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Abstract

This paper quantifies the separate contribution of idiosyncratic productivity and demand growth on aggregate Chinese exports. We develop firm, product, market and year-specific measures of productivity and demand. We use these measures to document a number of novel findings that distinguish the growth of Chinese exports. First, we document that changes in demand explain nearly 82 percent of aggregate export growth, while only 18 percent of export growth is determined by productivity growth. Second, our results highlight two mechanisms which contribute significantly to aggregate export growth: the rapid reallocation of market shares towards products with growing demand, and high rates of product exit among low demand products. Investigating the mechanisms underlying these results we find that new exporters suffer demand shocks which are 66 percent smaller than those observed for incumbent producers in the same product market. By comparison, we find that there is only an 8 percent difference on average between the productivity of new and incumbent exporters. Repeating our exercise with revenue productivity reveals much smaller differences. This is largely attributed to differential movements in prices and marginal costs.

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1 Introduction

A rich literature considers implications of firm heterogeneity on the growth of aggregate productivity and output. For instance, large cross-country differences in output per worker are often attributed to differences in market share across firms with widely different measures of firm efficiency.[1] Consistent with this finding, differences in firm turnover and product churning across heterogeneous firms have repeatedly been found to play an important role in determining resource allocation and the evolution of industry aggregates (Foster et al., 2001; Melitz and Polanec, 2015). Recently, a number of papers argue that firm survival and growth are at least as dependent on other dimensions of firm heterogeneity as they are on firm productivity.[2] These results drive natural questions for understanding the performance of trade aggregates: What is the contribution of idiosyncratic differences across firms and products to export growth? Likewise, since international trade is often characterized by a high degree of product turnover, how does the rapid entry and exit of products in export markets influence the evolution of trade flows?

This paper uses detailed data to re-examine product churning, reallocation, and aggregate export growth in a context which is of global interest: Chinese exports. The astonishing size and scope of Chinese export growth has had substantial economic impacts worldwide. Numerous developing countries have recommitted to export promotion as a key plank within their development platform so as to achieve similar growth in international markets. Importing countries have concurrently struggled to determine appropriate policy responses to large inflows of Chinese products. For example, Pierce and Schott (2016) argue trade liberalization with China caused significant manufacturing job loss in the US. Similarly, Autor et al. (2013) demonstrate that rising imports from China cause higher unemployment, lower labor force participation, and reduced wages in local US labor markets that are composed of import-competing manufacturing industries. In the latter paper, Chinese productivity growth is posited as a key determinant of export growth across destination countries. Our work examines this hypothesis in detail to determine whether rapid increases in firm-level efficiency have allowed Chinese exporters to expand across markets worldwide. Or rather, was the rapid expansion of Chinese exports, in contrast, demand driven?

Unfortunately, answering these questions is often complicated by a lack of adequate data. 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

[1] See Foster, Haltiwanger and Syverson (2008), Hsieh and Klenow (2009), for examples.

[2] Recent examples include Foster et al. (2008), Gervais (2015), Munch and Nguyen (2014) and Rivers (2010)

firm-behaviour. Likewise, Gervais (2015) 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 crucial for understanding 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. Although numerous analyses study one (the domestic market) or at most a few markets (e.g. domestic vs. export markets), a recent series of papers have begun to highlight differences in firm-behavior across heterogeneous export markets.[3] We contribute to this literature by characterizing how market-level characteristics influence the decision to enter and maintain a presence in vastly different export markets and exploring how idiosyncratic productivity and demand systematically affect export growth across heterogeneous export markets.

We study 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 the degree to which product turnover and resource allocation contribute to aggregate demand and productivity growth among Chinese exporters.

Across all Chinese exporters we find that aggregate demand growth explains nearly 82 percent of total export growth, while productivity growth contributes only 18 percent. Product churning, and in particular the exit of low demand products, accounts for a quarter of all demand growth, while the reallocation of market share towards high demand firms accounts for an additional 50 of demand growth in export markets. In this sense, our work links research of firm responses to trade policy[4] with studies of export growth by characterizing the relationship between firm-level determinants and aggregate outcomes.

To check the consistency of our findings, we study the magnitude of demand and productivity across heterogeneous exporters and investigate the separate influence they have on firm survival. We find that a 1 percent increase in demand has twice the impact of a 1 percent increase in production efficiency

[3]See Bernard et al. (2007), Eaton et al. (2008), Eaton, Kortum and Kramarz (2011), and Arkolakis and Muendler (2013) for examples of studies which characterize firm entry and growth across diverse countries.

[4]See, for example, Trefler (2004) and De Loecker (2007), which study the impact of trade liberalization on firm productivity in Canada and Slovenia, respectively. Likewise, Munch and Schaur (2016) study the impact of export promotion on firm-outcomes in Denmark.

on product survival for the typical Chinese exporter. Moreover, we find that while new and exiting producers are moderately less efficient than incumbent firms, the entering and exiting products have measured idiosyncratic demand shocks which are 66 percent smaller than those among similar incumbent products.

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; 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, 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).

Our work is naturally related to studies which examine the determinants of export entry and growth.[5] Manova and Zhang (2011, 2012) confirm large productivity, pricing, and quality differences across Chinese exporters and destinations worldwide.[6] In a closely related paper, Munch and Nguyen (2014) decompose Danish firm-level export sales into a firm and product specific component (productivity) and one that is firm, product and destination specific (demand). They find that variation in idiosyncratic demand accounts for roughly two thirds of the variation in firm-level export sales. Our study is complementary with this work in that we similarly measure productivity and firm and product specific differences in destination-specific demand. However, our focus is not to explain the variation in firm-level sales, but rather to (a) quantify the relative contribution of demand and productivity to *aggregate* export growth and (b) explore the nature of market share allocation across heterogeneous exporters.

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.[7] We highlight two mechanisms which sig-

[5]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 studies imply a significantly different relationship between productivity on exporting.

[6]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.

[7]In particular, Restuccia and Rogerson (2008), Foster, Haltiwanger, and Syverson (2008), and Hsieh and Klenow (2009) each suggest that selection and resource allocation have important effects on aggregate TFP.

nificantly contribute to aggregate demand growth: (1) the reallocation of market share towards products with growing demand and (2) high rates of product turnover among low demand products. We confirm that entering and exiting products have siginficant differences in measured demand relative to incumbent exporters and these differences are substantially larger than the observed productivity differences. Moreover, our empirical analysis suggests that idiosyncratic demand is always a key determinant of product selection across international markets.

In this sense, our work also confirms the insights of a series of papers which suggest that demand may play a particularly important role in determining export decisions and outcomes. The seminal Das, Roberts and Tybout (2007) study argues 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), Munch and Nguyen (2014), and Rho and Rodrigue (2016) further document that export market demand shocks are key determinants of exporter behaviour in Bangledesh, Denmark, and Indonesia, respectively. Likewise, Garcia-Marin and Voigtländer (2016) examine the impact of starting to export on the trajectory of within-firm physical productivity. They find that marginal costs drop substantially when plants begin to export and document that because exporting firms plants also initially charge lower prices, revenue-based productivity measures underestimate efficiency gains from exporting. Our work to Garcia-Marin and Voigtländer (2016) in the sense that we characterize the differential contribution of physical and revenue-based productivity measures for explaining aggregate export growth.

Similarly, Roberts et al. (2016) structurally estimate a model of Chinese footwear exporters. They find that the implied distribution of demand varies much more than that of productivity. They find that demand is at least as important productivity for explaining firm selection and export sales growth. 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 larger impact relative to productivity.[8] In contrast to Roberts et al. (2016) we also provide general measures of demand and productivity across Chinese manufacturing industries, quantify the separate impact of demand and productivity on *aggregate* export growth and characterize the degree to which reallocation across heterogeneous firms drives measured demand growth.

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,

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).

[8]The Supplemental Appendix provides a complementary set of findings for the footwear industry alone.

products and markets. It also documents the association of productivity and demand with key product-level export outcomes. Section 4 determines how much aggregate export growth is directly attributable to productivity or demand changes among Chinese exporters. The fifth section investigates the nature of product selection across international markets and documents the impact of product churning on the distribution of these characteristics across firms and products. The sixth section decomposes each component of aggregate export growth into a within-firm growth compenent, a reallocation component, and a product churning component. Section 7 concludes.

2 A Simple Model of Selection and Exporting

Our model is a small modification of the Bernard, Redding and Schott (2011) multi-product firm extension of the Melitz (2003) model and 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 final products, which we normalize to the interval [0,1]. 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 series market-and-variety-specific demand shocks, 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 and k_i units of capital.[9] The representative consumer chooses to consume y_i units of a homogeneous numeraire

[9] We assume that capital does not depreciate in the short-run. While this is clearly an abstraction, it is consistent with the empirical finding that firm-level capital stocks evolve slowly over time (see Aw, Roberts and Xu, 2011; Roberts et al., 2016) and our objective of characterizing short-run firm-level entry and exit decisions.

good and C_{ik} units of product k where their preferences are described by the utility function: $U_i = y_i^{\beta}[\int_0^1 C_{ik}^{\nu} dk]^{(1-\beta)/\nu}$ where $C_{ik} = [\sum_{i=1}^{I} \int_{\omega \in \Omega_{ik}} [\delta_{ik}(\omega) c_{ijk}(\omega)]^{\rho_k} d\omega]^{1/\rho_k}$, i and j index countries, ω indexes varieties of product k supplied from country i to j, Ω_{ik} is the endogenous set of product k varieties sold in country i, $\sigma_k = 1/(1-\rho_k)$ 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

$$q_{ijk}(\omega) = Q_{ik} P_{ik}^{\sigma_k} \frac{\delta_{ik}(\omega)^{\sigma_k - 1}}{p_{ijk}(\omega)^{\sigma_k}} = A_{ik} \frac{\delta_{ik}(\omega)^{\sigma_k - 1}}{p_{ijk}(\omega)^{\sigma_k}} \tag{1}$$

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

Capital and labor are supplied to either the perfectly competitive intermediate sector or the monopolistically competitive final good sector. Output in both sectors is characterized by Cobb-Douglas production. In the intermediate sector output is produced according to the production function $m = k^{\beta_m} l^{1-\beta_m}$, while in the final goods sector output of product k is described by $q_k = \varphi_k l_k^{\alpha_l} k_k^{\alpha_k} m_k^{\alpha_m}$. Inputs are purchased on competitive factor markets so that input prices are constant across producers located in the same country j, but can vary across source countries, $j = 1, ..., I$. The total product-specific cost of production for a firm located in country j is then $C_{jk}(q_k) = \frac{\omega_{jk}}{\varphi_k} q_k$ where ω_{jk} captures the combined input price for one unit of production. We further assume that to incur iceberg transport costs $\tau_{ijk} \geq 1$ per unit of product k 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 equal to $MC_{ijk} = \frac{\omega_{jk}\tau_{ijk}}{\varphi_k}$. Marginal costs 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.[10]

Profit maximization implies that the producer's optimal price in market i is a constant markup over marginal cost[11]

$$p_{ijk} = \frac{\omega_{jk}\tau_{ijk}}{\rho_k \varphi_k} \tag{2}$$

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

[10] We intentionally abstract from modeling the ranking of products within firms to allow for arbitrary correlation between demand and productivity. See Mayer et al. (2014) for an alternative structure which provides a clear ranking across products within a firm.

[11] It is also consistent with our later empirical findings that prices correlate strongly with productivity, but are uncorrelated with measures of demand.

as

$$\pi_{ijk} = \frac{R_{ik}}{\sigma_k}\left(\frac{\rho_k P_{ik}\varphi_k\delta_{ik}}{\omega_{jk}\tau_{ijk}}\right)^{\sigma_k-1} - f_{ik} = \frac{R_{ik}}{\sigma_k}\left(\rho_k P_{ik}\phi_{ijk}\right)^{\sigma_k-1} - f_{ik}$$

where $R_{ik} = P_{ik}Q_{ik}$. Following Foster, Haltiwanger and Syverson (2008) we define a product and market-specific profitability index $\phi_{ijk} = \frac{\varphi_k\delta_{ik}}{\omega_{jk}\tau_{ijk}}$. 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 profit function for ϕ^*_{ik} yields

$$\phi^*_{ik} = \left(\frac{\sigma_k f_{ik}}{R_{ik}}\right)^{\frac{1}{\sigma_k-1}} \frac{1}{\rho_k P_{ik}}$$

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 $\pi_{ijk} = \left[\left(\frac{\phi_{ijk}}{\phi^*_{ik}}\right)^{\sigma_k-1} - 1\right] f_{ik}$. 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 $\pi_j = \sum_k \pi_{jk}$.

2.1 Free Entry and Equilibrium

A product-level free-entry condition pins down the equilibrium values of ϕ^*_{ik} in each destination market. Specifically, $(\phi^*_{1k}, ..., \phi^*_{Ik})$ are such that the net expected value of expected entry into any product-market is equal to zero for all firms in all countries. That is, ϕ^*_{ik} must satisfy

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

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. In equilibrium, both idiosyncratic demand and productivity components jointly determine product entry and survival across markets.

2.2 Discussion

Our model, though simple, has a number of testable predictions for how product churning and resource allocation patterns will vary across products and countries. First, the model shows that product-level outcomes will vary with product-level productivity and demand in all markets. Moreover, revenue-

based TFP measures will be potentially misleading and the estimated impact of productivity on market entry and turnover may vary substantially with measurement. Second, declining iceberg trade costs, say through trade liberalization or improvements in shipping technology, unambiguously increase the equilibrium profitability cutoff, $\frac{\partial \phi^*_{ik}}{\partial \tau_{ijk}} < 0$. 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 industries where individual varieties are stronger substitutes for each other will also be characterized by higher equilibrium cutoff values, $\frac{\partial \phi^*_{jk}}{\partial \sigma_k} > 0$. 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 higher values of σ_k and will be more sensitive to productivity or demand shocks.[12] Although our results are admittedly small extensions of those in the existing theoretical literature, they guide the following empirical investigation into the nature of selection across Chinese products and export markets.

3 Data and Measurement

Our empirical work relies on merging two key sources of information. First, we use data on the universe of Chinese firms that participate in international trade over the 2000-2006 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, the quantity traded, and export prices for each product across destination countries.[13] The level of detail is an important feature of the customs data as it will allow us to construct a measure of firm-product-level efficiency that is not contaminated by aggregation across products, firms or markets.

The customs data is carefully matched with annual firm-level data from the Chinese manufacturing sector. Specifically, we use annual firm-level data for the period 2000-2006 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).[14] The firm-level data include detailed information on firm-level revenues, export sales, intermediate materials, employment, wages, capital stock, ownership and industry classification.

[12] Similar findings are documented in Melitz (2003), Melitz and Ottaviano (2008), Foster, Haltiwanger and Syverson (2008) or Bernard, Redding and Schott (2011) for example.

[13] 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.

[14] 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.

3.1 The Matching Process

We match the customs data with manufacturing data by using the firm names in each data set. We check the consistency of our matches using phone numbers and location-specific information.[15] 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. 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 presents the distribution of export revenues across firms in 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. Table 1 reports the percentage of exports for each two digit industry in both the (full) firm-level data set and our matched sample, while Appendix B documents summary statistics for key variables in both the full manufacturing data set and the matched sample. In almost every case, the matched sample data and the full sample data are very similar.[16]

3.2 Variable Construction

In this section we briefly summarize the construction of key variables. 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.[17]

We calculate the materials share as the average share of intermediate inputs in total revenues. The

[15] Note that both sets of data contain firm-identifiers which allow us to track firms over time in either data set, but, unfortunately, different firm-identifiers are used in each data set which prevent us from using this information to match firms to exported products.

[16] Notable exceptions include the the mean percentage of sales from exports for products beginning with HS codes 13, 23 and 31. See Table 1 for details.

[17] 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 omited further results and discussion from the main text.

labor share is calculated analogously with the exception that we follow Hsieh and Klenow (2009) 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 (2009) and assume constant returns to scale so that $\alpha_k = 1 - \alpha_l - \alpha_m$.

To complete our benchmark measurement of productivity, we apportion inputs to account for multi-product firms following 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 $x_{fkt} = \varrho_{it}\tilde{x}_{ft}$ where $\tilde{x}_{ft}$ is the total amount of input used in firm f in year t.[18]

3.3 Measuring Productivity

We first consider a model-consistent measure of productivity. Often called physical productivity ($TFPQ$), our measure is based on quantities of physical output and takes the typical index form common to the productivity literature (e.g. Foster, Haltiwanger and Syverson, 2008 or Hsieh and Klenow, 2009). Specifically, our primary measure of total factor productivity takes the form

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

where q_{fkt} is the number of physical units of 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.

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

[18] De Loecker et al. (2016) estimate the input shares across products 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 estimate product level shares of inputs as in De Loecker et al (2016) since our data does not include domestic sales by product for each firm. To the extent that inputs are not allocated consistently with revenues, we would expect that products which are allocated input shares which are too high (low) will be estimated to have productivity levels which are too low (high). As such, this method will attribute a greater degree of sales variation to productivity rather than demand.

A common concern with standard productivity estimates is that they conflate efficiency with product quality. For example, suppose that $\hat{m}_{fkt}$ represents the (observed) measure of material expenditures after having been deflated by a sector-specific input price index. For the sake of argument, we further suppose that firms producing higher quality products potentially use more expensive, higher quality inputs where material quantities, m_{fkt}, relate to expenditures as follows:

$$m_{fkt} = \hat{m}_{fkt} - w^m_{fkt}$$

and w^m_{fkt} captures the deviation of the unobserved log firm-product-specific input price from the log industry-wide materials price index. Substituting the expressions for physical materials into the production function we find that

$$q_{fkt} = \varphi_{fkt} + \alpha_k k_{fkt} + \alpha_l l_{fkt} + \alpha_m \hat{m}_{fkt} - \alpha_m w^m_{fkt} \tag{3}$$

and our measured productivity $\widehat{TFPQ}_{fkt}$ will then contain both elements of efficiency and φ_{fkt} and input prices w_{fkt},

$$\widehat{TFPQ}_{fkt} = \varphi_{fkt} - \alpha_m w^m_{fkt}.$$

As such, input price differences are likely to lead to biased productivity measures.

We have considered two alternative productivity measures to address this concern. First, we isolate industries which are classified as producing undifferentiated products according to the Rauch (1999) product classification. In this sense, we follow Foster, Haltiwanger and Syverson (2008) by considering a set of products with relatively small scope for quality differentiation. We have alternatively tried estimating the input shares, and productivity, using control function methods (De Loecker et al, 2016). A distinct advantage of this approach is that it provides a production function methodology which explicitly disentangles estimated physical productivity from product quality. A disadvantage of this methodology is that we cannot implement it broadly. In particular, we find that this method performs poorly in products classes where we have a limited number of observations (typically a few hundred or less) or in settings dominated by export processing or state-owned firms. 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 20 products with a large number of private, ordinary producers to implement the De Loecker et al. (2016) procedure. A detailed description of our application of their methodology can be found in the

Appendix along with all of the production function estimates.[19]

Numerous papers studying the nature of firm-level export growth have instead relied exclusively on revenue based measures of productivity ($TFPR$). 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.

3.4 Measuring Demand

Our approach to demand estimation follows those in Foster, Haltiwanger and Syverson (2008), Eslava, Haltiwanger, Kugler and Kugler (2009), Khandelwal (2010), Aw and Lee (2014), and Gervais (2015), but account for features which are unique to our setting. Specifically, we consider a product-level regression of demand,

$$\begin{aligned} \ln q_{fikt} &= \ln A_{ikt} - \sigma_k \ln p_{fikt} + (\sigma_k - 1) \ln \delta_{fikt} \\ &= \ln A_{ikt} - \sigma_k \ln p_{fikt} + \eta_{fik} + \epsilon_{fikt} \end{aligned} \tag{4}$$

where i indexes destination markets. We model the unobserved demand shock δ_{fikt} as the sum of a firm-product-destination fixed effect, η_{fik}, and an *iid* idiosyncratic demand shock ϵ_{fikt}. Under the strong assumption that the firm's price is exogenous to the demand shock ϵ_{fikt} we may estimate equation (4) by OLS. Rather, we expect that if there is a positive demand shock (a large δ_{fikt}) this is likely to be reflected in higher sales, q, and potentially higher prices, p.

To account for possible endogeneity bias we estimate equation (4) by IV. Strong instruments for destination specific prices are variables that shift the short run supply curve of the firm. Consistent with Foster, Haltiwanger and Syverson (2008), Eslava, Haltiwanger, Kugler and Kugler (2009) and Gervais (2015), we considered using a measure of the firm's own product-specific productivity, $TFPQ_{fkt}$, as an instrument. However, Aw and Lee (2014) argue that measures of productivity may be correlated with its own product quality and, as such, may not be exogenous. To address possible endogeneity bias we consider two alternative instruments.

[19] An additional potential concern is that some exporting firms are operating at less than full capacity. As such, firms with large existing capital stocks may have measured productivity which is biased downwards. Our Supplemental Appendix checks the robustness of our results across variation in capacity utilization. In each case we find results which are broadly consistent with those in the main text.

First, following Aw and Lee (2014), we allow that competitors' prices in the same product market are likely to be correlated to a firm's own price, but uncorrelated with individual demand shifters. Following Aw and Lee (2014) we use the simple average of the measured physical productivity ($TFPQ$) among all *other* firms which export the same product to the same destination and in the same year to instrument for price as an alternative to the firm's own productivity level as an instrument. Given that the exogeneity assumption for the Aw and Lee (2014) instrument is arguably stronger, we estimate equation (4) by IV product-by-product using the average competitor's $TFPQ$ in the same product-destination-year triplet to instrument for the firm's product-specific price. We use these estimates to compute our 'benchmark' measure of idiosyncratic demand.[20]

Second, as in Foster, Haltiwanger and Syverson (2008), Eslava, Haltiwanger, Kugler and Kugler (2009) and Gervais (2015), we also consider an instrument based on a firm's own measure of physical productivity. Specifically, we first regress each firm-product measure of physical productivity on measures of quality differentiation at the 10-digits HS level, as measured in Khandelwal (2010) by OLS. To the extent that the quality measures capture product-specific variation the scope of vertical differentiation, the residuals from this regression capture variation in physical productivity which is orthogonal to these quality controls. We then use the residuals from these regressions as instruments for prices in product-level regressions of equation (4). We refer to the demand measures computed using these estimates as our 'alternative' measurement of idiosyncratic demand.

Our benchmark IV estimates imply that the average estimate of σ_k across industries is 3.930 while the average elasticity parameter falls to 2.15 using our alternative estimation approach. These results are broadly in line with those found in other countries, markets and estimation methods. Table 2 documents a number of elasticity estimates across products. More differentiated products are associated with low elasticities, as we would expect.[21] We then construct a firm-product specific measure of export demand for each product, d_{fikt}, using equations (2) and (4) as

$$\ln d_{fikt} \equiv \ln A_{ikt} + (\sigma_k - 1)\ln(\delta_{fikt}) = \ln q_{fikt} + \hat{\sigma}_k \ln p_{fikt} \tag{5}$$

The measured demand shock d_{fikt} captures shocks which are common to all producers in a given product market and year, A_{ikt}, and those which vary across firms, δ_{fikt}, in the same product-market and year.

[20] When we estimate equation (4) by IV first stage F-statistic across all industries simultaneous, we recover a first-stage F statistic for the Aw and Lee (2014) instrument of 5353.90, which suggests that our instrument is relatively strong. When we compute the same F-statistic product-by-product we find that it has an F-statistic above 10 in over 60 percent of our first stage regressions.

[21] See Table 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.

3.5 Sample Properties

3.5.1 Product Churning in International Markets

Table 3 documents the rates of product turnover across export markets. Among Chinese firms which export a given product to a specific-market in any year, 54 percent did not export that product to the same market in the previous year. Likewise, among firms exporting to a given product-destination pair this year, 43 percent will exit that product market in the following year. The high rate of product turnover is well-established in the international literature (See Pavcnik, 2002; Bernard, Jensen and Schott, 2005; Besedes and Prusa, 2006a,b, 2007; Alessandria and Choi, 2007; Bernard, Redding and Schott, 2010; and Eaton, Eslava, Kugler and Tybout, 2008 for examples). Our contribution is to quantify the degree to which this behavior can be explained by productivity or demand, and the impact that product churning has in determining the aggregate growth of export sales. Table 3 further demonstrates that the average entry and exit rates across broad regions worldwide and degrees of product differentiation are markedly similar, confirming that this pattern is not specific to particular goods or destinations.

3.5.2 Sample Determinant Correlations

Table 4 collects correlations and standard deviations for 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 findings.

As expected, physical exports and export revenue are highly correlated. 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. Although a correlation coefficient of 0.78 between physical and revenue based productivity is not weak, it allows for quantitative results based on revenue-based measures of productivity to potentially be misleading. For this reason, we compare our benchmark findings from using physical productivity to those we would have found should we have employed the more common measure of revenue productivity.

Second, consistent with our model, demand is not strongly correlated with prices or productivity. In contrast, both physical and revenue productivity demonstrate strong, negative correlation with prices

reflecting the fact that, ceteris paribus, more productive firms tend to charge lower prices.

Third, we find that demand is much more dispersed than physical or revenue productivity. Our estimates suggest that demand is nearly 90 percent more dispersed than physical productivity and more than double that of revenue productivity.[22] Despite wide dispersion, the relative importance of each of these idiosyncratic differences to export growth remains unclear. Section 4 develops a theoretically-consistent decomposition to separately identify the contribution of demand and productivity to export growth.

3.6 Persistence

Although Table 4 suggests that there are substantial differences in correlation and variance of demand and productivity, it is unclear whether these measures similarly display differential degrees of intertemporal persistence.[23] To further investigate the persistence of these idiosyncratic determinants we consider a first-order autoregressive model

$$x_{fikt} = \zeta x_{fik,t-1} + \epsilon_{fikt} \tag{6}$$

where x_{fikt} is a firm, product, market and year-specific determinant (e.g. demand), ϵ_{fikt} is an *iid* error term, and ζ is the autocorrelation coefficient. 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 ζ 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 (6).[24] The

[22] Again, the difference across physical and revenue productivity is partly explained by the finding that product-level prices are negatively correlated with physical productivity, suggesting that more productive Chinese exporters tend to charge lower prices in export markets.

[23] A large number of studies document that productivity tends to be highly persistant. See Supina and Roberts (1996), Baily, Hulten and Campbell (1992), Foster, Haltiwanger and Krizan (2001), Das, Roberts and Tybout (2007) and Aw, Roberts and Xu (2012). In US the domestic market Foster, Haltiwanger and Syverson (2008) document that demand is also highly persistent.

[24] 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 $\overline{d}_{fk,t-1} = \sum_i d_{fik,t-1}$ and include this as a first stage regressor.

persistence parameters for demand, productivity, prices and revenues from our benchmark measurements are reported in Table 5. Physical productivity is consistently estimated to be slightly more persistent than demand, though the differences are admittedly small. Revenue productivity is estimated to be substantially more persistent than either physical productivity or demand. This difference reflects the high degree of persistence in export prices and confirms that using revenue productivity as measure of firm efficiency may obscure the degree to which marginal costs fluctuate over time.

When we compare the degree of persistence across various productivity and demand measurement approaches, we find again find that they exhibit similar degrees of persistence. Specifically, using our alternative productivity measurement we estimate an AR(1) coefficient of 0.764, which is somewhat less than our benchmark estimate of 0.811. In contrast, the persistence coefficient of our alternative demand measure is estimated to be 0.804 which is slightly larger than our benchmark estimate of 0.789.[25]

4 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 2006 than they were in 2000. We proceed by first quantifying the relative impact of changes in physical productivity and demand on export growth. We subsequently investigate the degree to which demand and productivity growth be attributed to changes within firm-product pairs, reallocation across products or product churning in international markets.

Specifically, summing over firm and product specific exports in a given year we write aggregate Chinese exports as

$$Q_{ikt} = \sum_{f \in \mathcal{F}_{ikt}} q_{fikt} = \sum_{f \in \mathcal{F}_{ikt}} C_{ik} \varphi_{fkt}^{\sigma_k} d_{fikt} \tag{7}$$

where $\mathcal{F}_{ikt}$ is the set of Chinese exporters to product-market ik in year t and $C_{ik} \equiv (w_j \tau_{ijk}/\rho_k)^{-\sigma_k}$ captures product market-specific constants across firms. Differentiating equation (7) with respect to time we find

$$\frac{\partial Q_{ikt}}{\partial t} = \sum_{f \in \mathcal{F}_{ikt}} q_{fikt} \left(\sigma_k \frac{\partial \varphi_{fkt}}{\partial t} \frac{1}{\varphi_{fkt}} + \frac{\partial d_{fikt}}{\partial t} \frac{1}{d_{fikt}} \right) \tag{8}$$

where we assume that C_{ik} does not change over time. This assumption is appropriate in this context

[25] We omit reporting the full persistance table for the alternative demand and productivity measurements since they are very similar to our benchmark findings. Full persistence tables are available by request.

since the most likely time-varying component of C_{ik} is Chinese factor prices, w_j, and these are already incorporated into our measures of productivity. Alternatively, should a there be unaccounted changes in tariffs or trade costs over time, these will be captured by our measure of demand. As such, it is important to recall that our measure of demand captures both a mean-zero idiosyncratic component and a common demand component. Using equation (8) we decompose the growth rate of Chinese exports into separable productivity and demand components:

$$\frac{\partial \ln Q_{ikt}}{\partial t} \equiv \frac{\partial Q_{ikt}}{\partial t}\frac{1}{Q_{ikt}} = \sum_{f\in\mathcal{F}_{ikt}} \frac{q_{fikt}}{Q_{ikt}}\left(\sigma_k \frac{\partial \ln \varphi_{fkt}}{\partial t} + \frac{\partial \ln d_{fikt}}{\partial t}\right) \tag{9}$$

We approximate the decomposition equation (9) using annual changes in exports, productivity and demand as

$$\Delta \ln Q_{ikt} \equiv \ln Q_{ikt} - \ln Q_{ik,t-1} = \sigma_k \sum_{f\in\mathcal{F}_{ikt}} \theta_{fikt}\Delta \ln \varphi_{fkt} + \sum_{f\in\mathcal{F}_{ikt}} \theta_{fikt}\Delta \ln d_{fikt} \tag{10}$$

where $\theta_{fikt} \equiv \frac{q_{fikt}}{Q_{ikt}}$. To determine the extent to which changes in export growth $\Delta \ln Q_{ikt}$ are a function of demand growth, $\Delta \ln \mathcal{D}_{ikt} \equiv \sum_{f\in\mathcal{F}_{ikt}} \theta_{fikt}\Delta \ln d_{fikt}$, or productivity growth, $\Delta \ln \Phi_{ikt} = \sigma_k \sum_{f\in\mathcal{F}_{ikt}} \theta_{fikt}\Delta \ln \varphi_{fkt}$. That is, we compute

$$\text{Productivity Contribution} = \sigma_k \frac{\Delta \ln \Phi_{ikt}}{\Delta \ln Q_{ikt}}, \qquad \text{Demand Contribution} = \frac{\Delta \ln \mathcal{D}_{ikt}}{\Delta \ln Q_{ikt}}.$$

These ratios capture the fraction of aggregate export growth, which are attributable to demand or productivity growth in each market. We use our measure of physical productivity for φ_{fkt} and our measure of firm-product-market specific demand (5) for d_{fikt}. 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 6.

Our benchmark computations reveal three striking results. First, Chinese exports were growing extremely quickly over our sample period. The annual average export growth across all markets was almost 15 percent per year. Second, both productivity and demand changes make substantial contributions to short-run aggregate export growth, but demand changes tend to dominate productivity growth. Overall, changes in demand explain 82 percent of aggregate export growth. Third, the finding that demand is the largest contributor to Chinese export growth is robust across all markets, firm types and degrees of product differentiation. We further document that demand is a particularly large contributor to aggregate export growth in developed countries (North America, Japan, Europe, Australia), among foreign-owned

firms and in differentiated product markets. In contrast, productivity plays a relatively large role for privately-owned exporters, less developed markets (Africa, Rest of Asia), and for undifferentiated product exporters. We would expect that in undifferentiated product markets there would be relatively less scope for firms to build brand reputation or establish long-term buyer-seller relationships. Nonetheless, consistent with evidence from Foster, Haltiwanger and Syverson (2008), we find that even among these exporters of undifferentiated products, demand explains nearly 65 percent of export growth.

Turning to our alternative measures of demand and productivity, our decomposition reports very similar results. Table 7 documents that regardless of our sample we find average export growth of 15-16 percent per year. Moreover, our alternative productivity measurement suggests that demand is responsible for a slightly smaller fraction of aggregate export growth; the alternative productivity measurement accounts for 22 percent of export growth while demand accounts for 78 percent. In contrast, our alternative demand measurement suggests an even larger contribution from demand. In this last case, we find that demand accounts for 89 percent of export growth.

An important caveat to these findings is that the demand measure d_{fikt} is a combination of both the idiosyncratic component δ_{fikt}, an aggregate demand shifter, A_{kit}, and potentially common shocks to trade costs or policy. As such, demand growth may reflect changes which are common to all exporters in a given product-market. Thus, understanding the sources of export requires furthers characterizing the extent to which growth in demand is driven by idiosyncratic differences across firms or by shocks which are common to all firms. Likewise, although demand and productivity drive both aggregate export growth, it is unclear whether this is driven within-firms changes productivity and demand changes, product-market turnover, or resource reallocation across heterogeneous firms. We tackle these issues next.

5 Product Churning in International Markets

This section examines the impact of productivity and demand from two different angles. First, we study the role of idiosyncratic differences across firms in determining product market survival across international markets. Second, we quantify the idiosyncratic differences between entering and exiting products and those that maintain a presence in export markets to characterize the role of product churning on the evolution of aggregate productivity and demand.

5.1 Survival

We first consider annual logit 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 idiosyncratic firm characteristics and destination-specific variables. Specifically, let $\chi_{fik,t+1}$ be a binary variable which takes a value of 1 if a firm which exports product k in year t to market i stops exporting the same product to the same market in year $t+1$. We 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. As in Manova and Zhang (2012) we use the average import price as a proxy for input quality and study the extent to which our demand measures correlate with standard measures of product quality.[26] 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, while year-fixed effects controls for changes in the broader macroeconomic environment over time.[27]

Table 7 presents the impact of each explanatory variable on the decision to drop a product from a given export market when we pool all of our data.[28] The first four columns study the individual effect of productivity, demand and prices on product market survival. Higher revenue productivity is found to significantly deter exit, while physical productivity, though negative has a much smaller impact; the marginal impact of revenue productivity is estimated to be nearly 5 times that of physical productivity across columns 1 and 2. In contrast, column 3 suggests that firms with higher demand shocks are much less likely to exit export markets, while column 4 indicates that firms which charge higher prices for their

[26] Gervais (2015) 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.

[27] Conditional MLE estimation is discussed in detail by Wooldridge (2002), Chapter 15.

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

product are less likely to drop those products in export markets. Column 5 examines the joint impact of productivity and demand, while column 6 adds other key firm-level determinants: age, log capital, and the log import price. In each case we observe that demand always has a large, and statistically significant effect on product market survival. Moreover, the marginal impact of demand is at least twice as large as productivity. Among the additional firm-level variables, both capital and import prices are found to have a statistically significant impact on exit. Although the addition of these firm-specific controls reduce the marginal effect of both productivity, we continue to find that the coefficient on demand is roughly double that on productivity. Tables 8 and 9 repeat the selection exercise for our alternative measures of productivity and demand. In each case, we find results which are very close to those from our benchmark exercise. The last three rows of each column present the impact of market-specific control variables. 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 repeating the regression exercise for different types of firm-ownership (private, foreign, state), for different degrees of product differentiation, and for different trading regimes (ordinary vs. processing trade).[29] Table 10 documents that our benchmark results hold broadly across different types of firms, the nature of trade and across product differentiation. In general, stronger demand always significantly deters product exit from export markets and the marginal impact of demand is always significantly larger than that of productivity.

5.2 Product Churning, Demand, and Productivity

This section examines the impact of product churning 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 a product entry dummy variable and let χ^X_{fikt} be an exit dummy variable. The entry dummy for year t equals one if the firm 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

[29] 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 been strong institutional preferences to allocate licenses differentially across Chinese manufacturing firms.

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 12 present the coefficients on the entry and exit variables in our benchmark regressions. Whether or not we conclude that new exporters are more productive than incumbent exporters in the same product market depends heavily on whether we are considering revenue or physical productivity. Our estimates imply that new exporters are 2 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 8 percent *less* productive than incumbent exporters.[30] Among exiting firms we find that physical productivity is 4 percent lower than that of incumbent exporters. In contrast, we do not find significant differences exiting firms and incumbents when we use revenue productivity.

The differences between the physical and revenue based productivity coefficients can largely be explained by pricing behavior. New entrants or exiting firms generally choose *high* prices; the results in Table 12 imply that new entrants are charging prices which are 4-10 percent higher than incumbent firms. This aspect of firm behaviour can be rationalized by the fact that new entrants and exiting firms are likely to be high cost (low productivity) producers relative to incumbent exporters.[31] Table 14 demonstrates that this pattern is common to most firm types with the possible exception of processing firms where we do not estimate significant differences in productivity among entering and exiting firms relative to incumbents.

Like physical productivity, we find that new firms also experience relatively small amounts of demand in a typical product market. However, the magnitude of these differences are much larger. Entering firms are to have demand measures which are 66 percent smaller than those of incumbent exporters, while demand shocks for exitors are found to be 80 percent smaller. Taken together with the estimated

[30] This may appear inconsistent with the results in Foster, Haltiwanger and Syverson (2008) for US manufacturers. However, it is important to recognize the substantial differences in the notion of exit across the two exercises. While exit in the Foster, Haltiwanger and Syversion paper reflects the death of a firm, in our case it is simply the decision of the firm to stop selling one product to a given export destination.

[31] This result does not imply that these firms are choosing high markups. Rather, as documented in by Garcia-Marin and Voitlander (2014) and Rodrigue and Tan (2016) for Chile and China, respectively, new exporters are often firms with relatively small markups.

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. That is, exiting firms are those which demonstrate particularly low demand, which suggests that a high degree of product churning in export markets may potentially be an important source of demand growth.

Table 13 repeats this exercise across our alternative measures of productivity and demand, while Table 14 documents the results across firm-type (private firms engaged in ordinary trade, private firms engaged in processing trade, foreign-owned firms and state-owned firms) for our benchmark estimates. We observe that the same qualitative patterns arise in every case.[32]

6 Sources of Demand Growth

In this section we further decompose our measure of demand growth into components capturing within-firm demand growth, the reallocation of demand across Chinese exporters and net entry of new products. This allows us to quantify the extent to which movements in aggregate demand or productivity growth are driven by changes common to all firms, market share reallocation towards growing firms or product churning. Specifically,

$$\begin{aligned}\Delta \ln \mathcal{D}_{ikt} &= \sum_{l\in C}\theta_{fik,t-1}\Delta \ln \delta_{fikt} + \sum_{l\in C}(\ln \delta_{fik,t-1} - \ln \mathcal{D}_{ik,t-1})\Delta\theta_{fikt} + \sum_{l\in C}\Delta \ln \delta_{fikt}\Delta\theta_{fikt} \\ &\quad + \sum_{l\in E}\theta_{fikt}(\ln \delta_{fikt} - \ln \mathcal{D}_{ikt}) - \sum_{l\in X}\theta_{fik,t-1}(\ln \delta_{fik,t-1} - \ln \mathcal{D}_{ik,t-1}) \qquad (11)\end{aligned}$$

where $\ln \mathcal{D}_{ikt}$ is our measure of aggregate demand for product k in market i and year t, 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.[33] Our decomposition closely follows the straightforward decomposition for "aggregate productivity" proposed by Foster, Haltiwanger and Krizan (2001).

The first term in this decomposition captures changes demand growth within firm-product pairs, weighted by the the previous period's (physical) market share in the same product market. If aggregate demand growth is driven by shocks which are common to all firms in a given product market we would expect that this term would account a substantial portion of total demand growth. The second term represents a between-variety component. It reflects changes in market shares weighted by the deviation

[32] A large majority of firms export in only one month per year. Even if we condition solely on these firms, we find very similar results.

[33] 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.

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, we also provide analogous decompositions of log physical productivity, log revenue productivity and our alternative demand measurement.

In the first row of Table 15 we find, not surprisingly, that export demand grew rapidly over the 2000-2006 period; the first column indicates that average firm-level demand grew by 32 percent annually. Market share reallocation among continuing firms is the primary mechanism through which demand grows; our estimates suggest that nearly half of demand growth can be attributed to the disproportionate growth of market share among firms with rapidly growing idiosyncratic demand shocks.

The remaining half of demand growth is split evenly between within-firm growth and net entry. Specifically, we find that the rapid entry and exit of products in export markets can account 25 percent of aggregate export demand growth. It would be erroneous, however, to interpret this finding as suggesting that Chinese exporters enter new markets and immediately achieve export success. In fact, the decomposition suggests that new entrants contribute negatively to demand growth. Rather, the large contribution of net entry to demand growth comes from the exit of low demand firms. High rates of churning in international markets that give rise to these large changes in the composition of exporters each year and, thus, growth in export demand. Similarly, among surviving exporters, share of export shares with a given product-market is rapidly reallocated to growing firms. Total resource reallocation, whether by resource reallocation through continuing firms or through product churning, accounts for 75 percent of total demand growth. Given that these patterns driven by differential changes in demand shocks across firms, our results suggest that a better understanding of how firms manipulate idiosyncratic demand shocks may be crucial for understanding the evolution of *aggregate* exports over time.

The second row of Table 15 reports the same decomposition for our alternative measure of demand. Total demand growth and the contribution from total resource reallocation are nearly identical to those from our benchmark estimates. However, in this second case, product churning independently explains 38 percent of demand growth.

We also provide analogous results for the average productivity of Chinese exporters. We find relatively little growth by comparison. Annual physical and revenue based productivity growth rates among exporting firms are 3.8 and 4.2 percent, respectively. Although this is indicative of substantial productivity growth, it is much less than that of export demand growth. Like demand growth, the majority of produc-

tivity growth is attributed to net entry and reallocation, which jointly account for 82 percent of aggregate physical productivity growth. In contrast, the same measures of product churning and resource reallocation only account for 50 percent of revenue productivity growth. As documented above, the negative covariance between prices and physical productivity reduces the dispersion of revenue productivity. The reduction in dispersion is in turn reflected in a misleadingly small contribution from resource reallocation across firms in a given product market.

Tables 16, 17 and 18 repeat the decomposition exercise across regions, firm types and product differentiation for our benchmark measurements. In each case we find that demand has grown substantially faster than productivity. Further, we consistently find that our measures of market share reallocation and net entry explain the majority of export demand and physical productivity growth. In contrast, the measures of reallocation are always biased downwards when using revenue productivity. Consistent with our intuition, firms which compete under relatively few distortions, such as private ordinary exporters, display substantially greater contributions from product churning and market share reallocation. In fact, net entry contributes 29 percent of all demand growth among private, ordinary exporters, while 56 percent is accounted by market share reallocation among continuing exporters. Likewise, we find that firms which compete in locations with relatively few distortions, such as developed markets, demonstrate a relatively large amount of turnover. Finally, it is not surprising that product-markets with greater scope for differentiation also find that entry, exit and market share are all closely tied to demand heterogeneity.

7 Conclusion

This paper studies the nature of product churning and market share allocation among Chinese exporters, and its implications for Chinese export growth across markets worldwide. We find that demand growth accounts for at least half of all export growth. We find that product churning, and in particular the exit of low demand products, accounts for 25-38 percent of all demand growth, while the reallocation of market share towards surviving high demand firms accounts for an additional 37-50 percent of demand growth in export markets.

We document that entering and exiting firms are systematically less productive and have little demand relative to incumbent exporters. 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 66-80 percent smaller than that of the average incumbent exporter to the same market. Similarly, while productivity and demand are found to be strong determinants of which products are dropped from export

markets, the marginal impact of a change in demand is estimated to be twice as large as that from an equivalent change in productivity.

References

[1] Alessandria, George and Horag Choi. 2007. "Do Sunk Costs of Exporting Matter for Net Export Dynamics?" *Quarterly Journal of Economics*, 122(1): 289-336.

[2] Arkolakis, Costas and Marc-Andreas Muendler. 2013 "Exporters and Their Products: A Collection of Empirical Regularities," *CESifo Economic Studies*, 59(2): 223-248.

[3] Atkeson, Andrew and Ariel Burstein. 2010. "Innovation, Firm Dynamics and International Trade," *Journal of Political Economy*, 188(3): 433-484.

[4] Asplund, Marcus and Volker Nocke. 2006. Firm Turnover in Imperfectly Competitive Markets, *Review of Economic Studies*, 73(2): 295-327.

[5] Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103(6): 2121-2168.

[6] Aw, Bee Yan, Sukkyun Chung, and Mark J. Roberts. 2000. "Productivity and Turnover in the Export Market: Micro-level Evidence from the Republic of Korea and Taiwan (China)," *World Bank Economic Review*, 14: 65-90.

[7] Aw, Been Yan and Yi Lee. 2014. "A model of demand, productivity and foreign location decision among Taiwanese firms," *Journal of International Economics*, 92(2): 304-316.

[8] Aw, Bee Yan, Mark J. Roberts, and Daniel Yi Xu. 2011. "R&D Investment, Exporting, and Productivity Dynamics," *American Economic Review*, 1010(4), 1312-1344.

[9] Baily, Martin N., Charles Hulten and David Campbell. 1992. "Productivity Dynamics in Manufacturing Establishments," *Brookings Papers on Economic Activity: Microeconomics*, 187-249.

[10] Bernard, Andrew B. and J. Bradford Jensen. 1999a. "Exporting and Productivity," NBER Working Paper w7135.

[11] Bernard, Andrew B. and J. Bradford Jensen. 1999b. "Exceptional Exporter Performance: Cause, Effect, and or Both?" *Journal of International Economics*, 47: 1-25.

[12] Bernard, Andrew B., J. Bradford Jensen, Stephen J. Redding, and Peter K. Schott. 2007. "Firms in International Trade," *Journal of Economic Perspectives*, 21(3): 105-130.

[13] Bernard, Andrew B., Jensen, J. Bradford and Peter K. Schott. 2005. "Importers, Exporters, and Multinationals: A Portrait of Firms in the U.S. that Trade Goods." NBER Working Paper 11404.

[14] Bernard, Andrew B., Stephen J. Redding, and Peter K. Schott. 2010. "Multiple-Product Firms and Product Switching," *American Economic Review*, 100(1): 70-97.

[15] Bernard, Andrew B., Stephen J. Redding, and Peter K. Schott. 2011. "Multi-product Firms and Trade Liberalization," *Quarterly Journal of Economics*, 126(3): 1271-1318.

[16] Besedes, Tibor and Thomas J. Prusa. 2006a. "Ins, Outs, and the Duration of Trade." *Canadian Journal of Economics*, 39(1): 266-95.

[17] Besedes, Tibor and Thomas J. Prusa. 2006b. "Product Differentiation and Duration of US Import Trade." *Journal of International Economics*, 70(2): 339-58.

[18] Besedes, Tibor and Thomas J. Prusa. 2007. "The Role of Extensive and Intensive Marginsd and Export Growth." NBER Working Paper 13628.

[19] Brandt, Loren, Johannes Van Biesebroeck and Yifan Zhang. 2012. "Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing," *Journal of Development Economics*, 97(2): 339-351.

[20] Clerides, Sofronis, Saul Lach, and James R. Tybout. 1998. "Is Learning by Exporting Important? Micro-Dynamic Evidence from Columbia, Mexico and Morocco," *Quarterly Journal of Economics*, 113: 903-947.

[21] Costantini, James and Marc J. Melitz. 2008. "The Dynamics of Firm-Level Adjustment to Trade Liberalization," in *The Organization of Firms in a Global Economy,* E. Helpman, D. Marin and T. Verdier (eds.) Harvard University Press.

[22] Crozet, Mattheiu, Keith Head and Thierry Mayer. 2012. "Quality Sorting and Trade: Firm-level Evidence for French Wine," *Review of Economic Studies,* 79(2): 609-644.

[23] Dai, Mi, Madhura Maitra and Miaojie Yu, 2011. "Unexeptional Exporter Performance in China? Role of Processing Trade," mimeo, Peking University.

[24] Das, Sanghamitra, Mark J. Roberts, and James R. Tybout. 2007. "Market Entry Costs, Producer Heterogeneity, and Export Dynamics," *Econometrica*, 75(3): 837-873.

[25] De Loecker, Jan. 2007. "Do Exports Generate Higher Productivity? Evidence from Slovenia," *Journal of International Economics*, 73: 69-98.

[26] De Loecker, Jan. 2011. "Product differentiation, multiproduct firms, and estimating the impact of trade liberalization on productivity," *Econometrica*, 79(5), 1407-1451.

[27] De Loecker, Jan and Frederic Warzynski. 2012. "Markups and Firm-Level Export Status," *American Economic Review*, 102(6), 2437-2471.

[28] De Loecker, Jan, Pinelopi K. Goldberg, Amit K. Khandelwal and Nina Pavcnik. 2016. "Prices, Markups and Trade Reform," *Econometrica*, 84(2): 445-510.

[29] Demidova, Svetlana, Hiau Looi Kee and Kala Krishna. 2012. "Do Trade Policy Differences Induce Sorting? Theory and Evidence From Bangladeshi Apparel Exporters," *Journal of International Economics*, 87(2):247-261.

[30] Eaton, Jonathan, Marcela Eslava, Maurice Kugler and James R. Tybout. 2008. "The Margins of Entry into Exports Markets: Evidence from Columbia," in E. Helpman, D. Marin and T. Verdier, eds., *The Organization of Firms in a Global Economy*, Harvard University Press.

[31] Eaton, Jonathan, Samuel Kortum, Francis Kramarz. 2011. "An Anatomy of International Trade: Evidence from French Firms," *Econometrica*, 79(5): 1453-1498.

[32] Eaton, Jonathan, Samuel Kortum, Brent Neiman and John Romalis. 2011. "Trade and the Global Recession," NBER Working Paper 16666.

[33] Ericson, Richard and Ariel Pakes. 1995. "Markov-Perfect Industry Dynamics: A Framework for Empirical Work," *Review of Economic Studies*, 62(1): 53-82.

[34] Eslava, Marcela, John C. Haltiwanger, Adriana D. Kugler and Maurice Kugler. 2009. "Trade Reforms and Market Selection: Evidence from Manufacturing Plants in Colombia," NBER Working Paper 14935.

[35] Evans, David S. 1987. "The Relation Between Firm Growth, Size, and Age: Estimates for 100 Manufacturing Industries," *Journal of Industrial Economics,* 35: 567-581.

[36] Foster, Lucia, John Haltiwanger and C.J. Krizan. 2001. "Aggregate Productivity Growth: Lessons from Microeconomic Evidence," in *New Developments in Productivity Analysis*, Edward Dean, Michael Harper, and Charles Hulten (eds.), University of Chicago Press.

[37] Foster, Lucia, John Haltiwanger and Chad Syverson. 2008. "Reallocation, Firm Turnover and Efficiency: Selection on Productivity or Profitability?" *American Economic Review*, 98(1): 394-425.

[38] Gervais, Antoine. 2015. "Product Quality and Firm Heterogeneity in International Trade," *Canadian Journal of Economics*, 48(3): 1152-1174.

[39] Hall, Bronwyn H. 1987. "The Relationship Between Firm Size and Firm Growth in the US Manufacturing Sector," *Journal of Industrial Economics*, 35: 583-606.

[40] Hopenhayn, Hugo A. 1992. Entry, Exit, and Firm Dynamics in Long Run Equilibrium, *Econometrica*, 60(5): 1127-1150.

[41] Hsieh, Chang-Tai and Peter J. Klenow. 2009. "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 124: 1403-1448.

[42] Jovanovic, Boyan. 1982. Selection and the Evolution of Industry, *Econometrica*, 50(3): 649-670.

[43] Khandelwal, Amit. 2010. "The Long and Short (of) Quality Ladders," *Review of Economic Studies*, 77(4): 1450-1476.

[44] Lu, Dan. 2010. "Exceptional Exporter Performance? Evidence from Chinese Manufacturing Firms," Mimeo, University of Chicago.

[45] Manova, Kalina and Zhihong Yu. 2011. "Firms and Credit Constraints along the Global Value Chain: Processing Trade in China," NBER Working Paper 18561.

[46] Manova, Kalina and Zhiwei Zhang. 2011. "Multi-Product Firms and Product Quality," NBER Working Paper w18637.

[47] Manova, Kalina and Zhiwei Zhang. 2012. "Export Prices across Firms and Destinations," *Quarterly Journal of Economics*, 127: 379-436.

[48] Mansfield, Edwin. 1962. "Entry, Gibrat's Law, Innovation, and the Growth of Firms," *American Economic Review*, 52(5): 1023-1051.

[49] Mayer, Thierry, Marc J. Melitz, and Gianmarco I.P. Ottaviano. 2014. "Market Size, Competition, adn the Product Mix of Exporters," *American Economic Review*, 104(2): 495-536.

[50] Melitz, Marc J. 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71(6): 1695-1725.

[51] Melitz, Marc J. and Gianmarco I.P. Ottaviano. 2008. "Market Size, Trade and Productivity," *Review of Economic Studies*, 75: 295-316.

[52] Melitz, Marc, and Saso Polanec. 2015. ""Dynamic Olley-Pakes Productivity Decomposition with Entry and Exit," *RAND Journal of Economic*, 46(2): 362-375.

[53] Munch, Jakob and Daniel Nguyen. 2014. "Decomposing Firm-Level Sales Variation," *Journal of Economic Behavior and Organization*, 106: 317-334.

[54] Munch, Jakob and Georg Schaur. 2016. "The Effect of Export Promotion on Firm-Level Performance," University of Tennessee.

[55] Pavcnik, Nina. 2002. "Trade Liberalization, Exit, and Productivity Improvements: Evidence From Chilean Plants," *Review of Economic Studies,* 69: 245-276.

[56] Rauch, James E. 1999. "Networks versus markets in international trade", *Journal of International Economics*, 48: 7-35.

[57] Restuccia, Diego and Richard Rogerson. 2008. "Policy Distortions and Aggregate Productivity with Heterogeneous Plants," *Review of Economic Dynamics*, 11: 707-720.

[58] Rho, Youngwoo and Joel Rodrigue. 2016. "Firm-Level Investment and Export Dynamics," *International Economic Review*, 57(1): 271-304.

[59] Rivers, David A. 2010. "Are Exporters More Productive than Non-Exporters?" mimeo, University of Western Ontario.

[60] Roberts, Mark J., Yi Xu, Xiaoyan Fan, Shengxing Zhang. 2016. "A Structural Model of Demand, Cost, and Export Market Selection for Chinese Footwear Producers," NBER Working Paper 17725.

[61] Trefler, Daniel. 2004. "The Long and Short of the Canada-U.S. Free Trade Agreement," *American Economic Review*, 94: 870-895.

[62] Wang, Zheng and Zhihong Yu. 2012. "Trading Partners, Traded Products, and Firm Performances of Chinas ExporterImporters: Does Processing Trade Make a Difference?" *The World Economy,* 35(12): 1795-1824.

[63] Wooldridge, Jeffrey M. 2002.*Econometric Analysis of Cross Section and Panel Data.* Cambridge: The MIT Press.

A Tables

Table 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	53.93	34.64	23	40.26	20.44	33	27.13	21.29
14	31.46	26.43	24	74.20	73.58	34	54.39	50.58
15	26.41	17.82	25	25.74	18.38	35	39.63	32.84
16	4.21	3.29	26	28.71	25.25	36	28.04	21.46
17	50.10	48.78	27	29.51	23.46	37	37.85	28.51
18	70.77	59.57	28	28.11	22.95	39	51.82	45.11
19	71.06	71.82	29	47.69	41.08	40	54.52	53.59
20	55.88	48.69	30	54.69	48.31	41	56.53	51.31
21	65.88	60.24	31	47.26	28.48	42	74.95	75.49
22	36.47	24.25	32	23.36	16.86			

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 2: Demand Estimation

	Price Coefficient $-\sigma_k$					
	IV		OLS			
Percentile	Estimate	Std. Error	Estimate	Std. Error	HS6 Code	Description
10	-29.016***	7.290	-14.220***	1.596	550690	Polyphenylene Sulfide
25	-11.035**	5.186	-4.571**	1.989	722920	Steel Alloy Wire
50	-4.435*	2.639	-2.641***	0.421	901420	Compasses
75	-2.225	1.415	-0.271***	0.049	940180	Children's Car Safety Seats
90	-1.469***	0.135	-1.441***	0.098	910111	Electrical Wrist Watches

Notes: The above results correspond to estimated isoelatic demand curves described in Section 3. All regressions include product-market-year and product-market-firm fixed effects. Robust standard errors are reported. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

Table 3: Product Turnover in International Markets

	Full Sample	North America	Europe	Japan	Australia	South America	Rest of Asia	Africa	Undiff. Prods	Diff. Prods
Product Entry	0.537	0.519	0.560	0.428	0.518	0.586	0.537	0.636	0.537	0.537
Product Exit	0.426	0.393	0.433	0.358	0.410	0.455	0.435	0.519	0.428	0.421

Notes: This table presents annual entry and exit rates for Chinese exporters across product type and broad regions worldwide. An entering firm is a firm that did not produce in a given country in the preceding period, but does in the current period. An exiting firm is a firm which does produce in a given country in the current period but does not in the next period.

Table 4: 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	0.919	1.000					
Physical Prod.	0.542	0.186	1.000				
Revenue Prod.	0.325	0.107	0.782	1.000			
Demand	0.155	0.209	-0.093	0.074	1.000		
Price	-0.568	-0.196	-0.758	-0.584	0.090	1.000	
Capital	0.731	0.887	-0.102	-0.241	0.121	0.034	1.000
Standard Deviations							
Standard Deviations	3.396	2.849	2.059	1.676	3.876	2.051	3.049

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 5: Persistence in Productivity and Demand

	Revenue TFP	Physical TFP	Demand	Price	Revenue
All firms and products	0.882***	0.811***	0.789***	0.942***	0.818***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Private Firms, Ordinary Trade	0.877***	0.779***	0.732***	0.937***	0.825***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.002)
Private Firms, Processing Trade	0.921***	0.855***	0.848***	0.966***	0.888***
	(0.003)	(0.003)	(0.004)	(0.002)	(0.004)
Foreign Owned Firms	0.872***	0.816***	0.778***	0.940***	0.848***
	(0.004)	(0.003)	(0.002)	(0.001)	(0.002)
State Owned Firms	0.839***	0.727***	0.656***	0.949***	0.801***
	(0.008)	(0.006)	(0.005)	(0.002)	(0.003)
Undifferentiated Products	0.947***	0.901***	0.873***	0.953***	0.882***
	(0.007)	(0.008)	(0.010)	(0.006)	(0.010)
Differentiated Products	0.894***	0.827***	0.810***	0.942***	0.820***
	(0.002)	(0.002)	(0.001)	(0.001)	(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 reported in parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

Table 6: Decomposition of Aggregate Export Growth

	Annual Export Growth	% Export Growth Explained By Physical Productivity Growth	Demand Growth
All Products and Countries	0.152	0.177	0.823
North America	0.127	0.195	0.805
Europe	0.102	0.095	0.905
Japan	0.074	0.163	0.837
Australia	0.071	0.179	0.821
South America	0.148	0.161	0.839
Rest of Asia	0.162	0.264	0.736
Africa	0.132	0.222	0.778
Private, Ordinary Trade	0.152	0.251	0.749
Private, Processing Trade	0.013	0.266	0.734
Foreign Firms	0.181	0.191	0.809
State-Owned Firms	0.112	0.217	0.783
Undifferentiated Products	0.110	0.353	0.647
Differentiated Products	0.165	0.077	0.923

Notes: The first column reports annual export growth (in percentages). The second and third column decompose annual export growth into demand and productivity components.

Table 7: Decomposition of Aggregate Export Growth

	Annual Export Growth	% Export Growth Explained By Physical Productivity Growth	Demand Growth
Benchmark	0.152	0.177	0.823
Alt. Productivity	0.151	0.218	0.781
Alt. Demand	0.159	0.105	0.895

Notes: The first column reports annual export growth (in percentages). The second and third column decompose annual export growth into demand and productivity components.

Table 8: Determinants of Selection: Benchmark Measurment

Revenue TFP	-0.050***					
	(0.004)					
Physical TFP		-0.009**			-0.013***	-0.008***
		(0.004)			(0.002)	(0.002)
Demand			-0.035***		-0.028***	-0.017***
			(0.005)		(0.004)	(0.004)
Price				-0.004**		
				(0.002)		
Age						0.0001
						(0.0001)
Capital						-0.003***
						(0.001)
Import Price						-0.0003***
						(0.0001)
Distance	0.011***	0.017***	0.021***	0.052***	0.015***	0.009***
	(0.001)	(0.001)	(0.004)	(0.007)	(0.003)	(0.003)
Income	-0.008***	-0.012***	-0.060***	-0.151***	-0.044***	-0.027***
	(0.001)	(0.001)	(0.008)	(0.012)	(0.007)	(0.007)
Size	-0.002***	-0.003***	-0.004***	-0.010***	-0.003***	-0.003***
	(0.0004)	(0.001)	(0.0001)	(0.002)	(0.001)	(0.001)
No. of Obs.	512,754	512,754	512,754	512,754	512,754	315,231

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 reported in parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level. The number of observations in the last column is smaller than the other columns because not all firms import materials.

Table 9: Determinants of Selection: Alternative Productivity Measurment

Revenue TFP	-0.005***					
	(0.001)					
Physical TFP		-0.003***			-0.004***	-0.004***
		(0.001)			(0.001)	(0.001)
Demand			-0.024***		-0.009***	-0.006***
			(0.008)		(0.002)	(0.002)
Price				0.0001		
				(0.002)		
Age						0.0001***
						(0.00001)
Capital						-0.001***
						(0.0002)
Import Price						-0.0000
						(0.0001)
Distance	0.003***	0.003***	0.016***	0.004**	0.003***	0.005***
	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
Income	-0.003***	-0.004***	-0.018***	-0.015**	-0.003***	-0.004***
	(0.001)	(0.001)	(0.003)	(0.007)	(0.001)	(0.001)
Size	-0.001***	-0.001***	-0.003***	-0.002**	-0.001*	-0.001***
	(0.0001)	(0.0001)	(0.001)	(0.001)	(0.0006)	(0.0003)
No. of Obs.	39,289	39,289	39,289	39,289	39,289	24,974

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 reported in parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

Table 10: Determinants of Selection: Alternative Demand Measurment

Revenue TFP	-0.050***					
	(0.004)					
Physical TFP		-0.015***			-0.001***	-0.0002**
		(0.004)			(0.0002)	(0.0001)
Demand			-0.011***		-0.009***	-0.004***
			(0.002)		(0.002)	(0.001)
Price				-0.004**		
				(0.002)		
Age						0.0001
						(0.0001)
Capital						-0.001
						(0.003)
Import Price						-0.001
						(0.030)
Distance	0.011***	0.032***	0.002***	0.052***	0.002***	0.001
	(0.001)	(0.005)	(0.0004)	(0.007)	(0.0004)	(0.003)
Income	-0.008***	-0.102***	-0.006***	-0.151***	-0.005***	-0.002**
	(0.001)	(0.011)	(0.001)	(0.012)	(0.001)	(0.001)
Size	-0.002***	-0.009***	-0.0001***	-0.010***	-0.001***	-0.0003***
	(0.0004)	(0.001)	(0.0000)	(0.002)	(0.0001)	(0.0001)
No. of Obs.	593,818	593,818	593,818	593,818	593,818	362,434

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 reported in parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

Table 11: 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	-0.005**	-0.007*	-0.002**	-0.008***	-0.008***	-0.010*
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.006)
Demand	-0.011***	-0.010*	-0.011***	-0.033**	-0.022***	-0.020*
	(0.003)	(0.006)	(0.003)	(0.014)	(0.004)	(0.012)
Distance	0.004**	0.004*	0.004**	0.012*	0.008***	0.009*
	(0.002)	(0.003)	(0.002)	(0.007)	(0.002)	(0.007)
Income	-0.014**	-0.009*	-0.012***	-0.037**	-0.022***	-0.018*
	(0.005)	(0.005)	(0.004)	(0.017)	(0.005)	(0.012)
Size	-0.001***	-0.0001	-0.001***	0.0005	-0.001***	-0.002**
	(0.0003)	(0.001)	(0.0003)	(0.001)	(0.0003)	(0.001)
No. of Obs.	175,115	41,597	176,265	72,221	415,934	44,009

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 reported in parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

Table 12: Evolution of Productivity and Demand

	Dependent Variable				
	Revenue TFP	Physical TFP	Demand	Price	Revenue
Entry	0.016***	-0.080***	-1.074***	0.096***	-0.712***
	(0.001)	(0.004)	(0.040)	(0.005)	(0.007)
Exit	-0.001	-0.042***	-1.598***	0.042***	-0.973***
	(0.002)	(0.005)	(0.040)	(0.005)	(0.007)
No. of Obs.			708,520		

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 parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

Table 13: Evolution of Productivity and Demand: Alternative Measurements

	Dependent Variable			
	Benchmark Physical TFP	Alternative Physical TFP	Benchmark Demand	Alternative Demand
Entry	-0.080***	-0.124***	-1.074***	-1.271***
	(0.004)	(0.004)	(0.040)	(0.008)
Exit	-0.042***	-0.101***	-1.598***	-1.575***
	(0.005)	(0.010)	(0.040)	(0.008)
No. of Obs.	708,520	39,289	708,520	786,948

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 parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

Table 14: Evolution of Productivity and Demand by Firm Type

	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	-0.003	-0.103***	-0.915***	0.101***	-0.566***	0.016***	-0.014	-0.909***	0.030**	-0.56***
	(0.002)	(0.008)	(0.065)	(0.008)	(0.010)	(0.004)	(0.012)	(0.136)	(0.012)	(0.020)
Exit	-0.001	-0.041***	-1.560***	0.041***	-0.822***	0.001	0.014	-0.803***	-0.013	-0.565***
	(0.002)	(0.007)	(0.063)	(0.007)	(0.010)	(0.004)	(0.012)	(0.139)	(0.012)	(0.020)
	Foreign Owned Firms					State Owned Firms				
Entry	0.002	-0.108***	-0.917***	0.111***	-0.768***	0.036***	-0.083***	-0.725***	0.120***	-0.509***
	(0.002)	(0.008)	(0.060)	(0.008)	(0.012)	(0.004)	(0.012)	(0.105)	(0.012)	(0.015)
Exit	0.029***	-0.034***	-1.553***	0.065***	-1.122***	-0.043***	-0.079***	-1.301***	0.037***	-0.611***
	(0.002)	(0.008)	(0.062)	(0.008)	(0.012)	(0.004)	(0.012)	(0.104)	(0.012)	(0.015)

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 parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level. 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 15: Decomposition of Demand and Productivity Growth

	Total	Components of Decomposition					
Determinant	Growth	Within	Between	Cross	Entry	Exit	Net Entry
Benchmark Log Demand	0.317	0.079	-0.022	0.181	-0.002	-0.080	0.078
Alternative Log Demand	0.306	0.075	-0.089	0.205	0.073	-0.042	0.115
Log Physical Productivity	0.038	0.007	-0.024	0.011	0.052	0.008	0.044
Log Revenue Productivity	0.042	0.022	0.000	0.002	0.018	-0.001	0.019

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 16: Decomposition of Demand and Productivity Across Regions

Determinant	Total Growth	Components of Decomposition					
		Within	Between	Cross	Entry	Exit	Net Entry
North America							
Log Demand	0.346	0.088	-0.073	0.234	-0.003	-0.100	0.097
Log Physical Productivity	0.048	0.004	-0.024	0.019	0.060	0.011	0.049
Log Revenue Productivity	0.043	0.021	0.002	0.004	0.014	-0.002	0.016
Europe							
Log Demand	0.318	0.087	-0.022	0.184	-0.009	-0.078	0.069
Log Physical Productivity	0.039	0.006	-0.023	0.009	0.056	0.008	0.047
Log Revenue Productivity	0.043	0.021	0.000	0.002	0.019	-0.001	0.020
Japan							
Log Demand	0.359	0.050	-0.043	0.305	-0.088	-0.135	0.047
Log Physical Productivity	0.054	0.014	-0.037	0.021	0.071	0.016	0.055
Log Revenue Productivity	0.042	0.024	-0.002	0.006	0.013	0.000	0.013
Australia							
Australia Log Demand	0.331	0.049	-0.055	0.243	-0.019	-0.113	0.094
Log Physical Productivity	0.031	0.001	-0.024	0.018	0.051	0.014	0.037
Log Revenue Productivity	0.044	0.022	-0.002	0.006	0.018	0.000	0.019
South America							
Log Demand	0.284	0.108	-0.005	0.126	0.000	-0.055	0.055
Log Physical Productivity	0.031	0.005	-0.021	0.008	0.044	0.005	0.039
Log Revenue Productivity	0.039	0.020	0.001	0.003	0.014	-0.002	0.016
Rest of Asia							
Log Demand	0.343	0.083	-0.013	0.182	0.002	-0.089	0.091
Log Physical Productivity	0.039	0.009	-0.027	0.011	0.054	0.008	0.045
Log Revenue Productivity	0.045	0.023	-0.001	0.002	0.020	-0.001	0.021
Africa							
Log Demand	0.383	0.132	-0.006	0.086	0.135	-0.036	0.171
Log Physical Productivity	0.019	0.007	-0.015	0.004	0.025	0.002	0.022
Log Revenue Productivity	0.034	0.023	-0.001	0.002	0.009	-0.001	0.010

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 17: Decomposition of Demand and Productivity by Firm-Type

Determinant	Total Growth	Components of Decomposition					
		Within	Between	Cross	Entry	Exit	Net Entry
Private, Ordinary Trade							
Log Demand	0.254	0.039	0.011	0.131	0.039	-0.034	0.073
Log Physical Productivity	0.041	0.011	-0.022	0.007	0.0507264	0.006	0.045
Log Revenue Productivity	0.035	0.022	-0.001	0.001	0.0124157	-0.001	0.013
Private, Processing Trade							
Log Demand	0.254	0.039	0.011	0.131	0.039	-0.034	0.073
Log Physical Productivity	-0.012	0.002	-0.021	0.008	0.0046658	0.006	-0.001
Log Revenue Productivity	0.018	0.014	-0.001	0.003	0.0035725	0.001	0.003
Foreign Firms							
Log Demand	0.396	0.155	0.013	0.165	-0.009	-0.071	0.062
Log Physical Productivity	0.024	0.011	-0.024	0.008	0.0360312	0.008	0.028
Log Revenue Productivity	0.041	0.032	-0.001	0.001	0.0091831	0.000	0.009
State-Owned Firms							
Log Demand	0.542	0.256	0.075	0.103	0.050	-0.058	0.108
Log Physical Productivity	0.029	0.006	-0.018	0.004	0.0395277	0.002	0.038
Log Revenue Productivity	0.046	0.018	0.002	0.000	0.0236182	-0.002	0.026

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.

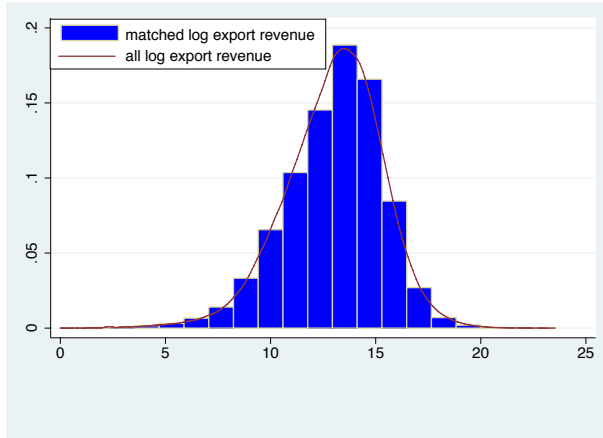
Table 18: Decomposition of Demand and Productivity by Product Differentiation

Determinant	Total Growth	Components of Decomposition					
		Within	Between	Cross	Entry	Exit	Net Entry
Undifferentiated Products							
Log Demand	0.470	0.263	0.078	0.090	-0.087	-0.126	0.039
Log Physical Productivity	0.042	0.020	-0.017	0.008	0.037	0.006	0.030
Log Revenue Productivity	0.046	0.033	-0.001	0.002	0.010	-0.001	0.012
Differentiated Products							
Log Demand	0.288	0.045	-0.041	0.198	0.014	-0.072	0.086
Log Physical Productivity	0.037	0.005	-0.025	0.011	0.054	0.008	0.046
Log Revenue Productivity	0.042	0.020	0.000	0.002	0.019	-0.001	0.020

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.

B Figures

Figure 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.

C Variable Construction

C.1 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.

C.1.1 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.

C.1.2 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 $d = 0.09$.

C.1.3 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 (2009) 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, $\tilde{\varrho}$, 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

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

where $\tilde{\varrho}$ 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 (2009) 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

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

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

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

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 (2009) 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., 2016). 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 Churning, Reallocation, and Chinese Export Growth"

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This appendix provides a variety of details related to model development and outlines additional results omitted from the main text. Section A provides the simple proofs omitted from the main text. Section B describes the matching algorithm in detail. Section C reports full results from the alternative measure of productivity. Note that this case, our measure of demand is derived using this alternative measure of productivity as an input. In Section D, we report the full set of results for our alternative demand measure, as described in Section 3.4 of the main text. Note that in this second case, we use our benchmark productivity measure the derivation of the demand measure. Section E and Section F document our findings when we consider only firms which export intensively or firms which use materials intensively. In Section G we report the results from the footwear industry alone, while Section H describes our aggregate decomposition findings when we use revenue-based productivity in place of physical productivity.

A 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_{ijk}. These results are analogous to that already demonstrated in Melitz (2003). The implicit function theorem implies $\frac{d\phi^*_{ik}}{d\tau_{ijk}} = \frac{-\partial V^E_k/\partial\tau_{ijk}}{\partial V^E_k/\partial\phi^*_{ik}} < 0$ and $\frac{d\phi^*_{ik}}{d\sigma_k} = \frac{-\partial V^E_k/\partial\sigma_k}{\partial V^E_k/\partial\phi^*_{ik}} > 0$.

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

$$\begin{aligned}
V^E_k &= \int_{\varphi_k}\int_{\delta_{1k}}...\int_{\delta_{Ik}} \pi_{ik}(\phi_{i1k},...\phi_{iJk},\phi^*_{1k},...,\phi^*_{Ik})g(\varphi_k,\delta_{1k},...,\delta_{Ik})d\delta_{Ik},...,d\delta_{1k}d\varphi_k - s_k = 0 \\
&= \int_{\varphi^l_k}^{\varphi^u_k}\int_{\frac{\phi^*_{1k}w_j\tau_{i1}}{\varphi_k}}^{\delta^e_{1k}} \left[\left(\frac{\phi_{i1k}}{\phi^*_{1k}}\right)^{\sigma_1-1} - 1\right] f_{1k}g(\varphi_k,\delta_{1k})d\delta_{1k}d\varphi_k \\
&\quad +...\int_{\varphi^l_k}^{\varphi^u_k}\int_{\frac{\phi^*_{ik}w_j\tau_{ijk}}{\varphi_k}}^{\delta^e_{ik}} \left[\left(\frac{\phi_{ijk}}{\phi^*_{ik}}\right)^{\sigma_i-1} - 1\right] f_{ik}g(\varphi_k,\delta_{ik})d\delta_{ik}d\varphi_k \\
&\quad +...\int_{\varphi^l_k}^{\varphi^u_k}\int_{\frac{\phi^*_{Ik}w_j\tau_{ijk}}{\varphi_k}}^{\delta^e_{Ik}} \left[\left(\frac{\phi_{Ijk}}{\phi^*_{Ik}}\right)^{\sigma_I-1} - 1\right] f_{Jk}g(\varphi_k,\delta_{Ik})d\delta_{Ik}d\varphi_k - s_k = 0
\end{aligned}$$

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

market separability of demand. Then,

$$\begin{aligned}\frac{\partial V_k^E}{\partial \tau_{ijk}} &= \int_{\varphi_k^l}^{\varphi_k^u}\left[\left(\frac{\phi_{ik}^*}{\phi_{ik}^*}\right)^{\sigma_k-1}-1\right] f_{ik}g(\varphi_k,\delta_{ik})d\delta_{ik}d\varphi_k \\ &\quad + \int_{\varphi_k^l}^{\varphi_k^u}\int_{\frac{\phi_{ik}^* w_j \tau_{ijk}}{\varphi_k}}^{\delta_{ik}^e}(1-\sigma_k)\left(\frac{\phi_{ijk}}{\phi_{ik}^*}\right)^{\sigma_k-1}\frac{f_{ik}}{\tau_{ijk}}g(\varphi_k,\delta_{ik})d\delta_{ik}d\varphi_k < 0\end{aligned}$$

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

$$\begin{aligned}\frac{\partial V_k^E}{\partial \phi_{ik}^*} &= \int_{\varphi_k^l}^{\varphi_k^u}\left[\left(\frac{\phi_{ik}^*}{\phi_{ik}^*}\right)^{\sigma_k-1}-1\right] f_{ik}g(\varphi_k,\delta_{ik})d\delta_{ik}d\varphi_k \\ &\quad + \int_{\varphi_k^l}^{\varphi_k^u}\int_{\frac{\phi_{ik}^* w_j \tau_{ijk}}{\varphi_k}}^{\delta_{ik}^e}(1-\sigma_k)\left(\frac{\phi_{ijk}}{\phi_{ik}^*}\right)^{\sigma_k-1}\left(\frac{1}{\phi_{ik}^*}\right)g(\varphi_k,\delta_{ik})d\delta_{ik}d\varphi_k < 0\end{aligned}$$

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

$$\begin{aligned}\frac{\partial V_k^E}{\partial \sigma_k} &= \int_{\varphi_k^l}^{\varphi_k^u}\int_{\frac{\phi_{1k}^* w_j \tau_{1j}}{\varphi_k}}^{\delta_{1k}^e}\left(\frac{\phi_{1jk}}{\phi_{1k}^*}\right)^{\sigma_k-1}\ln\left(\frac{\phi_{ijk}}{\phi_{ik}^*}\right) f_{1k}g(\varphi_k,\delta_{1k})d\delta_{1k}d\varphi_k \\ &\quad +\ldots\int_{\varphi_k^l}^{\varphi_k^u}\int_{\frac{\phi_{ik}^* w_j \tau_{ijk}}{\varphi_k}}^{\delta_{ik}^e}\left(\frac{\phi_{ijk}}{\phi_{ik}^*}\right)^{\sigma_k-1}\ln\left(\frac{\phi_{ijk}}{\phi_{ik}^*}\right) f_{ik}g(\varphi_k,\delta_{ik})d\delta_{ik}d\varphi_k \\ &\quad +\ldots\int_{\varphi_k^l}^{\varphi_k^u}\int_{\frac{\phi_{Ik}^* w_j \tau_{ijk}}{\varphi_k}}^{\delta_{Ik}^e}\left(\frac{\phi_{Ijk}}{\phi_{Ik}^*}\right)^{\sigma_k-1}\ln\left(\frac{\phi_{Ijk}}{\phi_{Ik}^*}\right) f_{Ik}g(\varphi_k,\delta_{Ik})d\delta_{Ik}d\varphi_k > 0\end{aligned}$$

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

■

B 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 2000 and named B in all other years, we treat that as one successful match in 2000. 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. For matches with complete location and contact information we check the consistency of our matches by comparing phone numbers and location information across each data set. Last, 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

Table 19: Summary Statistics

	Sample			
	Man. Survey Data		Matched Data	
Variable	Mean	Std. Error	Mean	Std. Error
Log Export Revenue	9.409	0.003	9.671	0.004
Log Total Revenue	10.431	0.002	10.624	0.003
Log Value Added	8.952	0.002	9.133	0.003
Log Capital Stock	8.631	0.003	8.948	0.004
Log Employment	5.274	0.002	5.396	0.002
Log Intermediate Materials	10.007	0.002	10.202	0.003
Log Export Prices			1.498	0.001
Log Export Quantity			8.123	0.002

Notes: This table reports summary statistics from the manufacturing survey and the matched sample for the primary variables used in our empirical exercises.

are successfully matched during the 2000-2006 period. Our matching algorithm and results are very similar to those in Manova and Yu (2011) and Wang and Yu (2012).

Table 19 documents summary statistics each of the key variables used in our empirical exercises. We find in each case that the mean value and standard error of each variable in the full manufacturing survey data is very close to the the mean value and standard error of the same variable in our matched sample.

C Alternative Productivity Measure

In this section we briefly describe an alternative productivity estimation methodology based on recent contributions from De Loecker et al. (2016) extended to our setting. We then repeat the primary experiments described in the main text to check the robustness of our results.

C.1 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 Section 3.3. However, as argued by De Loecker et al. (2016) 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 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:

$$q_{fkt} = \alpha_k k_{fkt} + \alpha_l l_{fkt} + \alpha_m m_{fkt} + \omega_{fkt} + \epsilon_{fkt} \tag{12}$$

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

$$\omega_{fkt} = \rho\omega_{fk,t-1} + \xi_{fkt} \tag{13}$$

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.[34] 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 price index.[35] Following De Loecker et al. (2016) we assume that product-level material quantities, m_{fkt}, relate to expenditures as follows:

$$m_{fkt} = \tilde{m}_{fkt} - w^m_{fkt} \tag{14}$$

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 (12) we write

$$q_{klt} = \alpha_k\tilde{k}_{klt} + \alpha_l l_{klt} + \alpha_m\tilde{m}_{klt} + \omega_{klt} - \alpha_k w^k_{klt} - \alpha_m w^m_{klt} + \epsilon_{klt} \tag{15}$$

Equation (15) 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.

Following Ackerberg, Caves and Frazer (2006) and De Loecker et al. (2016) 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. (2016) 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

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

[35] 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.

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

$$\omega_{fkt} = \hat{\phi} - \alpha_k \tilde{k}_{fkt} + \alpha_l l_{fkt} + \alpha_m \tilde{m}_{fkt} - \varphi(\bar{p}_{klt}, \bar{p}_{fkt} \times \tilde{k}_{fkt}, \bar{p}_{fkt} \times \tilde{m}_{fkt}; \delta) \tag{16}$$

As emphasized by De Loecker et al. (2016) 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 (13). Using equation (16) to project ω_{fkt} on $\omega_{fk,t-1}$ and $\hat{P}_{fkt}$ and their interactions:

$$\xi_{fkt}(\alpha_k, \alpha_l, \alpha_m, \delta) = \omega_{fkt}(\alpha_k, \alpha_l, \alpha_m, \delta) - \mathbf{E}(\omega_{fkt}(\alpha_k, \alpha_l, \alpha_m, \delta)|\omega_{fk,t-1}(\alpha_k, \alpha_l, \alpha_m, \delta), \hat{P}_{fkt}) \tag{17}$$

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. 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.[36] 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 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.[37]

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

[37] 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 C1: Production Function And Elasticity Estimates

Product Description	Product Code	α_k	α_m	α_l	σ_k
Prepared binders for foundry moulds	382490	0.013	0.625	0.033	-3.449
Polymers of ethylene	392321	0.413	0.016	0.237	-3.773
Stoppers, lids, caps and other closures	392350	0.345	0.140	0.222	-19.708
Leather accessories	420310	0.069	0.697	0.314	-3.146
Note books	482010	0.271	0.237	0.147	-6.804
Printed pictures and photographs	491199	0.322	0.415	0.075	-1.168
Men's or boy's cotton suits	610332	0.129	0.448	0.126	-1.818
Women's or girls' suits of synthetic fibers	610463	0.043	0.657	0.086	-1.807
Women's pajamas	610822	0.149	0.309	0.180	-2.796
Cotton T-shirts	610910	0.217	0.178	0.208	-1.956
Silk shirts	610990	0.223	0.181	0.187	-2.260
Knitted or crocheted pullovers	611030	0.020	0.537	0.193	-1.233
Women's down coats	620212	0.084	0.538	0.138	-2.383
Women's cotton blouses	620630	0.040	0.534	0.277	-1.362
Track suits	621142	0.005	0.674	0.099	-1.473
Socks	621710	0.045	0.446	0.298	-2.101
Framing components	730890	0.110	0.458	0.131	-4.087
Electric switches	853669	0.007	0.559	0.081	-4.185
Leather seats	940161	0.144	0.425	0.192	-21.451
Down comforters	940490	0.190	0.340	0.205	-2.007

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

Given the production function estimates we proceed to measure productivity as outlined in De Loecker (2016). Using the new productivity series 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.

C.2 Results Using the Alternative Productivity Measure

Tables C2-C5 produce analogous results to benchmark results reported in Tables 5-15 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 C2 where we find that demand growth explains nearly 78 percent of total export growth among the industries included in our robustness check. In Table C3 we again find that product churning and reallocation are primary determinants of demand growth and physical productivity growth. As in the main text, we cannot replicate this pattern for revenue productivity. Nearly all other results are likewise very similar to those in the main text and, as such, we largely omit further discussion here.

Table C2: Decomposition of Aggregate Export Growth (Alt. Productivity)

		% Export Growth Explained By	
	Annual Export Growth	Physical Productivity Growth	Demand Growth
All Products and Countries	0.151	0.218	0.781

Notes: The first column reports annual export growth (in percentages). The second and third column decompose annual export growth into demand and productivity components.

Table C3: Decomposition of Demand and Productivity Growth (Alt. Productivity)

Determinant	Total Growth	Components of Decomposition					
		Within	Between	Cross	Entry	Exit	Net Entry
Log Demand	0.453	0.076	0.095	0.220	0.021	-0.041	0.063
Log Physical Productivity	0.190	0.033	-0.124	0.231	0.030	-0.021	0.050
Log Revenue Productivity	0.047	0.015	-0.011	0.020	0.015	-0.007	0.022

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 C4: Determinants of Selection

Revenue TFP	-0.005***					
	(0.001)					
Physical TFP		-0.003***			-0.004***	-0.004***
		(0.001)			(0.001)	(0.001)
Demand			-0.024***		-0.009***	-0.006***
			(0.008)		(0.002)	(0.002)
Price				0.0001		
				(0.002)		
Age						0.0001***
						(0.00001)
Capital						-0.001***
						(0.0002)
Import Price						-0.0000
						(0.0001)
Distance	0.003***	0.003***	0.016***	0.004**	0.003***	0.005***
	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
Income	-0.003***	-0.004***	-0.018***	-0.015**	-0.003***	-0.004***
	(0.001)	(0.001)	(0.003)	(0.007)	(0.001)	(0.001)
Size	-0.001***	-0.001***	-0.003***	-0.002**	-0.001*	-0.001***
	(0.0001)	(0.0001)	(0.001)	(0.001)	(0.0006)	(0.0003)
No. of Obs.	39,289	39,289	39,289	39,289	39,289	24,974

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 parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

Table C5: Evolution of Productivity and Demand

	Dependent Variable				
	Revenue TFP	Physical TFP	Demand	Price	Revenue
Entry	-0.013***	-0.124***	-0.807***	0.037***	-0.686***
	(0.004)	(0.010)	(0.115)	(0.009)	(0.021)
Exit	-0.005	-0.101***	-1.655***	-0.008	-1.201***
	(0.005)	(0.010)	(0.117)	(0.009)	(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 parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

D Alternative Demand Measure

Tables D1-D4 produce analogous results to benchmark results reported in Tables 5-15 of the main text. In this case we use the alternative measure of demand, described in section 3.4 of the main text, in place of the benchmark measure of demand. Again, this set robustness results are very close to those reported in main text. In Table D1 we find that demand growth explains nearly 89 percent of total export growth among the industries included in our robustness check. The results reported in the main text were of a similar size, but slightly smaller. In Table D2 we again find that product churning and reallocation are primary determinants of demand growth and physical productivity growth. As above, the selection and turnover results are very similar to those reported in the main text.

Table D1: Decomposition of Aggregate Export Growth (Alt. Demand)

		% Export Growth Explained By	
	Annual Export Growth	Physical Productivity Growth	Demand Growth
All Products and Countries	0.159	0.105	0.895

Notes: The first column reports annual export growth (in percentages). The second and third column decompose annual export growth into demand and productivity components.

Table D2: Decomposition of Demand and Productivity Growth (Alt. Demand)

	Total	Components of Decomposition					
Determinant	Growth	Within	Between	Cross	Entry	Exit	Net Entry
Log Demand	0.306	0.075	-0.089	0.205	0.073	-0.042	0.115
Log Physical Productivity	0.062	0.015	-0.022	0.009	0.067	0.006	0.061
Log Revenue Productivity	0.042	0.022	0.000	0.002	0.018	-0.001	0.019

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 D3: Determinants of Selection

Revenue TFP	-0.050***					
	(0.004)					
Physical TFP		-0.015***			-0.001***	-0.0002**
		(0.004)			(0.0002)	(0.0001)
Demand			-0.011***		-0.009***	-0.004***
			(0.002)		(0.002)	(0.001)
Price				-0.004**		
				(0.002)		
Age						-0.00001
						0.0001
Capital						-0.0001
						0.0003
Import Price						-0.00001
						0.0003
Distance	0.011***	0.032***	0.002***	0.052***	0.002***	0.001
	(0.001)	(0.005)	(0.0004)	(0.007)	(0.0004)	(0.003)
Income	-0.008***	-0.102***	-0.006***	-0.151***	-0.005***	-0.002***
	(0.001)	(0.011)	(0.001)	(0.012)	(0.001)	(0.001)
Size	-0.002***	-0.009***	-0.0001	-0.010***	-0.001***	-0.0003
	(0.0004)	(0.001)	(0.0001)	(0.002)	(0.0001)	(0.0001)
No. of Obs.	593,818	593,818	593,818	593,818	593,818	362,434

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 parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

Table D4: Evolution of Productivity and Demand

	Dependent Variable				
	Revenue TFP	Physical TFP	Demand	Price	Revenue
Entry	0.015***	-0.077***	-1.271***	0.093***	-0.706***
	(0.001)	(0.004)	(0.008)	(0.004)	(0.009)
Exit	-0.004***	-0.027***	-1.575***	0.025***	-0.961***
	(0.001)	(0.004)	(0.008)	(0.004)	(0.006)

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. Standard errors are in parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

E High Intensity Exporters

Tables E1-E4 produce analogous results to benchmark results reported in Tables 5-15 of the main text for two different groups of firms. In this exercise we use our benchmark methodology, but apply the empirical exercises apply only to firms which receive at least 90 percent of their revenue from export sales. In general, our findings are broadly consistent to those reported in main text, though there a small number of significant quantitative differenes. In Table E1 we find that demand growth explains nearly 77 percent of total export growth among high intensity exporters. The results reported in the main text were of a similar size, but slightly larger.

In Table E2 we again find that product churning and reallocation are primary determinants of demand growth and physical productivity growth, though product churning is particularly important for demand growth among the high intensity exporters. Moreover, we find that demand is particularly high among new exporters, though exit also continues to make an important contribution to demand growth.

As in our benchmark findings, the selection findings and the results from regressions on entry and exit dummies are very similar to our benchmark results, though the marginal effects on the demand variables are slightly smaller than those reported in the main text.

Table E1: Decomposition of Aggregate Export Growth (High Intensity Exporters)

		% Export Growth Explained By	
	Annual Export Growth	Physical Productivity Growth	Demand Growth
All Products and Countries	0.189	0.234	0.766

Notes: The first column reports annual export growth (in percentages). The second and third column decompose annual export growth into demand and productivity components.

Table E2: Decomposition of Demand and Productivity Growth (High Intensity Exporters)

	Total	Components of Decomposition					
Determinant	Growth	Within	Between	Cross	Entry	Exit	Net Entry
Log Demand	0.291	0.024	-0.069	0.147	0.154	-0.035	0.189
Log Physical Productivity	0.003	-0.004	-0.016	0.006	0.019	0.002	0.017
Log Revenue Productivity	0.026	0.012	0.001	0.000	0.013	-0.001	0.014

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 E3: Determinants of Selection (High Intensity Exporters)

Revenue TFP	-0.005***					
	(0.002)					
Physical TFP		-0.006***			-0.002**	-0.003**
		(0.002)			(0.0001)	(0.002)
Demand			-0.007***		-0.004**	-0.006***
			(0.002)		(0.002)	(0.002)
Price				-0.004		
				(0.004)		
Age						-0.0001*
						(0.00001)
Capital						0.000
						(0.000)
Import Price						-0.0001**
						(0.0000)
Distance	0.001**	0.007***	0.003***	0.055***	0.001*	0.001*
	(0.001)	(0.003)	(0.001)	(0.012)	(0.0004)	(0.001)
Income	-0.003***	-0.025***	-0.010***	-0.186***	-0.004**	-0.005**
	(0.002)	(0.008)	(0.003)	(0.021)	(0.002)	(0.002)
Size	-0.000	-0.0002	0.000	-0.002	-0.0003*	-0.0004*
	(0.000)	(0.001)	(0.000)	(0.004)	(0.0002)	(0.0002)
No. of Obs.	83,353	83,353	83,353	83,353	83,353	44,256

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 parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

Table E4: Evolution of Productivity and Demand (High Intensity Exporters)

	Dependent Variable				
	Revenue TFP	Physical TFP	Demand	Price	Revenue
Entry	-0.026***	-0.065***	-0.724***	0.039**	-0.361***
	(0.005)	(0.016)	(0.034)	(0.016)	(0.029)
Exit	-0.055***	-0.048***	-0.814***	-0.007	-0.418***
	(0.005)	(0.016)	(0.033)	(0.015)	(0.029)

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 parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

F Materials-Intensive Exporters

This section documents the main findings for a sample of materials-intensive exporters. In particular, we consider firms which are in the top quartile of materials intensity (materials expenditures/capital stock) distribution. To the extent that our results may be driven by difference in capacity utilitization this sample focuses on the set of producers with material purchases suggestive of high capacity utilization. Across all exercises we find that these subsample results are very consistent with the results reported in the main text.

Table F1: Decomposition of Aggregate Export Growth (High Intensity Exporters)

	Annual Export Growth	% Export Growth Explained By Physical Productivity Growth	Demand Growth
All Products and Countries	0.137	0.266	0.734

Notes: The first column reports annual export growth (in percentages). The second and third column decompose annual export growth into demand and productivity components.

Table F2: Decomposition of Demand and Productivity Growth (High Intensity Exporters)

	Total	Components of Decomposition					
Determinant	Growth	Within	Between	Cross	Entry	Exit	Net Entry
Log Demand	0.311	0.080	-0.035	0.147	0.070	-0.049	0.119
Log Physical Productivity	0.018	0.004	-0.025	0.009	0.036	0.006	0.030
Log Revenue Productivity	0.030	0.018	0.000	0.002	0.009	-0.001	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 F3: Determinants of Selection (High Intensity Exporters)

Revenue TFP	-0.023***					
	(0.007)					
Physical TFP		-0.007***			-0.006***	-0.005**
		(0.002)			(0.002)	(0.002)
Demand			-0.018***		-0.015***	-0.008***
			(0.003)		(0.004)	(0.003)
Price				-0.002		
				(0.002)		
Age						-0.0001*
						(0.00001)
Capital						0.000
						(0.000)
Import Price						-0.0001**
						(0.0000)
Distance	0.005**	0.005***	0.005***	0.028***	0.007***	0.004**
	(0.003)	(0.002)	(0.001)	(0.008)	(0.003)	(0.002)
Income	-0.018**	-0.020***	-0.019***	-0.111***	-0.029***	-0.020***
	(0.008)	(0.005)	(0.003)	(0.019)	(0.008)	(0.006)
Size	-0.001***	-0.001***	-0.001***	-0.006***	-0.002***	-0.001**
	(0.001)	(0.0004)	(0.0003)	(0.002)	(0.0005)	(0.0006)
No. of Obs.	206,175	206,175	206,175	206,175	206,175	206,175

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 parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

Table F4: Evolution of Productivity and Demand (High Intensity Exporters)

	Dependent Variable				
	Revenue TFP	Physical TFP	Demand	Price	Revenue
Entry	0.003***	-0.102***	-0.913***	0.107**	-0.442***
	(0.005)	(0.019)	(0.038)	(0.019)	(0.025)
Exit	0.011**	-0.023***	-1.083***	0.035*	-0.501***
	(0.005)	(0.019)	(0.038)	(0.019)	(0.025)

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 parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

G Footwear Industry

Tables G1-G4 produce results to facilitate comparison with the findings in Roberts et al. (2016). First, in Table G1 we repeat the selection exercise for the footwear industry alone.

Table G1: Determinants of Selection in the Footwear Industry

Physical TFP	-0.013*
	(0.008)
Demand	-0.012**
	(0.006)
Age	0.0002
	(0.0002)
Capital	-0.003**
	(0.001)
Import Price	-0.0001
	(0.0004)
Distance	0.013**
	(0.006)
Income	-0.013***
	(0.004)
Size	-0.004**
	(0.002)
No. of Obs.	2,071

Notes: This table reports the results a 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 parentheses. $*$, $**$ and $***$ represent statistical significance at the 10, 5 and 1 percent level.

The results for the footwear industry are similar to our main results with the possible exception that physical productivity is only marginally significant. We then replicate the exercise in Table 11 of Roberts, Xu, Fan and Zhang (2016) to measure the impact of an increase in demand on the market exit rate. We find that an increase from the 10th (25th) to the 90th (75th) percentile of the distribution of idiosyncratic demand causes the exit rate to fall by 2.9 (1.2) percentage points. By comparison, an increase in physical productivity from the 10th (25th) to the 90th (75th) percentile of the distribution of productivity causes the exit rate to fall by 1.6 (0.8) percentage points. Overall, our findings are broadly consistent with results in Table 11 of

Roberts, Xu, Fan and Zhang (2016).

We also complete our decomposition exercises for the footwear industry to connect these findings to our main results. In Table E2 we find that demand growth explains nearly 81 percent of total export growth in the footwear industry. Likewise, as reported in Table E3, we again find that product churning and reallocation are primary determinants of demand growth and physical productivity growth. Broadly, the results for the footwear industry are very consistent with those reported for aggregate Chinese export growth.

Table G2: Decomposition of Export Growth in the Footwear Industry

		% Export Growth Explained By	
	Annual Export Growth	Physical Productivity Growth	Demand Growth
All Products and Countries	0.067	0.192	0.808

Notes: The first column reports annual export growth (in percentages). The second and third column decompose annual export growth into demand and productivity components.

Table G3: Decomposition of Demand and Productivity Growth in the Footwear Industry

	Total	Components of Decomposition					
Determinant	Growth	Within	Between	Cross	Entry	Exit	Net Entry
Log Demand	0.285	-0.023	-0.068	0.280	-0.088	-0.183	0.095
Log Physical Productivity	0.015	0.006	-0.016	0.005	0.038	0.018	0.020
Log Revenue Productivity	0.047	0.021	0.000	0.004	0.017	-0.005	0.023

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.

H Decomposing Aggregate Exports Using TFPR

The section presents the decomposition exercise described by equation (10) of the main text where we use $TFPR_{fikt}$ in place of $TFPQ_{fikt}$. Note we rederive our measures of demand, as described in Section 3.4, also using $TFPR_{fikt}$ in place of $TFPQ_{fikt}$ so that our decomposition equation continues to hold.

Table H1: Decomposition of Aggregate Export Growth Using $TFPR$

	Annual Export Growth	% Export Growth Explained By Physical Productivity Growth	Demand Growth
All Products and Countries	0.160	0.122	0.878
North America	0.128	0.165	0.835
Europe	0.070	0.072	0.928
Japan	0.110	0.215	0.785
Australia	0.073	0.055	0.945
South America	0.184	0.106	0.894
Rest of Asia	0.166	0.151	0.849
Africa	0.144	0.069	0.931
Private, Ordinary Trade	0.157	0.112	0.888
Private, Processing Trade	0.174	0.134	0.866
Foreign Firms	0.133	0.066	0.934
State-Owned Firms	0.027	0.106	0.894
Undifferentiated Products	0.195	0.185	0.815
Differentiated Products	0.134	0.087	0.913

Notes: The first column reports annual export growth (in percentages). The second and third column decompose annual export growth into demand and productivity components where we use revenue productivity ($TFPR$) in place of physical productivity ($TFPQ$).

We find that we find that using $TFPR_{fikt}$ in place of $TFPQ_{fikt}$, productivity (demand) explains 12 (88) percent of aggregate export growth. By comparison, $TFPQ$ (demand) in our benchmark exercise explains roughly 18 (82) percent of aggregate export growth. The intuition for the difference for these findings lies with fact that $TFPR$ demonstrates less variability than $TFPQ$ because prices adjust to mitigate productivity shocks. Because the degree of productivity variation in $TFPR$ is relatively low across heterogeneous firms, we find that $TFPR$ underestimates its contribution to aggregate export growth in our aggregate decomposition exercise. Nonetheless, our results are qualitatively consistent with those from the main text and continue to support the finding that demand growth is the primary determinant of aggregate export growth.