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Product churning, reallocation, and Chinese export growth[☆]

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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 78–89% of aggregate export growth, while only 11–22% 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% smaller than those observed for incumbent producers in the same product market. By comparison, we find that there is only an 8% 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.

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 also depend heavily on other dimensions of firm heterogeneity, such as idiosyncratic demand.[2] These results induce natural questions regarding the performance of trade aggregates: What is the contribution of idiosyncratic differences across firms and products to export growth? Likewise, since international trade is

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[1] See, for examples.
[2] Recent examples include and Rivers (2010).

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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 among Chinese exporters. 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 outcomes. 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 et al. (2008) show that revenue based measures of productivity tend to conflate the influence of both physical productivity and prices on US firm-behaviour. Likewise, Gervais (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 match customs-level data, which contains detailed information on the price, quantity and export destinations, with Chinese firm-level input and output data we are able to (1) disentangle idiosyncratic productivity and demand among Chinese exporters and (b) investigate the microeconomic determinants of export growth across heterogeneous export markets.

Across all Chinese exporters we find that aggregate demand growth explains 78–89% of total export growth, while productivity growth contributes only 11–22%. Our quantitative findings rely heavily on two key features of our analysis. First, given the data capturing inputs and physical output we develop a product-specific measure of productivity. Measured productivity, as such, reflects variation in the productive efficiency of the firm. Second, using detailed data on exported quantities and prices along with IV methods, we estimate an iso-elastic demand curve and recover a firm-and-product specific demand shock. Our measure of demand is composed of an idiosyncratic component, which is specific to the firm, product, destination and year, and a common component, which reflects broader changes that affect all firms in a given export product market.

We proceed to investigate the nature of demand growth and the firm-level mechanisms that characterize its evolution over time. In particular, we construct a theoretically consistent measure of aggregate demand and decompose it's evolution into within-firm, between-firm and product churning components. In this fashion, we characterize the degree to which demand shocks have a uniform impact across Chinese exporters or whether the role of demand growth is driven by idiosyncratic differences across heterogeneous firms.

We find that 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 which examines 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% increase in demand has twice the impact of a 1% increase in production efficiency 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% smaller than those of 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.

[3] See Bernard et al. (2007), Eaton et al. (2008, 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.

As such, we consider a framework which closely follows the literature studying multiproduct firms and international trade (Bernard et al., 2011; De Loecker, 2011; De Loecker et al., 2016).

We highlight two mechanisms which significantly 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 in export markets.[5] We confirm that entering and exiting products have significant 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.

We build on longstanding studies of the determinants of export entry and growth.[6] Manova and Zhang (2011, 2012) confirm large productivity, pricing, and quality differences across Chinese exporters and destinations worldwide.[7] 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. Likewise, Garcia-Marin and Voigtländer (2016) characterize 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. Although our work is complementary to the above studies, we do not attempt to explain the variation in firm-level sales or productivity. Rather, we aim 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.

Similarly, Roberts et al. (2016) structurally estimate a model of Chinese footwear exporters. They find that demand is at least as important as 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, products and markets, while Section 4 determines how much aggregate export growth is directly attributable to productivity or demand changes among Chinese exporters. Section 5 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. Section 6 decomposes each component of aggregate export growth into a within-firm growth component, 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 et al. (2011) multi-product firm extension of the Melitz (2003) model and maintains many of the benefits of these earlier models. In particular, we allow firms to choose to produce for I different destination markets, but characterize their decisions as a function of both idiosyncratic productivity, φ, and demand, δ. An important distinction in our case 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. After incurring s_k firms 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, $G_k(\varphi_k, \delta_{1k}, \ldots, \delta_{Ik})$. 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

[5] Likewise, Restuccia and Rogerson (2008), Foster et al. (2008), and Hsieh and Klenow (2009) each suggest that selection and resource allocation have important effects on aggregate TFP. The results mirror findings from the trade literature which strongly indicate that trade liberalization has led to substantial resource reallocation and productivity across countries (see, for example, Bernard and Jensen (1999a) for the US, Pavcnik (2002) on Chile, Trefler (2004) on Canada).

[6] Leading examples include Clerides et al. (1998), Bernard and Jensen (1999b) and Aw et al. (2000), among others. Dai et al. (2016) 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. Das et al. (2007), Demidova et al. (2012), Munch and Nguyen (2014), and Rho and Rodrigue (2016) document that export market demand shocks are key determinants of exporter behaviour in Columbia, Bangledesh, Denmark, and Indonesia, respectively.

[7] 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.

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

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 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 $\sigma_k > \kappa > 1$ 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, and 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, $j = 1, \ldots, I$. 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 firms 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 then 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 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 et al. (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. Rewriting profits from any market as $\pi_{ijk} = \left[\left(\frac{\phi_{ijk}}{\phi_{ik}^*}\right)^{\sigma_k-1} - 1\right] f_{ik}$, we can then specify total profits from the sale of a given product across all markets as $\pi_{jk} = \sum_i \max\{0, \pi_{ijk}\}$ and total firm profits across all products as $\pi_j = \sum_k \pi_{jk}$.

[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 et al., 2011; Roberts et al., 2016) and our objective of characterizing short-run firm-level entry and exit decisions.

[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.

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, $(\phi^*_{1k}, \ldots, \phi^*_{Ik})$ are such that the net expected value of entry into any product-market is equal to zero for all firms in all countries. That is, ϕ^*_{ik} must satisfy

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

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 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 these 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.

Following Manova and Yu (2016) and Wang and Yu (2012) we match the customs data with annual firm-level data from the Chinese manufacturing sector.[14] 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).[15] The firm-level data include detailed information on firm-level revenues, export sales, intermediate materials, employment, wages, capital stock, ownership and industry classification.

3.1. 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 et al., 2008; Hsieh and Klenow, 2009):

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

[12] Similar findings are documented in Melitz (2003), Melitz and Ottaviano (2008), Foster et al. (2008) or Bernard et al. (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 results of our matching process are also similar to Manova and Yu (2016) and Wang and Yu (2012). Details are reported in the Supplemental Appendix.

[15] The unit of observation is the firm, 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 et al. (2012) suggest that nearly 95% of all observations in a similar sample are single-plant firms.

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 input and materials, respectively, and α_k, α_l and α_m capture each input's share parameter. Capital and materials are measured in real terms and following Hsieh and Klenow (2009) we use the total wage bill to measure the quality-adjusted labor stock for each firm.[16]

We calculate the materials share as the average share of intermediate inputs in total revenues. The labor share is calculated analogously with the exception that we follow Hsieh and Klenow (2009) to adjust the reported wage bill to account for unreported employee compensation. Similarly, in the absence of reliable capital share information we again 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 et al. (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.[17]

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 since 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.

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. x 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 et al. (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 to this approach is that it provides a production function methodology which explicitly disentangles estimated physical productivity from product quality. A disadvantage to 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 twenty of large industries where private, ordinary firms make up a significant part of the industry to implement the De Loecker et al. (2016) procedure.[18]

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

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

[16] Inputs are deflated consistent with Brandt et al. (2012), while the capital stock series is constructed using perpetual inventory methods. Alternatively, we have tried using employment to measure labor input has little effect on the final results. A full data description can be found in the Supplemental Appendix.

[17] 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.

[18] A detailed description of our application of their methodology can be found in the Supplemental Appendix along with all of the production function estimates. 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 also checks the robustness of our results across variation in capacity utilization.

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

3.2. Measuring demand

Our approach to demand estimation follows those in, 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 Eq. (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 Eq. (4) by IV. Strong instruments for destination specific prices are variables that shift the short run supply curve of the firm. Consistent with 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.

First, following Aw and Lee (2014), we recognize that the prices of competing firms in the same product market are likely to be correlated to a given 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. To recover our 'benchmark' measure of demand we estimate Eq. (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.[19]

Second, as in 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 Eq. (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.[20] We then construct a firm-product specific measure of export demand for each product, d_{fikt}, using Eqs. (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.

3.3. Sample properties

Table 1 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 be potentially misleading. For this reason, we

[19] When we estimate Eq. (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% of our first stage regressions.

[20] The Supplemental Appendix documents further estimation results. See Foster et al. (2008), Eslava et al. (2013), and De Loecker and Warzynski (2012) further discussion and citations.

Table 1
Summary statistics for exports, price, productivity and demand.

Variables	Physical exports	Revenue exports	Physical Prod.	Revenue Prod.	Demand	Price	Capital
Correlations							
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							
	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.

compare our benchmark findings, which are based on measures of 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% more dispersed than physical productivity and more than double that of revenue productivity.[21] 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.

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

$$Q_{ikt} = \sum_{f \in \mathcal{F}_{ikt}} q_{fikt} = \sum_{f \in \mathcal{F}_{ikt}} C_{ik} \varphi_{fikt}^{\sigma_k} d_{fikt} \tag{6}$$

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 Eq. (6) with respect to time we find

$$\frac{\partial Q_{ikt}}{\partial t} = \sum_{f \in \mathcal{F}_{ikt}} q_{fikt} \left(\sigma_k \frac{\partial \varphi_{fkt}}{\partial t} \frac{1}{\varphi_{fkt}} + \frac{\partial d_{fikt}}{\partial t} \frac{1}{d_{fikt}} \right) \tag{7}$$

where we assume that C_{ik} does not change over time. This assumption is appropriate in this context 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. Further, it is important to recall that our measure of demand captures both a mean-zero idiosyncratic component and a common demand component. Should there be unaccounted changes in tariffs or trade costs over time, these will be captured by our measure of demand. Using Eq. (7) we decompose the growth rate of Chinese exports into separable productivity and demand components:

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

We approximate the decomposition Eq. (8) using annual changes in exports, productivity and demand as

$$\Delta \ln Q_{ikt} \equiv \ln Q_{ikt} - \ln Q_{ik,t-1} = \sigma_k \sum_{f \in \mathcal{F}_{ikt}} \theta_{fikt} \Delta \ln \varphi_{fkt} + \sum_{f \in \mathcal{F}_{ikt}} \theta_{fikt} \Delta \ln d_{fikt} \tag{9}$$

[21] 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.

Table 2
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 columns decompose annual export growth into demand and productivity components.

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

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

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 2.

Our benchmark computations reveal three striking results. First, Chinese exports were growing extremely quickly over our sample period. The average annual export growth across all markets was almost 15% per year. Second, both productivity and demand make substantial contributions to short-run aggregate export growth, but demand tends to dominate productivity growth. Overall, variation in demand explain 82% of aggregate export growth. Note, had we used *TFPR* in place of *TFPQ*, the contribution from productivity would have been only 12% rather than 18%. As documented by Khandelwal et al. (2013), many highly productive and low price Chinese firms grew rapidly into export markets shortly after China joined the WTO. Because prices move inversely with productivity *TFPR* growth tends to underestimate the contribution of productivity to export growth.[22]

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 et al. (2008), we find that even among these exporters of undifferentiated products, demand explains nearly 65% of export growth.

Turning to our alternative measures of demand and productivity, our decomposition reports very similar results. Table 3 documents that regardless of our sample we find average export growth of 15–16% 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% of export growth while demand accounts for 78%. In contrast, our alternative demand measurement suggests an even larger contribution from demand. In this last case, we find that demand accounts for 89% 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

[22] The Supplemental Appendix documents full results from using revenue productivity instead of physical productivity and provides greater discussion of the observed differences across experiments.

Table 3
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 columns decompose annual export growth into demand and productivity components.

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 by within-firm productivity and demand changes, product-market turnover, or resource reallocation across heterogeneous firms. We tackle these issues next.

5. Product churning in international markets

It is well-known that product turnover is particularly high in international markets. This is true among our sample as well; among Chinese firms which export a given product to a specific-market in any year, 54% 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% will exit that product market in the following year. These striking turnover patterns are persistent despite the fact that measured demand and productivity are both strongly persistent over time.[23]

This should not, however, suggest that demand and productivity play a similar role in determining product churning. Rather, this section studies the differential impact of productivity and demand on product churning 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

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

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.[24] 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 control for changes in the broader macroeconomic environment over time.[25]

Table 4 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.[26] 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 product are less likely to drop those products in export markets. Column 5 examines the joint impact of productivity and demand, while

[23] A detailed discussion can be found in our Supplemental Appendix.
[24] 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.
[25] Conditional MLE estimation is discussed in detail by Wooldridge (2002), Chapter 15.
[26] Marginal effects and the associated standard errors are reported.

Table 4
Determinants of selection: benchmark measurement.

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% level. The number of observations in the last column is smaller than the other columns because not all firms import materials.

Table 5
Determinants of selection: alternative productivity measurement.

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% level.

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 and demand, we continue to find that the coefficient on demand is roughly double that on productivity. Tables 5 and 6 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

Table 6
Determinants of selection: alternative demand measurement.

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% level.

Table 7
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% level.

trade).[27] Table 7 documents that our benchmark results hold broadly across different types of firms, the nature of trade and degrees of 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 evolution of continuing (or incumbent) producers in product market ik. Our regression is written as

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

[27] It is natural to expect that export relationships may vary across ownership and product classification. For example, it is well known that there have been strong institutional preferences to allocate Chinese export licenses differentially across ownership types.

Table 8
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% level.

Table 9
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% level.

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 8 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% *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% *less* productive than incumbent exporters. Among exiting firms we find that physical productivity is 4% lower than that of incumbent exporters. In contrast, we do not find significant differences between exiting firms and incumbents when we use revenue productivity.

This may appear inconsistent with the results in Foster et al. (2008) for US manufacturers. However, it is important to recognize the substantial differences in the notion of exit across the two exercises. Exit in the Foster, Haltiwanger and Syverson 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. Moreover, our findings are consistent with a long series of papers confirming that a cohort of new exporters are, on average, less productive than incumbent (continuing) exporters (e.g. Bernard and Jensen, 1995, 1999b; Arkolakis, 2010, 2016; Rho and Rodrigue, 2016; Ruhl and Willis, 2017).

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 8 imply that new entrants are charging prices which are 4–10% higher than incumbent firms. We emphasize that this result is not conditional on cost, but rather reflects the fact that entrants are typically higher cost producers and, thus, charge higher prices, on average, than lower cost incumbent exporters.[28] Table 10 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% smaller than those of incumbent exporters, while demand shocks for exitors are found to be 80% smaller. Taken together with the estimated coefficients on the entry dummy, we observe that the high turnover of firms in international markets likely reflects a recycling of firms with low demand shocks in export markets. As such, a high degree of product churning in export markets may potentially be an important source of demand growth.

Table 9 repeats this exercise across our alternative measures of productivity and demand, while Table 10 documents the results across firm-type (private firms engaged in ordinary trade, private firms engaged in processing trade, foreign-owned

[28] Moreover, this result does not imply that these firms are choosing high markups. Rather, as documented in by Garcia-Marin and Voigtländer (2016) and Rodrigue and Tan (2017) for Chile and China, respectively, new exporters are often firms with relatively small markups.

Table 10
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% 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 11
Decomposition of demand and productivity growth.

Determinant	Total growth	Components of decomposition					
		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 column 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 column reports the relative covariance term and captures the correlation between changes in demand/productivity and market shares. The final two columns capture the effect of product turnover.

firms and state-owned firms) for our benchmark estimates. We observe that the same qualitative patterns arise in every case.[29]

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,

$$\begin{aligned}\Delta \ln \mathcal{D}_{ikt} = & \sum_{l\in C}\theta_{fik,t-1}\Delta \ln \delta_{fikt} + \sum_{l\in C}(\ln \delta_{fik,t-1} - \ln \mathcal{D}_{ik,t-1})\Delta\theta_{fikt} + \sum_{l\in C}\Delta \ln \delta_{fikt}\Delta\theta_{fikt} \\ & + \sum_{l\in E}\theta_{fikt}(\ln \delta_{fikt} - \ln \mathcal{D}_{ikt}) - \sum_{l\in X}\theta_{fik,t-1}(\ln \delta_{fik,t-1} - \ln \mathcal{D}_{ik,t-1})\end{aligned} \tag{10}$$

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.[30] Our decomposition closely follows the straightforward decomposition for "aggregate productivity" proposed by Foster et al. (2001).

The first term in this decomposition captures changes in demand growth within firm-product pairs, weighted by 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 for 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 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

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

[30] 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.

Table 12
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: 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 column 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 column reports the relative covariance term and captures the correlation between changes in demand/productivity and market shares. The final two columns capture the effect of product turnover.

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 10 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% 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 for 25% of aggregate export demand growth. It would be erroneous, however, to interpret this finding as evidence of Chinese exporters entering new markets and immediately achieving export success. In fact, the decomposition suggests that new entrants contribute negatively to demand growth. Rather, the large, positive contribution of net entry to demand growth comes from the exit of low demand firms. High rates of churning in international markets give rise to the substantial change in the composition of exporters each year and, thus, growth in export demand. Similarly, among surviving exporters, export shares are rapidly reallocated to growing firms. Total resource reallocation, whether by resource reallocation among continuing firms or through product churning, accounts for 75% of total demand growth. Given that these patterns are 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 10 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% 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%,

Table 13
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: 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 column 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 column reports the relative covariance term and captures the correlation between changes in demand/productivity and market shares. The final two columns capture the effect of product turnover.

Table 14
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: 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 column 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 column reports the relative covariance term and captures the correlation between changes in demand/productivity and market shares. The final two columns capture the effect of product turnover.

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 productivity growth is attributed to net entry and reallocation, which jointly account for 82% of aggregate physical productivity growth. In contrast, the same measures of product churning and resource reallocation only account for 50% 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 11–14 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% of all demand growth among private, ordinary exporters, while 56% 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. We find that demand growth accounts for 78–89% of all export growth. Product churning accounts for 25–38% of all demand growth, while the reallocation of market share towards surviving high demand firms accounts for an additional 37–50% 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% smaller than that of the average incumbent exporter within the same export market. Similarly, the marginal impact of a change in demand is estimated to be twice as large as that from an equivalent change in productivity.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jebo.2017.09.015.

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