbent exporters we would expect to observe substantial differences in both productivity and demand. Moreover, given the preceding literature which documents the importance of productivity for firm and/or product survival in export markets, we would expect that demand shocks may play a similar role. Unfortunately, little is known about the separate impact of demand and productivity on firm and industry evolution in export markets. We address this issue in the Chinese context next.

1.5 Dynamics in International Markets

This section investigates three salient features of productivity and demand behaviour in international markets. First, we document the persistence of these characteristics within firms over time. Next, we study the impact of these determinants on product selection across international markets and quantify the importance of both firm-level characteristics and market-specific features. Finally, we examine the differences across entering, exiting and incumbent exporters.

1.5.1 Persistence

Export markets are generally characterized by very high rates of turnover.[20] Despite this, numerous papers demonstrate strong persistence in many of the determinants of firm-level behaviour. In particular, conditional on survival, productivity, demand and prices

[20] In Table A1 of the Appendix we document that one year exit and entry rates in our data are approximately 60 percent.

have been shown to be strongly persistent in both domestic and international markets.[21] We re-examine these findings with three small, but important differences: i) we study the extent to which using physical TFP in place of revenue based TFP changes our estimates of productivity persistence, ii) we study differences in the evolution of export demand across broad regions worldwide and iii) we study differences in the persistence across productivity and demand.

Consider a determinant x_{fikt} which is firm, product, market and year-specific (e.g. demand). A natural starting point for determining the persistence rates in this measure would be the OLS regression of a simple AR(1) model

$$x_{fikt} = \rho x_{fik,t-1} + \varepsilon_{fikt} \tag{1.10}$$

where ε_{fikt} is an *iid* error term. Unfortunately, a selection issue arises because many of the firms which export product k to market i in year $t-1$ will not export the same product to that market in year t. Further, as documented below, exiting firms systematically differ from those that survive to the next year. Since we cannot recover x_{fikt} for the exiting firms, our estimate of ρ is likely to be accordingly biased.

To account for this potential source of bias, we use a simple first stage selection correction to control for endogenous exit. We include last year's observed demand, productivity and market characteristics as explanatory variables and use the results from the selection regressions to form the inverse Mills ratio. We include the inverse Mills ratio as an additional regressor in the estimation of equation (1.10).[22] We focus on the persistence parameters for demand, productivity, prices and revenues reported in Table 1.6. In each case, we observe that idiosyncratic determinants of trade are strongly persistent over time. Revenue

[21]See Supina and Roberts (1996), Baily, Hulten and Campbell (1992), Foster, Haltiwanger and Krizan (2001), Das, Roberts and Tybout (2007), Foster, Haltiwanger and Syverson (2008) and Aw, Roberts and Xu (2012) among others.

[22]For variables which do not vary by location, such as productivity, it is unclear how to measure export demand across all markets since some firms export the same product to more destinations than others. To simplify our problem we capture lagged aggregate export demand across all destinations as $\bar{d}_{fk,t-1} = \sum_i d_{fik,t-1}$ and include this as a first stage regressor.

TFP appears somewhat less persistent than physical TFP. The autocorrelation coefficient on physical TFP is 0.81 while the estimated autocorrelation coefficient is 0.66 for revenue TFP. This suggests that temporal price shocks contribute to the relative lack of persistence in revenue-based productivity. Our measures of demand displays a similar degree of persistence to that of productivity with an estimated autocorrelation parameter of 0.85. Considering the high degree of persistence displayed in our measure of idiosyncratic demand and its contribution to export growth, we expect that understanding the evolution of product-level demand may be as important to characterizing product selection in export markets as that of productivity. Finally, given the observed persistence in productivity and demand, it is not surprising that revenue and prices also reflect a high degree of persistence with estimated autocorrelation coefficients above 0.75.

1.5.2 Selection Dynamics

In this section we explore the role of productivity and demand on product survival across markets worldwide and evaluate the extent to which each of these determinants has a significant impact on exit decisions. We consider annual logit exit regressions where we regress an indicator for firm f's decision to drop out of product market ik in year $t+1$ on our measures of producers' idiosyncratic characteristics and destination-specific variables. Specifically, let $\chi_{fik,t+1}$ be a binary variable which takes a value of 1 if a year t exporter to market i stops exporting product k to the same market in year $t+1$. We can then write the logit equation as

$$E(\chi_{fik,t+1}=1|X_{fikt}) \quad = \quad [1+\exp\{-(\beta_0+X_{fikt}\beta+\Lambda_{fk}+\Lambda_t)\}]^{-1}.$$

where X_{fikt} includes key explanatory variables such as productivity, demand, destination market-size (proxied by real GDP), destination market-income (proxied by real GDP per capita) and the distance between the destination country's capital city and Beijing (all in logarithms). We also consider specifications which include a number of additional firm-specific variables, such as: firm age, firm capital and the log of the average import price. The log average import price is often used as a measure of input quality (e.g. See Manova and Zhang, 2012). Since many of our exporting firms in the matched sample import at least one input, we are able to study the extent to which this measure captures the same heterogeneity as our demand measures. For instance, Gervais (2012) constructs very similar demand measures, but refers to them as product quality. Here, we can directly examine whether there is additional variation in import prices which is not captured by our demand residuals. Last, Λ_{fk} and Λ_t are vectors of firm-product and time dummies, respectively. The firm-product fixed effects are of particular importance in this context: it is widely reported that there exists important product-specific and/or firm-level differences in access to credit, government subsidies and export licenses in the Chinese manufacturing sector. Each of these are likely to affect product dropping decisions. Including firm-product fixed effects allows us to control for these unobserved time-invariant differences across firms.[23]

Table 1.7 presents the impact of each explanatory variable on product exit decisions when we pool all of our data.[24] The first four columns study the individual effect of productivity, demand and prices on exit. Higher revenue productivity is found to significantly deter exit, while physical productivity, though negative is never significantly different from zero. In contrast, column 3 suggests firms with higher demand shocks are much less likely to exit export markets, particularly when we compare the marginal impact of demand relative to productivity. Similarly, firms that charge higher prices for their product are less likely to drop those products in export markets. This suggests that the difference in the results between the first and second columns is likely driven by differences in prices rather than physical productivity across firms. Column 5 examines the joint impact of productivity and demand, while column 6 adds other key firm-level determinants: age, log capital,

[23] Conditional MLE estimation under the above specification is discussed in detail by Wooldridge (2002), Chapter 15.

[24] Marginal effects and the associated standard errors are reported.

and the log import price. In each case, we observe that demand always has a statistically significant effect on exit, while productivity does not. Moreover, the marginal impact of demand is much larger than that of product-level productivity. Among the additional firm-level variables, none of them are found to have a statistically significant impact on exit. The last two rows of each column present the impact of market-specific measures on product dropping. Not surprisingly, we consistently find that Chinese exporters are less likely to leave large markets, richer markets, and markets which are closer to China.

We check the robustness of our results by splitting our sample in a number of interesting dimensions. First, Table 1.8 examines the same regressions across different types of firms ownership (private, foreign, state), the type of trade (ordinary trade, processing trade) and degrees of product differentiation.[25] We find that our results hold broadly across different types of firms, the nature of trade and across product differentiation. In general, stronger demand is always found to significantly deter product exit from export markets, while productivity is never found to be significantly different from zero. Moreover, in all cases, the marginal impact of demand is always found to be substantially larger than that of productivity.

1.5.3 Evolution of Key Distributions

Finally, we consider the role of selection in export markets on macroeconomic outcomes by documenting differences in key variables across entering, continuing, and exiting products. We compute these differences by regressing each of the key product and firm specific measures (productivity, demand, prices, revenue) on entry and exit dummies and a complete set of product-by-market-by-year fixed effects. Specifically, let x_{fikt} be a product-firm-market specific variable (e.g. demand), let χ^{E}_{fikt} be an entry dummy variable and let χ^{X}_{fikt} be an exit dummy variable. The entry dummy for year t equals one if the firm

[25] It is natural to expect that export relationships may vary across ownership and products. For example, to export from China each firm must first acquire an export license. It is well-known that there have strong institutional preferences to allocate licenses differentially across Chinese manufacturing firms.

enters product-market *ik* between year $t-1$ and t. Likewise, the exit dummy equals one if the firm exits product-market *ik* sometime between t and $t+1$. The product-year-market dummies capture the evolution of continuing (or incumbent) producers in product market *ik*. Our regression is written as

$$x_{fikt} = \gamma_0 + \gamma_E \chi^E_{fikt} + \gamma_X \chi^X_{fikt} + \Lambda_{ikt} + \mu_{fikt}$$

where Λ_{ikt} is a collection of product-market-year dummies and μ_{fikt} is the *iid* error term. The coefficients γ_E and γ_X capture the average log point difference in x_{fikt} for entering and exiting firms, respectively, relative to incumbents.

The first two rows of Table 1.9 present the coefficients on the entry and exit variables in our regressions. Whether or not we conclude that new exporters are more productive than incumbent exporters in the same product market depends heavily on our measurement of productivity. Our estimates imply that new exporters are 1 percent *more* productive than incumbent exporters if we use the revenue based measure of productivity. In contrast, if we use our measure of physical productivity we find exactly the opposite: new exporters are 18 percent *less* productive than incumbent exporters. Among exiting firms we find that productivity is 2.4-5.7 percent lower than that of incumbent exporters once we control for capacity constraints.[26]

The differences between the physical and revenue based productivity coefficients among entering firms can largely be explained by pricing behavior. New entrants generally choose *high* prices; the annual results in Table 1.9 imply that new entrants are charging prices which are 18 percent higher than incumbent firms. This aspect of firm behaviour can be rationalized by the fact that new exporters are likely to be high cost (low productivity) producers relative to incumbent exporters.

Like physical productivity, we find that new firms also experience relatively small

[26]We also provide results conditioned on existing capital to control capacity constraints. See Rho and Rodrigue (2012) for discussion. We omit the results using capital-intensity since they are very similar.

amounts of demand in a typical product market. However, the magnitude of these differences are much larger. Entering or exiting firms are estimated to have demand measures which are 61-62 log points smaller than those of incumbent exporters. Taken together with the estimated coefficients on the entry dummy, we observe that the high turnover of firms in international markets likely reflects a recycling of firms with low demand shocks in export markets. Tables 1.10 and 1.11 document the results across product differentiation, high-and-low productivity firms, and firm-type (private firms engaged in ordinary trade, private firms engaged in processing trade, foreign-owned firms and state-owned firms). We observe that the same qualitative patterns arise in every every case. Given the dramatic differences in demand measures between incumbent and entering or exiting products, our results indicate that understanding how low demand entrants become successful, high demand incumbents is a rich area for future research.

1.6 Conclusion

This paper studies the nature of product selection among Chinese exporters, its implications for Chinese export growth across markets worldwide, and the evolution of productivity and demand in international markets. We find that idiosyncratic differences across firms account for at least half of all export growth. Moreover, while both idiosyncratic productivity and demand are strongly associated with key export outcomes, and contribute significantly to export growth, idiosyncratic demand contributes 2.7 times as much as productivity growth. Our empirical work further establishes that surviving products with small market shares are characterized by relatively fast demand and market share growth. Product churning alone is found to account for 7 percent of total export growth, largely through the exit of costly products with relatively little demand in export markets.

We further show that entering and exiting products tend to be less productive and have relatively little demand. However, it is the differences in measured demand that are by far the largest. Our estimates suggest that measured demand among entering and exiting varieties are 61-62 log points smaller than that of the average incumbent exporter to the same market. Similarly, despite the fact that both idiosyncratic productivity and demand are found be highly persistent, only demand is found to be a strong determinant of which products are dropped from export markets.

Table 1.1: Average Percentage of Revenues From Exports

Industry Code	Matched Sample	Full Sample	Industry Code	Matched Sample	Full Sample	Industry Code	Matched Sample	Full Sample
13	62.83	72.23	23	58.57	55.59	33	42.43	41.51
14	44.47	37.80	24	91.48	92.02	34	74.96	75.18
15	40.65	36.62	25	40.81	42.80	35	51.75	52.62
16	6.76	14.01	26	45.42	37.99	36	39.56	39.85
17	67.66	64.29	27	34.70	31.20	37	46.44	50.62
18	87.75	86.44	28	41.99	37.50	39	64.15	65.76
19	88.83	87.64	29	64.82	61.34	40	74.18	75.44
20	98.23	96.75	30	85.42	80.87	41	72.87	72.88
21	97.46	97.56	31	60.56	67.41	42	94.24	97.92
22	48.81	44.10	32	39.62	40.12			

Notes: The second, fifth and eighth columns document the average percentage of revenues from export sales in our matched sample. The third, sixth and ninth column presents the same information for the full firm-level sample.

Table 1.2: Summary Statistics for Exports, Price, Productivity and Demand

	Price Coefficient α_1					
	IV		OLS			
Percentile	Estimate	Std. Error	Estimate	Std. Error	HS6 Code	Description
10	-7.604	*0.043*	-7.004	*0.000*	292112	Diethylamine
25	-3.349	*0.954*	-1.358	*0.108*	621320	Cotton Handkerchiefs
50	-1.645	*0.577*	-1.221	*0.061*	611699	Gloves and Mittens[a]
75	-1.287	*0.418*	-1.002	*0.104*	902790	Microtones[b]
90	-1.100	*1.428*	-0.941	*0.135*	902810	Gas meters

Notes: The above results correspond to estimated isoelatic demand curves described in Section 3. We estimate an iso-elastic demand curve by IV and OLS. All regressions include product-market-year fixed effects. Standard errors, clustered by firm-product pair, are in italics. (*a*) Knitted or crocheted gloves and mitts. (*b*) Instruments for chemical analysis.

Table 1.3: Summary Statistics for Exports, Price, Productivity and Demand

Correlations							
Variables	Physical Exports	Revenue Exports	Physical Prod.	Revenue Prod.	Demand	Price	Capital
Physical Exports	1.000						
Revenue Exports	0.874	1.000					
Physical Prod.	0.608	0.407	1.000				
Revenue Prod.	0.275	0.445	0.705	1.000			
Demand	0.154	0.174	-0.115	-0.141	1.000		
Price	-0.509	-0.027	-0.532	0.224	-0.010	1.000	
Capital	0.401	0.429	0.002	-0.054	0.114	-0.063	1.000
Standard Deviations							
Standard Deviations	3.105	2.708	2.033	1.698	1.845	1.614	2.878

Notes: This table shows the correlations and standard deviations for key variables in our pooled sample of firm-product-market-year observations. We remove product-market-year fixed effects from each variable before computing the statistics. All variables are in logarithms.

Table 1.4: Decomposition of Aggregate Export Growth

	Total Export Growth	% Export Growth Explained By Avg. Pdt-Mkt-Yr Growth	Idiosyncratic Growth	% Idiosyncratic Growth Explained By Physical Productivity	Export Demand
All Products and Countries	0.273	0.533	0.467	0.270	0.730
North America	0.824	0.551	0.449	0.457	0.543
Europe	0.348	0.535	0.465	0.460	0.540
Japan	-0.178	0.505	0.495	0.112	0.888
Australia	0.071	0.575	0.425	0.066	0.934
South America	0.563	0.617	0.383	0.211	0.789
Rest of Asia	-0.101	0.436	0.564	0.513	0.487
Africa	0.212	0.492	0.508	0.466	0.534
Private, Ordinary Trade	0.191	0.525	0.475	0.074	0.926
Private, Processing Trade	0.872	0.435	0.565	0.101	0.899
Foreign Firms	0.269	0.521	0.479	0.185	0.815
State-Owned Firms	0.170	0.554	0.446	0.335	0.665
Undifferentiated Products	-0.064	0.604	0.396	0.028	0.972
Differentiated Products	0.281	0.534	0.466	0.258	0.742

Notes: The first column reports total export growth (in percentages). The second and third column decompose total export growth into an idiosyncratic component and average product-market-year growth, where the latter represents the average percentage change in sales of a given product in a given market over two years. The fourth and fifth columns decompose the idiosyncratic component of export growth into its productivity and demand components. Total export growth is the weighted average year-to-year export growth where firm sales are used weights.

Table 1.5: Decomposition of Productivity and Demand Growth

	Components of Decomposition					
Determinant	Within	Between	Cross	Entry	Exit	Net Entry
Log Demand	-0.118	-0.013	0.116	0.012	-0.013	0.025
Log Physical Productivity	-0.015	-0.009	0.039	-0.010	-0.025	0.015
Log Revenue Productivity	0.028	0.038	-0.095	-0.014	-0.024	0.010

Notes: This table decomposes the productivity and demand components of average exports. The first column captures changes in relative growth within firm-product pairs, weighted by the initial shares in the export product market. The second term represents a between-product component. It reflects changing shares weighted by the deviation of initial product demand/productivity from the initial product-market index. The third term is a relative covariance-type term and captures the correlation between changes in demand/productivity and market shares. The final two terms capture the effect of product turnover.

Table 1.6: Persistence in Productivity and Demand

	Revenue TFP	Physical TFP	Demand	Price	Revenue
All firms and products	0.657	0.810	0.850	0.753	0.819
	0.002	*0.002*	*0.002*	*0.002*	*0.002*
Private Firms, Ordinary Trade	0.629	0.823	0.848	0.739	0.828
	0.003	*0.002*	*0.002*	*0.003*	*0.002*
Private Firms, Processing Trade	0.672	0.821	0.861	0.829	0.776
	0.006	*0.005*	*0.005*	*0.005*	*0.005*
Foreign Owned Firms	0.645	0.808	0.857	0.814	0.715
	0.004	*0.003*	*0.003*	*0.003*	*0.003*
State Owned Firms	0.638	0.778	0.778	0.760	0.780
	0.006	*0.005*	*0.005*	*0.005*	*0.005*
Undifferentiated Products	0.472	0.877	0.752	0.743	0.807
	0.021	*0.010*	*0.016*	*0.017*	*0.012*
Differentiated Products	0.661	0.817	0.859	0.760	0.808
	0.002	*0.002*	*0.002*	*0.002*	*0.002*

Notes: This table reports the results of autoregressive regressions, corrected for selection. Reported coefficients are those on the lagged dependent variable. Standard errors are in italics.

Table 1.7: Determinants of Selection: Full Sample

Revenue TFP	-0.010					
	0.002					
Physical TFP		-0.00001			-0.00001	-0.00001
		0.00001			*0.00001*	*0.00001*
Demand			-0.046		-0.046	-0.046
			0.004		*0.004*	*0.005*
Price				-0.017		
				0.002		
Age						-0.0002
						0.0006
Capital						0.001
						0.001
Import Price						0.0004
						0.0008
Distance	0.054	0.055	0.038	0.056	0.037	0.041
	0.005	*0.005*	*0.005*	*0.005*	*0.005*	*0.007*
Income	-0.025	-0.025	-0.019	-0.025	-0.019	-0.021
	0.003	*0.003*	*0.002*	*0.003*	*0.002*	*0.003*
Size	-0.026	-0.027	-0.014	-0.027	-0.014	-0.016
	0.001	*0.001*	*0.001*	*0.001*	*0.001*	*0.002*
No. of Obs.	629,570	629,570	629,570	629,570	629,570	446,706

Notes: This table reports the results from various logit fixed effect regressions. Each regression controls for the distance from China, average income (measured by real GDP per capita), size (measured by real GDP) and time dummies. Marginal effects are reported and standard errors are documented in italics. The number of observations in the last column is smaller than the other columns because not all firms import materials.

Table 1.8: Determinants of Selection, by Firm or Product Type

Sample	Private, Ordinary Trade	Private, Processing Trade	Foreign Firms	State-Owned Firms	Differentiated Products	Undifferentiated Products
Physical TFP	-0.00001	0.000004	-0.00001	0.000004	-0.00001	-0.0003
	0.00001	*0.00001*	*0.00001*	*0.00002*	*0.00001*	*0.0002*
Demand	-0.029	-0.053	-0.041	-0.058	-0.041	-0.074
	0.005	*0.007*	*0.008*	*0.007*	*0.008*	*0.014*
Distance	0.015	0.071	0.035	0.058	0.035	0.124
	0.005	*0.005*	*0.008*	*0.011*	*0.009*	*0.029*
Income	-0.012	-0.021	-0.025	-0.021	-0.025	-0.038
	0.003	*0.008*	*0.005*	*0.005*	*0.005*	*0.020*
Size	-0.008	0.004	-0.014	-0.019	-0.014	-0.019
	0.001	*0.004*	*0.002*	*0.002*	*0.002*	*0.019*
No. of Obs.	249,356	55,710	198,111	87,052	520,284	55,456

Notes: This table reports the results from various logit fixed effect regressions. Each regression controls for the distance from China, average income (measured by real GDP per capita), size (measured by real GDP) and time dummies. Marginal effects are reported and standard errors are documented in italics.

Table 1.9: Evolution of Productivity and Demand

	Dependent Variable									
	Revenue TFP		Physical TFP		Demand		Price		Revenue	
Entry	0.012	0.009	-0.176	-0.255	-0.621	-0.613	0.185	0.192	-0.918	-0.886
	0.003	*0.003*	*0.003*	*0.003*	*0.016*	*0.016*	*0.003*	*0.003*	*0.004*	*0.004*
Exit	-0.020	-0.024	0.020	-0.057	-0.623	-0.613	-0.041	-0.035	-0.829	-0.808
	0.003	*0.003*	*0.003*	*0.003*	*0.015*	*0.015*	*0.003*	*0.003*	*0.004*	*0.004*
Capital		0.061		-0.074		-0.121		-0.102		-0.022
		0.001		*0.001*		*0.007*		*0.001*		*0.002*
No. of Obs.	1,208,771									

Notes: The above table presents the coefficients on the exit and entry dummy variables. All regressions include product-by-year-by-market fixed effects. Standard errors are clustered by firm-product pair and are reported in italics.

Table 1.10: Evolution of Productivity and Demand

	Dependent Variable									
	Revenue TFP	Physical TFP	Demand	Price	Revenue	Revenue TFP	Physical TFP	Demand	Price	Revenue
	Private Firms, Ordinary Trade					Private Firms, Processing Trade				
Entry	-0.032	-0.183	-0.425	0.150	-0.731	0.042	-0.127	-0.252	0.170	-0.435
	0.004	*0.005*	*0.022*	*0.004*	*0.006*	*0.007*	*0.009*	*0.042*	*0.008*	*0.0012*
Exit	-0.057	-0.031	-0.495	-0.024	-0.693	-0.003	0.062	-0.293	-0.066	-0.428
	0.004	*0.005*	*0.022*	*0.004*	*0.006*	*0.007*	*0.009*	*0.042*	*0.008*	*0.013*
	Foreign Owned Firms					State Owned Firms				
Entry	0.025	-0.170	-0.681	0.186	-0.998	-0.004	-0.163	-0.392	0.159	-0.675
	0.004	*0.005*	*0.029*	*0.005*	*0.008*	*0.006*	*0.007*	*0.028*	*0.007*	*0.009*
Exit	0.003	0.018	-0.587	-0.022	-0.905	-0.044	-0.017	-0.440	-0.025	-0.628
	0.004	*0.005*	*0.029*	*0.005*	*0.008*	*0.006*	*0.007*	*0.029*	*0.007*	*0.009*

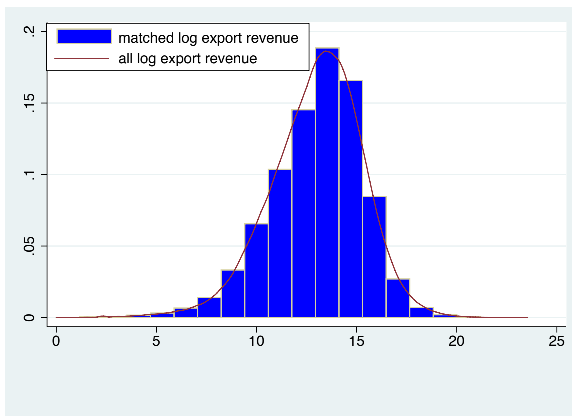
Notes: The above table presents the coefficients on the exit and entry dummy variables. All regressions include product-by-year-by-market fixed effects. Standard errors are clustered firm-product pair and are reported in italics. The number of observations in each panel are: 503,249 (private firms, ordinary trade), 108,784 (private firms, processing trade), 417,353 (foreign firms), 181,936 (state-owned firms).

Table 1.11: Evolution of Prices

	Sample					
	Differentiated Firms	Undifferentiated Firms	High Productivity Firms	Low Productivity Firms	High Demand Firms	Low Demand Firms
Entry	0.182	0.116	0.142	0.008	0.187	0.185
	0.003	*0.018*	*0.004*	*0.003*	*0.003*	*0.003*
Exit	-0.044	-0.014	-0.011	-0.002	-0.043	-0.041
	0.003	*0.018*	*0.004*	*0.003*	*0.003*	*0.003*
No. of Obs.	1,000,422	136,957	643,644	581,311	602,052	622,903

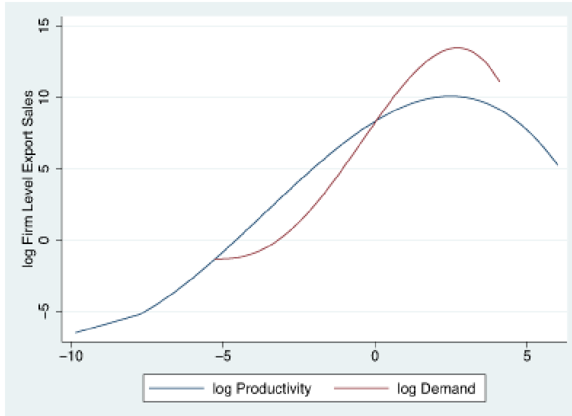
Notes: The above table presents the coefficients on the exit and entry dummy variables. All regressions include product-by-year-by-market fixed effects. Standard errors are clustered by firm-product pair and are reported in italics. High productivity products are defined, product-by-product, as products with a productivity level above the median product-level productivity. Low productivity firms are defined analogously. Likewise, high demand products are defined, product-market-by-product-market, as products a with demand shock above the median in each product-market.

Figure 1.1: Export Revenue Distribution in the Full and Matched Samples



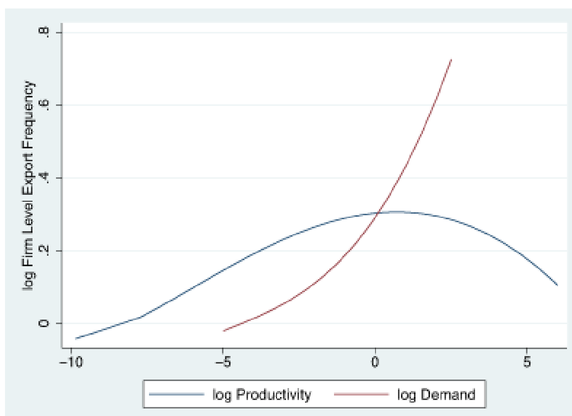
Notes: The blue histogram captures the log export revenue distribution in the matched sample. The red distribution presents the same information from the full firm-level sample.

Figure 1.2: Productivity, Demand and Export Sales



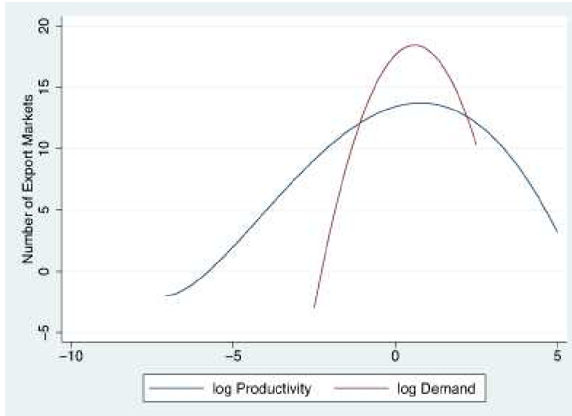
Notes: The blue line captures the fitted relationship between log export sales and productivity while the red line captures the fitted relationship between log export sales and average firm-product demand as defined in the text. In each case we use a flexible functional form to capture the relationship between variables (fractional polynomials).

Figure 1.3: Productivity, Demand and Export Frequency



Notes: The blue line captures the fitted relationship between the export frequency (months per year) of each firm and productivity while the red line captures the same relationship with average firm-product demand as defined in the text. In each case we use a flexible functional form to capture the relationship between variables (fractional polynomials).

Figure 1.4: Productivity, Demand and Export Market Entry



Notes: The blue line captures the fitted relationship between the number of export markets entered by each firm and productivity while the red line captures the same relationship with average firm-product demand as defined in the text. In each case we use a flexible functional form to capture the relationship between variables (fractional polynomials).

1.7 Appendix

1.7.1 Variable Construction

Prices, Quantities and Revenues We begin by calculating the average export price for each product using a revenue-weighted geometric mean. We then convert observed prices and revenues to a common year using the average annual price as a deflator. Last, we aggregate the data to the annual level, calculating average unit prices over the year, and repeat this exercise for each year and product in the data.

Variable Inputs We deflate intermediate materials with the Brandt, Van Biesebroeck and Zhang (2012) benchmark intermediate input deflators. Brandt, Van Biesebroeck and Zhang (2012) construct these deflators using detailed output deflators from the 2002 National Input-Output table. The intermediate input deflators are largely at the 3-digit industry level.

Capital Stock We do not directly observe the firm's capital stock. Instead, denote the book value of capital for firm f in year t as b_{ft}. Nominal new investment, ni_{ft}, is calculated in each year as

$$ni_{ft} = b_{f,t+1} - b_{ft}.$$

We then deflate nominal new investment ni_{ft} by the Brandt-Rawski (2008) investment deflator for China to get real investment, i_{ft}. In the first year of the sample, 2000, we define existing capital stock, $k_{f,t=2000}$ as the book value of fixed assets less accumulated depreciation. In subsequent years we calculate capital stock using the perpetual inventory method as

$$k_{f,t+1} = (1-d)k_{ft} + i_{ft}$$

where d is the depreciation rate. The depreciation rate is taken from Brandt, Van Biesebreck and Zhang (2012) and is set at $d = 0.09$.

Input Shares We assume that output of each product is produced by a Cobb-Douglas production function. To calculate productivity we will need to calculate input shares for labor, materials and capital, α_l, α_m and α_k, respectively, for each product. Let $\tilde{w}_{ft}$ denote firm f's total nominal wage payments and compensation in year t. Typically, we would calculate the labor share as total employee compensation divided by total revenue. Hsieh and Klenow (2008) suggest that the wage bill, $\tilde{w}_{ft}$, and compensation data are very likely to underestimate the labor share in the Chinese manufacturing data. We follow their approach whereby we multiply each firm's wage bill by a constant parameter, $\tilde{\rho}$, to inflate the wage bill in each firm. We determine the size of the constant parameter by choosing the parameter so that the aggregate labor compensation in the manufacturing sector matches the labor share in national accounts (roughly 50 percent).

Specifically, denote the total, observed payments to workers as

$$tw = \sum_f \sum_t \tilde{\rho}\tilde{w}_{ft} = \tilde{\rho} \sum_f \sum_t \tilde{w}_{ft} = \tilde{\rho}\widetilde{tw}$$

where $\tilde{\rho}$ is the unknown inflation parameter we need to determine and $\widetilde{tw}$ denotes the total observed labor compensation. Note that for this method to work we need to make sure that we are summing over *all* firms in *all* industries. Denote total revenues tr and total intermediate materials tm. Hsieh and Klenow (2008) suggest that the ratio of total wage payments to value added is roughly 50% from the Chinese national accounts and input-output tables. This implies that

$$\frac{tw}{tr - tm} = 0.5 \Rightarrow \frac{\tilde{\rho}\widetilde{tw}}{tr - tm} = 0.5 \Rightarrow \tilde{\rho} = 0.5\frac{tr - tm}{\widetilde{tw}}$$

Note that the procedure here is completed using all firms in each industry, not just those from our selected sample. After determining $\tilde{\rho}$ we can then calculate the labor share in each of the industries we focus on as

$$\alpha_l = \frac{1}{\tilde{N}} \sum_t \sum_f \frac{\tilde{\rho}\tilde{w}_{ft}}{\tilde{r}_{ft}}$$

where $\tilde{r}_{ft}$ are the firm's nominal revenues, and $\tilde{N}$ is the total number of firm-year observations. Likewise, we calculate the materials share as the average share of intermediate inputs in total revenues,

$$\alpha_m = \frac{1}{\tilde{N}} \sum_t \sum_f \frac{\tilde{m}_{ft}}{\tilde{r}_{ft}}$$

where $\tilde{m}_{it}$ is the total value of materials used by firm f in year t. Finally, in the absence of reliable capital share information we follow Hsieh and Klenow (2008) and assume constant returns to scale so that $\alpha_k = 1 - \alpha_l - \alpha_m$. We have alternatively tried estimating the input shares, and productivity, using control function methods (De Loecker et al., 2012). We find very similar measures of input shares and productivity. Moreover, our later results are all unaffected by this change. A detailed description of this alternative approach and the results from it can be found in the Supplemental Appendix.

Supplemental Appendix for "Product Selection and Export Growth: Evidence from Chinese Exporters"

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1.8 Supplemental Appendix

This appendix provides a variety of details related to model development and the robustness of the empirical results. Section A provides the simple proofs omitted from the main text. Section B describes the matching algorithm in detail. Section C documents additional results omitted from the main text while Section D checks the robustness of the results in the main text to an alternative measurement of demand and productivity.

1.8.1 Proofs

This section provides a simple proof for the effect of trade costs and the elasticity of substitution on exporting presented in the main text. Specifically, we consider the effect of a reduction in iceberg cost τ_{ij}. These results are analogous to that already demonstrated in Melitz (2003). The implicit function theorem implies $\frac{d\phi_{ik}^*}{d\tau_{ij}} = \frac{-\partial V_k^E/\partial\tau_{ij}}{\partial V_k^E/\partial\phi_{ik}^*} < 0$ and $\frac{d\phi_{ik}^*}{d\sigma_k} = \frac{-\partial V_k^E/\partial\sigma_k}{\partial V_k^E/\partial\phi_{ik}^*} > 0$.

Proof. Recall that the value of a product to the firm is

$$
\begin{aligned}
V_k^E &= \int_{\varphi_k}\int_{\delta_{1k}}\cdots\int_{\delta_{Ik}} \pi_{ik}(\phi_{i1k},\ldots\phi_{iJk},\phi_{1k}^*,\ldots,\phi_{Ik}^*)g(\varphi_k,\delta_{1k},\ldots,\delta_{Ik})d\delta_{Ik},\ldots,d\delta_{1k}d\varphi_k - s_k = 0 \\
&= \int_{\varphi_k^l}^{\varphi_k^u}\int_{\frac{\phi_{1k}^* w_j\tau_{i1}}{\varphi_k}}^{\delta_{1k}^e}\left[\left(\frac{\phi_{i1k}}{\phi_{1k}^*}\right)^{\sigma_1-1}-1\right]f_{1k}g(\varphi_k,\delta_{1k})d\delta_{1k}d\varphi_k \\
&\quad +\ldots\int_{\varphi_k^l}^{\varphi_k^u}\int_{\frac{\phi_{ik}^* w_j\tau_{ij}}{\varphi_k}}^{\delta_{ik}^e}\left[\left(\frac{\phi_{ijk}}{\phi_{ik}^*}\right)^{\sigma_i-1}-1\right]f_{ik}g(\varphi_k,\delta_{ik})d\delta_{ik}d\varphi_k \\
&\quad +\ldots\int_{\varphi_k^l}^{\varphi_k^u}\int_{\frac{\phi_{Ik}^* w_j\tau_{Ij}}{\varphi_k}}^{\delta_{Ik}^e}\left[\left(\frac{\phi_{Ijk}}{\phi_{Ik}^*}\right)^{\sigma_I-1}-1\right]f_{Jk}g(\varphi_k,\delta_{Ik})d\delta_{Ik}d\varphi_k - s_k = 0
\end{aligned}
$$

where $g(\varphi_k,\delta_{ik}) = \int_{\delta_{1k}}\cdots\int_{\delta_{i-1,k}}\int_{\delta_{i+1,k}}\cdots\int_{\delta_{Ik}} g(\varphi_k,\delta_{1k},\ldots\delta_{Ik})d\delta_{1k},\ldots,d\delta_{i-1,k},d\delta_{i+1,k},\ldots,d\delta_{I,k}$ and the second equation follows from our assumptions on constant returns in production and the market separability of demand. Then,

$$\frac{\partial V_k^E}{\partial \tau_{ij}} = \int_{\varphi_k^l}^{\varphi_k^u}\left[\left(\frac{\phi_{ik}^*}{\phi_{ik}^*}\right)^{\sigma_k-1}-1\right] f_{ik}g(\varphi_k,\delta_{ik})d\delta_{ik}d\varphi_k$$

$$+\int_{\varphi_k^l}^{\varphi_k^u}\int_{\frac{\phi_{ik}^* w_j\tau_{ij}}{\varphi_k}}^{\delta_{ik}^e}(1-\sigma_k)\left(\frac{\phi_{ijk}}{\phi_{ik}^*}\right)^{\sigma_k-1}\frac{f_{ik}}{\tau_{ij}}g(\varphi_k,\delta_{ik})d\delta_{ik}d\varphi_k<0$$

Likewise, consider the partial derivative of V_k^E with respect to ϕ_{ik}^*

$$\frac{\partial V_k^E}{\partial \phi_{ik}^*} = \int_{\varphi_k^l}^{\varphi_k^u}\left[\left(\frac{\phi_{ik}^*}{\phi_{ik}^*}\right)^{\sigma_k-1}-1\right] f_{ik}g(\varphi_k,\delta_{ik})d\delta_{ik}d\varphi_k$$

$$+\int_{\varphi_k^l}^{\varphi_k^u}\int_{\frac{\phi_{ik}^* w_j\tau_{ij}}{\varphi_k}}^{\delta_{ik}^e}(1-\sigma_k)\left(\frac{\phi_{ijk}}{\phi_{ik}^*}\right)^{\sigma_k-1}\left(\frac{1}{\phi_{ik}^*}\right)g(\varphi_k,\delta_{ik})d\delta_{ik}d\varphi_k<0$$

In each case, the first term in the derivative is equal to 0 while the second is strictly negative. This proves the first inequality in the above proposition. To complete the proof of the second inequality note that

$$\frac{\partial V_k^E}{\partial \sigma_k} = \int_{\varphi_k^l}^{\varphi_k^u}\int_{\frac{\phi_{1k}^* w_j\tau_{1j}}{\varphi_k}}^{\delta_{1k}^e}\left(\frac{\phi_{1jk}}{\phi_{1k}^*}\right)^{\sigma_k-1}\ln\left(\frac{\phi_{ijk}}{\phi_{ik}^*}\right) f_{1k}g(\varphi_k,\delta_{1k})d\delta_{1k}d\varphi_k$$

$$+\ldots\int_{\varphi_k^l}^{\varphi_k^u}\int_{\frac{\phi_{ik}^* w_j\tau_{ij}}{\varphi_k}}^{\delta_{ik}^e}\left(\frac{\phi_{ijk}}{\phi_{ik}^*}\right)^{\sigma_k-1}\ln\left(\frac{\phi_{ijk}}{\phi_{ik}^*}\right) f_{ik}g(\varphi_k,\delta_{ik})d\delta_{ik}d\varphi_k$$

$$+\ldots\int_{\varphi_k^l}^{\varphi_k^u}\int_{\frac{\phi_{Ik}^* w_j\tau_{Ij}}{\varphi_k}}^{\delta_{Ik}^e}\left(\frac{\phi_{Ijk}}{\phi_{Ik}^*}\right)^{\sigma_k-1}\ln\left(\frac{\phi_{Ijk}}{\phi_{Ik}^*}\right) f_{Ik}g(\varphi_k,\delta_{Ik})d\delta_{Ik}d\varphi_k>0$$

since $\phi_{ijk} > \phi_{ik}^*$ for all i in the range $[\frac{\phi_{ik}^* w_j\tau_{ij}}{\varphi_k}, \delta_{ik}^e]$.

■

1.8.2 The Matching Algorithm

We first match the customs data and manufacturing data using the firm names, while allowing that for some firms their names may change over time. Specifically, we match the firm names in the two data sets without considering which year the name was reported, e.g. if a firm was named *A* in the customs data in all years, but named *A* in the manufacturing data in 2002 and named *B* in all other years, we treat that as one successful match in 2002. If the name gets matched once, we treat the matched 9-digit firm code in manufacturing data and the 10-digit firm code in the customs data as successfully matched. Using these individual matches we create a correspondence between the 9-digit firm codes and the 10-digit firm codes in the respective data sets. Then we rematch the two data set by using the firm-codes in the two data sets and our constructed correspondence. There are 78,630 unique firms and 235,971 observations which are successfully matched during the 2002-

2005 period.

1.8.3 Additional Results

This section reproduces a number of results which were omitted from the main text. Specifically, Table A1 documents the relatively high degree of turnover among Chinese products in export markets. The exit and entry figures documented in Table A1 are consistent with those reported elsewhere in the literature. Table A2 decomposes aggregate demand growth into within-firm-product growth, between-firm-product growth, across-firm-product growth and net entry for each region in our analysis. Each component is described in Section 4.1 of the main text. Analogous results are also presented in Table A2 for physical and revenue productivity. Tables A3 and A4 repeat this decomposition exercise across different firm-types (ordinary exporters, processing trade, foreign-owned firms, state-owned firms) and product-types (undifferentiated, differentiated). In each case, we find results that are consistent with those reported in the main text for the full sample.

Table A1: Turnover in International Markets Across Firm Type

	Private, Ordinary Trade		Private, Processing Trade		Foreign Firms		State-Owned Firms	
	Entry	Exit	Entry	Exit	Entry	Exit	Entry	Exit
All	0.689	0.572	0.577	0.452	0.617	0.468	0.653	0.543
North America	0.667	0.556	0.534	0.409	0.593	0.445	0.628	0.523
Europe	0.686	0.562	0.574	0.443	0.616	0.462	0.650	0.530
Japan	0.653	0.563	0.589	0.462	0.602	0.474	0.604	0.545
Australia	0.664	0.557	0.533	0.420	0.579	0.436	0.628	0.526
South America	0.702	0.548	0.602	0.430	0.632	0.445	0.669	0.516
Rest of Asia	0.695	0.582	0.578	0.468	0.625	0.480	0.650	0.553
Africa	0.735	0.608	0.635	0.501	0.660	0.500	0.707	0.576
Undifferentiated Products	0.742	0.639	0.631	0.487	0.707	0.567	0.697	0.599
Differentiated Products	0.688	0.570	0.575	0.452	0.615	0.466	0.651	0.540

Notes: This table presents annual product-level entry and exit rates for Chinese exporter across firm type, product type and broad regions worldwide. An entering product is product produced by a specific firm for a specific destination market that did not produce the same product for the same country in the preceding period, but does in the current period. An exiting product is product produced by a specific firm for a specific destination market in the current period but does not in the next period.

Table A2: Decomposition of Demand and Productivity Across Regions

	Components of Decomposition					
Determinant	Within	Between	Cross	Entry	Exit	Net Entry
North America						
Log Demand	-0.072	-0.086	0.128	-0.006	-0.017	0.011
Log Physical Productivity	-0.239	-0.036	0.309	0.022	0.009	0.013
Log Revenue Productivity	0.114	0.037	-0.176	-0.018	0.013	-0.031
Europe						
Log Demand	-0.037	-0.068	0.062	-0.003	-0.003	0.000
Log Physical Productivity	-0.025	0.011	0.023	-0.002	0.0005	-0.0025
Log Revenue Productivity	0.074	-0.102	0.116	-0.007	-0.007	0.000
Japan						
Log Demand	-0.081	-0.085	0.093	-0.003	-0.014	0.011
Log Physical Productivity	0.005	-0.026	-0.003	0.002	0.011	-0.009
Log Revenue Productivity	0.047	0.109	-0.148	-0.030	-0.022	-0.003
Australia						
Log Demand	-0.046	-0.031	0.074	-0.006	-0.011	0.005
Log Physical Productivity	-0.113	0.0001	0.056	-0.002	-0.003	0.001
Log Revenue Productivity	0.025	-0.051	-0.008	0.007	-0.016	0.023
South America						
Log Demand	-0.017	-0.009	0.056	0.0003	-0.002	0.002
Log Physical Productivity	-0.011	0.005	0.011	-0.002	-0.011	0.009
Log Revenue Productivity	0.058	0.005	-0.096	-0.001	-0.007	0.006
Rest of Asia						
Log Demand	-0.059	-0.067	0.097	-0.004	-0.010	0.006
Log Physical Productivity	-0.001	-0.004	0.023	-0.017	-0.035	0.018
Log Revenue Productivity	0.077	0.024	-0.058	-0.007	-0.026	0.019
Africa						
Log Demand	-0.020	-0.042	0.042	0.004	-0.001	0.005
Log Physical Productivity	-0.009	0.009	-0.016	-0.010	-0.024	0.014
Log Revenue Productivity	0.240	0.032	-0.149	-0.018	-0.038	0.020

Notes: This table decomposes the productivity and demand components of average exports across regions. The growth of each component is the weighted average annual growth rate where firm sales are used weights.

Table A3: Decomposition of Demand and Productivity Across Firm-Type

Determinant	Within	Between	Cross	Entry	Exit	Net Entry
	Components of Decomposition					
Private, Ordinary Trade						
Log Demand	-0.060	-0.088	0.103	-0.005	-0.006	0.001
Log Physical Productivity	-0.529	-0.033	0.190	-0.082	-0.072	-0.010
Log Revenue Productivity	-0.037	0.049	-0.055	-0.001	-0.021	0.020
Private, Processing Trade						
Log Demand	-0.162	-0.155	0.167	-0.006	-0.004	-0.002
Log Physical Productivity	-0.043	0.083	-0.019	-0.0002	-0.053	0.053
Log Revenue Productivity	0.149	0.010	-0.065	-0.055	-0.034	-0.021
Foreign Firms						
Log Demand	-0.030	-0.050	0.101	-0.002	-0.016	0.014
Log Physical Productivity	0.037	-0.003	0.040	-0.008	-0.026	0.018
Log Revenue Productivity	0.002	-0.007	0.018	-0.011	-0.022	0.011
State-Owned Firms						
Log Demand	-0.011	-0.015	0.044	-0.003	-0.008	0.005
Log Physical Productivity	-0.040	-0.011	0.003	-0.001	0.008	-0.009
Log Revenue Productivity	0.027	0.052	-0.118	-0.022	-0.026	0.004

Notes: This table decomposes the productivity and demand components of average exports across firm-type. The growth of each component is the weighted average annual growth rate where firm sales are used weights.

Table A4: Decomposition of Demand and Productivity Across Product-Type

Determinant	Within	Between	Cross	Entry	Exit	Net Entry
	Components of Decomposition					
Undifferentiated Products						
Log Demand	-0.009	0.011	-0.003	-0.002	-0.011	0.009
Log Physical Productivity	-0.059	-0.047	0.064	0.003	0.008	-0.005
Log Revenue Productivity	-0.007	-0.055	0.008	-0.006	0.020	-0.026
Differentiated Products						
Log Demand	-0.060	-0.073	0.096	-0.004	-0.010	0.006
Log Physical Productivity	-0.013	-0.006	0.045	-0.011	-0.027	0.016
Log Revenue Productivity	0.031	0.046	-0.103	-0.015	-0.026	0.011

Notes: This table decomposes the productivity and demand components of average exports across different product types. The growth of each component is the weighted average annual growth rate where firm sales are used weights.

1.8.4 Alternative Measures of Productivity and Demand

In this section we briefly describe an alternative productivity estimation methodology based on recent contributions from De Loecker et al. (2012) extended to our setting. We then repeat the primary experiments described in the main text to check the robustness of our results. We proceed by briefly describing our estimator, particularly along dimensions in which it differs from that in De Loecker et al. (2012). We then reproduce the main results using our alternative productivity and demand measures and compare our findings with those in the main text.

Estimating Productivity

Our primary objective is to develop a measure of product and firm specific productivity which is consistent with the Cobb-Douglas production function posited in equation (1.3). However, as argued by De Loecker et al. (2012) standard estimates of the production function coefficients are likely to be biased if there are unobserved quality differences across firms. They address this issue in a context where they also simultaneously allow for firms which produce multiple products. Unfortunately, we cannot follow their procedure exactly since we only observe the physical quantity exported by product rather than the physical quantity of each product produced at the firm-level. Nonetheless, as described in Section 3, we rely on their finding that the amount of any input (capital, labor, materials) allocated to a given product is typically proportional to the revenue share of that product. In this sense, we continue to apply this simplifying assumption and generate an input series for each product in each firm. We then follow De Loecker et al. (2012) to estimate the production function coefficients using control function methods which correct for endogenous quality differences and simultaneously control for endogenous exit from export markets.

Suppose our true (log) production function takes the Cobb-Douglas form:

$$q_{fkt} = \alpha_k k_{fkt} + \alpha_l l_{fkt} + \alpha_m m_{fkt} + \omega_{fkt} + \varepsilon_{fkt} \tag{1.11}$$

where ω_{fkt} is the anticipated physical productivity level of product k in firm f for year t and ε_{fkt} is an unanticipated physical productivity shock to product k in firm f for year t. As is common in this literature we assume that productivity can be characterized as an AR(1) process

$$\omega_{fkt} = \rho\,\omega_{fk,t-1} + \xi_{fkt} \tag{1.12}$$

It is well known that unobserved productivity leads to well known simultaneity and selection biases which have been the predominant focus of the literature which studies the estimation of production functions.[27] An additional difficulty arises because we observe industry-wide deflated input expenditures rather than input quantities. This is not merely a measurement issue since firms generally use differentiated inputs to produce differentiated products. Specifically, let $\tilde{k}_{fkt}$ and $\tilde{m}_{fkt}$ represent the (observed) measures of capital and materials, respectively, where each measure has been deflated by a sector-specific input

[27] See Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2006) for further discussion.

price index.[28] Following De Loecker et al. (2012) we assume that product-level material quantities, m_{fkt}, relate to expenditures as follows:

$$m_{fkt} = \tilde{m}_{fkt} - w^m_{fkt} \tag{1.13}$$

where w^m_{fkt} captures the deviation of the unobserved log firm-product-specific input price from the log industry-wide materials price index. We similarly assume that an analogous relationship holds for capital $k_{fkt} = \tilde{k}_{fkt} - w^k_{fkt}$. Substituting the expressions for physical inputs into equation (1.11) we write

$$q_{klt} = \alpha_k \tilde{k}_{klt} + \alpha_l l_{klt} + \alpha_m \tilde{m}_{klt} + \omega_{klt} - \alpha_k w^k_{klt} - \alpha_m w^m_{klt} + \varepsilon_{klt} \tag{1.14}$$

Equation (1.14) suggests that even after controlling for the unobserved productivity differences using standard estimation techniques, the presence of input price differences across firms could lead to biased production function coefficients since input prices are likely correlated with deflated input expenditures. De Loecker et al. (2012) refer to this potential source of bias as the input price bias.

Following Ackerberg, Caves and Frazer (2006) and De Loecker et al. (2012) we control for unobserved productivity differences using a control function of capital and materials, $\phi(\tilde{k}_{fkt}, \tilde{m}_{fkt}; \alpha)$ where $\alpha = \alpha_k, \alpha_m, \alpha_l)$. Likewise, as in De Loecker et al. (2012) we proxy for unobserved quality differences using a control function where the arguments are the firms' average product price, $\bar{p}_{fkt}$, and interactions with capital and materials, $\varphi(\bar{p}_{fkt}, \bar{p}_{fkt} \times \tilde{k}_{fkt}, \bar{p}_{fkt} \times \tilde{m}_{fkt}; \delta)$ where δ is a unknown vector or parameters.

Finally, it is well-known that the endogenous exit of firms is a further potential source of bias. This is of particular concern in this instance since product turnover in export markets is known to be very high. To address the selection bias, we allow the threshold ω_{fkt} to be a function of the state variables (which we subsume into s_{fkt}) and the firm's information set at time $t-1$. The selection rule requires that the firm makes its decision to drop a product based on a forecast of these variables in the future. Denote an indicator function χ_{fkt} to be equal to 1 if firm f drops product k in year t and 0 otherwise. The selection rule can be written as:

$$\begin{aligned} \Pr(\chi_{fkt} = 1) &= \Pr[\omega_{fkt} \leq \bar{\omega}_{fkt}(s_{fkt}) | \bar{\omega}_{fkt}(s_{fkt}), \omega_{fk,t-1}] \\ &= \Pr(\kappa_{t-1}(k_{fk,t-1}, m_{fk,t-1})) \\ &= \hat{P}_{fkt} \end{aligned}$$

where κ is a non-parametric control function and $\hat{P}_{fkt}$ is the predicted probability that the firm drops product k in year t.

To estimate the parameters we follow Ackerberg et al. (2006) and form moments based on the innovation in the productivity shock ξ_{fkt}. Specifically, the above structure implies that we can write productivity as

$$\omega_{fkt} = \hat{\phi} - \alpha_k \tilde{k}_{fkt} + \alpha_l l_{fkt} + \alpha_m \tilde{m}_{fkt} - \varphi(\bar{p}_{klt}, \bar{p}_{fkt} \times \tilde{k}_{fkt}, \bar{p}_{fkt} \times \tilde{m}_{fkt}; \delta) \tag{1.15}$$

[28] We exclude labor here since we directly observe the number of employees in each firm. However, our method would be robust to the existence of quality differences across workers as well.

As emphasized by De Loecker et al. (2012) even though the input expenditures enter both the production function and the input price control function, φ, the production function coefficients are identified because the input expenditures only enter the input price control function interacted with prices. Identification rests on the fact that the control function for quality, and input prices, is derived from the demand side alone and does not include input expenditures. To estimate the production function parameters (α_k, α_l, α_m) and the input price control parameters δ we form moments based on the innovation in the productivity shock ξ_{fkt} in the law of motion for productivity (1.12). Using equation (1.15) to project ω_{fkt} on $\omega_{fk,t-1}$ and $\hat{P}_{fkt}$ and their interactions:

$$\xi_{fkt}(\alpha_k,\alpha_l,\alpha_m,\delta) = \omega_{fkt}(\alpha_k,\alpha_l,\alpha_m,\delta) - \mathbf{E}(\omega_{fkt}(\alpha_k,\alpha_l,\alpha_m,\delta)|\omega_{fk,t-1}(\alpha_k,\alpha_l,\alpha_m,\delta),\hat{P}_{fkt}) \tag{1.16}$$

The moments that identify the parameters are $\mathbf{E}[\xi_{fkt}(\alpha_k,\alpha_l,\alpha_m,\delta|\mathbf{Y}_{fkt}] = 0$ where $\mathbf{Y}_{fkt}$ contains lagged labor and materials, lagged and current capital, and their higher order and interaction terms, as well as lagged output prices and their appropriate interactions with the inputs.

We find that this method works well for most products, but on occasion performs poorly. The first case where it performs poorly is for products classes where we have a limited number of observations (typically a few hundred or less). Because our data is highly disaggregated there are only a relatively small number of observations when we consider (a) products with a relatively small number of producers, (b) products where turnover is particularly high and, as such, it is difficult to implement the above procedure over consecutive years, or (c) products which are characterized by both features simultaneously. Although the above procedure may lead to improved productivity estimates, implementing the above procedure over the full set of products in the data is not feasible. The second case where it performs poorly is product classes which are dominated by export processing or state-owned firms.[29] As such, we choose to focus on a small number of large industries where ordinary, private firms make up a large part of the industry. Specifically, we examine over 20 products with a large number of private, ordinary producers to implement the above procedure. The estimated production function coefficients are contained in Table A5 below.[30]

[29] Similar differences have been documented by Dai et al. (2011).

[30] We do not present the estimated quality control coefficients since these are not straightforward to interpret. However, we do examine the implications of our alternative productivity measurement below.

Table A5: Production Function And Elasticity Estimates

Product Description	Product Code	α_k	α_l	α_m	σ_k
Garlic, Fresh or Chilled	070320	0.035	0.082	0.933	-15.299
Heterocyclic Compounds	293299	0.182	0.010	0.812	-2.336
Synthetic Dyes	320411	0.027	0.115	0.709	-92.179
Pigments of Titanium Dioxide	320611	0.021	0.074	0.928	-105.084
Inorganic or Mineral Coloring	320649	0.326	0.611	0.342	-6.527
Synthetic Detergent in Powder Form	340220	0.690	0.072	0.206	-7.650
Self-Adhesive Strips	391910	0.015	0.381	0.613	-4.979
Paper, Paperboard, Cellulose Wadding	482312	0.027	0.108	0.822	-2.313
Woven Fabrics of Cotton	520932	0.002	0.106	0.833	-1.344
Plain Woven Fabrics of Cotton	521031	0.026	0.030	0.959	-73.318
Textured Filament of Yarn	540233	0.328	0.546	0.701	-46.694
Woven Fabrics of Synthetic Fibres (Dyed)	540792	0.001	0.025	0.947	-2.597
Plain Woven Fabrics	551311	0.189	0.076	0.736	-2.466
Woven Fabrics of Synthetic Fibres (mixed with rayon)	551511	0.176	0.054	0.690	-1.364
Twine, Cordage, Ropes and Fibres	560750	0.214	0.062	0.495	-3.239
Men's or Boy's Jackets and Blazers of Cotton	610332	0.577	0.190	0.098	-6.260
Men's or Boy's Jackets and Blazers of Synthetic Fibres	610333	0.156	0.047	0.975	-15.507
Track-Suits of Synthetic Fibres	611212	0.001	0.071	0.832	-18.178
Glazed Ceramic Flags and Paving, Hearth or Wall Tiles	690890	0.075	0.191	0.573	-15.144
Glassware	701329	0.020	0.033	0.949	-8.723
Household Hand Tools (Non-Mechanical)	820551	0.278	0.145	0.575	-18.145
Knives and Cutting Blades for Woodworking	820820	0.001	0.028	0.974	-3.355
Parts of Pneumatic Tools	846792	0.040	0.212	0.473	-5.393
Electric Lamps and Lighting Fittings, n.e.s.	940540	0.001	0.149	0.654	-19.886

Notes: This table documents the production function coefficients from our alternative estimation procedure.

Given the production function estimates in Table A5 we then proceed to measure productivity as outlined in Section 3.3 of the main text. Likewise, using the new productivity estimates we estimate a new value for the elasticity of substitution for each product and recover our demand measure d_{fikt} as discussed in Section 3.4 of the main text.

1.8.5 Revisiting the Impact of Demand and Productivity on Export Growth

The above measures of productivity and demand provide us with a second set of data which we use to repeat all of the experiments discussed in the main text. In fact, Tables A6-A10 produce analogous results to those contained in Tables 1.5-1.6 and Table 1.8-1.10 of the main text. In almost every case our robustness results are very close to those reported in main text. This is particularly true in Table 6 where we find that idiosyncratic component of export growth explains just over half of total export growth and 77 percent of the idiosyncratic component of export growth can be accounted for by demand. The results reported in the main text were of a similar size, but slightly smaller. In Table 1.4 we report that idiosyncratic component of export growth explains just under half of total export growth and 73 percent of the idiosyncratic component of export growth can be accounted for by demand. Since the results in the later tables are likewise very similar to those in the main text we omit further discussion here.

Table A6: Decomposition of Aggregate Export Growth

	Total Export Growth	% Export Growth Explained By: Avg. Pdt-Mkt-Yr Growth	% Export Growth Explained By: Idiosyncratic Growth	% Idiosyncratic Growth Explained By: Physical Productivity	% Idiosyncratic Growth Explained By: Export Demand
All Products and Countries	0.828	0.486	0.514	0.229	0.771

Notes: The first column reports total export growth (in percentages). The second and third column decompose total export growth into an idiosyncratic component and average product-market-year growth, where the latter represents the average percentage change in sales of a given product in a given market over two years. The fourth and fifth columns decompose the idiosyncratic component of export growth into its productivity and demand components. Total export growth is the weighted average year-to-year export growth where firm sales are used weights.

Table A7: Decomposition of Demand and Productivity Growth

	Components of Decomposition					
Determinant	Within	Between	Cross	Entry	Exit	Net Entry
Log Demand	-0.003	-0.041	0.086	-0.098	-0.120	0.022
Log Physical Productivity	-0.101	-0.032	0.049	0.052	-0.034	0.086

Notes: This table decomposes the productivity and demand components of average exports. The first column captures changes in relative growth within firm-product pairs, weighted by the initial shares in the export product market. The second term represents a between-product component. It reflects changing shares weighted by the deviation of initial product demand/productivity from the initial product-market index. The third term is a relative covariance-type term and captures the correlation between changes in demand/productivity and market shares. The final two terms capture the effect of product turnover.

Table A8: Persistence in Productivity and Demand

	Revenue TFP	Physical TFP	Demand	Price	Revenue
All firms and products	0.514	0.878	0.958	0.771	0.875
	0.019	*0.010*	*0.006*	*0.012*	*0.011*

Notes: This table reports the results of autoregressive regressions, corrected for selection. Reported coefficients are those on the lagged dependent variable. Standard errors are in italics.

Table A9: Determinants of Selection

Revenue TFP	-0.007					
	0.009					
Physical TFP		-0.00001			-0.00001	-0.00001
		0.00003			*0.00003*	*0.00005*
Demand			-0.039		-0.039	-0.058
			0.019		*0.017*	*0.026*
Price				-0.066		
				0.042		
Age						-0.001
						0.003
Capital						0.014
						0.013
Import Price						0.003
						0.007
Distance	0.047	0.050	0.055	0.045	0.055	0.064
	0.014	*0.013*	*0.012*	*0.016*	*0.013*	*0.017*
Income	-0.007	-0.007	-0.016	-0.007	-0.016	-0.030
	0.011	*0.012*	*0.013*	*0.011*	*0.013*	*0.022*
Size	-0.0001	-0.0001	-0.005	-0.001	-0.005-0.007	
	0.008	*0.008*	*0.008*	*0.008*	*0.008*	*0.015*

Notes: This table reports the results from various logit fixed effect regressions. Each regression controls for the distance from China, average income (measured by real GDP per capita), size (measured by real GDP) and time dummies. Marginal effects are reported while standard errors are documented in italics.

Table A10: Evolution of Productivity and Demand

	Dependent Variable				
	Revenue TFP	Physical TFP	Demand	Price	Revenue
Entry	-0.007	-0.101	-0.100	0.107	-0.478
	0.017	*0.022*	*0.086*	*0.024*	*0.041*
Exit	-0.010	0.012	-0.373	-0.039	-0.401
	0.016	*0.021*	*0.084*	*0.024*	*0.041*
Capital	0.017	0.008	-0.204	-0.011	-0.0127
	0.008	*0.004*	*0.043*	*0.012*	*0.021*

Notes: The above table presents the coefficients on the exit and entry dummy variables. All regressions include product-by-year-by-market fixed effects. Standard errors are clustered by firm-product pair and are reported in italics.

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Chapter 2

Time Varying Impacts of Internal Finance on Firm Exports

2.1 Introduction

Financial credits, either internal or external to the firm, tend to be of high importance for firm-level export decisions.[1] Entering export markets typically involves large start-up costs, as firms need to collect and analyze information on foreign markets, adapt products and packaging to fit foreign preferences, learn local bureaucratic procedures for market access, and set up distribution networks. Exporting abroad or expanding export sales similarly requires firms to incur significant fixed costs to engage in maintaining local offices and allocation channels in the foreign markets, paying rents for warehouses, and monitoring foreign customs procedures. In addition to these traditional cost concerns, Feenstra et al. (2014) provides a new argument for the relevant conjecture that the external financial credit is more important for exporters than non-exporters by theorizing that exporters have to face tighter credit constraints than non-exporters since the "time-to-ship" feature of exporting entails more uncertainty and reflects more incomplete information for lenders.[2]

Numerous papers in the literature have employed firm-level data to examine the link between financial credit to firm export decisions (we focus on this unidirectional link), i.e., whether the improvement in financial credit helps promote firm exports at either extensive (the number of exporting firms) or intensive (the exporting volume of each firm) margin (see Berman and Héricourt (2010) and Jarreau and Poncet (2014) for recent surveys). Yet, no unanimous results have been reached as researchers use quite different micro data sets from different countries to test this hypothesis. By treating the liquidity ratio (the dif-

[1] Here, financial credits refer to the resources that a firm could rely on to finance for a broad range of economic activities, such as investment, working capital, and entry of international markets. The credits could be either internal, like firms' retained earnings, or external, like loans from outside creditors.

[2] More specifically, as suggested by Amiti and Weinstein (2011), there exits a longer time lag between exporting production and the receipt of sales revenue (i.e. the longer "time to ship" for exports) and exporters also face intrinsically more uncertainty due to the difficulty with enforcing payment across countries.

ference between current assets and liability over current assets) as a measure of internal finance and the leverage ratio (short-term debt over current assets) as a measure of external finance, Greenaway et al. (2007) investigates the bidirectional link between firms' financial health and their export market participation using UK firm-level manufacturing data over the period 1993-2003. They find that financial health does not promote firm participation in exporting. In contrast, the reverse causality is confirmed:exporting improves firm-level financial health. Berman and Héricourt (2010) study the both intensive and extensive margins and obtain different results from Greenaway et al. (2007) on the extensive margin. By analyzing a dataset containing 5000 firms in 9 developing and emerging countries,[3] they find both external and internal financial health (defined as ratio of total debt over total assets and ratio of cash flow over total assets) promotes firm exporting at the extensive margin, even though they do not find a conclusive result for the intensive margin. Recently, more and more studies appear to support a positive result on both margins, especially the intensive margin whereby they indicate that tighter financial constraints reduce firm exports. Minetti and Zhu (2011) employ data from the Italian manufacturing sector which provides a direct measure of credit constraints and finds that credit rationing reduces firm exports on both extensive and intensive margins, especially for firms in industries which depend heavily on external finance.[4] Using product-level data from China Customs over the period 1997-2007, Jarreau and Poncet (2014) document that export performance of domestic privately owned firms is strongly constrained by the availability of internal finance relative to foreign-owned or joint-venture firms which can get internal finance from parent companies located aboard.

Our paper adds to the literature by showing that the improvements in internal finance

[3] Berman and Héricourt (2010) are among the few papers that deal with the potential endogeneity of the constructed financial variables (e.g. cash flow over total assets, liquidity ratio, and leverage ratio etc.), since finance tends to be correlated with the past, current and future expected health of the firm. In our empirical analysis, we follow their strategy to account for this endogeneity issue by replacing the current financial variables with lagged values of these variables.

[4] Minetti and Zhu (2011) construct a firm-specific measure of credit rationing based directly on firm's responses to the survey rather than indirectly on firms' financial statements. The survey incorporates "yes or no" questions like "In 2000, would the firm have liked to obtain more credit at the market interest rate?"

encourages firms to export more at the intensive margin.[5] However, our research is substantially different from the previous studies in two important aspects. First, the dataset we use matches Chinese firm-level data from two separate data sets and provides us an opportunity to directly examine the link from internal finance to firm export volumes in the context of the Chinese economy. We use firm name and from other characteristics to match the firm-level data from the Annual Surveys of Industrial Production from 1998 to 2007, conducted by Chinese National Bureau of Statistics, with the product-level data from Chinese Customs over the period 2000-2006. The matched data contains both firm balance sheet and exporting information, thus enabling us to directly investigate the link from internal finance to firm exporting behavior. In contrast, Jarreau and Poncet (2014) only conducted an indirect investigation as they only use Chinese Customs data. Second, the focus of our paper is not just to verify the static result that internal finance encourages firm exports, but to investigate the time varying effects of internal finance on Chinese firm-level exporting behavior in the context of current WTO accession in December 2001. We provide new insight to the existing literature which focuses on a single channel and time invariant results. To the best of our knowledge, this paper is the first to address how internal finance affects firm exporting behavior in a time varying manner at the intensive margin due to the institutional change. [6]

In this paper, we are primarily exploring the time varying effects of internal finance on firm export volumes when the firm switches from indirect to direct exporting as a result of China's WTO accession. As it has been discussed in Bai et al. (2013), China relaxed the regulation on the manner of trade, especially exporting modes to fulfill their WTO mem-

[5] This paper is also related to two other strands of literature, but to a lesser extent. The first study is on the intermediation in international trade that focuses on the role of intermediation in facilitating trade in terms of matching and information advantages (see Rubinstein and Wolinsky (1987) and Antràs and Costinot (2011) as examples). Our work differs from this literature by concentrating on the difference in cost structures and growth opportunities across trade with and without intermediation. The second is the literature which examines how changes in trade policies affect international trade (see Handley and Limão (2014) as a recent case investigating a reduction in trade policy uncertainty). Our paper is tangential to this literature as the time varying feature we are investigating has resulted from the change in China's policy on direct exporting rights.

[6] See Berman and Héricourt (2010) as an example for the financial credit channel and Bai et al. (2013) for the institutional change channel.

bership commitment. More specifically, before China joined the WTO, small to medium scale domestic (without foreign investment) firms that had different registered capital (or sales, exporting values, etc.) had to rely on state-owned exporting intermediaries to export abroad (we call this the indirect exporting mode) due to the government's regulation on the direct trading rights. When China became a member of the WTO, the accession clauses required that all firms become eligible to export directly (we call this the direct exporting mode). Thus, China gradually abolished the regulation on exporting modes over the period 2001-2004. The indirect and direct exporting modes have very different cost structures, which have been recovered using a dynamic discrete choice model in Bai et al. (2013). The most relevant information from the difference in cost structures is that indirect exporting mode saves firms from incurring large sunk start-up and fixed costs involved in exporting but also prevents them from learning local preferences and adopting technology, which tends to bring about more favorable outcomes in productivity and export performance in the future. Essentially, it also means that the direct exporting mode is more costly and requires further subsequent investment. It is a well-established fact that small domestic firms (especially small private domestic firms) are more financially constrained than large and foreign firms (Guariglia et al. (2011) provide a nice examination), and the important role of finance in covering the market entry cost and subsequent investment in upgrading or expansion. Given this, it is likely that a much larger impact of financial credits on firm export volume exists when the firm switches from being an indirect to direct exporter after China's WTO accession (the time period when more small firms' switched from indirect to direct exporters as the policy restriction in direct exporting rights was relaxed).[7]

Using a panel data difference-in-difference-in-differences estimation approach combined with instrumental variable methods to account for the potential endogeneity or sample selection issues associated with firms' export mode switches, we get strong evidence

[7] As our paper discusses the role of finance in the context of exporting mode switches (either indirect or direct exporters), we are excluded from talking about the extensive margin of exports. Thus, only the intensive margin of trade is investigated in this paper.

which supports the time varying hypothesis that financial credits have a large, positive impact on firm export and productivity growth when a firm switched from indirect to direct exporting mode after China's WTO accession. Essentially, our estimates show that on average a 10% increase in the firm-level internal finance will lead to a 6.1% to 30.8% higher firm's export volumes due to switching export mode before and as a result of the WTO accession. The positive increase substantiates the time varying hypothesis that the impact of internal finance on firm exports grow as China accessed WTO. We also find that the time varying impact is more pronounced when we choose an earlier critical year to divide our sample into pre-WTO and post-WTO periods. This probably results from the fact that China's restriction in direct exporting rights experienced a sharper reduction in the initial years of WTO entry.

The rest of the paper is organized as follows. Section 2 discusses how we construct the matched dataset. It also discusses the summary statistics. We introduce some information on the policy and institutional background, especially how the regulation on exporting modes evolved over the 2001-2004 period. In section 3, we talk about the empirical methodology we use to conduct statistical inference. Section 4 presents the empirical results. We conclude and mention potential future research questions in section 5.

2.2 Data Description And Policy Background

We first describe the two data sets we use in this paper and then explain the procedure by which we construct the matched sample which we use for the econometric analysis. We also present background information on the policy change with regards to restrictions in firm direct exporting rights since it is the source of the time varying effects of internal finance on firm exporting.

2.2.1 Data Description

In this paper, we match two separate Chinese micro-level data sets to get the sample we are employing in the econometric analysis. The first data set is the Annual Survey of Industrial Production over the period 1998-2007 (ASIP henceforth). This survey, which collects firm-level data, is conducted by the Chinese National Bureau of Statistics annually. This dataset is quite inclusive, in the sense that it incorporates all Chinese State-Owned Enterprises (SOEs) and non-SOEs with annual sales over 5 million RMB. In the survey, detailed firm-level information was collected, such as firms' geographic location, year of operation (i.e. the age of the firm), ownership type (state-owned, foreign, private, etc.), employment, production and sales variables, balance sheet variables, and tax variables. As for this research, we focus on sales (especially exporting sales values) and balance sheet information, from which we construct exporting and internal finance variables in the econometric exercise. The second dataset we use is product-level data from Chinese Customs, which were collected at a monthly frequency over the period 2000-2006. We add up values corresponding to the same exporting entity over 12 months to obtain annual data, and thus, we can match it with the industrial survey dataset. The Customs data cover the universe of transactions going through Chinese Customs, and contain firm-level information like geographic location, ownership type, exporting variables (values, quantities, and unit prices), type of trade, mode of shipment, transit country, and the export destination country.

First, we provide basic statistics for each data set. In the firm-level data set, ASIP, we list the statistics of the necessary variables to calculate firm level productivity (denoted as TFPR) in Table 2.1.[8] We inflate the labor share (total wage payment to value added) to match the number reported in the Chinese input-output tables and the national accounts (roughly 50%) as Hsieh and Klenow (2009) suggests. For the deflators of output, interme-

[8] In addition to our focus on the impact of internal finance on firm's export, we also check the effect of internal finance on firm's productivity (measured by TFPR) since many studies in the literature suggest that exporting has a positive impact on firm productivity through learning-by-exporting, see Kraay (1999) on China, Aw et al. (2000) on Taiwan and South Korea, Girma et al. (2004) on UK, Van Biesebroeck (2006) on sub-Saharan Africa, and De Loecker (2007) on Slovenia.

diate inputs and the capital depreciation rate, we follow the tables constructed by Brandt et al. (2012). It is worth noting that when comparing domestic firms to exporting firms, exporters have larger values of TFPR and value added in Table 2.1, which is consistent with the result in the literature that higher productivity firms export.

Basic statistics for the Customs dataset are presented in Table 2.2. We notice that Chinese exporters do expand rapidly during our sample period as Manova and Zhang (2012) suggests. During these seven years, the number of exporting firms has increased from 62,746 to 171,144 which is nearly 200% total growth in the number of exporters. The average number of products each exporter shipped aboard, measured by the distinct 10 digits HS codes, has also increased from 30 to 36.2. Firms, on average, exported to 6.9 countries in 2000 and this increased to more than 8 countries in 2006. To some extent, this evidence suggests that joining the WTO has helped Chinese firms' exporting performance in the global market.

Next, we explain how we match the two data sets. Our matching strategy is to make use of the firm name as the primary common variable for matching firms in the Customs dataset to those in the ASIP dataset. We construct a concordance based on the identifiers that exist on both sides of the data: *ID* in the ASIP dataset and *party_id* in the Customs dataset by matching their corresponding names. As a supplement to the names, we also link the firm's identifiers if they are sharing the same zip code and telephone number in both data sets. As such, the matching algorithm proceeds in 4 steps.[9]

Step 1: Given the existence of typographical errors in both data sets, we clean the data sets using a conservative approach. In the customs dataset, we use the non-missing mode (i.e. the most frequent value) of the party_id , zip code and telephone number of the monthly data as the annual value for our matching purposes. In both annual data sets, if the identifier or "concatenation of zip and telephone number" combination exists more than

[9] For the product-level Customs data, we first add up the entries to firm-level by exporting values. That is, if a firm exports more than one good, we add up the export values of all goods and then obtain just one entry for that firm.

once, we discard all the observations to avoid the case that an ID in one data set might link to multiple IDs in the other dataset. Only 0.01% of the observations are dropped each year due to typographical errors.

Step 2: To get the identifier concordance, we first match the Chinese names of the two data sets if same names appear in both datasets in the same year. This provides the most reliable matching results. Then we add concordances if the same name shows up in different years of the two data sets, which might be due to delays in information updating. If the second match generates a different identifier concordance from the first match, we dropped the second match results.

Step 3: We follow the same procedure for "concatenation of zip and telephone" combination for the two datasets. Again we think that the matches from the same year are more reliable than matches from different years.

Step 4: The order of confidence in the concordance is: same names in the same year, same telephone number and zip code in the same year, same names in different years, and same telephone number and zip code in the different years. Every time the latter matches generate a different identifier concordance from the earlier matches, we use the earlier matched results.

Using this matching procedure, we generate 93,222 pairs of identifiers during the length of our dataset (2000-2006). Comparing to the ASIP data that we are using as the master dataset, we are able to match 20% of the total firms and 58% of the exporters. Compared to the result in Manova and Zhang (2012), our matching results are highly comparable.

Third, using the matched sample, we document summary statistics to gain some intuition for our econometric analysis in the following sections. To conduct the econometric analysis, we need to distinguish different types of exporters. Firms which switched from indirect exporting to direct exporting under the relaxed WTO regulations are the firms which may have been most helped by an improvement in their financial conditions. Following Bai et al. (2013), we infer firms' exporting mode as follows. Firms from the ASIP dataset are tagged as exporters if they report positive exports (otherwise they are non-exporters), and as direct exporters if they are also observed in the Customs dataset. The fact that we observe the universe of transactions through Chinese Customs allows us to tag the remaining exporting firms (those which are not observed in the Customs dataset) as indirect exporters. Firms that report exports larger than their exports in the Customs dataset are exporting both directly and indirectly and are labeled direct exporters in this paper. Firms that do not sell domestically are removed from the sample.

In Table 2.3, we are comparing the three types of firms. Above all, we notice that the average export volume of direct exporters is systematically higher than that of the indirect exporters over our sample period. Though both exporting values increased dramatically after 2004, the huge level value difference between them remained largely unchanged. This persistent difference suggests that switching from indirect to direct exporting may help firms to grow. This also probably provides firms with an incentive to switch exporting modes. Next, aside from direct exporters entering more international markets, we find large productivity differences between direct exporters and indirect exporters/non-exporters over our sample period. The average productivity difference between direct exporters and indirect exporters was in the range of 5% and 20% across our sample period. This is consistent with the literature that more productive firms are exporting directly as they can afford large export entry costs. The average TFPR gap between direct exporters and non-exporters is also quite large; it lies between 10% and 30% across our sample period. Also, more firms have been engaged in exporting and more exporters have switched from indirect exporting into direct exporting during our sample period. From 2000 to 2006 the percentage of exporters has increased from 26.6% to 29.3%. In 2000, 10.9% of exporters are inferred to be direct exporters, while 14.7% are the indirect exporters. However, in 2006, 15.7% of the exporters are direct while only 13.5% of the exporters are indirect. The finding of more direct exporting firms is consistent with Ahn et al. (2011) and Bai et al. (2013) and can be explained by the fact that by switching exporting modes, financially healthy firms can grow faster. We explore the impact of this change in our regression.

As for the accuracy of the matched sample, we also pay attention to the relevance of trade types. In recent work, Bernard et al. (2010, 2012) and Dai et al. (2012) argue that carry-along trade is important in the data. This refers to firms who export for other firms, thereby acting as intermediaries. However, in this paper, we do not distinguish between such firms and those exporting only their own products, since the data *per se* provide no information for classification. We also dropped pure producer intermediaries, those who show up in the Customs dataset but do not report exporting in the survey data. Another issue that we are careful with is that processing and/or assembly trade are very different from ordinary trade. The former usually has lower value added and higher productivities due to the different kind of contracts (see Dai et al. (2012) and our Table 2.4). For simplicity, we are going to keep only the ordinary trade firms in our empirical analysis.[10]

2.2.2 Policy Background

This paper explores the time varying impact of internal finance on firm exporting behavior when the firm switches from indirect to direct exporting in the presence of a macroeconomic policy change primarily induced by China's WTO accession. The policy change that we emphasize here is China's regulation of firm direct exporting rights.

Ever since adopting the economic reform policy in 1978, China has been integrating into the global economy at an accelerated pace. However, as a typical planned (or centralized) economy, China still maintained differentiated degrees of government intervention in various markets. The international exporting market was highly regulated prior to China's accession into the WTO. At the turning point of 1978, less than 20 specialized Foreign Trade Corporations and around 100 subsidiaries of these corporations dominated Chinese

[10] More important, as Bai et al. (2013) points out, the processing and/or assembly trade bear quite different sunk cost and learning-by-exporting opportunities from the ordinary trade and thus it is reasonable for us to drop them as our topic closely hinges on the cost structure and learning-by-exporting channel.

exports with government-issued monopoly trading rights. If a firm wanted to export abroad at that time, it could only go through these Foreign Trade Corporations that acted as exporting intermediaries. It means that only indirect exporting mode was allowed for a typical Chinese firm in that period. As the open and reform policy took effect China gradually granted more and more firms the eligibility to export directly. In 1983, China allowed a few big state-owned enterprises the right to trade directly. All foreign-owned firms were granted direct exporting rights when the Foreign Trade Law was adopted in 1994. Reform was further encouraged the Chinese exchange rate reform was launched in 1994 (this reform allowed the previously government-controlled exchange rate to be partly determined by the market and thus provided incentives for firms to engage in international trade). In 1998, the Chinese State Council approved the issuing of direct exporting rights to the state-owned and private domestic firms over a critical size in terms of registered capital or other criteria like sales, net assets and the prospective exporting values (after January 2001, only the registered capital remained as the criterion). Yet, the registered capital requirement was in the beginning, with private domestic firms valued approximately around 8.5 million RMB to export. Over the 2001-2004 period, the reform pace accelerated for a second time when China tried to satisfy the requirements for WTO accession.[11] For example, the registered capital requirements for private domestic firms to get direct exporting right decreased from 8.5 million RMB to 5 million RMB in January 2001, and was further reduced to 3 million RMB in July 2001. After China entered the WTO in December 2001, the requirement dropped to 0.5 million RMB in September 2003, which in practice means there was almost no restrictions on firm exporting as those who want to export typically have a higher registered capital than 0.5 million RMB. Finally, starting from June 2004, the registered capital requirement fell to zero and the restriction was fully removed.[12] Though

[11] To have a more detailed perception of how the reform or policy change was accelerated over the period 2001-2004, please see the Table A.1 in the appendix of Bai et al. (2013).

[12] Though the restriction on direct exporting righted were eliminated then, there still exist numerous international trade intermediaries in China, since many small firms are relying on them to export under optimal decision processes. As discussed by Ahn et al. (2011), the set of intermediary firms could be identified from the ASIP dataset using the Chinese characters that have the English-equivalent meaning of

the registered capital requirement showed a dramatic drop over the 2001-2004 period for most of China, Special Economic Zones like *Shenzhen* and *Zhuhai* applied some special requirements and showed a different evolution path. To be specific, the registered capital requirement for Special Economic Zones stayed at a very low level of 2 million RMB ever since 1998, and dropped 0.5 million RMB in September 2003. Given this difference, it might be of great importance for us to exclude the firms from Special Economic Zones from our matched sample when implementing the econometric analysis, as they were relatively unconstrained in direct exporting even at the beginning of our sample period.[13]

In the following sections, when exploring the time varying impacts of internal finance on firm exporting mode changes, we will take into account this policy change by distinguishing the periods before and after 2002, 2003, and 2004, as main part of the policy change was phased in over the 2001-2003 period. We expect a more pronounced impact of internal finance on firm exporting when the firm switches from indirect to direct exporting mode as direct exporting was almost universally available for all of them after 2003 and the direct exporting mode entails both higher sunk/fixed costs and more incentive to invest for future growth (thus providing a better opportunity for the internal finance to have an effect). Comparing direct exporters and firms through intermediaries, we expect frms choose direct export mode will experience a better growth path. Firms that use the intermediary sector incur a one-time global fixed cost that provides indirect access to all markets which

"importer" "exporter", and/or "trading" in the firm's name. When the set is identified, they conclude that in China the intermediaries differ along several notable and dimensions: intermediaries are more likely to engage in both importing and exporting relative to direct exporters, they could also handle products that span entirely unrelated sectors; intermediaries have a relative "country" focus, i.e., they export more products per country. In sum, Chinese intermediaries appear to have a lower product concentration and export more varieties per country on average than direct exporters. Moreover, in terms of underlying specific roles, as Ahn et al. (2011) suggests, China's intermediaries probably provide a services ranging from promoting matches with foreign customers, exploring quality specifications required in foreign markets, and helping firms adapt their products for foreign consumers. More generally, they help firms establish channels to export their products in destinations where the firms themselves could not cover the set-up and fixed costs to achieve the goal.

[13] One interesting topic is that Special Economic Zones *per se* could be an angle for us to investigate the space varying impacts of financial credits on firm exports, as the firms in these zones enjoyed preferential policies that imposed much lower registered capital requirement for direct exporting and thus smaller firms in those zones could engage in direct exporting and financial credits might be of more importance for them.

allows firms to save on market-specific bilateral fixed costs. The disadvantage is that intermediation results in higher marginal costs of foreign distribution which raises the price to foreign consumers. Like in Ahn et al (2011), the intermediation technology here benefits less productive firms. Direct exporters, paying market-specific bilateral fixed costs, are still likely to grow faster than their counterparties due to productivity advantages.

2.3 Empirical Methodology

Before implementing the econometric analysis, we construct the following relevant measures for our study from the two raw data sets and the matched sample. We first construct the measures of internal finance. There are various ways to measure internal finance based on firms' balance sheet information. We follow Berman and Héricourt (2010) and Guariglia et al. (2011) by defining it as the ratio of cash flows over total assets, as it is a direct measure of the ability of a firm using its own accumulated liquidity to finance new investments. Then, we estimate firm-level productivity using the method introduced by Hsieh and Klenow (2009).

Since we do not have firm-level price data, we focus on the "revenue productivity" TFPR. The estimation of TFPR is conducted using the Annual Surveys of Industrial Production dataset and the relevant variables for this estimation are firm-level value added, labor and capital stock. Next, we define a core measure for this research, i.e., *exporting mode*, as a dummy variable which switches value from 0 to 1 when a firm moves from indirect exporting in the previous year to direct exporting in the current year (note that it takes value 0 when staying as indirect exporter in the current year). Finally, we obtain measures of export volumes directly from the Annual Surveys of Industrial Production, in which the exporting values measure the intensive margin of firm export.

The primary empirical strategy we employ in this paper are a classical panel data difference-in-differences regression (DID) and a difference-in-difference-in-differences (DDD) regression. With completely different institutional structure and growth evolution, the Chinese exporters with different exporting modes has also served as an interesting subject for applying the DID methods. During the WTO accession period, the Chinese government has lowered the registered capital requirement which allowed exporting firms to switch from the indirect exporters to direct exporters. The policy change thus become a natural experiment that allows us to study the impact of regulation on firm's export performance. To study the encouraging effect of firm-level internal finance on firm-level export values, we consider firms that switched from indirect trade to direct trade as the treatment group and the firms that continued to use indirect trade as the control group. The impact of switching export mode on firm-level export performance might not be time invariant over the WTO accession period since most of the deregulation happened in during 2001-2003. To capture the time varying impact of the treatment effect, we divide the sample to pre-WTO and post-WTO periods to compare the cross period differences using the panel data difference-in-difference-in-differences method.

First, we want to show that, by switching export modes, greater internal finance will have a larger impact on the firm's intensive export margin. Further by directly accessing export markets, exporting firms are more likely to be associated with productivity-enhancing research and development which requires large investments. Thus, higher internal finance will have a larger impact on a direct exporter's productivity as well (see Chen and Guariglia (2013) and Bai et al. (2013)). Following the framework of Imbens and Wooldridge (2007), we conduct our first estimation using a panel data difference-in-differences model for multiple time periods (in our sample, the time period is 2000-2006):

$$y_{it} = \alpha + \eta_j * d200j_t + \tau_1 * dExportingmode_{it} * x_{it}$$
$$+ \mathbf{z}_{it}\gamma + c_i + u_{it},\ t = 1,...,T;\ j = 1,...,6$$

where y_{it} is the firm-level export or productivity, and x_{it} is our measure of internal financial credit, and $\mathbf{z}_{it}$ are controls. The dummy variable $dExportingmode_{it}$ captures the change from indirect to direct exporting, it equals 1 if a firm switches from indirect to direct exporting and equals to 0 if it remains an indirect exporter. The coefficient τ_1 is the treatment effect of switching the manner of exporting, and we expect a significant and positive τ_1 for both export values and productivity (TFPR) regressions. We construct time dummies for the years 2001, 2002, 2003, 2004, 2005, and 2006. The expression $\eta_j * d200j_t$ is a linear combination of the time dummies capturing the aggregate year specific factors that would influence the change in τ_1. As for the baseline case, we estimate the empirical equation above using the fixed effect (FE) panel data methods to control for the firm-level fixed effect. However, it must be noted that in our context that empirical analysis is based on the classic panel data difference-in-differences model might be unreliable since it subject to the endogeneity (or the self-selection) issue. If a firm's exporting decision (i.e. exporting more) encourages the firm to switch from indirect to direct exporting, then the $dExportingmode_{it}$ variable in the difference-in-differences equation is endogenous and the FE estimation is invalid.[14] We address the selection issue using the IV methods. Specifically, we instrument the switch in the exporting mode variable $dExportingmode_{it}$ with the product of firm's initial productivity and provincial-level aggregate capital supply.[15] Exploring the idea used by Jarreau and Poncet (2014), we characterize aggregate capital supply by a financial market deepening variable, which is the market share of China's four biggest state-owned banks (namely, Industrial & Commercial Bank of China, Bank of China, China Construction Bank, and the Agricultural Bank of China) in total bank credits. A lower market share of these state banks in total bank credits implies a higher degree of financial market liberaliza-

[14] Another kind of selection problem occurs due to our first-differencing method when firms disapear from our sample (e.g. Some firms stop exporting for a few years). Firms that stop exporting may not be as productive as continuous exporters thus the probability they are observed is related to our independent variables, the fixed effect and the error term. The selection will lead to an upward bias.

[15] A higher firm-level TFP implies a larger profit which covers the cost associated with entering international market and technology upgrading. We also think a higher regional capital supply shock might help easing the financial needs of firm-level export mode switching. We carefully choose the IV components to reduce their correlations with the our independent firm-level variables. We use firm's initial period TFP instead of the current year TFP to avoid contemporaneous correlation, and interact it with province level shocks to further mitigate the correlation on the firm level.

tion, and thus more financial access or capital supply for individual firms.[16] We construct this variable for each province of China and all firms within a province share the same capital supply shock.

Secondly, we want to show the time-varying impact of treatment, specifically the impact of internal finance on export values before and after the WTO deregulation. Following the framework of Meyer (1995), we conduct our difference-in-difference-in-differences (DDD) estimation for multiple time periods (in our sample, the time period is 2000-2006):

$$
\begin{aligned}
y_{it} = \alpha + \eta_j * d200j_t + \tau_1 * dExportingmode_{it} + \tau_2 * dExportingmode_i * dWTO_t \\
+ \tau_3 * dExportingmode_{it} * dWTO_t * x_{it} + \mathbf{z}_{it}\gamma + c_i + u_{it},\ t = 1, ..., T;\ j = 1, ..., 6
\end{aligned}
$$

In the DDD regression, we are interested in the triple interaction of time, group and policy intervention(before or after WTO). With all time and group effects being captured by η_j, c_i in our fixed-effect panel regression, the remaining terms in the regressions are double interaction terms of time and WTO accession and time and treatment group. The dummy variable WTO_t captures the impact of China's policy change in exporting mode induced by the WTO accession, it equals 1 if the year is after 2001 (or 2002, or 2003, depending on how we divide the sample into pre-WTO and post-WTO periods). The variable $dExportingmode_i * dWTO_t$ will be 1 if a firm switched from indirect to direct exporting and the year is later than 2001 (or 2002, or 2003). The coefficient τ_3 measures the difference in the treatment effect before and after China's WTO accession across firms with varying internal finance. Again, we estimate the empirical equation above using the fixed effect (FE) panel data methods to control for firm-level fixed effects and control for selec-

[16] In China, the market share of these big state banks in total bank credits was basically declining and it was a natural outcome following the gradual financial reforms since the 1990s. Primarily completed financial reforms include the promulgation of the Commercial Bank Law that provides a legal basis for changing the specialized state banks to state-owned commercial banks. It also meant the transformation of the shareholding system in the four biggest state-owned banks which helped establish a standardized corporate governance and an internal system of rights and responsibilities in accordance with the requirements for modern commercial banks. Other reforms like establishing privately owned small banks, accelerating interest rate liberalization, developing a deposit insurance scheme and improving financial institutions' market exit mechanism are already well underway.

tion by using the instrument variable methods we considered above.

2.4 Results and Discussion

This section presents the empirical results. We start with the panel data difference-in-differences estimation to discuss the increased role of internal finance in promoting firm exports and productivity when a firm switches from being an indirect to direct exporter.[17] Next, we employ panel data difference-in-difference-in-differences estimation to investigate how the increased role of internal finance captured by the previous difference-in-differences analysis varies across time as China's WTO accession reduced restrictions in direct exporting rights. For both types of estimation, we include both the results with and without the instrumental variable to account for the endogeneity issue in switching exporting mode.

2.4.1 Difference-in-Differences Estimates

Table 2.5 shows the difference-in-differences estimation results for firm-level export value with internal finance. We estimate four scenarios distinguished on two dimensions, that is, whether the switch in exporting mode is instrumented by the product of initial productivity and provincial-level aggregate capital supply or not and whether the firm's age and size (measured by firm's capital stock) are controlled for or not. As the young and small firms tend to rely more on internal finance to grow, we control for them in the estimation to rule out the effects of age and thus make sure that we are isolating the impact of exporting mode.[18] The first two columns of Table 2.5 present results for the scenarios without instru-

[17] As mentioned above, to account for the potential endogeneity issue of internal finance, we instrument the current value of this variable by its first lagged value in all estimations.

[18] In all estimations, we also control for the yearly aggregate effect that would cause the changes in the difference-in-difference or difference-in-difference-in-differences estimates even in the absence of treatment,

menting the switch in exporting mode. It turns out that the estimates are unchanged when we control for firm's age and size. The estimates show that there is a significant increase in the role of internal finance in encouraging firm's export volume when the firm switches from indirect exporting to direct exporting. The effect of internal finance in promoting firm's export volume increased by 11% when the firm switches exporting mode. If we instrument the switch in exporting mode, the increase in the encouraging effect of internal finance is even larger and observe a 44% increase in both scenarios (with and without firm's age and size). Furthermore, the Cragg-Donald Wald F Statistic implies that the instrument for the switch in exporting mode is quite strong and the F-statistic value is much higher than 10 (see Stock and Yogo (2005)).

The difference-in-differences estimation results for firm-level productivity with internal finance are presented in Table 2.6. We consider the same four scenarios as in Table 2.5. It is noticeable that estimates are essentially the same whether we control for firm's age and size or not. Also the estimates show that the increase in the encouraging effect of internal finance in promoting firm's productivity is both statistically and economically significant. In the scenarios with and without the instrumented variable for the switch in exporting mode, the effect of internal finance increased the average impact of switching export modes by 1.4% and 7.8%, respectively. Compared to the estimates for export values, it suggests that there is not a perfect transmission from the increase in firm's export volume to that in productivity though the transmission channel is positive.

2.4.2 Difference-in-Difference-in-Differences Estimates

In Table 2.7, we report the results for the difference-in-difference-in-differences estimation of export volume with internal finance. For simplicity, we only present the estimates when the switch in exporting mode is instrumented by the product of firm's initial productiv-

i.e., the switch in exporting mode.

ity and provincial-level aggregate capital supply. The estimation captures the change in the impact of treatment (firm switches from indirect into direct exporter) before and after WTO on internal finance promoting firm's export volume. Since China's WTO accession process was phased in in terms of how it removed the restrictions in direct trading rights, we consider different critical years to divide our sample span (2000-2006) into pre-WTO and post-WTO periods. Specifically, as discussed in the policy background, we consider three critical years: 2002, 2003, and 2004. Above all, Table 2.7 exhibits that the estimates basically remain unchanged whether we control for firm's age and size or not. Next, we show that the increase in the treatment effect always exists; i.e., there is an increase in the encouraging role of internal finance in promoting firm's export volume when the firm switches from indirect into direct exporter if the firm is observed in the post-WTO period, no matter how we distinguish pre-WTO and post-WTO periods. This increase in the role of internal finance in promoting firm-level export volumes substantiates the time-varying hypothesis of this paper. We show that the improvement in firm-level internal finance has a much more significant impact on firm-level exports when the firm switches from indirect exporting to the direct one after China's WTO accession. This might due to the reason that more and more previously financially constrained, small to medium scale domestic firms switched from indirect to direct exporting modes and the direct mode requires more financing for the larger start-up costs, fixed costs, and subsequent investment in upgrading technologies through the learning-by-exporting.

Table 2.7 also shows the time varying effect is larger when we choose an earlier critical year to divide our sample into pre-WTO and post-WTO periods. If we treat 2002-2006 as the post-WTO period, the impact of internal finance in promoting firm's export value will be on average quadrupled if the firm is observed in the post-WTO period rather than in the pre-WTO period. Specifically, a 10% increase of average firm-level internal finance when the firm switches exporting mode leads to a 30% increase in the export sales after the WTO accession if we set the critical year to 2001. When we postpone the critical year to 2003, a 10% increase in internal finance only causes an 8.5% increase of export volumes on average. It is further decreases to a 6.1% increase on average if the critical year is 2004. This difference arising due to the choice of the critical years is related to the fact that China's removal of direct exporting restrictions wasf a gradual process. This allowed different cohorts of firms to satisfy the direct exporting requirement in each year. As discussed in Section 2, the registered capital requirement in direct exporting for China's domestic firms dropped dramatically from 8.5 million (or 5 million if publicly owned) RMB to 3 million RMB in 2001, which allowing more than 60% of the firms to be able to export directly. While in 2002 and 2003 combined, the requirement only dropped from 3 million RMB to 0.5 RMB. Thus, many more previously financially constrained small to medium domestic firms engaged in the switch from indirect exporting to direct exporting when the dramatic drop happened in 2001. Combined with the fact that firms with registered capital less than 3 million RMB typically tend not to be direct exporters as they are not large enough to bear the uncertainty involved in direct exporting, the increase in the role of internal finance in promoting firm's export fell quickly when the critical year is treated as 2003 or 2004. Similarly, it is worth to notice that the Cragg-Donald Wald F Statistic suggests that the instrument for the switch in exporting mode is quite strong and reasonable in the difference-in-difference-in-differences as the statistic value is much higher than 10.

2.5 Conclusions

This paper examines the time varying feature of the impacts of internal finance on firm export behavior when the firm switches from indirect to direct exporting mode in the context of China's WTO accession. To meet WTO accession promises, China gradually abolished direct exporting restrictions over the 2001-2004 period. As direct exporting features more favorable future outcomes through the learning-by-export, as suggested by Bai et al. (2013), we show by the data that more firms were switching from indirect to direct exporting after China's WTO accession. It is also noticeable that the exporting mode restrictions prevent small and medium scale firms from exporting directly while big firms were exempted, as their registered capital was sufficiently large. Given the fact that small to medium scale firms are typically financially constrained, we conjectured that the impact of internal finance on firm exports when the firm switches from indirect to direct exporting mode will be particularly large after China's WTO accession when many small firms have the opportunity to engage in direct exporting and direct exporting typically entails greater costs and subsequent investment for them.

Using a panel data difference-in-difference-in-differences approach combined with instrumented variable methods to control for potential endogeneity issues associated with switching export modes, we find strong evidence to substantiate our time varying hypothesis. The difference-in-difference-in-differences estimation produces a further increase in the role of internal finance in promoting firm's export volume between pre-WTO and post-WTO periods. On average a 10% increase in firm-level internal finance will lead to a 6.1% to 30.8% higher firm-level export volumes, depending on how we divide the whole sample into pre-WTO and post-WTO periods.

In the following steps, we are extending our current work in several aspects. First, we plan to eliminate the Special Economic Zone effect, as suggested in Section 2. Firms in Special Economic Zones were relatively less constrained in direct exporting even prior to China's WTO accession, thus they tend to mitigate the time varying impact of switching export mode. Secondly, there still exists a potential reverse causation issue in our difference-in-differences or difference-in-differences estimations. This may occur because the firms engaging in international trade tend to accumulate more internal finance. There are several classic ways to address this potential issue. One is the instrumental variable method where the simplest one is to use the lag of internal finance as its instrument. Two, the system of equations method which treats both export volume and internal finance as endogenous variables. We have not checked this one on account that the system of equations method typically requires more intricate theoretical modeling before implementing empirical estimation as in the example of Röller and Waverman (2001). However, this is the most promising method. Three, the vector autoregression (VAR) method which treats all relevant variables like export volume and internal finance as explained variables of their lagged values and allows a fully dynamic relationship between all variables.

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Table 2.1: Basic Statistical Summary of the ASIP Dataset

Year	# of Firms	# of Exporters	TFPR	TFPR of Exports	Vadd.	Vadd. of Exports	Labr.	Captl	Inter.Input
2000	146898	36759	1.46	1.62	14105	28573	354	25247	39597
2001	153958	39997	1.55	1.71	14833	28992	296	24348	41570
2002	165491	44886	1.64	1.77	16600	31738	287	24274	45893
2003	180696	50534	1.73	1.83	19410	37006	276	24294	55254
2004	258390	76482	1.79	1.88	17235	31645	224	20400	49465
2005	250467	74250	1.85	1.91	21492	38993	240	24123	59697
2006	278014	78052	1.9	1.95	24101	45515	229	25227	65822

Table 2.2: Basic Statistical Summary of the Customs Dataset

Custom	# of Obs	# of firms	Export Value	Total destinations	Average destinations	# of products
2000	1882359	62746	296791.4	213	6.9	30
2001	2121515	68487	286292.2	222	7.3	30.9
2002	2613005	78612	270810.7	222	7.5	33.2
2003	3243538	95686	276459.1	220	7.8	33.9
2004	4029789	120590	297836.6	220	8.3	33.4
2005	5103048	144030	298019.1	221	8.3	35.4
2006	6187856	171144	301018.7	220	8.1	36.2

Table 2.3: Three Types of Firms in the Matched Dataset

Year	Exporting mode	# of Firms	Mean TFPR	Custom Export Value	Average Destinations
2000	Direct	15639	1.63	55120.52	6.46
	Indirect	21,120	1.47	26580.81	
	Nonexporters	106,994	1.37		
2001	Direct	17957	1.71	55482.69	7.00
	Indirect	22,040	1.53	26678.49	
	Nonexporters	110,188	1.48		
2002	Direct	21,157	1.77	60235.41	7.66
	Indirect	23,729	1.65	29911.51	
	Nonexporters	115,891	1.57		
2003	Direct	25,392	1.85	68748.30	8.27
	Indirect	25,142	1.74	37509.51	
	Nonexporters	124,233	1.66		
2004	Direct	41,392	1.88	64746.70	8.09
	Indirect	37,431	1.81	37237.03	
	Nonexporters	174,321	1.73		
2005	Direct	38683	1.93	78127.19	9.21
	Indirect	35,567	1.85	47413.39	
	Nonexporters	166,285	1.78		
2006	Direct	41,944	1.97	90630.63	9.81
	Indirect	36,109	1.91	61387.64	
	Nonexporters	188,714	1.84		

Table 2.4: Two Trade types in the Matched Dataset

Year	Trade Types	# of firms	Mean TFPR	Value Added	Average destinations
2000	Ordinary	12608	1.61	33529	6.8
	Non_ord	3030	1.81	14489	4.8
2001	Ordinary	14846	1.69	34006	7.4
	Non_ord	3111	1.85	15352	5
2002	Ordinary	18103	1.77	36508	7.9
	Non_ord	3054	1.80	15005	5.8
2003	Ordinary	22250	1.85	41442	8.5
	Non_ord	3142	1.90	19255	6.3
2004	Ordinary	36690	1.88	34335	8.3
	Non_ord	4702	1.88	17329	6.2
2005	Ordinary	34452	1.93	41758	9.4
	Non_ord	4232	1.91	21429	6.8
2006	Ordinary	38053	1.98	46047	10
	Non_ord	3891	1.96	23434	7.1

Table 2.5: Difference-in-difference Estimation for Export Value with Internal Finance

Explained Variable	Export Value (1)	Export Value (2)	Export Value (3)	Export Value (4)
dExportingmode internalfinance*	0.1096**	0.1097**		
dExportingmode_IV internalfinance*			0.4384*	0.4456*
Time Dummies	YES	YES	YES	YES
Age	NO	YES	NO	YES
Size	NO	YES	NO	YES
Cragg-Donald Wald F statistic			413.01	412.42
R squared	0.14	0.14	0.14	0.14
Number of Obs.	25728	25721	25593	25586

Notes: time dummies are 2001-2006; size is measured by firms capital stock; *dExportingmode_IV* is constructed as the product of initial productivity and provincial-level aggregate capital supply; Cragg-Donald Wald F Statistic is used to test the weakness of instrument variable; * indicates significance at the 10% confidence level; ** indicates significance at the 5% confidence level.

Table 2.6: Difference-in-difference Estimation for TFPR with Internal Finance

Explained Variable	Export Value (1)	Export Value (2)	Export Value (3)	Export Value (4)
dExportingmode internalfinance*	0.0144**	0.0142**		
dExportingmode_IV internalfinance*			0.0778*	0.0783*
Time Dummies	YES	YES	YES	YES
Age	NO	YES	NO	YES
Size	NO	YES	NO	YES
Cragg-Donald Wald F statistic			12000	12000
R squared	0.03	0.03	0.02	0.03
Number of Obs.	37630	37618	37438	37426

Notes: time dummies are 2001-2006; size is measured by firms capital stock; *dExportingmode_IV* is constructed as the product of initial productivity and provincial-level aggregate capital supply; Cragg-Donald Wald F Statistic is used to test the weakness of instrument variable; * indicates significance at the 10% confidence level; ** indicates significance at the 5% confidence level; *** indicates significance at the 1% confidence level.

Table 2.7: Difference-in-difference-in-differences Estimation for Export Value with Internal Finance

Explained Variable	Export Value (2002)	Export Value (2002)	Export Value (2003)	Export Value (2003)	Export Value (2004)	Export Value (2004)
*dExportingmode * internalfinance * dWTO*	3.0891***	3.0832***	0.8580**	0.8548**	0.6127**	0.6109**
Time Dummies	YES	YES	YES	YES	YES	YES
Age	NO	YES	NO	YES	NO	YES
Size	NO	YES	NO	YES	NO	YES
Cragg-Donald Wald F statistic	102.25	102.37	282.69	283.24	441.87	442.97
R squared	0.18	0.18	0.16	0.16	0.18	0.16
Number of Obs.	26458	26451	26458	26451	26458	26451

Notes:2002, 2003, 2004 denote the critical years that we use to define dWTO; time dummies are 2001-2006; size is measured by firms capital stock; *dExportingmode_IV* is constructed as the product of initial productivity and provincial-level aggregate capital supply; Cragg-Donald Wald F Statistic is used to test the weakness of instrument variable; * indicates significance at the 10% confidence level; ** indicates significance at the 5% confidence level; *** indicates significance at the 1% confidence level.

Chapter 3

Immigration, Capital Distortions and the Business Cycle: Evidence from China

3.1 Introduction

Immigration has a non-trivial economic impact on the economy involved. Each year nearly 2.8 million people migrate to the European Union, while the US accepts approximately 1 million foreigners each year with one third coming from Mexico competing for unskilled jobs. In China, the urban population has grown by 440 million from 1979 to 2009. Of the 440 million, about 340 million is attributed to the net migration, which makes it the largest migration volume in human history (Chan 2012). An analysis of migration flows by province shows that the flows are between provinces and mostly unidirectional from inland to coastal provinces. In fact, over 100 million inter-province immigrants in 2010 (Cai 2011) have been considered the backbone of China's coastal export industry and inextricable to China's development path.

This paper argues that firm-level capital distortions and regional TFP differences play important roles in explaining Chinese inter-province labor allocation. This paper serves as the first study to relate firm employment decisions and factor market distortions to immigration patterns. The capital disortion which arises from local government favorable credit policy will affect the firm's optimal employment decision and local labor allocation. It highlights a new channel that adds to the existing literature that barriers to labor movement matters.

One reason for the inland-coastal immigration flow is capital distortions of the firms. Capital distortions, which refers to the difference between a firm's marginal revenue capital to the market rate for capital, are prevalent in many developing countries (Heish and Klenow 2009). Heterogeneities in size, product or locations can all lead to capital distortions across firms. In China, capital distortions are largely attributed to political influence that affects firms employment decisions. With high employment being a political objective of local government leaders (Qian and Zhu 2013), local governments try to influence the firm's employment decision through credit policy. A firm which employs more workers often faces lower marginal costs of capital. During the recent transition period, with more private enterprises taking over SOEs[1], government influence has been weakened and capital distortions across locations have decreased over time[2](Brandt, Tombe and Zhu 2013). This has encouraged an influx of immigrants to coastal regions from the more politically influenced inland regions.

Another reason in the literature for the sizable immigration flows is the persistent TFP differences across regions. Without any barriers or distortions, wage differences across regions are not persistent. Immigration barriers alone cannot lead to differences in the marginal product of labor as well. Recent work concludes that large TFP differences account for the bulk of the differences in output per worker. This has been documented by Caselli (2005), Klenow and Rodriguez-Clare (1997), and Hendricks (2002), among others. These output and productivity differences coexist with widespread barriers to labor movement. These barriers along with the presence of productivity differences have made marginal product of labor differences persistent, which prevents immigration and suggests strongly misallocated labor across locations (Klein and Ventura 2009). This paper also documents a persistent TFP difference between coastal and inland regions of China.

The correlation between TFP or capital wedge and immigration is consistent with expectations of the empirics from the literature. As shown in Table 3.1, both larger TFP differences and smaller capital wedges can lead to immigration flows. Following Heish and Klenow(2009) I estimate the firm level TFP and the marginal revenue product of capital using the Annual Survey of Industrial Production data (ASIP henceforth) for all Chinese

[1]SOE stands for State-owned enterprises. These are companies owned by the local, provincial, and national governments.

[2]By conducting the experiment of Heish and Klenow(2009), Gao(2012) finds a reduction of capital distortion equivalent to 10% TFP gains

firms during 2000-2007[3]. Migration figures are drawn directly from statistics published by the Ministry of Public Security (MPS) annually.

With this evidence in mind, this paper uses a simple two region DSGE model to study labor immigration flows and their policy implications. The model is in line with Heathcote and Perri (2002) but allows for endogenous labor immigration and capital market distortions. The model studies the impact of TFP differences and capital distortion on immigration and evaluates the impact of capital distortion in welfare. This paper is related to existing literature that quantifies the effect of migration in both static frameworks (Borjas 1996, Iranzo and Perri 2009) and dynamic frameworks (Storesletten 2000). It is closely related to Klein and Ventura (2009) and Urrutia (1998), who model endogenous labor movements to assess the welfare effects of removing barriers to migration. However, those models are based on a growth setup designed to compare long-run outcomes, thus abstracting from cyclical fluctuations. In the context of DSGE models of international business cycles, this paper is related to Mandelman and Zlate (2012), which includes immigration shocks and remittance endowment shocks in a two country framework. However, they avoid modeling institutional differences. Finally, the paper is also related to Hsieh and Klenow (2009) and Qian and Zhu (2013), which quantify the labor and capital market distortions in China. This model complements those works by explaining how labor adjusts to distortions which affect welfare in a dynamic setting.

By setting the capital wedge difference across regions to zero and evaluating the welfare gains, the paper finds it is not necessary that inland households benefit from the change. With high immigration barriers, the cost is high to overcome the potential gain from immigration and inland household will have a 3.7% welfare loss across regions. Only when the immigration barriers are reduced do households in both regions benefit.

The rest of the paper is organized as follows. In section 2, I describe the data and provide empirical evidence for the stylized the facts. In section 3, I introduce the model.

[3]In Heish and Klenow (2009), capital wedge is in proportionate to marginal revenue product of capital. So I use the marginal product of capital as an proxy for the capital wedge.

Section 4 reports counterfactual exercises where I change capital distortion levels and provides welfare implications. Section 5 concludes the paper.

3.2 The Data and Empirical Facts

3.2.1 Data

The data used in this paper comes from three separate sources. The first data set, a migration series, is obtained from statistics published by the MPS[4] annually. The series captures the number of immigrants who are formally granted *hukou*[5] status in the destination region each year. Net-immigration numbers represent the number of the total official approved changes in residential status in a given location within a particular year. A potential problem with this series is the lack of knowledge about unofficial migration, which in some cases can be very different from MPS estimates.[6] Since there is no consistent nationwide measure for the floating population (and regional estimates vary a lot in the literature), I only consider the MPS data in this paper.

The second data set was obtained from the National Bureau of Statistics of China. The data sample is collected annually from 2000-2011 for all provinces in China[7]. I use output, consumption, investment and the consumer price index for each province. Each data series has been detrended using a Hodrick-Prescott filter, with the smoothing parameter set to 400. Table 3.2 panel A reports the mean correlations of the key variables across provinces.

The third data set I use in this paper is the ASIP data for all Chinese firms during the 2000-2007. I use this data set to construct firm level labor income share, productivity and

[4]Ministry of Public Security.

[5]A *hukou* is a record in the system of household registration required by law in China. Because of its entrenchment of social strata, especially as between rural and urban residency status, the *hukou* system is often regarded as a caste system of China. Migrant workers may qualify to work in provinces other than their own but not entitled for grain rations, employer-provided housing, or health care without the *hukou*.

[6]Kam Wing Chan discussed estimates of the floating population in his book chapter China, Internal Migration.

[7]Although I would have preferred the quarterly frequency, I am unable to obtain all the data at the state-level.

then I estimate the TFP spillover process. The procedure for estimating firm-level productivity is identical to that in Heish and Klenow (2009).

3.2.2 Empirical Facts

As suggested in Zhu and Qian (2013), factor markets in China are distorted. In inland China where there is a great concentration of state-owned enterprises, higher employment is a political objective for local government leaders. Government leaders try to influence firm employment decisions through credit policy. A firm that employs more workers will face lower marginal costs of capital. Following Zhu and Qian (2013)'s approach, this paper consider a capital distortion that is linked to a firm's employment problem,

$$R_i = RN_i^{-\kappa}, \kappa > 0$$

Here R_i is the capital rental rate of firm i, A_i is the productivity, N_i is the labor employed, K_i is capital stock and κ governs the degree of the distortion ($\kappa = 0$ means there is no distortion). For firm i, the profit maximization problem becomes:

$$\max_{Ki,N_i} A_i K_i^{\alpha} N_i^{1-\alpha} - RN_i^{-\kappa} K_i - W_i N_i$$

Solving the standard firm profit maximization problem gives the wage:

$$W_i = (1 - \alpha + \kappa\alpha) A_i K_i^{\alpha} N_i^{-\alpha}$$

which provides an implication on the labor income share: $\beta_s = \frac{W_i N_i}{A_i K_i^{\alpha} N_i^{1-\alpha}} = (1 - \alpha + \kappa\alpha)$.

When $\kappa > 0$, this structure has two key features. First, the distorted firm has lower marginal costs of capital relative to the market rate. Second, the labor income share, estimated by wage bills over value added, of the distorted firms are higher than that of the undistorted firms. As seen in Figure 3.1, during the early transition period, SOEs have higher labor income shares than their private counterparties in the same region. As the capital distortion has fallen over time, private firms in the coastal region have had higher labor income shares while in the inland region, the gap has decreased. This indicates a decreasing κ over time in the inland. With a market capital rental rate, inland firms are less willing to employ labor and endogenously create emigration to the coastal region.

3.3 Model

The world consists of two regions, coastal and inland China. The coastal region has higher productivity and thus attracts labor immigration from the inland region. Immigrants and local workers are perfect substitutes. The two regions are similar in size and indexed by i, where $i = 1$ denotes the coastal region and $i = 2$ denotes inland. this paper divide the economy to capture the imbalanced development across regions.

3.3.1 Consumers and final good producers

Each region is inhabited by a continuum of identical consumers. Perfectly competitive firms in each region produce a homogeneous final good that is used for consumption and investment. The asset market is incomplete in that only a single non-contingent bond is traded. The financial market is integrated in that people in both regions are trading the same bond, but the market is not complete. There is no perfect consumption risk-sharing. Unlike other two country models, labor can move across regions.

Coastal region economy

The representative household in the coastal region consumes C_{1t} units of the home composite basket. In addition it supplies N_{1t} amount of labor, which when combined with leisure cannot exceed unity, the period endowment of time. The period utility function takes the form

$$U(C_{1t}, 1-N_{1t}) = \frac{(C_{1t}^{u}(1-N_{1t})^{1-u})^{\gamma}}{\gamma}$$

Households supply labor and rent capital to perfectly competitive intermediate good producing firms (firm type 1 in the coastal region). Type 1 intermediate firms in the coastal region produce one good called a. The production functions are Cobb-Douglas. They hire labor from both coastal and inland regions.

$$F(K_{1t}, N_{1t}, N_{it}) = \chi A_1 K_{1,t}^{\alpha}(N_{1,t} + N_{i,t})^{1-\alpha}$$

where K_1, N_1, A_1 are the capital stock, labor and productivity in the coastal region. N_i is the immigrant labor from the inland region. The variable χ is defined as the average TFP difference in the coastal region relative to the inland region. The value of χ is later estimated as the average difference over the sample period from the ASIP data. Let r_1 and w_1 be the rental rate on capital and wage in the coastal region in terms of the intermediate goods produced in the coastal region respectively. The firm's static maximization problem in the coastal region is given by

$$\max_{K_1, N_1, N_i} F(K_{1t}, N_{1t}, N_{it}^{*}) - w_{1,t}(N_{1,t} + N_{i,t}) - r_{1,t}K_{1,t}$$

subject to the constraint: $K_{1t}, N_{1t} > 0, N_{it} > 0$

In each region the law of one price holds where households can trade intermediate goods to the final-goods-producing firms in each region. In return households receive the final good which can be consumed or invested. Investment augments the capital stock in the standard way

$$K_{1,t+1} = (1-\delta)K_{1,t} + X_{1,t}$$

where δ is the depreciation rate and X_1 is the amount of final good devoted to investment in the coastal region.

Inland region economy

Inland households can choose either to work at home or in the coastal region. In each period the household sends an amount, l_{et} of new emigrant labor to the coastal region, where the stock of immigrant labor $N_{i,t}$ is built overtime. The time-to-build assumption implies that the new immigrants start working one period after arriving at the destination (the coastal region). They will continue to work in all subsequent periods with a probability δ_l of dying or being sent back. This shock occurs exogenously each period. Under these assumptions, the rule of motion for the stock of immigrant labor is: $N_{i,t} = (1-\delta_l)N_{i,t-1} + l_{et-1}$.

Similar to the coastal region, the period utility function of an inland household takes the form

$$U(C_{2t}, 1-N_{2t}) = \frac{(C_{2t}^{u}(1-N_{2t})^{1-u})^{\gamma}}{\gamma}$$

Inland intermediate firms choose optimal level of labor and capital to maximize profit and produce intermediate good b

$$\max_{K_2, N_2} F(K_{2t}, N_{2t}, N_{it}) - w_{2t}(N_{2t} - N_{it}) - r_{2t}(N_{2t} - N_{it})^{-\kappa} K_{2t}$$

subject to $K_{2t}, N_{2t} > 0$.

The production function for the firms is

$$F(K_{2t}, N_{2t}, N_{it}) = AK_{2t}^{\alpha}(N_{2t} - N_{it})^{1-\alpha}$$

where w_2 and r_2 are the wage and capital rental rate for inland firms. Because the inland region has greater capital distortion, I add the term $r_{2t}(N_{2t} - N_{it})^{-\kappa} K_{2t}$ to control for the lower capital rental rate and the higher labor income ratio. The inland household investment augments the capital stock analogously to the process in the coastal region

$$K_{2,t+1} = (1-\delta)K_{2,t} + X_{2,t}$$

Armington aggregation

The coastal region specializes in producing good a and the inland region specializes in producing good b. The two regions' final good producers are firms using intermediate goods a and b as inputs with a constant returns to scale technology.[8]

The composite functions for the final good G are defined as follows in the two regions:

$$\begin{aligned} G_1(a_{1t}, b_{1t}) &= (\omega a_{1t}^{(\sigma-1)/\sigma} + (1-\omega) b_{1t}^{(\sigma-1)/\sigma})^{\frac{\sigma}{\sigma-1}} \\ G_2(b_{2t}, a_{2t}) &= (\omega b_{2t}^{(\sigma-1)/\sigma} + (1-\omega) a_{2t}^{(\sigma-1)/\sigma})^{\frac{\sigma}{\sigma-1}} \end{aligned}$$

where σ is the elasticity of substitution between goods a and b. Note $\omega > 0.5$ implies the extent to which there is a home bias in producing final goods. The final goods firm's static maximization problem, in either region, is given by:

$$\max_{\{a_i, b_i\}} \{G_i(a_i, b_i) - q_i^a a_i - q_i^b b_i\}$$

where q_i^a and q_i^b are the prices of goods a and b in region i in units of the final goods produced in region i. And the real exchange rate RER is defined by price of good a in unit of good b.

$$RER = q_1^a / q_2^a = q_1^b / q_2^b$$

I will now describe the representative households' budget constraints for both regions.

Bond economy

In this model only a single non-contingent bond is traded. Let $B_{1,t}$ be the quantity and Q be the price (in units of good a) of the bond for the coastal region. The bond pays one unit of good a in the next period.

Thus $RER_t Q_t$ is the real exchange rate adjusted bond price in units of good b. q_{1t}^a is the

[8]The Armington aggregator is commonly used in the IRBC literature

price of coastal intermediate good a in units of consumption good C. The general form of the budget constraint for the representative household in the coastal region is:

$$C_{1,t} + X_{1,t} + q^a_{1t} Q_t B_{1,t} = q^a_{1,t}(r_{1,t} K_{1,t} + w_{1,t} N_{1,t}) + q^a_{1t} B_{1,t-1}$$

For the inland region, the household budget constraint is more complicated due to the household immigration decisions. The paper assumes that the immigrant household can split time between working from home and working in the coastal region. In each period, there is a fixed cost f_{et} to move labor from the inland to the coastal region. Remittances are sent back to the inland region. The immigrant wage earned in the coastal region is $w_{it} = w_{1t}$, so that the emigrant labor income expressed in units of the inland composite good is $q^a_{1,t} w_{1t} RER_t^{-1} N_{i,t}$. I assume in the extreme case, immigrant households consume all of their income inland, so the labor income contains the remittances sent back. On the spending side, the emigration sunk cost is f_{et} units of immigrant labor, which equals $q^a_1 w_{1t} RER_t^{-1}$ units of the inland composite good. When the government subsidizes inland firms by lowering the interest rate, the subsidy is collected from the local economy. I assume a lump sum tax τ_t is applied to the local consumer's budget constraint which equal the amount of subsidy ($\tau_t = \kappa \alpha A_{2t} K_{2t}^{\alpha} (N_{2t} - N_{it})^{1-\alpha}$). ε is an arbitrarily small number which ensures that the bond holdup equals zero in the steady state. The inland household's budget constraint is written as

$$\begin{aligned} & q^a_{1t} f_{et} w_{1t} RER_t^{-1} l_{et} + C_{2,t} + X_{2,t} + q^b_{2t} Q_t (B_{2,t} - \frac{1}{2} \varepsilon B^2_{2,t}) + \tau_t \\ = \quad & q^b_{2,t}(r_{2,t} K_{2,t} + w_{2,t}(N_{2,t} - N_{i,t})) + q^a_{1,t} w_{1,t} RER_t^{-1} N_{i,t} + q^b_{2,t} B_{2,t-1} \end{aligned}$$

From the first order condition for labor, the wage earned from working in the coastal region is

$$w_{1t} = w_{it} = \chi(1-\alpha)A_{1t}K_{1t}^{\alpha}(N_{1t}+N_{it})^{-\alpha}$$

and the wage of working inland is

$$w_{2t} = (1-\alpha+\kappa\alpha)A_{2t}K_{2}^{\alpha}(N_{2t}-N_{it})^{-\alpha}$$

In the steady state, the fixed cost of moving equals the net present value of the gain from emigration,

$$f_e RER^{-1}w_i = \frac{\beta(1-\delta_l)}{1-\beta(1-\delta_l)}(w_i RER^{-1}-w_2) \Longrightarrow \frac{w_i}{w_2 RER} = [1-\frac{1-\beta(1-\delta_l)}{\beta(1-\delta_l)}f_e]^{-1}$$

where $\frac{w_i}{w_2 RER}$ is the real wage ratio across regions.

National Balance account

The paper assumes that inland households working in the coastal region consume the same amount of consumption per labor as their inland counterpart. The national accounts for the coastal and inland region are defined as follows: For the coastal region, the final output $G_1(a,b)$ will take into account not only the consumption and investment of the native population, but also the consumption of immigrant workers established in the coastal region.

$$G_{1t}(a,b) = (C_{1,t}+X_{1t}+C_{i,t})$$

For households in the inland region, the final output is invested in physical capital and used for investment in migration (to cover the sunk cost of sending new emigrant labor to the coastal region):

$$G_{2t}(a,b) = (C_{2,t}+X_{2t}+f_{e,t}w_{i,t}RER_t^{-1}l_{e,t})$$

where $l_{e,t}$is the new immigrant being created every period. The equilibrium condition of location choices of inland households is

$$N_{i,t}RER_t/C_{it} = N_2/C_2$$

Definition of Equilibrium

An equilibrium is a set of prices such that when households maximize utility taking prices as given and all markets clear.
The market clearing conditions for intermediate goods are

$$a_{1t} + a_{2t} = F(K_{1t}, N_{1t}, N_{it})$$
$$b_{1t} + b_{2t} = F(K_{2t}, N_{2t}, N_{it})$$

and bond market clearing requires

$$B_{1t} + B_{2t} = 0$$

Other variables of interest are terms of trade, GDP in the coastal region, and the inter-trade share of coastal GDP. In equilibrium, these variables are:

$$TOT_t = q^b_{1t}/q^a_{1t}$$
$$GDP = q^a_{1t} * F_{1t}$$
$$NX = (q^a_{1t} * a_{2t} - q^b_{1t} * b_{1t})/GDP_t$$

Calibration

The model economy is characterized by 10 parameters. Some parameters are fixed for estimation: $\beta = 0.96$ is the discount factor; $\alpha_s = 0.50$ is the share of capital in output;[9] $\delta = 0.025$ is the depreciation rate of the capital stock; Risk aversion γ = -1 is selected in accordance with BKK(1994)[10]. I set the annual immigration return rate to $\delta_l = 0.03$. This is a relatively low number to choose. However, I feel this number accurately represents the given scenario there are a large number of seasonal immigrants working in the coastal region repeatedly every year. As in Mandelman et al. (2013), I set the degree of home bais $\omega = 0.75$. The consumption share is set to $\mu = 0.34$. The elasticity of substitution between home and foreign good is 0.9. Both of these parameters are taken from BKK(1994). The TFP ratio across regions is estimated from the data to be $\chi = 1.24$[11].

For the baseline model with a symmetric elasticity of substitution between capital and each type of labor (native and immigrant), the calibration results are described in Table 3.3. There are two paremeters left to calibrate: f_e and κ, where f_e is the sunk cost of labor migration and κ governs the labor ratio difference between coastal and inland regions. To this end, I choose two empirical moments that the model needs to match in steady state: (1) The share of inland's labor force residing in the coastal region is $\frac{N_i}{N_1+N_i} = 0.10$ (Chan,2002);[12] (2) The difference in the labor ratio between the inland and coastal firms is 0.042. Finally, I set $\kappa = 0.12$ (the parameter which characterizes labor ratio capital wedge) and $f_e = 1.36$ (the sunk cost of labor migration).

3.3.2 Model Results

Impulse Response Analysis

[9] α_s is close to the data when I adjust labor shares to 50% of revenue following Heish and Klenow's suggestion.

[10] Backus, Kydland and Kehoe (1994)

[11] The calculation of TFP in each region is described in the appendix

[12] The calibration here is based on the numbers of total immigrants with *hukou*, that people officially approved to change their residences within a particular year. There is another type of immigrant defined as a person living in an administrative unit (usually city, town or street) without acquiring legal status which prevents them from access to the local social welfare system. I could not find reliable estimates to the numbers of inland to coastal informal immigrants, but according to Chan (2002), the number of unofficial immigrants living in one place for 6 months or 1 year is usually close to the number immigrants with *hukou* status changes.

To illustrate the inner workings of the model, this paper considers the response paths of key variables (percent deviations from steady-state) to an unanticipated productivity innovation in the coastal region. As shown in Figure 3.2, following a transitory 1 percent increase in productivity in the coastal region, the immigrant wage premium increases and encourages immigrant entry. Inland output declines because the bond instrument allows capital to migrate towards coastal economy with a relatively high rate of return. Thus even immigration barriers prevent inland labor from moving in the beginning, inland output still declines. As the coastal region borrows from the inland region and accumulates capital, the coastal trade balance becomes negative. In turn, the coastal region becomes relatively more capital intensive which improves the productivity of labor and encourages more immigration over the business cycle.

3.3.3 Productivity Process

As in the standard international real business cycle literature, the paper assumes that productivity follows an autoregressive bivariate process:

$$\begin{pmatrix} A_{1,t} \\ A_{2,t} \end{pmatrix} = \begin{bmatrix} \rho_{11} & \rho_{12} \\ \rho_{21} & \rho_{22} \end{bmatrix} \begin{pmatrix} A_{1,t-1} \\ A_{2,t-1} \end{pmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}$$

where the error term is distributed normally and independently over time with variance $\sum$. Since the annual data only covers eight years from 2000-2007, I cannot use the seemingly unrelated regression (SURE) method as Heathcote and Perri (2002) have done in the literature. Instead, given that the data only has 8 periods but a large number of observations (over 400 industries), this paper uses a standard GMM estimator for the basic short-panel VAR model while controlling for fixed effects and endogeneity (Holtz-Eakin, Newey, and Rosen, 1988). The estimates for the transition matrix of the productivity process A and for the variance-covariance matrix $\sum$ are given below

$$A = \begin{bmatrix} 0.73 & 0.06 \\ (.058) & (.062) \\ 0.23 & 0.53 \\ (.090) & (.041) \end{bmatrix}, \Sigma = \begin{bmatrix} 0.067^2 & 0.570 \\ 0.570 & 0.025^2 \end{bmatrix}$$

The paper finds out that the productivity persistence and spillovers vary differently for firms that reside in different locations. Converting the annual persistence measure to quarterly rates, the coastal firms show a much stronger persistency parameter at 0.92 in comparison to the inland firms 0.85. This suggests a smaller turnover rate of the coastal firms which in my opinion indicates that coastal firms are more market orienated. The coastal firms also have higher TFP spillover to inland counterparties relative to the reverse channel. These estimates suggest that the quarterly TFP spillovers of coastal firms to inland firms is about 0.051 which is about 4 times the size of the inland to costal spillover. To have a better understanding of the difference in magnitudes, I draw an impulse response function based on the estimates and conduct a Monte-Carlo exercise 1000 times to have the confidence interval (in figure 3.3).

In Table 3.4 I report the empirical correlations of immigrants with (1) the ratio of GDP in coastal and inland China, (2) GDP in coastal China, and (3) GDP in inland China. Immigrant entry to the coastal region is pro-cyclical with the GDP ratio, pro-cyclical with coastal GDP and counter-cyclical with inland GDP. As we can see from the Table 3.4, the model suggests a much stronger correlation between immigrants and inland GDP than the empirical data suggests. This might be the case that TFP shocks are the only shocks that drive the GDP variation in both regions and also determines people's incentive to move.

3.4 Implications

The study analyzing regional imbalances and dispartities at the macroeconomic level agree on the conclusion that economic reform since 1978 led to widening regional imbalance between coastal and inland regions. The imbalance peaks at 2004 and continue to be serious. Although central government initiate the "rise of Central China" to mitigate the disparity and inland China also gains from shifting comparative advantages with uprising of land and labor price in the east coast, the differences in income, productivity and economic development still exist.

The paper observes an inverse U-shape TFP ratio between coastal and inland firms during the sample period 2000-2007 which in line with literature. The TFP ratio increases from 1.14 to 1.34 at 2003 and has been reduced to 1.06 at 2007. Essentially just by comparing the calibrated steady state results between year 2000 and year 2007, along with a significant immigration cost, my model suggests no immigration is induced by TFP. Only when combining TFP changes with a 0.03 decrease in capital wedge during 2000-2007 does my model suggest 2.9% of immigrants migrate from inland to coastal. Giving the total estimates of 10% people living in the coastal regions are immigrants at 2009, the model explains 29% of the total immigration. Actually all the migrations are coming from changes in the capital wedge as the TFP differences are too small to overcome the sunk immigration cost in my model.

If I only look at the contribution of TFP difference during 2000-2003, my calibrated model suggests it attracts 14% of immigrants from inland to coastal. In reality, the TFP difference in the initial years is large enough to overcome the immigration cost and the persistent wage difference keeps immigrants stay in the coastal region even when TFP difference become smaller later on. Although not discussed in the paper, I believe a gradually reduced immigration cost would keep the flow sustainable due to better institutional and transportation infrastructure.

In the following section, the model framework is explored by considering a number of hypothetical changes that affect TFP or wedges, and which have consequences for labor mobility. Highlighting the long-run effects and various of forces at work, the impact on immigration is evaluated at different immigration costs. In the next two paragraphs the paper discusses the impact of changes to TFP and capital distortions. Then I compare the welfare of coastal and inland economies with different immigration barriers.

3.4.1 Evaluating the impact of TFP: steady state effects to labor mobility

TFP differences can lead to wage differences which affect the steady state distributions of labor across regions. To quantitatively measure the size of the impact on immigrants, this paper consider three scenarios: (1) no migration barriers, (2) the benchmark calibrated migration barriers, and (3) a high barrier case which people is considered much harder to move(the fixed cost of immigration is three times that of the calibrated cost). The key results for the steady state changes are summarized in Table 3.5. In the benchmark model, a 1% increase in coastal TFP leads to 0.088% change in immigration. With no immigration barriers where $f_{et} = 0$, inland workers requires a smaller coastal wage premium to move. A 1% increasing in coastal TFP leads to a higher 0.101% of increase in immigration. With a higher migration cost, a 1% increase in coastal TFP only leads to a 0.06% increase in migration.

3.4.2 Evaluating the impact of capital distortions: steady state effects to labor mobility

Lowering the capital wedge in the inland region can also lead to increased immigration from the inland region to the coastal. Firms in inland China cannot retain their low capital rental rate which forces them to substitute labor for capital. The decreasing wedge between coastal and inland China leads to larger immigration flow. The results suggest that one standard deviation of capital distortion has a similar impact on the reallocation of labor when compared to one standard deviation of TFP changes. In the calibrated model, a 1% change in the wedge leads to 0.107% change in immigration. Without barriers, a 1% reduction in capital distortion leads to a 0.122% change in immigration and 0.074% change in immigration of high barrier type. Overall, the size of labor reallocation related to TFP and wedge changes explains a large portion of inland to coastal region Chinese immigration, which in data is about 0.6% a year for the last 20 years.

3.4.3 Welfare Implications

In this section I analyze the welfare effects of a sudden and permanent change in the sunk immigration cost in the baseline setup that can be related to better transportation infrastructure or a less restrictive residential policy in the coastal region. I solve the model using a second-order approximation around the steady state and study the welfare effect of a permanent change in the capital wedge over a wide range of values for the baseline model, i.e. $\kappa \in [0, 0.18]$

I define welfare (υ_0) as the present discounted value of the stream of expected utility in the baseline model. The paper then compares the welfare changes for both inland and coastal households when the sunk cost of immigration changes. The new steady state welfare is defined as (υ_1). The change is defined in percentage terms as $\lambda = \left[\frac{\upsilon_1}{\upsilon_0} - 1\right] * 100$. The results in Figure 3.4 show that by removing the capital wedge completely, the welfare of the coastal region household is permanently increased by 7%, and the welfare of inland household is permanently decreased by 3.7%.

For the inland firms, the capital wedge not only distorts the labor allocation but also decreases the unit cost of production since firms are renting the capital at a lower rate. So reducing the capital distortion without removing migration barrier does not necessarily increase the welfare for inland households. The paper conducts a similar exercise by removing the migration completely to show this is the case. By setting the migration barrier to 0 (Figure 3.5), we can see the welfare for both inland and coastal households increases by 4.3% and 7% respectively.

3.5 Conclusion

This paper attempts to bridge the gap between firm-level distortions and immigration theory. In contrast to other immigration theories, this paper considers the dynamics of other macro aggregates during the process of immigration. In contrast to the factor distortion literature, this paper considers the reallocation effect over time. In this paper, I study the long run effect of changing TFP and capital distortions on the reallocation of labor.

In the baseline model, I introduce a two region business cycle model with labor migration flows. The incentive to emigrate depends on the expected future earning differences between working inland and working in the coastal region, as well as the sunk cost to move. Both TFP and capital distortion differences across regions can affect the decision to move. In summary, this paper suggests that capital distortions and TFP play a similarly important role in the labor immigration process. With the existence of immigration barriers, removing capital distortions will increase welfare for coastal households but decrease welfare for inland households. If I remove both barriers, there will be a welfare improvement for households in both regions.

Table 3.1: Correlation Coefficients of TFP and Capital Wedge on Immigration

	TFP Diff	Capital Wedge Diff
Net Immigration	0.7951	0.3887

Table 3.2: Model and Empirical Moments

	Absolute std. dev.		Relative std. dev.		Other Correlation	
(A)Empirics						
	Coast	Inland	Coast	Inland		
Output	0.032	0.026	1.00	1.00		
Consumption	0.015	0.014	0.465	0.532	Y^C,Y^I	0.95
Investment	0.072	0.065	2.250	2.2177	C^C, C^I	0.22
Q	0.018	0.018	0.562	0.692	I^C,I^I	0.79
(B)Labor migration, trades in bonds						
	Coast	Inland	Coast	Inland		
Output	0.256	0.095	1.00	1.00		
Consumption	0.039	0.030	0.153	0.315	Y^C,Y^I	0.33
Investment	0.234	0.215	0.911	2.225	C^C, C^I	0.99
Q	0.006	0.006	0.023	0.063	I^C,I^I	-0.33

Table 3.3: Baseline Model Calibration

Parameters	Descriptions	Set to match
κ =0.12	governs labor ratio difference between coastal and inland	
f_e=1.36	the sunk cost of labor migration	
α_s=0.5	capital share	HK (2009)
$\beta = 0.96$	discount factor	BKK (1994)
$\delta = 0.025$	capital depreciation rate	BKK (1994)
$\delta_l = 0.03$	immigration return rate	Mandelman et al. (2013)
$\omega = 0.75$	home bias	Mandelman et al. (2013)
$\sigma = 0.9$	elasticity of substitution	BKK (1994)
$\mu = 0.34$	consumption share	BKK (1994)
$\chi = 1.24$	TFP difference	

Table 3.4: Correlations of Labor Migration Flows and GDP

(A)	Empirical Moments		
	$\frac{GDP_c}{GDP_i}$	GDP_c	GDP_i
Immigrants	0.28	0.28	-0.16
(B)	Bond Economy		
	$\frac{GDP_c}{Q*GDP_i}$	GDP_c	GDP_i
Immigrants	0.99	0.19	-0.72
Immigrants labor income	0.19	0.94	0.73

Table 3.5: Steady State Effects on Key Variables

	Low Cost:f_e=0	Calibrated Cost: f_e=1.36	High Cost: f_e=4
Case 1: Increasing Coastal TFP by 1%	0.101	0.088	0.060
Case 2: Reducing Inland Capital Wedge by 1%	0.122	0.107	0.074

Figure 3.1: Labor Income Shares

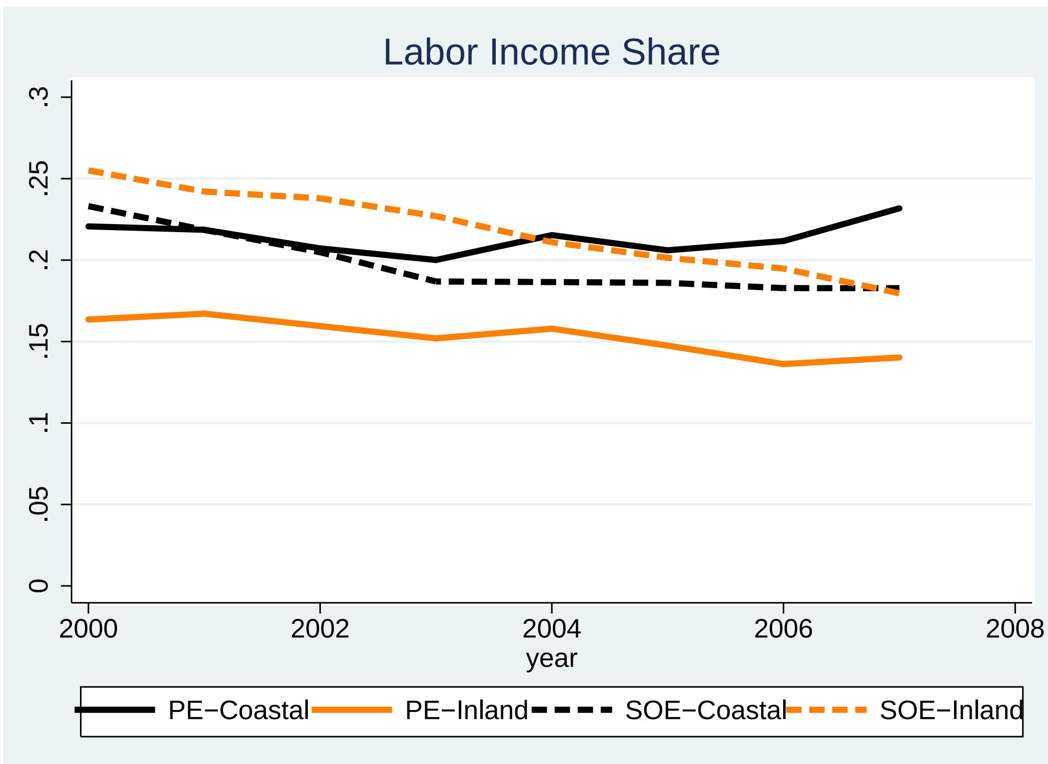


Figure 3.2: Impluse Response for 1% Productivity Shock in the Coastal Region

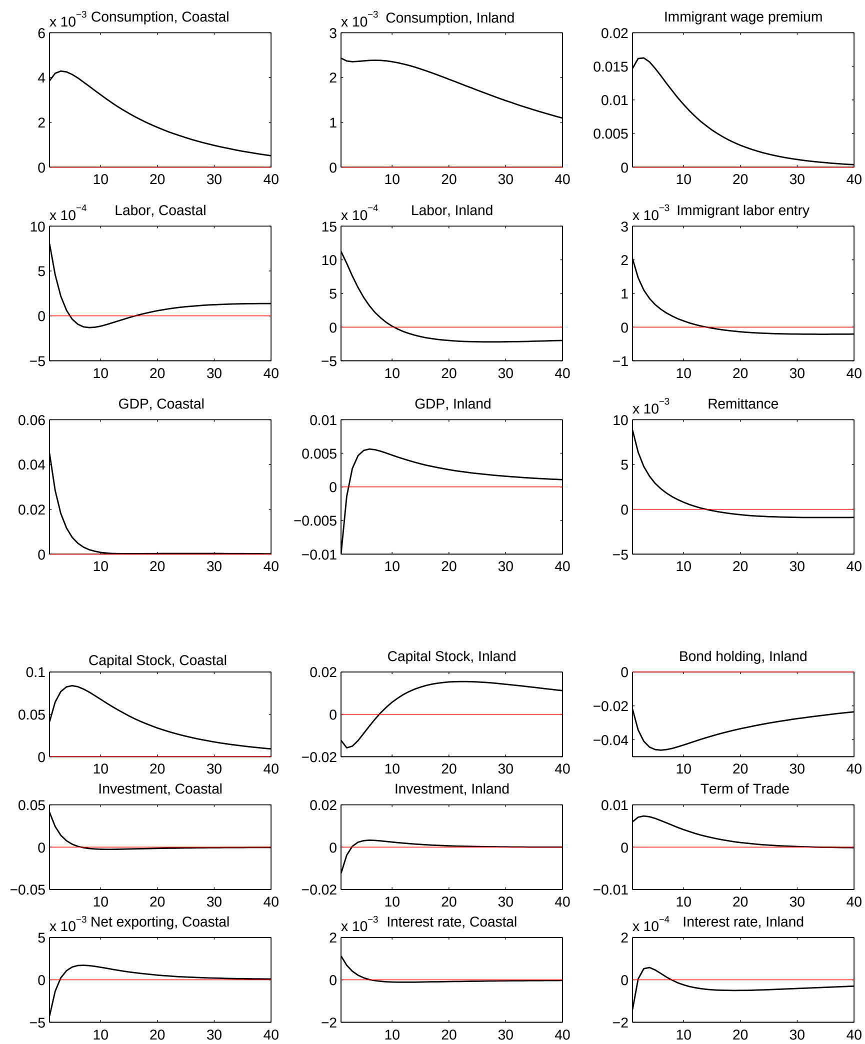


Figure 3.3: IRF of TFP Shocks

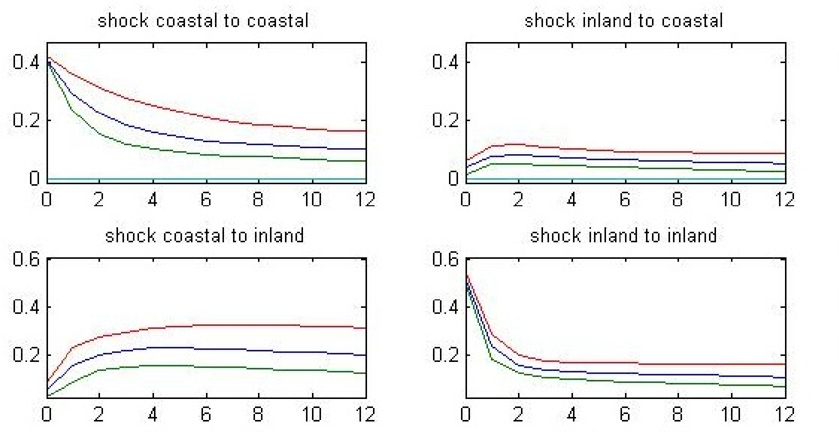
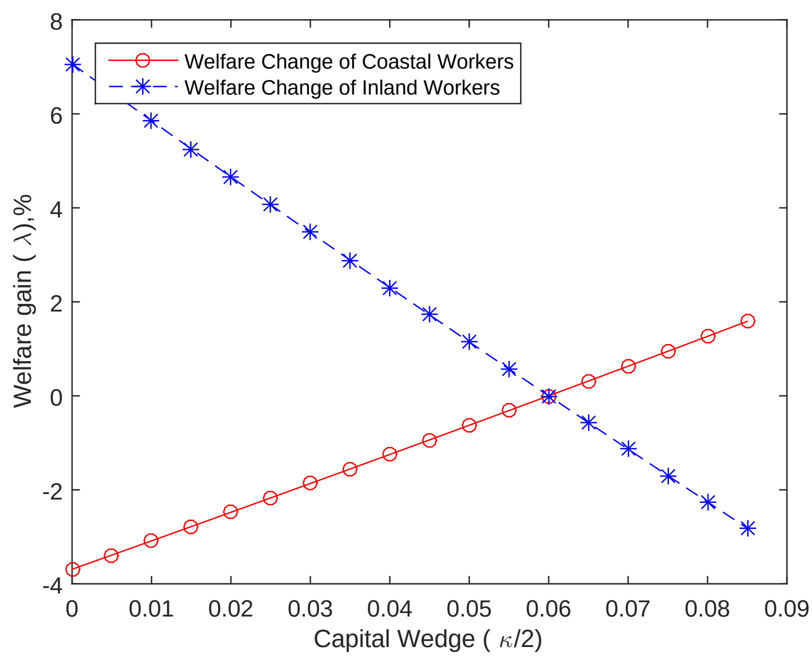
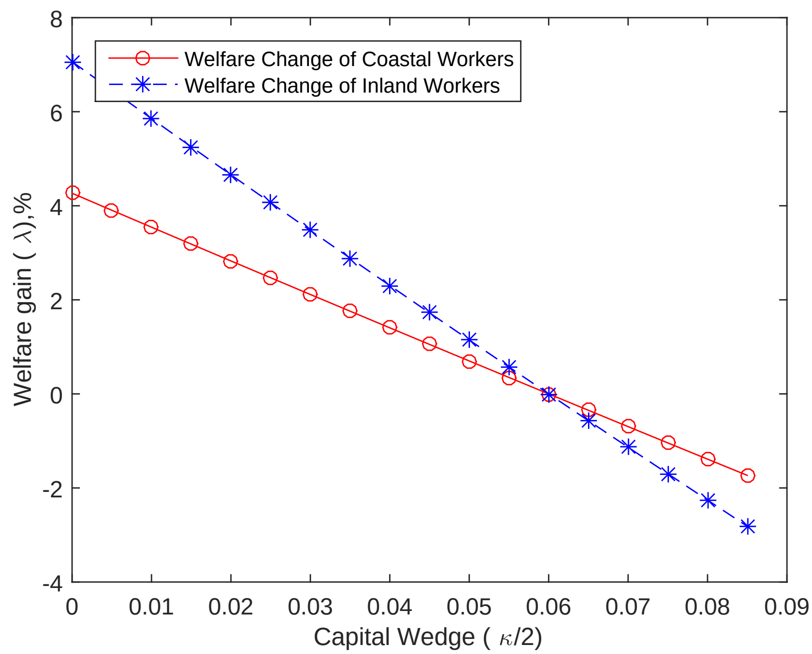


Figure 3.4: Welfare Analysis, Implications on Changing the Capital Wedges with Calibrated Migration Cost



Welfare gain/loss with a permanent changes in capital wedges. The X-axis has been scaled that 1% of change in capital wedge is equivalent to 1% of change in interest rate.

Figure 3.5: Welfare Analysis, Implications on Changing the Capital Wedges with Zero Migration Cost



Welfare gain/loss with a permanent changes in capital wedges. The X-axis has been scaled that 1% of change in capital wedge is equivalent to 1% of change in interest rate.

3.6 Appendix

3.6.1 Estimating the firm and industrial productivity

To estimate the process for productivity shocks the paper needs the estimates of productivity for Chinese firms. Since only sales value data is available and cannot be separated for price and quantity, the paper follows the standard approach to estimate the revenue based productivity (TFPR) as

$$\ln a_{i,t} = \ln(p_{i,t} y_{i,t}) - \alpha \ln(k_{i,t}) - \beta \ln(l_{i,t}) - (1-\alpha-\beta)\ln(im_{i,t})$$

where $p_{i,t} y_{i,t}$ is the value-added output of firm i in year t. $k_{i,t}, l_{i,t}$,and $im_{i,t}$ are the capital stock, number of employed, and intermediate inputs, respectively. I inflate thef labor share (total wage payment to value added) to match the number reported in the Chinese input-output tables and the national accounts (roughly 50%) as Heish and Klenow(2009) suggests. For the deflator of output and intermediate inputs and capital depreciation rate, I use the tables constructed by Brandt, Van Biesebroeck and Zhang (2012). I also create industrial TFPR by using OP decomposition to take out the size effects in productivity levels.

$$TFPR_{s,t} = (1/N_t)\sum_i TFPR_{is,t} + \sum_i (\theta_{it} - \overline{\theta}_t)(TFPR_{is,t} - \overline{TFPR}_{s,t})$$

where N_t is the number of firms in the industry s and $TFPR_{s,t}$ is the revenue based productivity measure for industry s.

3.6.2 Estimating the process for productivity

Due to a relatively short time period and numerous cross-sectional observation units, the standard Seemingly Unrelated Regression Procedure (SURE) method to calculate the transition matrix is not applicable. The paper uses the short-panel VAR method, which accounts for heterogeneity across industries and abstracts from the common factor of technology spillover across institutions and regions. I aggregate the firm-level TFP to the industry level and use industry TFP in each region as observations to estimate the persistence and spillover parameter.

After calculating TFPs across regions and sectors for all the industries, I have a 2×1 vector $[TFPR_{s,t}^{coastal}, TFPR_{s,t}^{inland}]$describing TFP for industry s at time t. For the coastal region, the productivity process would be:

$$TFPR_{s,t}^{coastal} = a_{0t} + \rho TFPR_{s,t-1}^{coastal} + \beta_2 TFPR_{s,t-1}^{inland} + \psi_t \eta_s + \varepsilon_{st} \tag{3.1}$$

where $s = 1, ..., N$ and ε_{st} is predetermined

$$E[\eta_s^j \varepsilon_{st}] = E[\overline{TFPR_s}^j \varepsilon_{st}] = 0$$

for $s < t$.

To eliminate the individual effect, I multiply equation (1) at time period $t-1$ by $\frac{\psi_t}{\psi_{t-1}}$. The valid instruments are $\{1, y_{s,t-2}^j, ...y_{s,1}^j, \overline{TFRP_{t-2}}^j, ...\overline{TFRP_1}^j\}$. By applying a standard GMM estimator for the above basic short-panel VAR model(Holtz-Eakin, Newey, Rosen (1988)), I am able to obtain the persistence and spillover parameter for firms in the coastal region. I can repeat the exercises for the inland region to obtain all other parameters. Converting the annual parameter values to quarterly ones, I obtain persistence estimates similar to that in the literature. Spillovers are greater but can be explained by smaller frictions within China as opposed to across countries. For the innovation variance of regions, I use the variance of the average innovations across industries.

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