ESSAYS ON FIRMS' ENTRY AND GROWTH

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Dissertation

Submitted to the Faculty of the

Graduate School of Vanderbilt University

in partial fulfillment of the requirements

for the degree of

DOCTOR OF PHILOSOPHY

in

Economics

August, 2013

Nashville, Tennessee

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I dedicate this dissertation to my wife Ying Feng and my parents, who have always been beside me and given me sufficient support. It was their encouraging words that pushed me to move further in my research. I also dedicate this dissertation to all my friends and church family who give their continuous support to me. I appreciate all they have done for me, especially Tim Su who brings me to God and teaches me how to live in a completely new environment. In addition, I dedicate this dissertation to my advisor Joel Rodrigue, who has spent considerable time to discuss the details with me. Without his help, I cannot overcome the difficulties in my research so easily. I also thank my classmate Richard Qiu, whose suggestions are valuable to my dissertation.

ACKNOWLEDGMENTS

I am grateful to Joel Rodrigue for his continuous advice and extremely helpful comments. He is always patient with my questions and encourages me when I encounter challenging issues in my research. Without his help it will be much harder to finish my dissertation. I also give my gratitude to Andrea Moro, who has made many suggestions which improved my dissertation. I should not neglect the discussions with Jeffrey Dotson, which are valuable to the empirical part of my dissertation. I also thank Ronald Gallant for sharing their data set with me, and Kamal Saggi's valuable suggestions.

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CHAPTER I

Introduction

Firm-level market entry decisions, post-entry survival, and growth are at the core of the industrial organization literature. A strand of this literature tries to rationalize firms' market-entry or market-exit decisions and post-market-entry-behaviour. Firm turnover and churning in either domestic markets or international markets play a significant role on industry aggregates, and firms' price schemes directly affect market structure, thereby affecting social welfare. Dynamic models are offen used in the context to explain lots of empirical facts, such as why firms are willing to enter some unprofitable markets. As firms make their entry decision, it not only depends on the current return, but also relies on the future payoff. For instance, when firms anticipate a series of market openings, the literature claims that the production cost is the key dynamic variable, which may be reduced in future markets if a firm enters the current market. This reduction is due to a learning-by-doing mechanism. However, demand may also be an important dynamic variable, which may be increased in future markets if a firm enters the current market. This increase could be interpreted as the firm accumulating a customer base or a good reputation in the current market. Although both supply and demand factors affect firm-level entry decisions, they have very different implications: when facing a series of market openings, if cost dynamics dominate, more and more firms will enter in the later markets. This is because firms obtain production experience in the earlier markets, and become more efficient, and as such, they are more likely to enter in the following markets. However, if the demand dynamics dominate, some firms will be squeezed out by some other in later markets. The reason is that firms which enter markets more frequently tend to have larger market shares in the future markets, which discourage firms with little entry experience to enter future markets. If we cannot unravel the impact of demand and cost dynamics, we cannot predict firms' entry decisions precisely. In Chapter 2, the impact of demand and supply factors on firm-level entry decisions in the pharmaceutical industry has been disentangled.

Cost and demand are two of the most important determinants of firm-level dynamics, both of which affect firm-level market entry, survival, growth and consequently affect the degree of churning in a market. Recently, one of the most significant phenomena in world trade is the success of Chinese manufacturing exports. However, it is not clear that Chinese exporters' success is driven by demand increases or productivity improvements. On one hand, the firm-level costs are closely associated with firm-level productivity. We believe that more efficient firms have lower marginal cost, and as such, they are more likely to enter a market, survive and grow faster. On the other hand, firm-level demand determines the firm's profitability also, and we anticipate that a firm with higher demand would behave more aggressively in a given market, and is more likely to be successful. To clearly understand the success of Chinese exporters, the impact of productivity and demand on firms need to be separately identified. In Chapter 2, we analyze the determinants of Chinese exporters' market selection, survival and subsequent growth in international markets.

It is also of policy importance to distinguish firm-level cost and demand and their dynamics. For instance, if a policy marker wants to increase market entry rate, he can simply decrease the entry barriers in the earlier markets when cost dynamics are dominant. Whereas this policy will lead to lower entry rate in the future markets when demand dynamics are dominant because some entrants become monopolist in the future markets.

Literature Review for Chapter 2

Firm-level productivity has received considerable attention as an explanation for firm-level market entry decisions, survival and subsequent growth. Jovanovic (1982) builds a "passive learning model" to explain why small firms tend to grow fast, and are more likely to fail. Pakes and Ericson (1995) attribute firm-level growth to the growth of firm-level productivity. Benkard (2004) uses the example of wide-bodied aircraft to emphasize the impact of productivity spillovers on firm-level performance: previous production experience improves a firm's profitability in future production. Similarly, Gallant et al. (2010) use productivity spillovers to rationalize the entry behavior of pharmaceutical firms. They argue that the reason that firms are willing to enter a currently unprofitable market is because they reduce their costs in future markets. By comparison, the firm-level idiosyncratic demand shocks received less attention. Firm-level idiosyncratic demand also affects firms' profitability and its corresponding market entry decisions. One example is that many airline companies like to concentrate their purchases from the same air plane company. American Airlines and South West purchase from the Boeing Fleet, while Aer Lingus and Germanwings buy from the Airbus Fleet. Another example is that firms can bundle their new product to their other existing products to discourage entrants from new product markets. In this way firms bundling their products increase their demand in the new product market, and exclude potential entrants. This impact of demand from existing product markets to a new product market is called the market foreclosure effect by Whinston (1990), and this effect can be treated as a sourse of demand loyalty. Klemperer and Padilla (1997) claim that by providing an additional product a firm can capture customers from its competitor. This effect is called demand spillovers: loyalty effects encourage customers to concentrate their purchases from the same provider. A number of reasons can rationalize loyalty effect, such as customers' search costs, the cost of learning how to use a new product, uncertainty over new product quality, or product compatibility with existing products. Gavazza (2011) further confirms the importance of demand spillovers in the U.S mutual fund market: The largest four fund families experience disproportional growth and almost double their market share from 1992-2007. The mechanism which leads to the demand spillovers is that customers have loyalty to a product they have purchased and this loyalty can easily extend to another product under the same brand. As such, firms with larger historical sales tend to have higher sale in the future, and firms can leverage this demand spillovers to their other products. Foster et al (2010) attribute the slow convergence of US manufacturing firms' sales to firm-level demand: *growth of a customer base or building a reputation, for example—that take considerable time to play out.*[9] Disney et al (2003) also point out that the performance of an plant depends on other plants owned by the same firm. They argue that if a plant is owned by a "group" owner, the exit rate tends to be lower as this plant has a larger customer base built by other plants owned by the same firm.

Starting from Bresnahan and Reiss (1991a), there is a growing empirical literature that studies firms' entry and exit decisions. The early literature focuses on a static entry game. Berry (1992) analyzes airlines' decisions to set up non-stop flights between city-pairs; Scott-Morton (1999) estimates which characteristics of the generic drug market openings attract more entrants; Mazzeo (2002) studies the US motel market by allowing the representative motel to simultaneously choose his service quality and locations. Seim (2006) further extends Mazzeo (2002) by adding firm side heterogeneities to his model, and applies his model to predict US videotape firms' location and product decisions. Benkard (2004) first mentions dynamic supply side spillovers in aircraft industry. Gallant, Hong, and Khwaja (2010) similarly estimate supply side spillovers in the pharmaceutical industry to explain firm-level over-entry patterns, when new drug market openings appear. They find that each entry reduces future costs by approximately 7% at the next entry opportunity. In contrast to Benkard (2004) and GHK (2010), Foster et al. (2010) stress demand side spillovers. They attribute firms' market share growth to their idiosyncratic demand growth, and this demand growth will significately affects firm-level entry and exit diecisions. Gavazza (2011) also emphasizes demand side spillovers in the U.S fund market: firms with more demand are less likely to exit the market.

Literature Review for Chapter 3

In addition to domestic market, firm-level productivity is also emphasized in international markets. Melitz (2003) explains the difference of firm-level export decision to international markets by the heterogeneity of firm-level productivity. In particular, firms with higher productivity are more likely to export and survive in international markets. Aw et al (2000) confirm this idea by using the data from Taiwanese exporters. Branstetter and Lardy (2008) point out that the success of Chinese exporters is because of their low labor and input cost. Manova and Zhang (2011, 2012) also document that among Chinese exporters the differences of pricing and quality are large. Although received less attentions, the demand impact also be documented in the international trade literature. Das, Roberts and Tybout (1997) argue that among exporters with nearly identical productvity have distinguished export outcomes. Rho and Rodrigue (2012), and Hu et al. (2013) claim that demand factors affect exporters profit, survival and growth by using the evidences from Indonesian and Chinese exporters. Hu et al. (2013) argue that among Chinese exporters, the demand dispersions are several times larger than productivity dispersion, and the demand heterogeneity is the key determinant of firm-level market entry, survival and growth, while the effect of productivity is negligible. Roberts et al. (2013) separately identify the demand and productivity effect in the Chinese footwear industry, and find that demand and productivity are equally important to firm-level pricing, and quantity of sales. In the next two chapters, we estimate the impact of demand and productivity on firm-level market entry decision, survival and growth in pharmaceutical industry and international markets in Charter 2 and Chapter 3, respectively.

BIBLIOGRAPHY

[1] 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.

[2] Benkard, L. 2004. "A Dynamic Analysis of the Market for Wide-bodied Commercial Aircraft," *The Review of Economic Studies*, Vol. 71, pp. 581-611.

[3] Branstetter, L. and N. Lardy. 2008. "China's Embrace of Globalization," in L.Brandt, and T. Rawski (eds), *China's Great Economic Transformation, Cambridge University Press.*

[4] 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.

[5] Demidova, Svetlana, Hiau Looi Kee and Kala Krishna. 2011. "Do Trade Policy Dierences Induce Sorting? Theory and Evidence From Bangladeshi Apparel Exporters," *NBER Working Paper,*12725.

[6] Disney, Richard, Haskel, Jonathan and Heden, Ylva. 2003. "Entry, Exit and Establishment Survival in UK Manufacturing," *The Journal of Industrial Economics*, Vol. 51, No.1, pp. 91-112.

[7] Hu, Zhongzhong, Rodrigue, Joel, Tan, Yong, and Yu, Chunhai. 2013. "Firm Selection Across International Markets," *NBER Working Paper, 12725.*

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

[9] Lucia Foster, John Haltiwanger, and Chad Syverson. 2010. "The Slow Growth of New Plants: Learning about Demand?" *Working paper.*

[10] Gavazza, A. 2011. "Demand Spillovers and Market Outcomes in the Mutual Fund Industry," *The Rand Journal of Economics,* Vol. 42, pp. 776-804.

[11] Gallant, A. Ronald, Han Hong, and Ahmed Khwaja. 2010. "Dynamic Entry with Cross Product Spillovers: An Application to the Generic Drug Industry," *Working paper.*

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

[13] Klemperer, P. and Padilla, A.. 1997. "Do Firms' product lines include too many varieties?" *The Rand Journal of Economics*, Vol. 28 (1997), pp. 427-482.

[14] Manova, Kalina and Zhiwei Zhang. 2011. “Multi-Product Firms and Product Quality,” *NBER Working Paper,* w18637.

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

[16] Roberts, Mark, Xu, Daniel, Zhang, Shengxing. 2012 “A Structural Model of Demand, Cost, and Export Market Selection for Chinese Footwear Producers,” *NBER Working Paper,*17725.

[17] Rho, Youngwoo and Joel Rodrigue. 2012. “Firm-Level Investment and Export Dynamics,”mimeo, Vanderbilt University.

[18] Whinston, M.D.(1990) “Tying, Foreclosure and Exclusion,” *The American Economic Review*, Vol. 80, pp. 837-859.

CHAPTER II

Dynamic Entry with Demand and Supply Side Spillovers: The Case of Pharmaceutical Industry

Introduction

In this chapter I disentangle different types of spillovers on firm-level entry decisions by separately identifying demand and supply side spillovers on firm-level profitability. One of the most significant decisions a firm makes is whether or not to enter a new market. In a dynamic environment, a firm's current decision not only affects current profit, but also has spillovers upon its future profitability. For instance, experience in one market may potentially improve firm performance in another related product market. This improvement implies that a firm's decision to enter a product market is determined not only by the profits associated with this market, but also the enhanced profitability in future markets. The literature attributes the spillovers to the supply side, in particular, the type of spillovers which reduce a firm's cost in later markets given that it has previous entry experience. The cost reduction has been deemed the main reason of over-entry phenomenon. This phenomenon is a well known empirical pattern that many firms enter small markets which only can accommodate a small number firms, and some or all of them receive negative profits.

Demand side spillovers have received less attention. Demand side spillovers could also improve a firm's profitability in later markets if previous entry allows the firm to increase market share in other markets. The increase in market share may result from brand loyalty or an enlarged customer base from previous market entry. There are a number of explanations for brand loyalty, such as the cost of establishing new trading relationships, learning how to use a new product, uncertainty over product quality, or product compatibility with existing products.

To understand the different implications of demand side spillovers and supply side spillovers, consider similar firms with different entry experience. One of them has entered a lot of markets (with many product varieties), and the other is completely new. When a new market opening appears, supply side spillovers harm the profitability of the new firm indirectly by increasing the more experienced firm's entry probability. Similarly, demand side spillovers generate losses to the new firm by indirectly increasing the other firm's entry probability and directly shrinking the new firm's post-entry market share. The direct impact of demand side spillovers is called market foreclosure effect (Whinston (1990)). The identification of the two types of spillovers are intuitive: supply side spillovers affect a firm's entry through its own entry expirience (a more experienced firm is more likely to enter new market), while demand side spillovers affect the firm's entry through the relative entry rates of himself and his competitors, (a relatively more experienced firm inclined to enter more offen). Therefore, the variation in the rates of absolute and relative entry identify the two types of spillovers.

In the generic pharmaceutical industry, future benefits from current entry could arise from future cost reductions, or from an increased customer base, brand reputation, or loyalty. The previous channel is frequently mentioned in the learning literature, in which firms learn the production, advertising, and sale process after entering a current market. This experience reduces the subsequent costs associated with future markets; for the demand channel, Klemperer and Padilla (1997) show that a firm is able to capture business from his competitors in a product market by offering an additional product when consumers prefer to concentrate their purchases with a single supplier. Although this claim is made in a static framework, it can be easily applied to a dynamic setting by treating different markets as different products. The only difference is that under a static framwork, a firm needs to decide how many produts he wants to offer at one time, while in a dynamic setting, a firm has to sequentially make market-entry decisions. Regardless of which channel determines entry, a firm may enter a currently unprofitable market to gain advantages in future markets. In this paper, a model incorporating both dynamic supply and demand spillovers is built to explain a firm's market entry decision. This model allows a firm's current market share and total costs to vary with past entry experience. A firm's market share and cost evolves endogenously with the firm-level entry decisions. Endogenous entry causes heterogeneity across firms, even if they are ex ante identical.

While supply spillovers play a role in future cost reductions, demand side spillovers play a role in future market share increases. Both types of spillovers indicate that a firm's past entry (and production) enhances his performance in future markets. This paper separately identifies demand side spillovers and supply side spillovers in the pharmaceutical industry. Intuitively, both spillovers may exist in the pharmaceutical industry, since firms may simultaneously reduce future costs and build brand reputation through past entry.

In order to estimate our model, there are two main methodological challenges that need to be addressed. One challenge in our dynamic game setting is that a firm's entry decision depends not only on their own states, but also his rivals' entry decisions. This strategic interaction invalidates the methods proposed by Rust (1987), and Hotz and Miller (1993). In these papers, the individual's decision only depends on his own state, whereas in our paper, the estimation is based on non-cooperative equilibrium among firms. The second challenge is the continuous state variables. The continuity features rule out the method of Aguirregabiria and Mira (2007), which requires the conditional choice probabilities (CCP) at all possible states. Instead, the estimation technique here follows GHK (2010), and uses Bayesian MCMC methods to overcome these difficulties.

In this paper, we find that past entry experience has an important impact on firm performance in subsequent markets. When only supply side spillovers are allowed, the costs in the future markets may fall by as much as 7%. This result is close to its counterpart in GHK (2010). In contrast, when we incorporate demand side spillovers, the supply spillover effect becomes insignificantly different from zero, whereas demand spillovers increase firms future market share by 3–4 percent at the next market opening. The results show that demand side spillovers dominate supply spillovers in the pharmaceutical industry when both of them are considered together. The results indicate that lowering entry barriers is not an efficient method to encourage competition in the pharmaceutical industry, as experienced firms will squeeze out new firms in future makets by attenuating market share for new ones.

The rest of the chapter is organized as follows: in section 2, the background of generic pharmaceutical industry and the corresponding data are introduced. A dynamic model containing both demand and supply side spillovers is formally presented in section 3. Section 4 discusses the model's solution, and section 5 presents the likelihood function. We introduces the choice of priors for all parameters, and the estimated results are discussed in section 6. Section 7 performs a policy experiment based on model estimates. Finally, we conclude this chapter in section 8.

Background and Data

Generic drugs, which are substitutes for brand-name drugs, are almost bioequivalent to the brand-name drugs, but less expensive. Generic pharmaceutical sales account for a considerable share in GDP in U.S. In 2007, total sales were valued at $58.5 billion. In the same year, 65% prescriptions in the U.S were made up of generics. In order to promote generics as well as lower the drug price, the Drug Price Competition and Patent Term Restoration Act of 1984 (usually referred to as the Waxman-Hatch Act) was enacted to lower barriers to entry for generic firms by permitting Abbreviated New Drug Applications (ANDAs). This act promotes market entry, because generic firms only need to submit bioequivalence studies, instead of repeating all the expensive and time consuming tests that the manufacturer of the pioneer branded product had gone through to gain Food and Drug Administration (FDA) approval. The Waxman-Hatch act has resulted in a lot of biologically equivalent drugs. According to a report of the FDA in 2004, there were 941 new drug and biologics license application approvals between 1995 and 2004, only one third were defined by the FDA as "containing an active substance that has never before been approved for marketing in any form in the United States."

Although the Waxman-Hatch act lowers entry barriers for entry, there remains a significant sunk entry cost associated with submitting an ANDA, even if it is much less than the cost of inventing a new drug. These sunk entry costs range from $250,000 to $20 million (Scott-Morton (1999)). In addition, the generic drug market is risky. Empirical experience shows that only 3 out of every 20 approved drugs bring in sufficient revenue to cover their costs. These significant sunk costs and uncertainties in each market cause the number of entrants to be small. In 1989, the notorious "generic scandal" was exposed, in which some FDA reviewers confessed to accepting bribes to expedite ANDAs, and some data submitted by firms was falsified in order to pass the FDA process. During this "scandal period", the market structure may be different from the post-scandal period. Because of the possibility of structural change, the data points in the scandal period are disposed of to avoid biasing the analysis.

As discussed in Scott-Morton (1999), entry is rarely announced, because firms who have private information do not want to signal the common market value, attract potential entrants and increase competition. They also fear that the delay in the approval will invite competition. There are few late sequential movers who withdraw in response to rivals' approvals. As such, simultaneous entry decisions are a striking feature of the pharmaceutical industry.

The original data was assembled by Scott-Morton (1999), and was sorted by GHK (2010) later. This data set consists of all ANDA approvals between 1984 to 1994. To implement the estimation, the variables we are using for each market opportunity include the ANDA approval date, market revenue in the year before the patent expires, and entry decision of potential entrants. Because uncertainty and exogenous factors may alter firms-level decisions during the scandal period, we focus on the period after the scandal, 1990-1994. In this period there are 40 market openings for which the previous revenue data are not missing, and 51 firms who entered at least once. The top 3 dominant firms in the sample after 1989 are Mylan, which entered 45 percent of the markets, Novopharm entered 28, and Lemmon entered 25 of the markets.

In our analysis, we only consider the strategic interaction of the top 3 firms. The remaining firms are referred to as "other firms", and their small size and market share are assumed not to affect the top firms' entry decision. In this analysis, the market share occupied by other firms is simply neglected.

Model

In this section we present a dynamic model of firm entry with both demand side and supply side spillovers. Because of the computational burden of solving the model in markets with many entrants, we restrict the strategic interaction to the 3 dominant firms. Each dominant firm maximizes his discounted profits in an infinite series of market openings $t = 1, 2...\infty$. Each market opening opportunity is defined as the time when a drug's patent protection expires. In a bid to maximize the discounted profits, each firm makes their entry decision at market t based on the current profits associated with market t and the impact of the decision on future profitability. Since market openings appear in the time horizon, in the following context, t will be used interchangeably to denote a market opening or the time period associated with it. If a firm decides to enter a market, he collects profits over all future periods, instead of realizing all profits in one period. However, this feature makes the dynamic model hard to estimate, because two time horizons are entangled in this model: one is within each market t, the other is over different market openings. To make the model computationally feasible, we assume firms realize all profits in each market in a lump-sum form.

When market t opens, firm i's entry decision is denoted by $A_{it} = \{0, 1\}$. If firm i chooses to enter market t, $A_{it} = 1$, otherwise, $A_{it} = 0$. In each market t, firms' decisions are observed by whether they submit an ANDA or not. The number of total entrants in market t is given by

$$N_t = \sum_{i=1}^{3} A_{it} \tag{II.1}$$

The possible sources of dynamics are through cost and market share. If a firm entered a previous market, their profitability may be enhanced later. This increase in profits could be the result of a cost reduction from previous experience, or a demand increase from an enlarged customer base. To separately identify the sources of dynamics, we impose some structure on the model. Particularly, current costs, C_{it} are determined by previous entry decisions and random shocks. We assume evolution of cost is governed by the following equation:

$$c_{it} = \log(C_{it}) = u_c + \rho_c(c_{i,t-1} - u_c) - k_c A_{i,t-1} + \sigma_c e_{it} \tag{II.2}$$

where u_c is a location parameter representing the average log cost; k_c is the direct cost spillover effect in current market t if firm i enters market $t-1$, and the cost spillovers last more than one period through the persistence parameter $\rho_c; \sigma_c e_{it}$ is the cost shock which follows a normal distribution with zero mean and variance σ_c^2. Equation (II.2) implies that if k_c is positive, a firm's past entry experience reduces their cost in later markets.

Firm i's expected market share[1] S_{it} conditional on all firms entering market t is governed by the following equation:

$$S_{it} = \frac{\exp\left(\lambda \sum_{m=1}^{t-1} A_{it-m}\right)}{\sum_{j=1}^{3} \exp\left(\lambda \sum_{m=1}^{t-1} A_{jt-m}\right)} \tag{II.3}$$

where the parameter λ measures the magnitude of the demand spillovers. Equation (II.3) implies that if λ is positive, a firm's previous entry experience increases his market share given that his rivals keep the same strategies. If there are firms which do not enter market t, we assume their market shares are split by the other firms proportionally to their conditional market shares. The actual market share for firm i in market t is:

$$\rho_{it} = A_{it} S_{it} / \left[\sum_{j=1}^{3} A_{jt} S_{jt}\right] \tag{II.4}$$

We assume, as in GHK (2010), that this is a game with complete information.

[1]This expected market share can be generated by consumers' heterogeneous preference toward different products in a market. In particular, consumers in general prefer a brand which has been seen or used before. Therefore, a firm with more market entry experience could ensure a large expected market share, whereas a firm, which rarely enter markets before, only anticipates a small expected market share.

Hence, all firms observe each other's costs, as well as expected their market shares[2]. Total revenue in market t is approximated by the revenue in the previous year, when the drug was on patent. Therefore, when firms make their entry decision at market t, the revenue R_t associated with this market is treated as known, because firms can observe the previous year's revenue.

The uncertainties originate from the corresponding costs and revenue in future markets. The realization of revenue $R_{t+1} = \exp(r_{t+1})$ is assumed to take the following form:

$$r_{t+1} = u_r + \sigma_r e_{r,t+1} \tag{II.5}$$

where, u_r is a location parameter, and $e_{r,t+1}$ is a random shock to the revenue in market $t+1$, with standard normal distribution. Equation (II.5) implies that when firms make decisions at time t, they conjecture on the revenue in market $t+1$.

This structure allows us to write the profits π_{it} for dominant firm i in market t as:

$$\pi_{it} = A_{it}(\rho_{it} R_t - C_{it}) \tag{II.6}$$

The firm's discounted profits at time t are

$$\sum_{j=0}^{\infty} \beta^j A_{i,t+j} \left(\rho_{i,t+j} R_{t+j} - C_{i,t+j}\right) \tag{II.7}$$

where β is a discount parameter within the interval $(0, 1)$. The firm maximizes the sum of discounted profits by making his entry decision in each market given that other firms adopt their equilibrium actions.

[2]Since a firm's market entry history is observable, the expected market share is given by (3a).

The choice specific Bellman equation can be written as:

$$
\begin{aligned}
& V_i(A_{i,t}, A_{-i,t}, C_{i,t}, C_{-i,t}, \rho_{it}R_t, \rho_{-i,t}R_t) \qquad \text{(II.8)} \\
= \;& A_{it}(\rho_{it}R_t - C_{it}) \\
& +\beta EV_i \left[(A^E_{i,t+1}, A^E_{-i,t+1}, C_{i,t+1}, C_{-i,t+1}, \rho_{i,t+1}R_{t+1}, \rho_{-i,t+1}R_{t+1}) | ST_{it} \right]
\end{aligned}
$$

where S_{it}=$(A_{it}, A_{-it}, C_{it}, C_{-it}, \rho_{it}R_t, \rho_{-it}R_t)$, $-i$ represents all the other firms with respect to firm i, $A^E_{i,t+1}$ is the equilibrium strategy for firm i, and $A^E_{-i,t+1}$ is a equilibrium strategy vector of other firms. The choice specific value function (II.8) gives the discounted profits for firm i if he chooses action A_{it} at time t and all firms play equilibrium actions from $t+1$ onwards. The expectation is over the distribution of cost shocks, revenue, and actual market shares in market $t+1$ conditional on all the realizations of states and actions taken at time t.

The best response strategy profile (A^E_{it}, A^E_{-it}) as the stationary pure strategy Markov perfect equilibrium of the dynamic game satisfies:

$$
V_i(A^E_{it}, A^E_{-it}, C_{it}, C_{-it}, \rho_{it}R_t, \rho_{-it}R_t) \geq V_i(ST_{it}) \qquad \text{(II.9)}
$$

The value function (not the choice specific value function) is

$$
\begin{aligned}
& V_i(C_{it}, C_{-it}, \rho_{it}R_t, \rho_{-it}R_t) = A^E_{it}(\rho_{it}R_t - C_{it}) \qquad \text{(II.10)} \\
& +\beta E \left[V_i(C_{i,t+1}, C_{-i,t+1}, \rho_{i,t+1}R_{t+1}, \rho_{i,t+1}R_{t+1}) | A^E_{it}, A^E_{-it}, C_{it}, C_{-it}, \rho_{it}R_t, \rho_{-it}R_t \right]
\end{aligned}
$$

Our estimation strategy relies on the pure strategy Markov perfect equilibrium. Because of this we cannot apply the single agent methods Rust (1987) or Hotz and Miller (1993). The equilibrium based estimation raises two difficulties. The first is to calculate the equilibrium. Without knowing what actions the rivals will take, a representative firm needs to compare his discounted profits under every possible action profile of his rivals. Within Bayesian estimation, the required parameters can be drawn from a prior, and updated by comparing likelihoods computed under different sets of parameters.

The second difficulty is the number of equilibria. One possibility is that there may be no pure strategy equilibrium at some given parameters, an other is multiple equilibria at some given parameters, while last one the model may deliver an a unique Nash equilibrium in each market. If there is no equilibrium, we simply dispose of that set of parameters, and draw a new set of parameters. In other words the parameters are only updated when they generate an equilibrium in pure strategies. When there are multiple equilibria, we follow Berry (1992) in the selection of equilibrium. Specifically, when there are multiple equilibria, the equilibrium with the minimum total cost will be chosen as the equilibrium to be used in estimation. The details about estimating the model under pure strategies and unique equilibrium are discussed in section 4.

Solving the Model

In the estimation, a nested approach is employed to solve the dynamic model. The broad outline of the computational strategy is as follows: (1) Draw a set of parameters by means of the MCMC algorithm. (2) For each set of parameters, generate the state variables over the sample period. (3) Solve the dynamic game to compute the equilibrium outcome as a function of the state variables. (4) Use the equilibrium outcome to compute the likelihood relying on the observed entry data. (5) Use the likelihood depending only on observed variables to make an acceptance-rejection decision within the MCMC algorithm. Repeat steps (1)–(5) to generate an MCMC chain which is drawn from the posterior distribution of the parameters. In the above outline, the two main tasks are computing the equilibrium and calculating the likelihood. In this section, we describe the details for solving the equilibrium of the dynamic game. In section 5, we discuss how to calculate the likelihood function with the solved equilibrium and latent parameters.

Within the dynamic model, we look for a stationary Markov perfect equilibrium, which requires solving the fixed point of the Bellman equation (II.10). At each market opening t, firms make their entry decisions. The strategy profile A_t played by all firms at time t is denoted as

$$A_t = (A_{1t}, A_{2t}, A_{3t}) \tag{II.11}$$

The equilibrium strategy profile should be a function of state variables

$$(C_{1t}, C_{2t}, C_{3t}, \rho_{1t}R_t, \rho_{2t}R_t, \rho_{3t}R_t)$$

costs and market share of all firms. The vector of the log of the state variables at time t is

$$s_t = (c_{1t}, c_{2t}, c_{3t}, \log(\rho_{1t}), \log(\rho_{2t}), \log(\rho_{3t}), r_t) \tag{II.12}$$

Given a set of parameters, the game is solved as follows:

1. Approximate the value function at each market opening t by a linear equation, $V^*(s_t) = b^* + B^* s_t$, where b^* is a constant vector, and B^* is a coefficient matrix.

2. Search for the fixed point of $V^*(s) = (V_1^*(s), V_2^*(s), V_3^*(s))$ by initializing the value function $V^0(s) = 0 + 0 \times s_t$, where the superscript indicates the number of iterations. Here the search starts with (b^0, B^0) being set to 0.

3. Compute best response strategy for each firm over sample period. The best response strategy requires the formula of the expected future value function

$$E\left[V_i^0(s_{t+1})|A_t, s_t\right]$$

for each firm i. We obtain the above formula as follows: at each s_t, given any strategy profile A_j of all firms, we generate the next period state variables s_{tj}, where $j = 1, 2, ...J$. The variable s_{tj} is the future possible states around s_t, but shifted by strategy profile A_j. Each s_{tj} contains the dynamic effect of strategy profile A_j and systematic cost shocks and demand shocks. The expectation is the sum of the value function at different s_{tj}.

$$\begin{aligned} EV(s_{t+1}|A_t, s_t) &= E\left[b^0 + B^0 s_{t+1}\right] \\ &\approx b^0 + \frac{1}{J}\sum_{j=1}^{J} B^0 s_{tj} \end{aligned} \tag{II.13}$$

4. Calculate the value function at all possible strategy profiles, and make use of equation (II.9) to select the best response strategy profile A_j^E. We record the value function with the best response strategy profile for each market t as $V^0(s_t) = (V_1^0(s_t), V_2^0(s_t), V_3^0(s_t))$.

5. Regress $V^0(s_t)$ on a constant and state variables to get b^1 and B^1. The new (b^1, B^1)

is an update of (b^0, B^0).

6. Iterate step 3 to step 5 to find the new equilibrium profile under new coefficients (b^1, B^1) to update (b^1, B^1) to (b^2, B^2). Keep doing this until (b^k, B^k) becomes stable.

7. The fixed point of the value function is $V^*(s) = b^k + B^k s$.

To summarize the procedure, we first solve the equilibrium by guessing the coefficients of the value function. After solving the corresponding equilibrium given the coefficients, the value function $V(\cdot)$ at each state s_t can be computed. T value functions are calculated over the sample periods, and these values are regressed on state variables to update the coefficients of value function. This procedure continues until all coefficients become stable. In the procedure, it is possible that no equilibrium exists for some sets of parameters. In this case, these parameters are considered to be an irrelevant portion of the parameter space, and are rejected in the MCMC likelihood comparison step.

Our model may also deliver multiple equilibria. For example, suppose we have a situation where one firm entering a market is profitable, but two entrants make loss for both. In this situation, either firm entering the market is an equilibrium. Alternatively it may be that taking the same strategy as the rival does is profitable for the firm[3]. In the last case, having both firms enter or having both stay out of the market are equilibria.

We follow Berry (1992) to deal with multiple equilibria by adopting a selection rule. The rule is to select the equilibrium with the minimum total cost of all firms as the equilibrium. Specifically, at market t, there is a total cost of $C_t = C_{1t} + C_{2t} + C_{3t}$ associated with an action profile $A_t = (A_{1t}, A_{2t}, A_{3t})$. These action profiles are ordered by their associated total cost: the first action profile is associated with the lowest total costs

[3]This case can be interpreted as firms choosing to protect their comparative advantage in future markets. That is they may like to take the same strategy as their rival to keep themselves in a safe position.

and the last action profile has highest total costs. The equilibrium action profile with the smallest costs is the equilibrium action profile selected.

In this section, the procedure of solving for the equilibrium given a set of parameters was described. This can be treated as an inner routine. The outer routine consists of sequentially drawing different sets of parameters, comparing their corresponding likelihood functions, and saving the draws which increase the likelihood function with a certain probability. We will discuss the construction of the likelihood function next.

Likelihood Computation

Because we are estimating a game of pure strategies, a density for the strategy profile A_t that depends only on state $S_t = (C_{it}, C_{2t}, C_{3t}, \rho_{1t}R_t, \rho_{2t}R_t, \rho_{3t}R_t)$ and the model parameters would generate a value of one for the likelihood when the prediction is coincident with observed actions, and a value of zero for likelihood when the prediction is not. This feature would generate mass of one on a single value of A_t.

To solve this problem, we follow GHK (2010) by defining a misclassification probability $q_a = a - p_a, 0 < p_a < 1$, and the likelihood function for an observed action profile A_t^0 is defined as follows

$$p(A_t^0|C_{it}, C_{2t}, C_{3t}, \rho_{1t}R_t, \rho_{2t}R_t, \rho_{3t}R_t, \theta) = \prod_{i=1}^{3}(p_a)^{I(A_{it}^0 = A_{it})}(1-p_a)^{I(A_{it}^0 \neq A_{it})} \tag{14}$$

where A_{it} is predicted entry decision computed from the model given state S_t and θ is the set of parameters to be estimated.

$$\theta = (u_1, \sigma_1, u_c, \sigma_c, \sigma_r, \rho_c, k_c, \lambda) \tag{II.14}$$

The full likelihood for the data is

$$\prod_{t=1}^{T} p(A_t^0|C_{it}, C_{2t}, C_{3t}, \rho_{1t}R_t, \rho_{2t}R_t, \rho_{3t}R_t, \theta) \tag{II.15}$$

We interpret the misclassification probability as follows. Consider a firm which decides to enter a market and submit his ANDA. However, with some probability his ANDA will be rejected, even if he decides to enter. This rejection does not allow his entry decision to be realized, and the rejection probability is the misclassification probability.

Because the pre-scandal data may be generated from a different market structure, we focus on the post-scandal data to compute the likelihood. Between 1990 and 1994 there are forty markets in total without missing revenue date after the scandal. In the first period, there is no information about the demand and supply spillovers. We use two pre-scandal periods' entry behavior to generate the firm-level entry histories. Alternatively, the first period is treated as the initial period, in which all firms are ex-ante equivalent. The results suggest that no significant difference between the two approaches.

Identification

Another critical question is the identification of the structural model. Supply side spillovers affect a firm's entry likelihood by this firm's entry history. The fluctuation of entry histories for each firm helps to identify supply side spillovers. Demand side spillovers affect a firm's entry likelihood by this firm's entry history relative to competitors. Given this firm's entry history, its entry likelihood varies when competitors have different histories. The variation of relative entry histories allow us to identify demand side spillovers. For instance, consider two firms with the same entry histories. If they enter the same future markets, revenues are always evenly split. The two firms' entry behaviors help to identify supply side spillovers, as they always have the same relative entry history; no demand spillover is associated with entry. The identification of demand side spillovers comes from another firm with a different entry history: when all three firms simultaneously enter some markets, the third firm has a different market share from the other two firms. The difference of market shares, along with the identified supply spillovers by the two firms with the same entry history, identifies the demand side spillovers. The correlation coefficient of firms' absolute and relative entry histories is 0.33. The low correlation further implies that we can make use of the variation of absolute and relative entry histories to separately identify demand and supply side spillovers.

Parameter Estimation

As discussed in section 4, the estimation method contains an inner routine and an outer routine. The outer routing the MCMC method is used to draw the parameters from a one–move-at-a-time random walk proposal density. Given the old draw θ^o, a new draw is made from a conditional distribution $q(\theta^*|\theta^o)$. Denote the likelihood by $L(\theta)$, and the piror by $\pi(\theta)$. The actual next period parameter θ' is generated as follows:

1. Draw θ^* according to $q(\theta^*|\theta^o)$.

2. Let $a = \min\left\{1, \frac{L(\theta^*)\pi(\theta^*)q(\theta^*|\theta^o)}{L(\theta^o)\pi(\theta^o)q(\theta^o|\theta^*)}\right\}$.

3. If there is no equilibrium at parameter θ^*, set $\theta' = \theta^o$, otherwise with probability a, set $\theta' = \theta^*$ and with probability $(1-a)$ set $\theta' = \theta^o$.

We choose $q(\theta^*|\theta^o)$ to be a conditional normal distribution, in which θ^* is drawn from a normal distribution with mean θ^o, so as to facilitate the outer routine computation.

In this way, $q(\theta^*|\theta^o) = q(\theta^o|\theta^*)$, and the acceptance probability in step 2 can be written as $a = min\left\{1, \frac{L(\theta^*)\pi(\theta^*)}{L(\theta^o)\pi(\theta^o)}\right\}$.

Because we do not want to impose many restrictions on the parameters, we use a non-informative prior $\pi(\theta)$ with flat tails: $\log u_1 \sim U[-3,3], \log u_c \sim U[-3,3], \log \sigma_1 \sim U[-3,3], \log \sigma_c \sim U[-3,3], \log \sigma_r \sim U[-3,3], k_c \sim U[-1,1], \rho_c \sim U[0,1]$, and $\lambda \sim U[0,2]$. The time discount parameter β and the misclassification parameter p_a are not estimated in the program. Following the literature we set $\beta = 0.95$, and $p_a = 0.9375$.

Results

GHK (2010) claim that firms' over-entry behavior is caused by supply spillovers, which reduce the total costs by 7 percent. To make the estimates comparable to GHK, we first estimate the model under supply side spillovers only by shutting off the demand side spillovers, $\lambda = 0$, and update the remaining parameters. We then repeat the exercise with both demand and supply side spillovers. The key parameter in the second column of Table 1 is k_c, which is the measure of supply spillovers. The estimate of k_c is close to its counterpart in GHK (2010), likewise, the other parameters are close to those previously estimated in the literature. The results from the model with supply side spillovers implies that firms can reduce future costs by 7 percent if they enter the current product market. In the third column, we report the results when both demand and supply spillovers are introduced in the model. It is not surprising to find that the magnitude of supply spillovers falls after introducing demand spillovers, while the parameter of λ measuring demand side spillovers is significantly positive. Past entry experience has negative impact[4] (if we temporarily ignore the huge variance in k_c) on costs in the later markets, but firms can increase their market

[4]There are a number of explanations for the negative impact of past entry on future profitability. These include diseconomies of scale or diseconomies of scope on technogical investment costs.

share in the later markets through demand spillovers. It is worthwhile to point out that λ itself is not a direct measure of market share increase, but market share increase can be calculate from λ. The detailed market share increase caused by demand side spillovers is presented in Table 2. The difference in the value of k_c across columns implies that in the pharmaceutical industry, the pattern of firm-level over-entry behavior is largely determined by demand spillovers. Moreover, if we ignore demand spillovers, the researchers will incorrectly estimate the supply spillover effect.

Table 1: Posterior Distribution

	Posterior Distribution with Supply Spillovers Only	Posterior Distribution with Supply and Demand Spillovers
Parameter	3-Firm Case	
u_c	10.3488 (0.2993)	10.5238 (0.2188)
u_r	11.8320 (0.4253)	10.2971 (0.2275)
σ_c	0.4811 (0.0452)	0.2485 (0.0881)
σ_r	1.6902 (0.0138)	1.6625 (0.0127)
k_c	0.0677 (0.0206)	-0.0787 (0.1363)
ρ_c	0.8405 (0.1086)	0.8553 (0.1098)
β	0.95	0.95
p_a	0.9375	0.9375
λ		0.1664 (0.0128)
MCMC Rep	10000	10000

To shed light on the role of demand spillovers, we define $f_{1t}(A_{ij}, A_{-i,j})$ as firm i' market share in market $t+1$ conditional on having entered market t, and $f_2(A_{ij}, A_{-i,j})$ as firm i's market share in market $t+1$ given that he has not entered market t:

$$f_1(A_{ij}, A_{-i,j}) = \frac{\exp\left[\left(\sum_{j=1}^{t-1} A_{ij} + 1\right) \cdot \lambda\right]}{\exp\left[\left(\sum_{j=1}^{t-1} A_{ij} + 1\right) \cdot \lambda\right] + \exp\left[\sum_{j=1}^{t} A_{-i,j} \cdot \lambda\right]} \tag{II.16}$$

$$f_2(A_{ij}, A_{-i,j}) = \frac{\exp\left[\left(\sum_{j=1}^{t-1} A_{ij}\right) \cdot \lambda\right]}{\exp\left[\left(\sum_{j=1}^{t-1} A_{ij}\right) \cdot \lambda\right] + \exp\left[\sum_{j=1}^{t} A_{-i,j} \cdot \lambda\right]} \tag{II.17}$$

Then, firm i's marginal market share from entering market t, conditional on the actual entry history, can be computed as follows:

$$MMS_{it} = f_1(A_{ij}, A_{-ij}) - f_2(A_{ij}, A_{-i,j}) \tag{II.18}$$

where MMS_{it} is marginal market share of firm i at market t.

The average marginal share increase caused by demand spillovers for each firm over all markets are reported in Table 2. Market level results are reported in Table 4 (in the Appendix). Table 2 shows that in our sample, the past entry increases the current market share of each firm by 3% to 4% on average, given that his rivals keep the same entry decision. The increase in market share enhances firms' profitability, and hence gives them the incentive to enter markets even associated with relatively low revenue.

Table 2: The Average Marginal Market Share Gain From Entry

	$AMMS$
Firm 1	0.0406
Firm 2	0.0331
Firm 3	0.0313

As discussed above, firm-level market-entry decisions depend on expected profits. I use a simple example to show how the two types of spillovers differently affect these expected profit. Consider two firms that face a market opening. Firm i has no entry experience before, but firm j has entered many past markets. Since firm i has no entry history, it is isolated from neither cost spillovers nor demand spillovers. While cost spillovers alone affect firm i's expected profit by changing firm j's entry probability, demand spillovers not only change firm j' entry probability, but also firm i's after-entry-revenue. In this example, the impact of supply spillovers on firm i is indirect (through changing the entry probability of firm j only), but the demand spillovers have both indirect and direct impact on firm i.

Policy Experiments

The benefit of estimating a structural model is the ability to perform the counterfactual policy experiments. To distinguish the different implications of demand side spillovers and supply side spillovers, three experiments have been performed. The objective of these experiments is to measure how a policy maker could encourage entry by lowering entry barriers in different scenarios. These experiements are of policy interests as entry can affect the market structure, and further the social welfare. Policy marker may want to interefare the market structures to change some characteristics of market to increase the social welfare. In the first experiment, the average number of entrants before and after barrier reduction is computed by assuming no spillover. The second and third experiments repeat the exercise with only supply spillovers and only demand spillovers, respectively.

In each experiment, 50 market openings are simulated, and a policy maker is able to decrease the total costs of potential entrants by 20 percent in the first 10 markets through lowering the entry cost. Particularly, in the first 10 markets, the cost location parameter becomes $0.8u_c$. The features of markets and potential entrants are characterized by the parameters estimated in the last section. In particular, the revenue, and costs associated with each market are respectively drawn from $N(u_r, \sigma_r)$, and $N(u_c, \sigma_c)$. In the no spillovers' and demand spillovers' cases, we used parameters from the third column of Table 1. In the supply spillovers' case, we used parameters from the second column of Table 1. Each potential entrant makes its entry decision based on state variables, which are different in different experiments. The first and second columns are the entry rate before and after cost reduction, and the third column reports the change of Herfindahl index change before and after cost reduction.

Table 3: Average Entry Before and After Cost Reduction

	Average # of Entrants No Cost Reduction	Average # of Entrants with Cost Reduction	Change of Herfindahl Index Before and After Cost Reduction
Benchmark (No Spillovers)	1.08	1.21	-0.06
Supply Spillovers	1.68	1.80	-0.10
Demand Spillovers	1.24	1.13	+0.03

Table 3 first shows that with and without cost reduction (lowering entry barrier), if supply spillovers exist solely in an indstry, that industry tends to have the highest entry rate[5]. This result is reasonable in a sense that supply spillovers increase firms' average profitability in later markets, whereas demand spillovers only shift the market share among firms, which raise the profitability for one firm by hurting the other firms. Second, in the benchmark and supply spillovers case, a policy maker could enhance market entry rate and competition by lowering entry barrier, but in the demand spillover case, lowering entry barrier results in lower entry rate and less competition (more concentration). The reason is that with demand spillovers, one firm that entered early markets became very powerful,

[5]We need to be aware that the mean of u_r is higher in the supply spillovers' case than that of the no spillovers' and demand spillovers' case. This higher average revenue partly leads to a higher entry rate in the supply spillovers' case.

and it squeezes out other firms in later markets, even in those high revenue markets, as the market share left for other firms is too small to make profits. The result indicates that if a policy maker is about to lower entry barriers to encourage entry in an industry with demand spillovers, he is likely to cultivate monopolists in this industry and induce a lower entry rate, possibly even lower than in the benchmark case, in future markets.

Conclusion

This paper investigates cost and demand spillovers which determine firm-level entry decisions in the pharmaceutical industry. In contrast to previous literature which attributes over-entry in the pharmaceutical industry to supply side spillovers, this paper finds that demand side spillovers play a significant role in firm-level entry patterns. The results show that when demand side spillovers are neglected, the effect of supply side spillovers tends to be biased upwards. Furthermore, after taking into account both types of spillovers, the effect of supply side spillovers is negative on average. Ignoring demand side spillovers leads to misleading results. Particularly, lowering entry barrier increases competition when supply side spillovers plays its role, but decreases competition when demand side spillovers are dominant. In addition, supply side spillovers raise social welfare by decreasing average costs, but the effect of demand side spillovers is ambiguous: market share may be shifted to more or less productive firms. Subsidizing only new firms is a way to increase competition when demand side spillovers are significant. If more firm-level characteristics can be observed, such as productivity, by the policy maker, he can subsidize more efficient firms to increase social welfare. In contrast, as only supply side spillovers take effect, the policy maker does not need to distinguish between firms. Subsidizing all firms can increase social welfare and competition.

BIBLIOGRAPHY

[1] Aguirregabiria, V., and P. Mira. 2007. "Sequential estimation of dynamic discrete games," *Econometrica*, Vol. 75, pp. 1-53.

[2] Berry, S. 1992. "Estimation of a model of entry in the airline industry," *Econometrica*, 60(4), 889-917.

[3] Benkard, L.. 2004. "A Dynamic Analysis of the Market for Wide-bodied Commercial Aircraft," *The Review of Economic Studies*, Vol. 71, pp. 581-611.

[4] Bresnahan, T., and P. Reiss. 1991a. "Empirical Models of Discrete Games," *Journal of Econometircs*, Vol. 48, pp. 57-81

[5] Douced, A. De Freitas, and N. Gordon. 2001. "An Introduction to Sequential Mote Carlo Methods," in *Sequential Monte Carlo Methods in Practice*, ed. by A. Douced, N. de Freitas, and N. Gordon, pp. 3-13. Springer.

[6] Dutta, p. k, and R. K. Sundaram. 1998. "The Equilibrium Existence Problem in General Markovian Games," in *Organizations with Incomplete Information*, ed. by M. Majumdar, pp. 159-207. Cambridge University Press.

[7] Gavazza, A. 2011. "Demand Spillovers and Market Outcomes in the Mutual Fund Industry," *The Rand Journal of Economics,* Vol. 42, pp. 776-804.

[8] Gallant, A. Ronald, Han Hong, and Ahmed Khwaja. 2010. "Dynamic Entry with Cross Product Spillovers: An Application to the Generic Drug Industry," *Working paper.*

[9] Hotz, J., and M. Miller. 1993. "Conditional Choice Probability and the Estimation of Dynamic Models," *The Review of Economic Studies*, Vol. 60, pp. 497-529.

[10] Keane, M. and K. Wolpin. 1997. "The Career Decisions of Young Men," *The journal of Political Economy*, Vol. 105, pp. 473-522.

[11] Klemperer, P. and Padilla, A.. 1997. "Do Firms' product lines include too many varieties?" *The Rand Journal of Economics*, Vol. 28 (1997), pp. 427-482

[12] Lucia Foster, John Haltiwanger, and Chad Syverson. 2010. "The Slow Growth of New Plants: Learning about Demand?" *Working paper.*

[13] Mazzeo, M. 2002. "*Product Choice and Oligopoly Market Structure*," *The Rand Journal of Economics*, Vol. 33, pp. 221-242.

[14] Rust, J. 1987. "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher," *Econometrica*, Vol. 55, pp. 999–1033.

[15] Scott-Morton, F.. 1999. “Entry Decisions into Generic Pharmaceutical Markets,” *The RAND Journal of Economics*, Vol. 30, pp. 421-440.

[16] Siem, K. 2006, “An empirical model of firm entry with endogenous product-type choices,” *The RAND Journal of Economics*, Vol. 37, pp. 619-640.

[17] Whinston, M.D. 1990. "Tying, Foreclosure and Exclusion," *The American Economic Review*, Vol. 80, pp. 837-859.

Appendix

Robustness

Table 4: Posterior Distribution with Supply and Demand Spillovers (with Splited State-Space)

Parameter	3-firm case
u_c	10.7887 (0.3866)
u_r	10.6395 (0.2389)
σ_c	0.2810 (0.0887)
σ_r	1.5025 (0.0966)
k_c	-0.0732 (0.0893)
λ	0.1722 (0.0656)
ρ_c	0.8951 (0.1489)
β	0.95
p_a	0.9375
MCMC Rep	10000

Notes:Table 4 reports the results of estimates after I split the state-space by market revenue. Particularly, I allow the coefficients of value function $V^*(s_t) = b + Bs_t$ different when the realized market revenues is above or below their median revenue. The results show that demand side spillovers still dominate supply side spillovers.

Goodness of fit

Table 5.1: Goodness of Fit of Entry

	Actual Entry Rate	Predicted Entry Rate
Firm 1	45%	37.5%
Firm 2	27.5%	27.5%
Firm 3	25%	22.5%

Notes:Table 5.1 reports the goodness of fit of the structural model with demand and supply side spillovers. The second column is firm-level actual entry rate in all 40 markets. The second column is the predicted firm-level entry rate in all 40 markets. The predicted entry rate is compute with the posteriors mean of parameters in Table 1 (The third column).

Table 5.2: Goodness of Fit of Market Revenue

Average Log Actual Revenue	Average Log Predicted Revenue
10.4737 (2.1213)	10.2971 (1.6625)

Notes:Table 5.2 reports the mean of actual market revenues and the average predicted market revenues. The standard deviation is in the parenthesis.

CHAPTER III

Firm Selection Across International Markets

This paper uses rich data to re-examine firm-level survival, turnover, and performance in a context which is of global interest: the growth of Chinese exports. It is widely reported that Chinese exports have grown dramatically over the past two decades. The astonishing size and scope of Chinese export growth have had important economic impacts worldwide. Numerous developing countries have recommitted to export promotion as a key plank within their development platform so as to achieve similar growth and success in international markets. Importing countries have concurrently struggled to determine the appropriate policy response in the face of large inflows of Chinese products. However, little is known about the micro-economic evolution of firm-level Chinese exporters. Have rapid increases in firm-level efficiency allowed Chinese exporters to expand across markets worldwide? Was the rapid expansion of Chinese exports, in contrast, demand driven? Were key changes to export behavior occurring at the industry or firm-level?

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

We are able to shed new insight on firm selection 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 productivity and demand on firm-level entry and exit behaviour across worldwide markets. Specifically, we characterize turnover across markets, the persistence in export demand and the selection of firms across markets in each year between 2002 and 2005.

Our approach follows a long tradition which characterizes industries as collections of heterogeneous producers with widely different levels of technological efficiency (e.g. Jovanovic (1982), Hopenhayn (1992), Ericson and Pakes (1995), Melitz (2003), and Asplund and Nocke (2006)). A key feature in each of these models is the strong link between producers' productivity levels and their performance in a given market. Further, endogenous selection mechanisms are often found to drive movements in industry aggregates as market shares are reallocated to more efficient producers. Over time less productive plants decline and exit markets entirely while more efficient plants enter and grow into new markets, encouraging selection-driven aggregate sales growth across markets.

We find that export markets are characterized by a very high levels of churning. Our results suggest that this exit and entry are most closely related to firm-level demand differences which vary widely across firms. In particular, our calculations suggest that standard measures of dispersion for demand are several times larger than the same measures of productivity dispersion. Despite high degrees of international turnover we do not intend to suggest that the determinants of firm-level entry into export markets vary widely over time. Rather, almost all of the key determinants of exporting - productivity, prices and demand- demonstrate very strong degrees of persistence.

There is near universal support for the notion that productivity is a key determinant of export behaviour.[1] Likewise, Manova and Zhang (2011, 2012) document large pricing and quality differences across Chinese exporters and destinations worldwide. Crozet et al. (2012) document that among French wine producers those that produce high quality wines export to more markets, charge higher prices, and sell more in each market. We study to which similar effects are found in the context of Chinese manufacturing and the impact that demand differences have on aggregate export growth.

An increasing number of papers suggest that demand may play a particularly important role in determining export decisions and outcomes. A seminal piece studying firm-level entry to export markets by Das, Roberts and Tybout (1997) argues strongly that among nearly identical exporters with very similar measures of firm-level efficiency, the set

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

of export outcomes varies widely. Demidova, Kee and Krishna (2012) and Rho and Rodrigue (2012) recently document that export market demand shocks are key determinants of exporter behaviour in Bangledesh and Indonesia, respectively. In a paper closely related to ours, Roberts et al. (2012) structurally estimate a model of Chinese footwear exporters. Analogous to the results in our empirical exercise, they find that the implied distribution of demand varies much more than that of productivity. Further, they find that both productivity and demand are strongly associated with export revenues, export market entry and export frequency. Our results indicate that firm-level demand differences are strong predictors of annual firm-level market selection, but physical productivity is not.

High rates of turnover in international markets have a large impact on the evolution of productivity and demand across Chinese exporters. We document that entering and exiting firms are strongly characterized by very small measures of idiosyncratic demand relative to incumbent exporters. These differences in demand, in combination with high rates of churning, appear to have a significant effect on firm-level pricing. We find that new entrants are typically less productive than incumbent exporters and they choose relatively high prices. Our results suggest that entrants are choosing prices which are on average 12 percent higher than incumbent 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.[2] In each country in our data, we show that aggregate export growth can be related to changes in firm-level productivity, changes in firm-level demand and market-specific changes. We find that at least 18 percent of short-run export growth (year-to-year) can be attributed

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

to growth in firm-level demand. In contrast, productivity changes explain at most 5 percent of short-run export growth. In this sense our findings indicate strong differences in the margins through which aggregate exports grow. We find a number of novel findings by further decomposing demand and productivity across firms and markets. In particular, we highlight two mechanisms: the rapid growth of demand among surviving firms and the short-export spells of firms with low measured demand. The impact of this second effect should not be underestimated; our estimates suggest that net entry accounts for nearly 60 percent of the total growth in export demand across markets.

This chapter proceeds by outlining a simple model to motivate the empirical exercises that follow. Section 3 describes our data and disentangles our measures productivity and demand across firms and markets. It also describes the nature of turnover in our data, the persistence of key firm-level determinants, and documents the association of productivity and demand with key firm-level export outcomes. The fourth section studies firm selection in international markets and investigates the role of entry and exit on shaping the distribution of these characteristics across firms. Section 5 examines aggregate export growth and decomposes aggregate export growth in two steps. In the first step we study the extent to which demand and productivity separately influence export growth, while in the second step we decompose each component to study the role of within-firm growth, reallocation and net entry on the evolution of aggregate demand and productivity among exporting firms. Section 6 concludes.

A Simple Model of Selection and Exporting

We begin by outlining a model to motivate our empirical work. The model is purposefully simple and a close variant to those used elsewhere in the trade and industrial organization literature. In particular, the framework we present below is effectively a marriage of the trade model in Melitz and Ottaviano (2008) and its extension in Foster, Haltiwanger and Syverson (2008) which accounts for firm-specific demand.[3] Our model maintains many of the benefits of these earlier models. In particular, we will allow firms to choose to produce in M different destination markets (as in Melitz and Ottaviano, 2008), but will characterize their decisions as a function of both firm level productivity, ω, and demand, δ, (as in Foster, Haltiwanger and Syverson, 2008). An important distinction in our case, however, is that each firm will have a firm-specific demand component in each of the M markets in which it can enter.

Consider an industry which is comprised of a continuum of producers of measure N. We index individual producers by i, each of which makes a distinct variety. A fraction of firms in this industry N_m/N are actively producing for (destination) market m, $m = 1, ..., M$.[4] Each market m is populated by L_m homogeneous consumers who supply 1 unit of labor each and consume both a homogeneous numeraire good y_m and a differentiated good, q_{im}. Demand for the firm's product is captured by the firm's residual (inverse) demand function in market m:

$$p_{im} = \alpha_m + \delta_{im} - \gamma_m q_{im} - \eta_m \bar{q}_m$$

where $\alpha_m > 0$, $\eta_m > 0$, and $\gamma_m \geq 0$. The variable δ_{im} is a variety and market-specific mean-zero taste shifter (i.e. a firm-specific demand shock), q_{im} is the quantity of good i consumed and $\bar{q}_m = N_m^{-1} \int_{i \in I} q_{im} di$. The parameter γ_m captures the extent to which varieties are substitutable for each other in market m; lower values of γ_m induce higher

[3]Foster, Haltiwanger and Syverson (2008) effectively considers a closed economy version of Melitz and Ottaviano (2008) where firms differ in terms of productivity and demand. While Melitz and Ottaviano (2008) allow for trade across many countries, firms only differ in one fundamental dimension, productivity.

[4]As we describe below a fraction of N_m^c/N_m originate in country $c = 1, ..., M$ where we consider each market a separate country, $N_m = N_m^1 + ... + N_m^M$.

degrees of substitutability across varieties. The parameters α_m and η_m shift overall demand for the industry′s output relative to the numeraire, and δ_{im} shifts demand for particular goods relative to the level of α_m.[5]

Output is produced with a single input x_i according to the production function $q_i = \omega_i x_i$ where ω_i is producer-specific productivity. The input can be purchased on competitive factor markets at a price r_c which is constant across producers located in the same country c, but can vary across countries, $c = 1, ..., M$. The total cost of production for a firm in country c is then $C_{ic}(q_i) = \frac{r_c}{\omega_i} q_i$. We assume further that accessing market m is costly. Specifically, in order to sell in market m firms in country c incur iceberg transport costs $\tau_{cm} \geq 1$ per unit shipped from source country c to destination country m. Firm-level marginal costs of producing and selling a unit in market m are $MC_{imc} = \frac{r_c \tau_{cm}}{\omega_i}$ which vary across firms located in the same source country c and exporting to the same destination country m because of firm-level productivity.

Utility and profit maximization jointly imply that the producer's optimal price

[5] The representative consumer's preferences over varieties which generates the residual demand function is given by

$$U_m = y_m + \int_{i \in I} (\alpha_m + \delta_{im}) q_{im} di - \frac{1}{2} \eta_m \left(\int_{i \in I} q_{im} di \right)^2 - \frac{1}{2} \gamma_m \int_{i \in I} q_{im}^2 di$$

where y_m is the quantity of a numeraire good. Consumer utility is composed of three distinct terms. The first term is quadratic in total consumption of the industry's output while the second is a term which captures market-specific tastes for particular varieties. The third term, which enters utility negatively, is increasing in the variance of consumption across varieties. As $\gamma_m \to 0$, only the total taste-adjusted quantity of industry varieties consumed affects utility. Note that in equilibrium the number of active producers and the average price level will depend on γ_m.

and quantity sold in market m are

$$p_{icm} = \frac{1}{2}\left(\frac{\gamma_m}{\eta_m N_m + \gamma_m}\alpha_m - \frac{\eta_m N_m}{\eta_m N_m + \gamma_m}\bar{\delta}_m + \frac{\eta_m N_m}{\eta_m N_m + \gamma_m}\bar{p}_m + \delta_{im} + \frac{r_c \tau_{cm}}{\omega_i}\right) \tag{III.1}$$

$$q_{icm} = \frac{L_m}{2\gamma_m}\left(\frac{\gamma_m}{\eta_m N_m + \gamma_m}\alpha_m - \frac{\eta_m N_m}{\eta_m N_m + \gamma_m}\bar{\delta}_m + \frac{\eta_m N_m}{\eta_m N_m + \gamma_m}\bar{p}_m + \delta_{im} - \frac{r_c \tau_{cm}}{\omega_i}\right) \tag{III.2}$$

The optimal price is intuitively increasing in the demand for the industry's output, the average price of competing firms ($\bar{p}_m$), producer-specific demand and the transport cost between where the product is produced and the market where it is sold. It is decreasing in their competitors' average quality ($\bar{\delta}_m$) and productivity since the average industry price is decreasing in average costs[6]

$$\bar{p}_m = \frac{\gamma_m}{\eta_m N_m + 2\gamma_m}(\alpha_m + \bar{\delta}_m) + \frac{\eta_m N_m + \gamma_m}{\eta_m N_m + 2\gamma_m}\overline{\left(\frac{r\tau_{cm}}{\omega_m}\right)}$$

Using the equations for optimal price and quantity we can write maximized profits as

$$\pi_{icm} = \frac{L_m}{4\gamma_m}\left(\frac{\gamma_m}{\eta_m N_m + \gamma_m}\alpha_m - \frac{\eta_m N_m}{\eta_m N_m + \gamma_m}\bar{\delta}_m + \frac{\eta_m N_m}{\eta_m N_m + \gamma_m}\bar{p}_m + \delta_{im} - \frac{r_c \tau_{cm}}{\omega_i}\right)^2$$

Following FHS (2008) we define a market-specific profitability index $\phi_{icm} = \delta_{im} - r_c\tau_{cm}/\omega_i$. Firm-level profits imply a critical value of this index, ϕ^*_m, where producers with $\phi_{icm} < \phi^*_m$ will not find operations profitable in market m. Solving the optimal profits equation for ϕ^*_m gives us

$$\phi^*_m = -\frac{\gamma_m}{\eta_m N_m + \gamma_m}\alpha_m + \frac{\eta_m N_m}{\eta_m N_m + \gamma_m}\bar{\delta}_m - \frac{\eta_m N_m}{\eta_m N_m + \gamma_m}\bar{p}_m$$

A key feature of this index is that it holds for all firms selling in market m regardless of

[6]The average quality $\bar{\delta}_m$ and the average marginal costs $\overline{(r\tau_m/\omega_m)}$ are functions of the composition of firms (domestic and exporting firms) which enter into market m.

whether they reach market m 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.[7] Although the cutoff does not directly depend on the size of the market L_m, it does depend on the number of competitors N_m, which will vary with L_m. We can then rewrite profits for any firm in any market as $\pi_{icm} = \frac{L_m}{4\gamma_m}(\phi_{icm} - \phi^*_m)^2$ and total profits as $\pi_{ic} = \sum_m \max\{0, \pi_{icm}\}$.

Free Entry and Equilibrium

A large pool of ex-ante identical potential entrants decide whether to enter the industry in each country c. They first choose whether to pay a sunk cost s_c in order to receive demand and productivity draws from a joint distribution with probability density function $f(\omega, \delta_1, ..., \delta_M)$. The marginal distributions of ω and δ_m are defined over $[\omega_l, \omega_u]$ and $[-\delta_{me}, \delta_{me}]$, respectively, where $\delta_{me} < \alpha_m$ and $\omega_l > 0$. If they choose to receive draws, they then determine whether to begin production, which markets to serve and earn the corresponding profits. A free-entry condition pins down the equilibrium values ϕ^*_m in each market. Specifically, the $(\phi^*_1, ..., \phi^*_M)$ must set the net expected value of entry into the industry by firms in each country equal to zero. That is, ϕ^*_m must satisfy

$$V_c^E = \int_\omega \int_{\delta_1} ... \int_{\delta_M} \pi_{ic}(\phi_{i1}, ...\phi_{iM}, \phi^*_1, ..., \phi^*_M) f(\omega, \delta_1, ..., \delta_M) d\delta_M, ..., d\delta_1 d\omega - s_c = 0$$

The above expression summarizes the industry equilibrium. It combines the condition that producers only enter markets where they make non-negative profits with the condition which specifies that entry occurs until the expected value of the firm is zero. The

[7] This index also allows for the possibility that the domestic market is more competitive than some export markets. As argued by Lu (2010), in many industries Chinese exporters are less productive than their non-exporting counterparts. Dai et al. (2011) argue that this finding in Lu (2010) is feature of sample construction. We take no stand on the issue here as we will not be directly comparing exporting and non-exporting firms but simply note that our model allows for this possibility.

equilibrium requires that successful producers receive large enough idiosyncratic productivity and demand draws to meet the profitability thresholds. As such, the model suggests that demand and productivity jointly determine entry and survival across markets.

Measures of Productivity and Demand

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

$$TFPQ_i = \frac{q_i}{x_i} = \frac{\omega_i x_i}{x_i} = \omega_i \tag{III.3}$$

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

$$TFPR_i = \frac{p_i q_i}{x_i} = p_i \omega_i = \frac{1}{2}\frac{\gamma_m \alpha_m}{\eta_m N_m + \gamma_m}\omega_i + \frac{1}{2}\frac{\eta_m N_m}{\eta_m N_m + \gamma_m}(\bar{p}_m - \bar{\delta}_m)\omega_i + \frac{1}{2}\delta_{im} + \frac{1}{2} r_c \tau_{cm} \tag{III.4}$$

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

Discussion

Our model, though simple, provides us with a number of key implications about the relationship between exogenous parameters and the equilibrium cutoff profitability level. These in turn provide us with a sense of how entry and exit patterns will vary across products and countries. The first result pertains to the relationship between iceberg trade costs and the equilibrium cutoff ϕ_m^*. We find that a decrease in iceberg trade costs, say through trade liberalization or improvements in shipping technology, unambiguously increases the equilibrium profitability cutoff, $\frac{\partial \phi_m^*}{\partial \tau_{cm}} < 0$. This implies that as trade costs fall relatively unprofitable firms - firms with low productivity or demand - will struggle to survive in equilibrium. Similarly, it is straightforward to show that in industries where individual varieties are stronger substitutes for each other will also be characterized by higher equilibrium cutoff values, $\frac{\partial \phi_m^*}{\partial \gamma_m} < 0$. Again, this result is hardly surprising. If consumers are less able to substitute away from a given product, producers with less appealing products or higher costs are implicitly protected from being driven out of business by high-demand and/or low-cost competitors. Intuitively we expect that industries which produce more homogeneous products will typically be characterized by a lower value of γ_m and, as such, have higher equilibrium profitability cutoffs, ceteris paribus.[8]

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

[8]These results are very small extensions of those already shown in the literature. The first is an extension of that already shown in Melitz and Ottaviano (2008) extended to a model with idiosyncratic demand and productivity shocks. As such, we relegate further discussion and the proofs to the Supplemental Appendix. The second is the same result presented in Foster, Haltiwanger and Syverson (2008) extended to a multi-country setting. Due to the separability of markets in our model, the proof is essentially identical to that in Foster, Haltiwanger and Syverson (2008). We refer the interested reader to their 2005 NBER working paper for details.

with trade costs and the size of trading economies.

Data and Measurement

Our objective is to characterize the nature of firm-level selection across countries using firm and product level data from China. To accomplish this goal we match two key sources of information. First, we use data on the universe of Chinese firms that participated in international trade over the 2002-2005 period. These data have been collected by the Chinese Customs Office and report the f.o.b.value of firm exports in U.S. dollars across destination countries and products in the Chinese eight-digit Harmonized System. The data set also provides information about the quantities traded.[9] The level of detail in the customs data is an important feature in the construction of export prices and quantities because they are not contaminated by aggregation across firms or markets. Further, we will exploit this key feature in order to capture a measure of firm-product-level efficiency which will not reflect movements in export prices (as with revenue productivity) or the aggregation of different prices across markets or time.

The customs data is carefully matched with annual firm-level data from the Chinese manufacturing sector. Specifically, we use annual firm-level data for the period 2000-2007 on all industrial firms that are identified as being either state-owned, or are non-state-owned firms with sales above 5 million RMB. These data come from annual surveys conducted by the National Bureau of Statistics (NBS). In aggregate, the data cover an unbalanced panel of manufacturing firms that increases in size from 162,883 firms in 2000

[9] 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.

to 336,768 firms in 2007.[10] The firm-level data include detailed information on firm-level revenues, export sales, intermediate materials, employment, wages, capital stock, ownership and industry classification.

The Matching Process

Matching the firm-level data with the corresponding customs data is a key step in our empirical exercise. Both sets of data contain firm-identifiers which allow us to track firms over time in either data set. Unfortunately, different firm-identifiers are used in each data set which prevents us from using this natural metric to match firms to export products.

Instead, we rely on reported plant-specific location and communication information contained in both data sets. Specifically, both data sets provide detailed information on the location of the plant of origin (a disaggregated area code) and the plant's primary telephone number. Our matching algorithm searches for plants in both data sets which consistently report the same area code and phone numbers over time. Any export product and firm which are associated with consistent location and telephone number information are included in our matched sample. Nonetheless, for many firms/export records we are not able to find any suitable match. In total we are able match 21,621 firms across data sets. This accounts for approximately one quarter of all Chinese exporters in the customs data.

The relatively small number of matches occur for a number of plausible reasons. First, a number of our records report the same phone numbers (the same last 4 digits) in the same area code, but are associated with different firm-level identifiers. This affects roughly 3.5 and 7 percent of observations in the firm-level and customs data, respectively.

[10]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 very similar sample are single-plant firms.

We eliminate all of the records associated with these firm identifiers before matching the remaining data. Second, our firm-level data only captures relatively large firms. Because of this we often cannot match small exporters in the customs data with any record in the firm-level data. Third, we cannot match many firms which report more than one plant or more than one phone number. Nonetheless, we are confident that our matched sample is strongly comparable to the sample of Chinese manufacturing exporters from the firm-level 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 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.[11] Likewise, Table 1 reports the percentage of exports for 10 specific manufacturing products on which we focus our later analysis in both the (full) firm-level data set and our matched sample. In each case, the mean percentage of sales from exports are relatively close.

Rules for Inclusion in the Sample

Our data is very rich, but we need to make a number of restrictions on the set of firms we include in our final sample. First, we choose to focus on specific products. Although this greatly reduces our sample size, it has a number of important benefits. In particular, we are able to exploit our highly disaggregated information on exports without

[11] We note that the right tail of the export revenue distribution is slightly thicker in the matched sample possibly capturing that larger, more established firms are more likely to present consistent location and telephone number information over time.

having to worry about aggregation bias across multiple products within the same industry. We choose to focus on ten distinct products. The first five products are chosen because they are arguably relatively homogeneous products: plywood, inorganic salt, iron alloys, dyestuff and silk fabric. This choice is made specifically to avoid large quality variation in producers' physical outputs and allows us to highlight the quantity-versus-revenue distinction that is otherwise confounded in the literature. The second set of products are purposefully chosen to represent industries where different varieties are likely to represent very different levels of quality. By including these industries we can then compare how our results change when we examine a set of highly differentiated industries and consider the role that differentiation may play in determining demand and productivity measurement across firms.[12]

Second, we impose a product specialization criterion: a firm must obtain at least 50% of its export revenue from sales of our export of interest. The purpose of this restriction is to reduce measurement problems in calculating physical TFP. As is common in most firm-level data sets, factor inputs are reported at the firm-level rather than by product. By focusing on highly specialized exporters we minimize the degree of measurement error in productivity arising from differences in product scope across firms. Table 1.1 presents the number of observations for each product in each year.

Variable Construction

In this section we briefly summarize the construction of key variables. Full details are provided in the Appendix. We first calculate the average export price for each product

[12]We check that the products we describe as undifferentiated and differentiated satisfy Rauch (1999) classification of undifferentiated or differentiated products. An additional advantage of choosing ten specific products is that it is straightforward to verify whether there has been any trade disputes associated with these Chinese exports. While a number of our products have been subject to trade disputes in recent years, none of our products are subject to WTO action during our sample period.

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, $k_{i,t+1} = (1-d)k_{it} + i_{it}$ where d is the depreciation rate.[13]

We calculate the materials share as the average share of intermediate inputs in total revenues. The labor share is calculated analogously with the exception that we follow Hsieh and Klenow (2008) to adjust the reported wage bill to account for unreported employee compensation. Similarly, in the absence of reliable capital share information we follow Hsieh and Klenow (2008) and assume constant returns to scale so that $\alpha_k = 1 - \alpha_l - \alpha_m$. We have alternatively tried estimating the input shares, and productivity, using control function methods (Olley and Pakes, 1996). We find very similar measures of input shares and productivity. Moreover, our later results are all unaffected by this change.

Last, we need to apportion inputs in a fashion to account for multi-product firms. We do this as in Foster, Haltiwanger and Syverson (2008). For each firm we first calculate the percentage of total revenues from the primary export in each year, ϱ_{it}. Then for any input variable (capital, intermediate materials, labor) we calculate the total amount of each

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

input x_{it} allocated to the production of the primary export as $x_{it} = \varrho_{it}\tilde{x}_{it}$ where $\tilde{x}_{it}$ is the total amount of input used in firm i in year t.[14]

Measuring Productivity

Our primary measure of total factor productivity is

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

where q_{it} is the physical units of output of firm i's primary export in year t across destinations. Similarly, k, l and m represent the firm-product measures of capital, labor and materials, respectively, and α_k, α_l and α_m capture each input's share parameter.

Numerous papers studying the selection of firms into export markets have relied exclusively on revenue based measures of productivity. For purposes of comparability we also compute a measure of revenue based productivity as

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

where p_{it} is the firm's (deflated) export price.

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 logged 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

[14] De Loecker et al. (2012) estimate the input share across product for multi-product firms. They find that input allocations across products are highly correlated with allocating inputs according to product revenue shares. We cannot follow their procedure since we do not have product-level information for domestic sales. However, since our sample is composed of firms which are specialized in the production of one product this effect should be very small.

each variable will have a similar, but not necessarily identical, impact on firm behaviour.

Measuring Demand

We seek to separate the influence of demand and productivity on firm-level entry behaviour and study the impact of both on firm sorting across markets and export growth. We first consider a measure of market based demand consistent with our simple model. For robustness, we also use a simple empirical model to develop an alternative measure of demand shocks consistent with an iso-elastic demand curve.

Measure 1: Linear Demand

Our model suggests that total demand in market m for firm i's product in period t is $q_{imt} = C_{mt} + \frac{L_m}{\gamma_m}\delta_{imt} - \frac{L_m}{\gamma_m}p_{imt}$ where C_{mt} is a collection of market and time specific constants. Rearranging terms we write

$$v_{imt} \equiv p_{imt} + \frac{\gamma_m q_{imt}}{L_m} = \frac{\gamma_m C_{mt}}{L_m} + \delta_{imt}x$$

If we knew the true values of γ_m and L_m then we can calculate v_{imt}. An OLS regression of v_{imt} on a set of market-specific time dummies, Λ_{mt}, and a set of firm-market specific dummies, $\bar{u}_{im}$

$$v_{imt} = \Lambda_{mt} + \bar{u}^L_{im} + \tilde{u}^L_{imt} \tag{III.5}$$

reveals the firm-market-year specific component of the demand shock, $\tilde{u}^L_{imt}$. Using the residuals from the above regression, $\hat{\tilde{u}}^L_{imt}$, we can construct a measure of firm-specific demand, $u^L_{imt} = \hat{\bar{u}}_{im} + \hat{\tilde{u}}_{imt}$.

To operationalize our strategy we make three mild assumptions. First, we assume that we can proxy market size, L_m, by real GDP for each country in the initial year of our sample, $L_m = \beta_L \ln(GDP_m)$.[15] Second, we will need to assume that γ_m is constant across markets $\gamma_m \equiv \gamma$ (though we will allow it to vary across products). Last, we need a measure of τ_m. We will likewise assume that transport costs are proportional to log distance,[16] $\tau_m = \beta_\tau \ln(DISTANCE_m)$. The coefficients β_L and β_τ are additional parameters we will need to estimate.

The ratio of sales by firm i to any two markets m and m' can then be written

$$\frac{q_{imt}}{q_{im't}} = \frac{L_m}{L_{m'}} \left(\frac{p_{imt} - \frac{r\tau_m}{\omega_{it}}}{p_{im't} - \frac{r\tau_{m'}}{\omega_{it}}} \right) = \frac{\ln(GDP_m)}{\ln(GDP_{m'})} \left(\frac{p_{imt} - \frac{\beta_\tau \ln(DISTANCE_m)}{\omega_{it}}}{p_{im't} - \frac{\beta_\tau \ln(DISTANCE_{m'})}{\omega_{it}}} \right)$$

Rearranging terms we can identify a value for β_τ for any firm that exports to at least two locations

$$\beta_\tau^{im,m'} = \frac{\omega_{it}(q_{imt} \times \ln(GDP_{m'}) \times p_{im't} - q_{im't} \times \ln(GDP_m) \times p_{imt})}{q_{imt} \times \ln(GDP_{m'}) \times \ln(DISTANCE_{m'}) - q_{im't} \times \ln(GDP_m) \times \ln(DISTANCE_m)}$$

We estimate β_τ for each product as the simple mean from the data $\hat{\beta_\tau} = \frac{1}{\tilde{N}_\tau} \sum_i \sum_t \sum_{m \neq m'} \beta_\tau^{im,m'}$ where $\tilde{N}_\tau$ is the number of distinguishable within-firm country pairs in the data and r_c has been normalized to 1.

Using equations (III.1)-(III.2) we then write

$$\gamma = \frac{L_m}{q_{imt}} \left(p_{imt} - \frac{r\tau_m}{\omega_{imt}} \right) \Rightarrow \frac{\gamma}{\beta_L} = \frac{\ln(GDP_m)}{q_{imt}} \left(p_{imt} - \frac{\beta_\tau \ln(DISTANCE_m)}{\omega_{imt}} \right)$$

We pin down the ratio of γ to β_L as

$$\widehat{\left(\frac{\gamma}{\beta_L}\right)} = \frac{1}{\bar{N}} \sum_i \sum_c \sum_t \frac{\ln(GDP_m)}{q_{imt}} \left(p_{imt} - \frac{\hat{\beta}_\tau \ln(DISTANCE_m)}{\omega_{imt}} \right)$$

where $\bar{N}$ is the total number of observations in the industry over all years and destinations.

[15]The variable GDP_m is measured as real GDP (constant prices). The data is sourced from the Penn World Tables.

[16]The distance variable is calculated as the air distance between Beijing and each destination country's capital city. The distance data are obtained from CEPII, available at www.cepii.fr.

Given our estimate of the ratio $\widehat{\frac{\gamma}{\beta_L}}$ we can compute the LHS of (III.5) for each observation as

$$\hat{v}_{imt} = p_{imt} + \widehat{\left(\frac{\gamma}{\beta_L}\right)} \frac{q_{imt}}{\ln(GDP_m)}$$

We repeat this exercise separately for each product and construct a measure of $\hat{v}_{imt}$, and thus demand, for each observation in our data.

Measure 2: Iso-elastic Demand

Although the above method corresponds to our model, it requires a number of strong assumptions on L_m, γ and τ_m. Below we discuss an alternative measure of market-specific demand. Although it is not strictly consistent with our model, the second demand measure is consistent with an iso-elastic demand function, a common feature of many modern trade models. Our demand estimation methodology here follows those in Foster, Haltiwanger and Syverson (2008) and Eslava, Haltiwanger, Kugler and Kugler (2009), but allows for features that are unique to our setting. Specifically, we begin by considering the following simple regression of firm-level demand

$$\ln q_{imt} = \alpha_0 + \alpha_1 \ln p_{imt} + \Lambda_{jmt} + \lambda_{ijm} + \nu_{imt}$$

where i, j, m and t index firms, product groups, destination markets and time, respectively. The vectors Λ_{jmt} and λ_{ijm} collect product-market-year specific variables and firm-product-market variables which affect export demand, respectively, while ν_{imt} is an error term.

We begin by taking first differences to eliminate the time-invariant component of demand.

$$\Delta \ln q_{imt} = \alpha_1 \Delta \ln p_{imt} + \Delta\Lambda_{jmt} + \Delta\nu_{imt} \tag{III.6}$$

We allow for each market in each year to receive a demand shock unique to their market. As discussed in Manova and Zhang (2012) export prices often reflect destination market differences in size, income, distance and isolation. The product-market-year fixed effects control for both time-invariant and time-varying fixed effects in each product market.[17]

Finally, we expect that if there is a positive demand shock (a large ν_{imt}) this is likely to be reflected in higher prices, p, and sales, q. To account for possible endogeneity bias we estimate equation (III.6) by IV. As argued in Foster, Haltiwanger and Syverson (2008), Eslava, Haltiwanger, Kugler and Kugler (2009) and Gervais (2012) a natural instrument for output prices in this context is our measure of firm-level physical productivity. As we demonstrate below, our measure of physical productivity is strongly, negatively correlated with prices even though it was not constructed using any output price information. Moreover, our measure of physical productivity should capture shocks to firm-costs and are arguably uncorrelated with market-specific demand shocks. We proceed by using changes in the log physical productivity to instrument for changes in log prices.

Estimating equation (III.6) by IV we find that the estimate of α_1 is -3.1. If we were to interpret these as the elasticities in a CES demand framework, we would compute firm-level markups in our data to be in the range of 45 to 48 percent. These results are broadly in line with those found in other countries, markets and estimation methods.[18] We then construct the iso-elastic measure of export demand, u^I_{imt}, as the estimated difference between observed sales and the price effect, $\ln u^I_{ijmt} = \ln q_{ijmt} - \hat{\alpha}_1 \ln p_{ijmt}$.

Sample Properties

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

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

Sample Correlations

Table 1.3 collects correlations and standard deviations for each of the core variables of our study. Specifically, we document summary statistics for our two measures of firm exports (log physical units sold and log revenue), our two measures of productivity ($TFPQ$ and $TFPR$), our two measures of product-market-time specific demand shocks (u^L and u^I), 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 results.

The first point we wish to make is that the measures of exports (physical units shipped and export revenue), productivity ($TFPQ$ and $TFPR$), and demand (linear and iso-elastic) are, in general, highly correlated. The correlation between physical and revenue sales reflects the wide dispersion in firm-level heterogeneity within industries as evidenced by the large standard deviations for each of these measures. Second, we also observe that our two measures of total factor productivity are also positively correlated with each other, but this correlation is relatively weak (approximately 0.2). This is hardly surprising; heterogeneous exporters vary substantially in their location, duration and size of export sales. The positive, but weak, correlation between physical and revenue based productivity suggests that quantitative results based on revenue-based measures of productivity have the potential to be misleading. Third, it is encouraging that our two measures of demand (linear and iso-elastic) are highly correlated. Either measure of demand suggests a much larger degree of dispersion in demand relative to firm-level productivity.

Firm-level prices are negatively correlated with physical productivity, suggesting that more productive Chinese exporters tend to charge lower prices in export markets. Despite wide price dispersion across producers, the negative covariance between prices and physical productivity causes the dispersion of revenue productivity to be smaller than that of physical productivity. Perhaps surprisingly, prices are also strongly negatively correlated with our measures of demand, though this correlation is substantially weaker than the correlation with physical productivity or physical exports. As we explore below, we find that this result is largely due to exceptionally high turnover in export markets.[19]

Export Sales, Entry and Frequency

We observe large firm-level differences in both measures of demand and productivity. What is less obvious from our preceding decomposition, however, is the extent to which these are related to export performance. We begin by studying the impact of demand and productivity on key export outcomes: export sales, export frequency and the number of active export markets.

To keep our exercise simple, and easy to read in 2-dimensional space, we make a number of simplifying transformations of the data. First, we normalize firm-specific physical productivity by subtracting the product-specific average productivity from each variable and dividing the difference by standard deviation of product-specific physical productivity. We repeat this normalization exercise for demand, except, in this second case, the normalization is firm-and-market specific since we observe a demand shock for each market a firm enters. To develop a measure of firm-specific, rather than firm-market specific demand, we take the simple average over all markets the firm entered in each year. The idea is to roughly measure whether a firm generally finds itself in the upper or lower part of the demand distribution across markets. We then renormalize our measure of firm-specific demand so that both normalized demand and productivity have a mean of zero and a standard deviation of

[19] A similar table examining *first-differences* in key variables can be found in the Supplemental Appendix.

one. Last, we use a flexible specification (fractional polynomials) to regress the resulting distributions of firm-specific productivity and demand against the log of each firm's total export sales in the same year.

Figure 2 plots the estimated relationship between productivity or demand and total firm-level export sales. We find that export sales are strongly increasing in both productivity and demand. Under the admittedly strong assumption that the demand shocks in each market are independent of each other, our normalization will equalize the standard deviation of both productivity and demand. The slope of each line (productivity or demand) is suggestive of each component's individual relationship with export sales. We observe that the slope of the demand curve is steeper than the productivity curve almost everywhere.

Figure 3 plots a similar relationship between productivity, demand and the frequency of exporting. Likewise, Figure 4 captures the relationship between productivity/demand and the number of active export markets. The dependent variable in this exercise is the number of distinct countries to which the firm exports in a given year. Export frequency and the number of export markets are both clearly positively associated with productivity and demand. Again, casual observation, though hardly conclusive, would suggest that a one standard deviation increase in demand may potentially have a substantially larger impact on entry or export frequency than a one standard deviation increase in productivity.

Turnover in International Markets

We document entry and exit rates across international markets in Table 1.4. Among Chinese firms which export to any market in any year nearly 53 percent did not export to that market in the previous year. Likewise, among firms exporting to a given market this year 40 percent will exit that market in the following year. These rates are extremely high relative to those commonly cited in domestic markets, even for China. For instance, we calculate that the average domestic market entry and exit rate among all manufacturing firms in China as 25 and 18 percent, respectively.[20]

Table 1.4 also presents mean entry and exit rates across broad regions worldwide. Entry and exit appear to be strongly correlated worldwide; markets with the highest entry rates also tend to display the highest exit rates. Regions with higher average incomes tend to display markedly less churning. This potentially indicates that export entry in smaller and less developed markets is of shorter duration.

Persistence

Above we observed extremely high rates of international turnover. Despite this, numerous papers demonstrate strong persistence in many of the determinants of firm-level behaviour. In particular, conditional on survival, productivity, demand and prices have been shown to be strongly persistent in both domestic and international markets.[21] We briefly re-examine these findings with three small, but important differences: i) we study the extent to which using physical TFP in place of revenue based TFP changes our estimates of productivity persistence, ii) we study differences in the evolution of export demand across broad regions worldwide and iii) we study differences in the persistence across productivity and demand.

Consider a determinant x_{imt} which is firm, market and year-specific (e.g. demand).

[20]These calculations are made using the firm-level data described in Section 3. They may be biased downwards since the firm-level data only covers relatively large firms. Note, however, that this same bias would be true of our matched sample.

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

A natural starting point for determining the persistence rates in this measure would be the OLS regression of a simple AR(1) model

$$x_{imt} = \rho x_{im,t-1} + \epsilon_{imt} \tag{III.7}$$

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

To account for this potential source of bias, we use a simple first stage selection correction to control for endogenous exit. We include last year's observed demand, productivity and market characteristics as explanatory and use the predicted probabilities 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 (III.7). Standard errors are obtained by bootstrapping firms over both steps of this procedure. We discuss the nature of firm selection at length in the next Section.[22] Instead, for now, we focus on the persistence parameters for demand, productivity, prices and revenues reported in Table 1.5. In each case, we observe that the determinants of trade are strongly persistent over time. Revenue TFP appears slightly more persistent than physical TFP. The annual autocorrelation coefficient on physical TFP is 0.89 while the estimated autocorrelation coefficient is nearly 1 for revenue TFP. This suggests that price responses to temporal productivity shocks mitigate changes in revenue-based productivity. Both measures of demand are strongly persistent though the linear demand measure is markedly more persistent across years than our mea-

[22]It is unclear how measure export demand across all markets since some firms export to more destinations than others. To simplify our problem we capture lagged aggregate export demand across all destinations as $\overline{u}^L_{i,t-1} = \sum_m \hat{u}^L_{im,t-1}$ and include this as a first stage regressor.

sure of iso-elastic demand. Given the observed persistence in productivity and demand, it is not surprising that revenue and prices also reflect a high degree of persistence over time with estimated autocorrelation coefficients above 0.91.

Dynamics in International Markets

This section investigates two salient features of firm behaviour in international markets. We first study the role of firm-level characteristics, namely productivity and demand, in determining firm selection across international markets. We document the importance of both firm-level characteristics and market-specific features. Second, we examine the firm-level differences across entering, exiting and incumbent exporters. In markets with a high degree turnover, the entry and exit behaviour of heterogeneous exporters plays an important role in determining the evolution of the distribution of productivity and demand. These, in turn, affect the growth of aggregate exports.

Selection Dynamics

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

$$E(D_{im,t+1} = 1|X_{imt}) = [1 + \exp\{-(\beta_0 + X_{imt}\beta + \Lambda_i + \Lambda_t)\}]^{-1}.$$

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

Table 2 presents the impact of each explanatory variable on firm exit decisions when we pool all of our data. The first five columns of the top panel study the individual effect of productivity, demand and prices on exit. Productivity, revenue or physical, is found to deter exit, although this effect is only statistically significant for revenue productivity. Higher demand is always found to discourage exit, while prices do not have any statistically significant effect when we study their individual impact. Columns 6 and 7 examine the joint impact of productivity and demand, while columns 8 and 9 add other key firm-level

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

determinants: age, log capital, and the log import price. In each case, we observe that productivity never has a statistically significant effect on exit, while higher demand is consistently estimated to strongly discourage exit at standard levels of statistical significance. Among the additional firm-level variables, only age is estimated to have a statistically significant impact; younger firms are more likely to exit export markets relative to older, established incumbent exporters. The last two rows of each column present the impact of market-specific measures on firm exit. Not surprisingly, we consistently find that Chinese exporters are less likely to exit large markets and markets which are closer in distance.

We check the robustness of our results by splitting our sample in a number of interesting dimensions. First, Table 2.1 examines the same regressions across different types of firms ownership (private, foreign, state), the type of trade (ordinary trade, processing trade) and product differentiation.[24] We find that our results hold broadly across different types of firms, the nature of trade and across product differentiation. In particular, productivity is never found to be a significant determinant of firm selection. Firm demand, in contrast, is almost always a highly significant determinant of export market selection.

Evolution of Key Distributions

As a first step in studying the role of firm selection in export markets on macro outcomes we document differences in key variables across entering, continuing, and exiting firms. We compute these differences by regressing each of the key firm level measures (productivity, demand, prices, revenue) on entry and exit dummies and a complete set of product-by-year-by-market fixed effects. Specifically, let x_{imt} be a firm-market specific

[24]It is natural to expect that export relationships may vary across ownership and products. For example, to export from China each firm must first acquire an export license. It is well-known that there have strong institutional preferences to allocate licenses differentially across Chinese manufacturing firms. It is widely reported that privately owned firms are far less likely to be given export licenses relative to state-owned firms.

variable (e.g. demand), let D^E_{imt} be an entry dummy variable and let D^X_{imt} be an exit dummy variable. At the annual level, the entry dummy for year t equals one if the firm enters market m between year $t-1$ and t. Likewise, the exit dummy equals one if the firm exits market m sometime between t and $t+1$. The product-year-market dummies capture the evolution of continuing (or incumbent) firms. The coefficient on the entry (or exit) dummy measures the average log point difference between the determinant of interest among entering (or exiting) firms and incumbent producers in export markets. Our regression is written as

$$x_{imt} = \gamma_0 + \gamma_E D^E_{imt} + \gamma_X D^X_{imt} + \Lambda_{jmt} + \mu_{imt}$$

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

The first two rows of Table 3 present the coefficients on the entry and exit variables in our regressions. Whether or not we conclude that new exporters are more productive than incumbent exporters in the same market depends heavily on our measurement of productivity. Our estimates imply that new exporters are 3 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 3 percent less productive than incumbent exporters. Among exiting firms we find that productivity is 3.4 percent higher than that of incumbent exporters. The puzzling positive coefficient on the physical TFP of exiting firms can largely be attributed to capacity constraints among growing firms. In particular, once we condition on existing capital stock (or capital-intensity) we find no significant productivity difference between exiting and incumbent exporters.[25]

[25] We omit the results using capital-intensity since they are very similar.

The differences between the physical and revenue based productivity coefficients among entering firms can largely be explained by pricing behavior. New entrants generally choose high prices; the annual results in Table 3 imply that new entrants are charging prices which are 12 percent higher than incumbent firms. This aspect of firm behaviour can be rationalized by the fact that new exporters are likely to be high cost (low productivity) producers relative to incumbent exporters.

Regardless of how we measure productivity, these differences are much smaller than the observed differences in demand. Rather, we find that entering firms have demand shocks which are 55 to 66 percent smaller than incumbent firms. Our coefficients further imply that the demand among exiting firms is estimated to be 18 to 39 percent smaller annually. Taken together with the estimated coefficients on the entry dummy, we observe that the high turnover of firms in international markets likely reflects a recycling of firms with low demand shocks in export markets. Tables 3.1 and 3.2 document the results across product differentiation, high-and-low productivity firms, and firm-type (private firms engaged in ordinary trade, private firms engaged in processing trade, foreign-owned firms and state-owned firms). We observe that the same qualitative patterns arise in almost every case.[26]

Sources of Aggregate Export Growth

It is widely reported that Chinese exports have grown dramatically over the past two decades. Even in our short sample, this pattern is striking; in many export markets we observe that aggregate exports are 4 or 5 times larger in 2005 than they were in 2002. Little is known, however, regarding the differential contributions of demand and productivity to Chinese export growth. We first decompose annual changes of real export sales into changes

[26] The sole exception is the coefficients on entrant productivity for foreign-owned firms.

in aggregate physical productivity and aggregate demand. Then, we further decompose each individual aggregate component (productivity and demand) to determine the extent to which each of these (growth in demand and growth in productivity) can be attributed to within-firm growth or reallocation across firms.

We calculate the weighted average firm-level exports in each product market as $Q^L_{mt} = \sum_i \theta_{imt} q_{imt}$ where q_{imt} is the quantity of firm i's exports to market m in year t and $\theta_{imt} = \frac{q_{imt}}{\sum_i q_{imt}}$ is firm i's market share of exports to market m in year t. Our model implies that the quantity sold by firm i in market m can be written as

$$q_{imt} = \frac{L_m}{2\gamma_m}\left(\tilde{C}^L_{mt} + \delta_{imt} - r\tau_m\tilde{\omega}_{it}\right)$$

where we maintain the assumption that $\gamma_m = \gamma$, collect market-product-year specific effects which are constant across firms in a given year as $\tilde{C}^L_{mt}$, and to simplify notation we write productivity effects as $\tilde{\omega}_{it} = \frac{1}{\omega_{it}}$.[27] We have model-consistent measures of δ_{imt}, $\tilde{\omega}_{imt}$ and $r\tau_m$ from our preceding work. Inserting the individual demand function into the aggregate export growth equation gives us

$$\Delta Q^L_{mt} = \frac{L_m}{2\gamma_m}\left(\Delta D^L_{imt} - \hat{\beta}_\tau \ln(DISTANCE_m)\Delta\Omega^L_{it} + \Delta\tilde{C}^L_{mt}\right)$$

where $D^L_{imt} = \sum_i \theta_{imt}\delta_{imt}$, $\Omega^L_{imt} = \sum_i \theta_{imt}\tilde{\omega}_{it}$ and $\Delta Q^L_{mt} = Q^L_{mt} - Q^L_{m,t-1}$. The first quantities of interest for the decomposition exercise correspond to the percentage of aggregate export growth ΔQ^L_{mt} which can be attributed to aggregate demand growth ΔD^L_{imt} and cost

[27]The market-product-year specific effects which are constant across firms in a given year are $\tilde{C}^L_{mt} = \frac{\gamma}{\eta_m N_{mt}+\gamma}\alpha_m - \frac{\eta_m N_{mt}}{\eta_m N_{mt}+\gamma}\bar{\delta}_{mt} + \frac{\eta_m N_{mt}}{\eta_m N_{mt}+\gamma}\bar{p}_{mt}$.

reductions/productivity growth, $\Delta\Omega^L_{imt}$, respectively. That is, we want to compute

$$\begin{aligned} \text{Demand Contribution} &= \frac{\Delta D^L_{imt}}{\Delta\tilde{Q}^L_{imt}} \\ \text{Productivity Contribution} &= -\hat{\beta}_\tau \ln(DISTANCE_m)\frac{\Delta\Omega^L_{imt}}{\Delta\tilde{Q}^L_{imt}} \end{aligned}$$

where $\tilde{Q}^L_{imt} = 2Q^L_{imt}\left(\widehat{\frac{\gamma}{\beta_L \ln(GDP)}}\right)$. These ratios capture the fraction of aggregate export growth which is attributable to demand or productivity growth in each market.

Because our level decomposition exercise uses the level of exports, productivity and demand, it may be highly influenced by outlier observations. Specifically, given that we examine over 200 distinct markets, some of which are very small, large demand outliers may play an inordinately large role in the magnitude of our findings. To control for this effect we drop the top and bottom 5 percent of all of the linear demand observations in each market. We then take a simple average of the contributions over the nearly 200 export markets and report our results in the top panel of Table 4.

We find three striking results. First, Chinese exports were growing extremely quickly over our sample period. The annual average export growth across all markets was almost 55 percent per year. Second, year-to-year productivity changes contribute almost nothing to these short-run aggregate export flows. Although the evolution of productivity, and its interaction with trade, has received notable attention in recent literature, we caution that it would be surprising to find a large contribution from productivity changes in our context. Specifically, given the short time period we study and the relatively long time it takes to develop, install and implement technological improvements it would surprising if the productivity contribution were large.[28] Third, changes in firm-level demand explain 18 percent of the aggregate export growth (the remaining export growth is attributed to

[28]For example, it is common to assume that it takes a year to install new capital equipment in firm-level data. We are not likely to observe many large changes in firm-level technology over our four-year sample.

market-product-year fixed effects). Across all markets, the component of demand which applies equally to all firms in a given product market is increasing in most export markets. Remarkably, the same pattern emerges in almost all markets, and across firm and product types.[29]

Iso-Elastic Demand: An Alternative Decomposition

Our decomposition exercise can be criticized on at least three dimensions. First, we examine changes in the level of exports, while a more standard exercise would examine the changes in log exports. As reported in Section 3, our measures of log demand demonstrate substantially more variability than our measures of log productivity. Transforming these variables into levels exacerbates this difference. Second, using levels, as argued above, results in our decomposition exercise being very sensitive to outlier observations. While we can remove observations where we observe large changes, we also potentially discard the most informative firms. Third, we only use our linear demand measure of firm-specific demand. While our previous results suggest that either measure gives us similar qualitative findings, they often indicate non-trivial quantitative differences.

To check the robustness of our results we also use a second model for decomposition. Consider an iso-elastic demand function common to Melitz (2003)-type models augmented for demand shocks: $q_{imt} = \frac{R_{mt}}{P_{mt}} \left(\frac{P_{mt}}{p_{imt}}\right)^{-\sigma} e^{u^I_{imt}}$ where the variables R_{mt} and P_{mt} are revenue and price aggregates which reflect market size and competitiveness. The firm-specific variables p_{imt} and u^I_{imt} represent the firm's price and demand shock. The optimal pricing rule in this context allows us to write prices as a function of shipping costs, factor costs and firm-specific productivity: $p_{imt} = \frac{\sigma}{\sigma-1}\frac{r_c \tau_{cm}}{\omega_{imt}}$. Substituting the pricing rule into the

[29] A potential concern is that we have dropped the firms with the largest productivity improvements, thus overstating the contribution from demand growth. However, as shown in Supplemental Appendix, if anything, including outlier firms suggest even larger average contributions from idiosyncratic demand.

demand function and taking logs we can derive the following demand function

$$\ln q_{imt} = \tilde{C}^I_{mt} - \sigma \ln \omega_{imt} + u^I_{imt}$$

where $\tilde{C}^I_{jmt}$ captures market-product-year specific effects. Our iso-elastic demand estimates from Section 3 implies that an estimate of σ for our sample would be $\hat{\sigma} = 3.14$.

Define average log exports for each product market as $\tilde{Q}^I_{mt} = \sum_i \theta_{imt} \ln q_{imt}$ where θ_{imt} is defined as before, $\theta_{imt} = \frac{q_{imt}}{\sum_i q_{imt}}$. The change in log aggregate exports is then $\Delta\tilde{Q}^I_{mt} = \Delta\tilde{C}^I_{mt} - \hat{\sigma}\Delta\Omega^I_{mt} + \Delta D^I_{mt}$ where $\Omega^I_{mt} = \sum_i \theta_{imt} \ln \omega_{imt}$, $D^I_{mt} = \sum \theta_{imt} u^I_{imt}$ and $\Delta\tilde{Q}^I_{mt} = \tilde{Q}^I_{mt} - \tilde{Q}^I_{m,t-1}$. Analogous productivity and demand contributions can then be written as

$$\begin{aligned} \text{Productivity Contribution} &= \frac{\hat{\sigma}\Delta\Omega^I_{mt}}{\Delta\tilde{Q}^I_{mt}} \\ \text{Demand Contribution} &= \frac{\Delta D^I_{mt}}{\Delta\tilde{Q}^I_{mt}} \end{aligned}$$

Our alternative decomposition addresses three concerns. First, we measure demand and productivity in logs, rather than levels, shrinking the measured of large measured swings in level demand. Second, we include all of the data in this exercise. Third, this exercise allows us to present results from using the iso-elastic demand shock developed in Section 3. We repeat this exercise separately for each product and market and report the results in the bottom panel of Table 4.

We find that the contribution from demand is even larger than that reported in the top panel of Table 4, while the contribution from productivity growth grows substantially. Across all markets and products, our results suggest that exports grew by over 37 percent per year. Demand accounted for nearly 45 percent of total growth, while productivity accounted for 4.8 percent. Broadly, this finding is again robust across various geographic regions, firm-type, and product differentiation. The bottom panel of Table 4 does, however, reflect the fact that productivity growth did show a noticeably stronger contribution in most regions of the world in our second decomposition, with the exception of Asia. Nonetheless, even among regions where productivity growth explained the largest percentage of export growth, the explanatory power of demand growth was always nearly double that of productivity, if not more. Our results strongly suggest that understanding how firms succeed in acquiring and growing demand in foreign markets is essential not only for determining firm-level decisions across markets, but also how aggregate trade evolves over time.

Within Firm Demand Growth vs. Net Entry

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

$$\begin{aligned}\Delta \tilde{D}_{mt} &= \sum_{i \in C} \theta_{im,t-1} \Delta \tilde{\delta}_{imt} + \sum_{i \in C} (\tilde{\delta}_{im,t-1} - \tilde{D}_{m,t-1}) \Delta \theta_{imt} + \sum_{i \in C} \Delta \tilde{\delta}_{imt} \Delta \theta_{imt} \\ &\quad + \sum_{i \in E} \theta_{imt} (\tilde{\delta}_{imt} - \tilde{D}_{mt}) - \sum_{i \in X} \theta_{im,t-1} (\tilde{\delta}_{im,t-1} - \tilde{D}_{m,t-1})\end{aligned}$$

where $\tilde{D}_{mt}$ is our measure of aggregate demand is market m and year t, C is the set of continuing firms, X is the set of exiting firms and E is the set of entering firms in year t.[30] For our demand measure, $\tilde{\delta}_{imt}$, we consider both our measure of log linear demand, $\tilde{\delta}_{imt} = \ln u^L_{imt}$, and our measure of iso-elastic demand, $\tilde{\delta}_{imt} = \ln u^I_{imt}$.

The first term in this decomposition captures a within firm component based on

[30] To be clear, we define an entering firm as a firm which did not export in market m in year $t-1$ but exports to market m in year t. An exiting firm is a firm which exported to market m in year $t-1$, but did not export to market m in year t. Our decomposition closely follows the straightforward decomposition for "aggregate productivity" proposed by Foster, Haltiwanger and Krizan (2001).

firm-level changes, weighted by the initial shares in the export product market. The second term represents a between-firm component. It reflects changing shares weighted by the deviation of initial firm demand from the initial product-market index. The third term is a covariance-type term and captures the correlation between changes in demand and shares. The final two terms captures the effect of entry and exit, respectively.[31]

The first row of Table 4.1 reports the results for our decomposition of average export demand. We find, not surprisingly, that export demand grew rapidly over the 2002-2005 period; the first column of Table 4.1 indicates that average firm-level demand grew by 29 log points annually. Our decomposition indicates that net entry and within-firm demand growth are key contributors to total demand growth across export markets. Net entry alone accounts for 53-63 percent of export demand across markets. It would be mistaken, 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. The large contribution of net entry to demand growth comes from the exit of low demand firms. Thus, it is the very high rates of churning in international markets that give rise these large changes in the composition of exporters each year and, thus, growth in average export demand. Similarly, among surviving exporters firm-level demand grows very strongly within firms. Just as demand was a strong predictor of export survival, we also observe that among those that survive, we expect large gains to existing demand shocks. In fact, our results suggest that within-firm growth in

[31]For purposes of comparison we also provide an analogous decomposition of average log productivity. We decompose productivity as follows

$$\begin{aligned} -\Delta\tilde{\Omega}_{mt} \quad = \quad & -\Bigg(\sum_{i\in C}\theta_{im,t-1}\Delta\tilde{\omega}_{imt} + \sum_{i\in C}(\tilde{\omega}_{im,t-1} - \tilde{\Omega}_{m,t-1})\Delta\theta_{imt} + \sum_{i\in C}\Delta\tilde{\omega}_{imt}\Delta\theta_{imt} \\ & + \sum_{i\in E}\theta_{imt}(\tilde{\omega}_{imt} - \tilde{\Omega}_{mt}) - \sum_{i\in X}\theta_{im,t-1}(\tilde{\omega}_{im,t-1} - \tilde{\Omega}_{m,t-1})\Bigg) \end{aligned}$$

demand is nearly as important as net entry.

For comparison, we also provide analogous results for average productivity of Chinese exporters. We find very little growth by comparison. Annual physical and revenue based productivity growth rates among exporting firms are only 1 or 2 percent, respectively. However, a similar decomposition pattern presents itself. Within-firm growth and net entry appear to be key sources of annual productivity growth, even if the changes are relatively small.[32]

Conclusion

This paper studies the nature of firm selection across markets worldwide and the evolution of firm-level productivity and demand in international markets. While both idiosyncratic productivity and demand are strongly associated with key export outcomes, annual market selection is largely determined by firm-specific demand rather than productivity. Entering and exiting firms are also found to be substantially different than incumbent exporters. New exporters tend to be less productive, to have lower demand, and to charge higher prices relative to incumbent exporters. Exiting firms, in contrast, tend to be less productive, to have lower demand, and to charge lower prices on average. While important differences are found on each of these dimensions, it is the differences in measured demand that are by far the largest. Our estimates suggest that the measured demand of new exporters is 55 to 66 percent smaller than that of the average incumbent exporter to the same market.

These findings also have important policy implications, particularly for developing countries. We find that growth in firm-level demand is the primary firm-level determinant

[32]The Supplemental Appendix presents a similar decomposition across regions of the world, types of firms and product differentiation. In each case, we find qualitatively similar results.

of year-to-year export growth, rather than productivity. Our decompositions imply that firm-specific idiosyncratic demand growth explains at least 18 total export growth, while productivity growth, in contrast, explains at most 5 percent. Further, the net entry of firms into export markets explains 53-63 percent of export demand growth.

BIBLIOGRAPHY

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

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

[3] 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.

[4] 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.

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

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

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

[8] 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.

[9] 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.

[10] 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.

[11] 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.

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

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

[14] De Loecker, Jan and Frederic Warzynski. 2012. "Markups and Firm-Level Export Status," *American Economic Review*, forthcoming.

[15] De Loecker, Jan, Pinelopi K. Goldberg, Amit K. Khandelwal and Nina Pavcnik. 2012. "Prices, Markups and Trade Reform." *NBER Working Paper,* w17925.

[16] Demidova, Svetlana, Hiau Looi Kee and Kala Krishna. 2011. "Do Trade Policy Differences Induce Sorting? Theory and Evidence From Bangladeshi Apparel Exporters." *NBER Working Paper,* 12725.

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

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

[19] 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.

[20] 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.

[21] 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.

[22] Gervais, Antoine. 2012. "Product Quality and Firm Heterogeneity in International Trade." University of Notre Dame, *Working Paper*.

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

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

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

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

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

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

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

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

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

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

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

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

[35] Rho, Youngwoo and Joel Rodrigue. 2012. "Firm-Level Investment and Export Dynamics." mimeo, Vanderbilt University.

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

[37] Roberts, Mark J., Yi Xu, Xiaoyan Fan, Shengxing Zhang. 2012. "A Structural Model of Demand, Cost, and Export Market Selection for Chinese Footwear Producers." *NBER Working Paper,* 17725.

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

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

Appendix

Variable Construction

Prices, Quantities and Revenues

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

Variable Inputs

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

Capital Stock

We don't directly observe the firm's capital stock. Instead, denote the book value of capital for firm i in year t as b_{it}. Nominal new investment, ni_{it}, is calculated in each year as

$$ni_{it} = b_{i,t+1} - b_{it}.$$

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

$$k_{i,t+1} = (1-d)k_{it} + i_{it}$$

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

Input Shares

We assume that output of each product is produced by a Cobb-Douglas production function. To calculate productivity we will need to calculate input shares for labor, materials and capital, α_l, α_m and α_k, respectively, for each product. Let $\tilde{w}_{it}$ denote firm i's total nominal wage payments and compensation in year t. Typically, we would calculate the labor share as total employee compensation divided by total revenue. Hsieh and Klenow (2008) suggest that the wage bill, $\tilde{w}_{it}$, 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

$$tw = \sum_i \sum_t \tilde{\varrho}\tilde{w}_{it} = \tilde{\varrho} \sum_i \sum_t \tilde{w}_{it} = \tilde{\varrho}\widetilde{tw}$$

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, not just the industries we are going to focus on. Denote total revenues tr and total intermediate materials tm. Hsieh and Klenow (2008) suggest that the ratio of total wage payments to value added is roughly 50% from the Chinese national accounts and input-output tables. This implies that

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

Note that the procedure here is completed using all firms in each (4-digit) 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

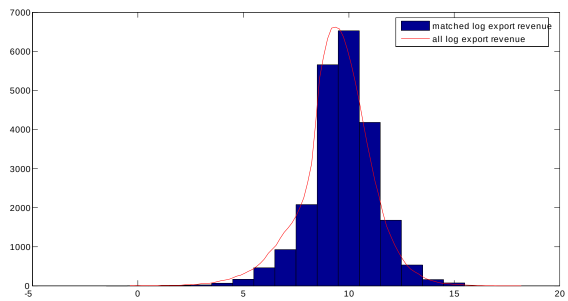
$$\alpha_l = \frac{1}{\tilde{N}} \sum_t \sum_i \frac{\tilde{\varrho}\tilde{w}_{it}}{\tilde{r}_{it}}$$

where $\tilde{r}_{it}$ 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,

$$\alpha_m = \frac{1}{\tilde{N}} \sum_t \sum_i \frac{\tilde{m}_{it}}{\tilde{r}_{it}}$$

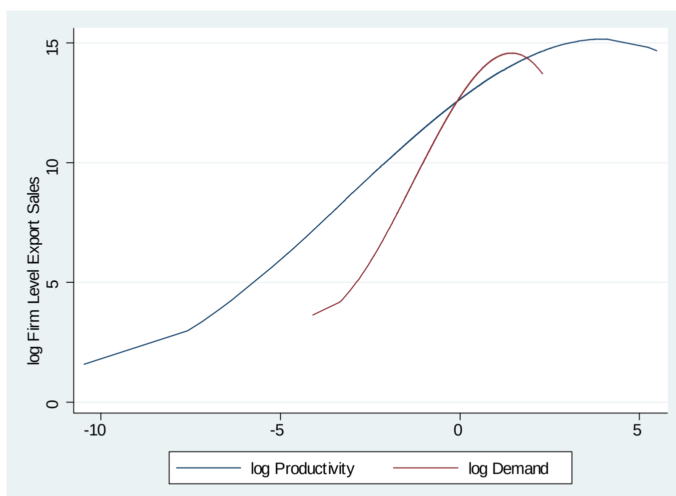
where $\tilde{m}_{it}$ is the total value of materials used by firm i in year t. Finally, in the absence of reliable capital share information we follow Hsieh and Klenow (2008) and assume constant returns to scale so that $\alpha_k = 1 - \alpha_l - \alpha_m$. We have alternatively tried estimating the input shares, and productivity, using control function methods (Olley and Pakes, 1996). We find very similar measures of input shares and productivity. Moreover, our later results are all unaffected by this change. Results are available upon request.

Figure 1: Export Revenue Distribution in the Full and Matched Samples



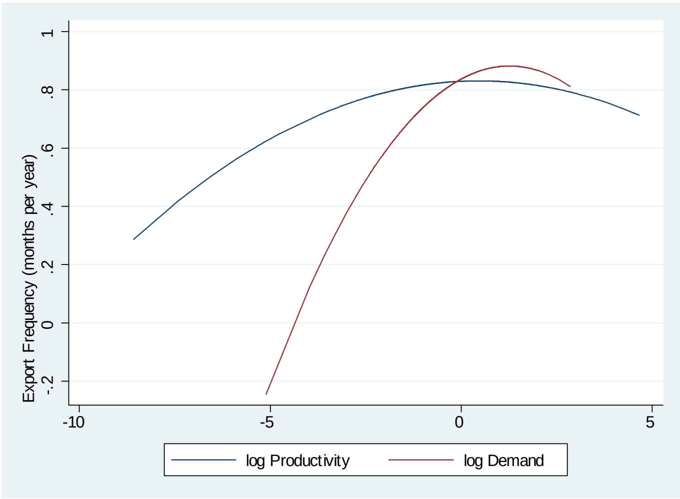
Notes: The blue histogram captures the log export revenue distribution in the matched sample. The red distribution presents the same information from the full firm-level sample.

Figure 2: Productivity, Demand and Export Sales



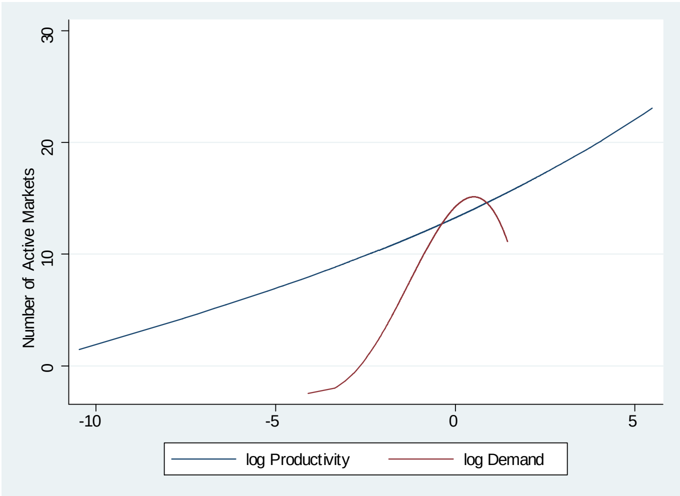
Notes: The blue line captures the fitted relationship between log export sales and productivity while the red line captures the fitted relationship between log export sales and average firm-level linear demand as defined in the text. In each case we a flexible functional form to capture the relationship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

Figure 3: Productivity, Demand and Export Frequency



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

Figure 4: Productivity, Demand and Export Market Entry



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

Table 1: Average Percentage of Revenues From Exports

Undifferentiated Product	Matched Sample	Full Full Sample	Differentiated Product	Matched Sample	Full Sample
Inorganic Salt	26.8	26.2	Wood Furniture	61.5	74.6
Ferroalloys	22.7	40.9	Wearing Apparel	62.4	71.3
Plywood	39.4	35.9	Seafood	55.2	49.3
Dyestuffs	31.7	36.2	Kitchen Equipment	68.9	72.4
Silk Fabric	35.3	41.5	Metal Fittings	45.9	67.8

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

Table 1.1: Characteristics of the sample

	Number of Observations			
Product	2002	2003	2004	2005
Undifferentiated Products				
(Inorganic) Salt	162	293	275	305
Ferroalloys	64	124	210	135
Plywood	54	110	216	288
Dyestuffs	192	236	433	337
Silk Fabric	336	540	337	411
Differeniated Products				
Wood Furniture	524	750	1,231	1,305
Wearing Apparel	1,450	2,063	2,077	2,546
Seafood	206	259	333	366
Kitchen Equipment	955	981	1,247	1,176
Metal Fittings (for Construction)	313	475	612	590

Notes: This table reports the number of observations in each product category and year.

Table 1.2: Demand Estimation

Price Coefficient α_1	IV	OLS
Estimate	-3.140	-0.560
Standard Error	*0.141*	*0.031*

Notes: The above results correspond to estimated isoelatic demand curves described in Section 3. We estimate an iso-elastic demand curve by IV and OLS. All regressions include product-market-year fixed effects. Standard errors, clustered by firm, are in italics.

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

	Correlations							
Variables	Physical Exports	Revenue Exports	Physical Prod.	Revenue Prod.	Model Demand	Red.-Form Demand	Price	Capital
Physical Exports	1.000							
Revenue Exports	0.867	1.000						
Physical Prod.	0.259	-0.050	1.000					
Revenue Prod.	0.004	0.065	0.194	1.000				
Linear Demand	0.643	0.503	0.261	0.002	1.000			
Iso-Elastic Demand	0.173	0.127	0.096	-0.000	0.752	1.000		
Price	-0.470	0.032	-0.608	0.108	-0.331	-0.233	1.000	
Capital	0.135	0.196	-0.218	-0.222	0.133	0.027	0.069	1.000
	Standard Deviations							
Standard Deviations	2.15	1.90	0.81	0.27	2.15	2.237	1.07	1.57

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

Table 1.4: Turnover in International Markets

	Full Sample	North America	Europe	Japan	Australia	South America	Rest of Asia	Africa	Undiff. Prods	Diff. Prods
Entry	0.530	0.398	0.502	0.307	0.402	0.543	0.492	0.596	0.565	0.508
Exit	0.397	0.317	0.320	0.276	0.321	0.493	0.404	0.462	0.431	0.376

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 1.5: Persistence in Productivity and Demand

	Revenue TFP	Physical TFP	Linear Demand	Iso-Elastic Demand	Price	Revenue
Persistence, ρ	1.000	0.894	0.954	0.649	0.919	0.957
	0.007	*0.008*	*0.011*	*0.011*	*0.039*	*0.013*

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

Table 2: Determinants of Selection: Full Sample

Revenue TFP	-0.162								
	0.053								
Physical TFP		-0.021				0.033	-0.008	0.022	-0.026
		0.030				*0.040*	*0.038*	*0.057*	*0.055*
Linear Demand			-0.348			-0.351		-0.345	
			0.011			*0.012*		*0.015*	
Iso-Elastic Demand				-0.052			-0.080		-0.080
				0.004			*0.005*		*0.007*
Price					0.037				
					0.020				
Age								0.450	0.370
								0.052	*0.049*
Capital								0.098	0.008
								0.061	*0.059*
Import Price								0.016	0.019
								0.016	*0.016*
Distance	-0.022	-0.022	0.163	0.177	0.198	0.163	0.187	0.183	0.223
	0.025	*0.025*	*0.033*	*0.026*	*0.031*	*0.033*	*0.032*	*0.044*	*0.042*
Income	-0.125	-0.125	-0.227	-0.220	-0.288	-0.229	-0.263	-0.238	-0.290
	0.011	*0.011*	*0.015*	*0.012*	*0.014*	*0.015*	*0.015*	*0.020*	*0.020*

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) and time dummies. Standard errors are reported in italics.

Table 2.1: Determinants of Selection by Firm-Type

Sample	Private, Ordinary Trade		Private, Processing Trade		Foreign Firms		State-Owned Firms	
Physical TFP	0.019	-0.039	0.059	0.134	-0.125	-0.152	0.139	0.127
	0.057	*0.055*	*0.108*	*0.109*	*0.089*	*0.090*	*0.080*	*0.077*
Linear Demand	-0.328		-0.423		-0.416		-0.343	
	0.017		*0.032*		*0.033*		*0.022*	
Iso-Elastic Demand		-0.070		-0.116		-0.112		-0.082
		0.007		*0.015*		*0.015*		*0.010*
Distance	0.146	0.150	0.241	0.220	0.102	0.162	0.159	0.220
	0.045	*0.044*	*0.085*	*0.081*	*0.085*	*0.082*	*0.071*	*0.068*
Income	-0.244	-0.269	-0.232	-0.270	-0.221	-0.222	-0.259	-0.324
	0.021	*0.021*	*0.038*	*0.037*	*0.037*	*0.036*	*0.034*	*0.032*

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) and time dummies. Standard errors are reported in italics.

Table 2.2: Determinants of Selection: Product Differentiation

	Diff.		Undiff.	
Physical TFP	0.066	-0.006	0.039	-0.027
	0.044	*0.057*	*0.042*	*0.055*
Linear Demand	-0.348	-0.340		
	0.013	*0.015*		
Iso-Elastic Demand			-0.079	-0.081
			0.005	*0.007*
Import Price		0.035		0.036
		0.018		*0.018*
Distance	0.165	0.196	0.186	0.226
	0.038	*0.047*	*0.026*	*0.045*
Income	-0.227	-0.232	-0.263	-0.283
	0.017	*0.021*	*0.016*	*0.020*

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) and time dummies. Standard errors are reported in italics.

Table 3: Evolution of Productivity and Demand

	Dependent Variable											
	Revenue TFP		Physical TFP		Linear Demand		Iso-Elastic Demand		Price		Revenue	
Entry	0.023	0.005	-0.030	-0.080	-0.793	-0.707	-1.085	-1.171	0.121	0.144	-0.682	-0.574
	0.003	*0.003*	*0.015*	*0.015*	*0.029*	*0.029*	*0.029*	*0.076*	*0.018*	*0.018*	*0.023*	*0.023*
Exit	0.003	-0.006	0.034	0.009	-0.488	-0.441	-0.199	-0.412	-0.020	-0.008	-0.505	-0.445
	0.003	*0.003*	*0.015*	*0.015*	*0.029*	*0.029*	*0.024*	*0.076*	*0.018*	*0.018*	*0.023*	*0.023*
Capital		-0.039		-0.112		0.186		0.009		0.056		0.241
		0.001		*0.004*		*0.008*		*0.022*		*0.005*		*0.007*

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 at the firm-level and are reported in italics.

Table 3.1: Evolution of Productivity and Demand

	Dependent Variable					
	Revenue TFP	Physical TFP	Linear Demand	Iso-Elastic Demand	Price	Revenue
	Private Firms, Ordinary Trade					
Entry	0.012	-0.051	-0.729	-1.153	0.133	-0.616
	0.003	*0.020*	*0.037*	*0.097*	*0.023*	*0.030*
Exit	0.010	0.060	-0.399	-0.378	-0.020	-0.427
	0.003	*0.020*	*0.037*	*0.097*	*0.023*	*0.030*
	Private Firms, Processing Trade					
Entry	-0.002	-0.051	-0.581	-0.828	0.093	-0.497
	0.007	*0.036*	*0.059*	*0.155*	*0.037*	*0.051*
Exit	-0.008	0.037	-0.469	-0.372	-0.040	-0.502
	0.007	*0.036*	*0.059*	*0.155*	*0.037*	*0.051*
	Foreign Owned Firms					
Entry	0.036	0.104	-0.630	-0.562	-0.027	-0.674
	0.006	*0.030*	*0.057*	*0.145*	*0.034*	*0.049*
Exit	-0.017	0.031	-0.431	-0.313	-0.041	-0.472
	0.006	*0.030*	*0.057*	*0.145*	*0.034*	*0.049*
	State Owned Firms					
Entry	0.021	-0.005	-0.384	-0.611	0.070	-0.322
	0.005	*0.023*	*0.052*	*0.127*	*0.029*	*0.044*
Exit	0.025	0.016	-0.159	-0.094	-0.019	-0.173
	0.005	*0.023*	*0.052*	*0.127*	*0.029*	*0.044*

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 at the firm-level and are reported in italics.

Table 3.2: Evolution of Prices

	Sample					
	Differentiated Firms	Undifferentiated Firms	High Productivity Firms	Low Productivity Firms	High Demand Firms	Low Demand Firms
Entry	0.135	0.091	0.237	-0.046	-0.042	0.060
	0.020	*0.035*	*0.023*	*0.020*	*0.023*	*0.011*
Exit	-0.002	-0.084	0.198	-0.045	-0.128	-0.106
	0.020	*0.035*	*0.023*	*0.020*	*0.023*	*0.011*

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 at the firm-level and are reported in italics. High productivity firms are defined, product-by-product, as firms with a productivity level above the median product-level productivity. Low productivity firms are defined analogously. Likewise, high demand firms are defined, product-market-by-product-market, as firms a with linear demand shock above the median in each product-market.

Table 4: Decomposition of Aggregate Export Growth

Linear Demand Model (Trimmed Sample)				
		Percentage Explained By		
	Mean Annual Export Growth (%)	Physical Productivity Growth	Export Demand Growth	Market-Product-Year Shocks
All Prods/Countries	54.99	-0.114	18.00	82.11
North America	60.38	0.018	60.38	39.60
Europe	33.43	0.000	15.87	84.13
Japan	62.09	0.000	23.72	76.28
Australia	81.43	0.002	65.66	34.34
South America	109.15	0.000	21.34	78.66
Rest of Asia	45.47	-0.281	13.29	86.99
Africa	44.47	0.000	15.72	84.28
Private, Ord. Trade	46.78	-0.215	3.84	96.38
Private, Proc. Trade	31.66	0.031	9.90	90.07
Foreign Firms	37.19	0.000	18.58	81.42
State-Owned Firms	69.44	0.000	13.84	86.16
Undiff. Products	43.75	-0.343	11.79	88.55
Diff. Products	55.34	0.000	15.60	84.40

Iso-Elastic Demand Model				
		Percentage Explained By		
	Mean Annual Export Growth (%)	Physical Productivity Growth	Export Demand Growth	Market-Product-Year Shocks
All Prods/Countries	37.44	4.78	44.95	50.27
North America	125.94	10.92	24.02	65.06
Europe	5.62	24.01	52.46	23.53
Japan	74.47	9.47	78.09	12.44
Australia	163.61	14.98	37.57	47.45
South America	55.46	19.72	91.27	-10.99
Rest of Asia	40.88	-26.69	11.94	114.75
Africa	69.25	53.40	103.52	-56.92
Private, Ord. Trade	54.08	6.09	78.57	15.34
Private, Proc. Trade	8.29	5.72	50.11	44.17
Foreign Firms	13.03	16.33	55.15	28.52
State-Owned Firms	74.91	10.41	17.17	72.42
Undiff. Products	41.78	-9.92	59.93	49.99
Diff. Products	36.31	14.83	37.04	48.13

Notes: The top panel decomposes product level aggregate exports into its productivity and demand components. Because our first stage decomposition is based on the model, we present results using our linear demand measurement. The bottom panel decomposes product level aggregate log exports into its productivity and demand components. Because our second decomposition is based on the iso-elastic demand curve, we present results using our iso-elastic measure of demand. In both panel, average export growth is the weighted average year-to-year export growth where firm sales are used weights.

Table 4.1: Decomposition of Demand and Productivity Growth

Determinant	Total Growth	Within	Between	Cross	Entry	Exit	Net Entry
		Components of Decomposition					
Log Linear Demand	0.2872	0.0971	-0.3441	0.3831	-0.1130	0.2641	0.1512
Log Iso-Elastic Demand	0.8308	0.5254	-0.7901	0.5698	-0.1548	0.6804	0.5256
Log Physical Productivity	0.0099	0.0053	-0.0042	0.0021	-0.0005	0.0072	0.0067
Log Revenue Productivity	0.0183	0.0092	-0.0001	-0.0007	0.0009	0.0089	0.0099

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