

Demand Volatility and Export Entry

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Abstract

Demand from some export destinations are more predictable than others. Do these differences in the volatility of demand influence international trade patterns? Specifically, should export entry depend on destinations' demand volatility? To answer the question, I develop a simple model of trade with heterogeneous firms facing stochastic demand. This model predicts lower levels of export entry for destinations with high demand volatility, as changes to marginal costs with demand shocks decrease exporters' expected profits. The model's predictions are supported by tests on firm-level data covering the universe of Chinese export transactions from 2000 to 2006. The results imply non-trivial impacts of volatility on import-dependent developing economies.

JEL classification: F12, F14

1 Introduction

Volatility has been shown to consistently discourage investment (e.g. Pindyck, 1982; Guiso and Parigi, 1999; Leahy and Whited, 1996). This paper examines whether exporters, like investors in other contexts, respond to volatility, given the large differences in the pattern of demand shocks observed across export destinations. The up-front cost of establishing trading relationships overseas represent a nontrivial investment for exporting firms.

To explain the effects of demand volatility on exporters' entry decisions, I develop a model of trade with stochastic demand from product-market destinations with inherently differing levels of volatility. Export entry in the model, which follows in the Melitz (2003) tradition of firms with heterogeneous productivities, is observed for only product-market destinations that meet a firm's *expected* zero-profit condition. The zero profit condition is expected because it is based on evaluations of product markets before entry. A related precedent is the model in Allen (2014) where producers first obtain information about multiple markets before

choosing to sell in a few. Similarly, this paper describes firms that first obtain information on the size and volatility of product-market destinations, before choosing to export. In this framework firms form their expectations of profit using the pattern of historical demand, and demand shocks from each product-market destination. The model predicts that as demand volatility and its associated costs increase, fewer firms are productive enough to find entry profitable.¹

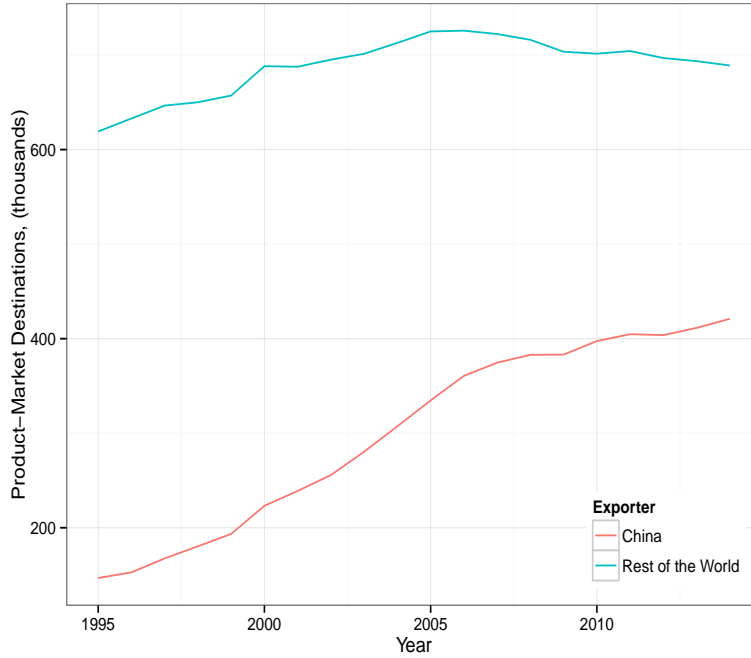
Figure 1 motivates the paper’s empirics. From 2001 when China joined the WTO to 2006, Chinese exporters expanded into more than 114,000 new product-market destinations, from a start of about 226,000 product-market destinations in 2000. The firm-level data used for the paper covers this period of export expansion into new products and markets, shedding light on how Chinese exporters chose product-market destinations out of the 738,000 possible options in that period. Product-market destinations, the unit of observation in the paper, represent imports into unique product-country combinations, e.g. the US imports of bicycles. The size and volatility of these product-market destinations are derived from UN COMTRADE data, while export entry came from firm-level data covering the universe of Chinese export transactions from 2000 to 2006.

The paper’s findings are consistent with the model’s predictions. Historical demand volatility affects exporters’ entry patterns - one is more likely to observe zero Chinese entry into product-market destinations with high demand volatility. These findings complement the work in earlier notable papers that explain the zeros in international trade (e.g. Baldwin and Harrigan, 2011; Helpman et al., 2008). Furthermore, conditional on entry by at least one Chinese exporter, fewer exporters enter destinations with high demand volatility. The baseline estimates suggest that increasing demand volatility by one (1) standard deviation above the mean leads to 8% fewer exporters in the average export destination (28% in the Poisson specification). The entry-volatility relationship is stronger for sectors which require greater production scale adjustments for output changes. In addition to the foregoing, I find that the minimum threshold for proxies of firm-level productivity increases with demand volatility. This finding is also consistent with the zero-profit condition derived from the model.

Two things are particularly novel in this paper: First, the unit of observation is not a

¹ In considering market-driven demand shocks, this paper follows a long tradition of scholarship (e.g. Fitzgerald et al., 2016; Blum et al., 2013; Foster et al., 2008; Rob and Vettas, 2003; Staiger and Wolak, 1992; Viner, 1922). I leave the discussion of why volatility varies by market for another paper - it is sufficient for this paper that several others provide evidence that shocks to producers or exporters do not explain all variations in the market. The pattern observed of producers avoiding volatile markets in this paper is consistent with other papers on farmers in India (Allen and Atkin, 2016) and large US firms (Heiland, 2016).

Figure 1: Entry Into Export Destinations



Data Source: UN COMTRADE

market, defined as a country or a product. It is the unique combinations of products and countries. Selecting product-markets as the unit of observation reflects the reality that most firms are product specialists. The typical firm does not target - say Ireland as a country, but the Irish market for imported bicycles could be the target for a bicycle maker. By focusing on the decisions of firms to enter specific product-country combinations, I provide an approach for explaining firm level trade choices that country-level measures like GDP, exchange rates and geographic distance do not capture. The GDP of the US may not be relevant to a Chinese exporter of bicycles, if bicycle imports are not well-predicted by GDP. To such a bicycle exporter, information on the historical demand pattern for bicycles in the US is more valuable.²

Second, this paper works from the presumption that product market destinations have intrinsically different levels of demand volatility. These differences in volatility are *not* due to productivity differences or production shocks. The difference become clear in comparing the demand for necessities like breakfast cereal with the demand for optional items like tuna. Within narrow product categories, it is expected that volatility varies by importing country,

²Most exporters focus on five (5) HS6 product categories or fewer. 20% of exporters focus on only one.

so that the volatility of breakfast cereal imports into the U.K. is not equal to that for Morocco. The premise of this paper is that firms can, for the products they specialize in, observe the historical volatility in foreign markets, and use that information to estimate expected future profits. The firms will export to only product-market destinations with positive *expected* profits. This approach complements, but differs from the body of work that predicts lower export entry with supply-side or productivity shocks (e.g. Ramondo and Rappoport, 2010; Impullitti et al., 2013; Ramondo et al., 2013). The approach is motivated by recent findings that market specific shocks could explain as much of the variation in international trade as firm-specific shocks (Kramarz et al., 2016; di Giovanni and Levchenko, 2012).

The paper makes two other contributions. It adds to the growing literature on drivers of exporter behavior. If the initial costs of setting up overseas trading networks are framed as investments made in the expectation of future returns, this paper relates investment under uncertainty to the context of international trade. This builds on recent related papers that show policy uncertainty reduces exports, when trade costs are driven by policy (Handley and Limão, 2013; Handley and Limao, 2012). The papers on policy uncertainty show exporters are more likely to make the investments required to enter foreign destinations with stable tariff regimes. This work is also consistent with recent papers that also show uncertainty about demand conditions reduce export sales and the likelihood of exporting or FDI at the firm-level (e.g. De Sousa et al., 2016; Fillat and Garetto, 2015; Ramondo et al., 2013). Earlier work by Dixit (1989) shows that with uncertain prices, firms require prices above a certain threshold to invest in expansion. Similarly, other papers show that exchange rate uncertainty reduces investment (e.g. Das et al., 2007; Frankel and Rose, 2002; Glick and Rose, 2002).

The paper's second contribution is a simple and intuitive measure of volatility - the sum of squared deviations from historical demand trends. This measure provides results that improve on the most commonly used measure of volatility, i.e. the standard deviation of growth. For this paper, the trend used to derive the volatility measure is linear, though the definition is flexible enough to admit other trend specifications. Related papers define volatility as the standard deviation of year-on-year growth rates, but how does one measure the growth rate from a starting value of zero? The index of volatility introduced by this paper avoids such issues of measurement.

The rest of the paper is organized as follows: Section 2 presents a stylized model in the tradition of Melitz (2003) and Chaney (2008) to motivate the empirics. Section 3 follows, with the data, formal definitions for key variables, empirical specifications and results. Section 4 discusses the implications and Section 5 concludes.

2 Model

This section develops the zero-profit condition for export entry, in a framework with known stochastic demand from product-market destinations. The setup begins with firms observing their own productivity within a product category, then collecting information about potential product-market destinations. The firms use the information about the size and volatility of destinations to estimate the expected profits over a short time horizon from each product-market destination. Volatility plays into the firms expected costs and profits because firms anticipate the higher costs of layoffs or production surges associated with demand shocks. The modeling framework ends at the point where export entry is only observed for firms with positive expected profits.

In other words, before export entry, the risk-neutral firms in this model form unbiased expectations of demand and profits for each year in a forward-looking planning horizon, given the trajectory of past demand for each product-market destination. Demand learning is not necessary in this model, because its focus is on factors that exporters consider before entry, not after. As this model is based on what exporters *expect*, not realizations of demand over time, it will not include a fully developed general equilibrium. (The paper solves no general equilibrium optimization). The zero-profit condition from the model is enough to achieve the paper’s goals of studying how historical demand volatility drives export entry.³

The demand process built into the model below rests on the following assumptions: [1] Volatility is an intrinsic feature of markets, resulting from variations in consumer tastes, habits and interactions with aggregate product and country events. Firms understand this, and understand that product market destinations have varying levels of demand volatility. (Equation 1 captures the assumption). [2] Firms obtain information about markets and form expectations of export profits before entry into foreign destinations. The expected profits are estimated for a short future planning horizon. (For clarity and ease, I use a linear sum and abstract away from the discount rate). [3] The expected profits reflect firm-level productivity, as well as marginal costs. *Marginal costs are convex*. The underlying idea is that each firm has an ideal level of demand that matches a prospective production scale. Deviations from that ideal production scale could lead to overtime wage premiums for labor or downtime costs for capital assets and other inputs. The changes to marginal costs with production

³ For a discussion on demand learning, see, for example, Piveteau (2015), Timoshenko (2015), Akhmetova and Mitaritonna (2012) and Nguyen (2011). Papers that discuss demand uncertainty post-entry and exports include Albornoz et al. (2012), where the conditional distribution of possible demand outcomes is taken as unknown, unlike this paper, where exporters simply use historical demand to forecast future demand.

scale are embedded in a cost adjustment factor a_{ijk} . (Equations (4) and (5) capture the idea of changing expected profits with marginal costs, and marginal costs with a quadratic form). [4] Firms enter only product-market destinations that offer positive expected profits. The number of firms in each product category is taken to be exogenous and the distribution of productivities for firms making varieties within each category follows the Pareto distribution. Prices are another proxy for firm-level productivity and do not change in the short run.

In sum, this section describes a partial equilibrium that focuses on the zero-profit condition.

2.1 Demand Volatility

Aggregate demand is stochastic in this model. Equations (1) and (2) present a simple description of the demand growth trajectory for product-market destination jk - imports of product j into country k . Using information on past aggregate demand Q_{jkt} , exporters form expectations of growth \hat{g}_{jk} and growth shocks ν_{jkt} for each product-market destination. (The growth trajectory can be over a multi-year planning horizon that goes from period 1 to H). In this stochastic demand framework, growth \hat{g}_{jk} , growth shocks ν_{jkt} and the historical baseline \bar{Q}_{jk0} completely describe demand Q_{jkt} in any year t , past or future:

$$Q_{jkt} = \bar{Q}_{jkt}(1 + \nu_{jkt}) \tag{1}$$

\bar{Q}_{jkt} , period t 's expected aggregate demand is estimated from the trajectory;

$$\bar{Q}_{jkt} = \bar{Q}_{jk0}(1 + \hat{g}_{jk})^t \tag{2}$$

The equations represent firms' characterizations of the first and second moments of demand Q_{jk} in each product-market destination, using historical demand. This characterization comes before, and is the basis for the export entry decision.

Demand volatility is the variance σ_{jk}^2 of growth shocks ν_{jkt} . The economic case for a relationship between export entry and demand volatility is simply that, producers expect marginal costs to change as they modify production levels in response to demand shocks. Fitzgerald et al. (2016) among others, show that the effects of demand shocks are non-trivial. A car-maker considering a foreign product-market destination with projected demand of 1.5 million units in one year and 1 million units in the following year for example, must plan for changes to the level of capital and labor assigned to customize products for that market. The costs of those changes will reduce the expected profits for product-market destination, so that an otherwise identical destination with 1.25 million demand in both years is preferable.

The expected demand for cars and estimates of demand volatility can be obtained reasonably from historical demand - its level, trend and past demand shocks.

In sum, for firms with a known productivity or product appeal, the expected costs of adjusting production capacity in response to demand shocks play into the decision to serve foreign product-market destinations.

2.2 Export Entry in a Modified Melitz Model

With CES demand preferences, exporter i producing its unique variety of product j for market k can expect sales of q_{ijkt} in period t :

$$q_{ijkt} = \frac{p_{ijk}^{-\varepsilon}}{P_{jk}^{1-\varepsilon}} Q_{jkt} \quad (3)$$

p_{ijk} is the price firm i expects to set, P_{jk} is the Dixit-Stiglitz aggregate price index and ε is the elasticity of substitution between varieties of j . The steps that follow assume no exporter is large enough to affect the P_{jk} index. As specified in equation (1), firms understand that Q_{jkt} , the aggregate demand for product-market destination jk , is stochastic. Firms, as in Melitz (2003) have different productivity draws.

Firms must decide on a production scale \bar{Q}_{ijkt} before entry. If firms anticipate higher marginal costs when production slumps, or when demand exceeds production capacity, as in Soderbery (2013), the optimal production scale will minimize the cost of adjusting production levels from the set scale to meet demand. With well-behaved cost functions, the optimal production scale equals the expected demand $\bar{Q}_{ijkt} = E(q_{ijkt})$. (The expectations operator is necessary because firms plan to produce and export for more than one year). Firms in the model use the observed values of Q_{jkt} to estimate the production scale \bar{Q}_{ijkt} , as well as the expected year-to-year adjustments $(q_{ijkt} - \bar{Q}_{ijkt})$.

This paper specifies a general form for marginal costs, $\hat{c}_{ijk}(1 + a_{ijkt})$. The form recognizes that adjusting production scale in response to demand shocks can be costly, where \hat{c} is the hypothetical marginal cost at the expected production scale \bar{Q}_{ijkt} - with no adjustment a required. The non-negative adjustment cost factor, a_{ijkt} will reflect the aforementioned demand-driven changes to labor costs, capital and other costs of serving customers.

The paper will define a as a function of scale-adjusted demand shocks $(q_{ijkt} - \bar{Q}_{ijkt})/\bar{Q}_{ijkt}$ anticipated for product-market destination jk . (The definition recognizes differences in production scales across firms and product-market destinations). Soderbery (2013) specifies marginal costs as $c_i + r$, with r being the adjustment associated with production scale

changes. Blum et al. (2013) and Ahn and McQuoid (2012) also make similar proposals for measuring how per-unit costs change as firms update production capacity. The idea extends beyond variable production costs - one expects demand shocks to affect shipping costs, the costs of activating and deactivating physical production capital and other costs tied to production volume. It helps to define export profits before specifying a form for the adjustment cost factor, a .

Formally, the expected profits for a producer i in product-market destination jk :

$$E(\Pi_{ijk}) = E\{p_{ijk} * q_{ijkt} - \hat{c}_{ijk}(1 + a_{ijkt})q_{ijkt}\} - S_{jk} \quad (4)$$

p_{ijk} = expected price

q_{ijk} = expected quantities demanded

$\hat{c}_{ijk} = \tau_{jk}/\phi_{ij}$ = baseline marginal costs

S_{jk} = fixed and sunk costs of production and exporting

\hat{c}_{ijk} , the baseline marginal cost captures τ_{jk} , the combined per-unit costs of inputs like labor and materials, which are specific to product j , and trade factors like shipping and tariffs for product-market destination k . \hat{c}_{ijk} also accounts for the firm's productivity ϕ_{ij} . Firms with higher productivity ϕ have lower marginal costs and higher profits per unit sold. The sunk costs of entry and fixed costs are rolled into one term, S_{jk} , (as the fixed costs are summed over the firm's planning horizon). For parsimony, the model ignores temporal discounting and simply sums profits across periods; a reasonable approximation for short planning horizons and small discount rates.

The marginal cost adjustment factor a is assumed to follow the convex quadratic form proposed in Cooper and Haltiwanger (2006). This keeps the model tractable, while ensuring that costs are always non-negative. More general forms are considered in Section A.2.1.

$$a_{ijkt} = \gamma_j [(q_{ijkt} - \bar{Q}_{ijkt})/\bar{Q}_{ijkt}]^2 \quad (5)$$

The γ_j term is a product-specific scaling parameter to enable comparisons in the cross-section of product-market destinations. γ_j is necessary because changing output capacity by 20% from one year to the next implies different profit outcomes for, say an auto manufacturer compared to a maker of tee-shirts.⁴

⁴The quadratic form in equation (5) makes the model tractable, even if its assumed symmetry for costs around \bar{Q} only crudely approximates the data.

From equations (5), (1) and (3):

$$\begin{aligned}
a_{ijk} &= \gamma_j \left[\frac{\frac{p_{ijk}^{-\varepsilon}}{P_{jk}^{1-\varepsilon}} (Q_{jkt} - \bar{Q}_{jkt})}{\frac{p_{ijk}^{-\varepsilon}}{P_{jk}^{1-\varepsilon}} \bar{Q}_{jkt}} \right]^2 \\
&= \gamma_j (\nu_{jkt})^2
\end{aligned} \tag{6}$$

The expected profits over the planning horizon, (with risk-neutral exporters and known sunk costs S), from equation (4):

$$E(\Pi_{ijk}) = E\left\{ \left[p_{ijk} - \frac{\tau_{jk}}{\phi_{ij}} (1 + a_{ijk}) \right] q_{ijk} \right\} - S_{jk}$$

taking a_{ijk} from equation (6) and discarding t subscripts:

$$\begin{aligned}
E(\Pi_{ijk}) &= \left(p_{ijk} - \frac{\tau_{jk}}{\phi_{ij}} \right) E(q_{ijk}) - \frac{\tau_{jk}}{\phi_{ij}} \gamma_j E(q_{ijk} \nu_{jk}^2) - S_{jk} \\
&= \left(p_{ijk} - \frac{\tau_{jk}}{\phi_{ij}} \right) \bar{Q}_{ijk} - \frac{\tau_{jk}}{\phi_{ij}} \gamma_j \{ E[(q_{ijk} - \bar{Q}_{ijk})(\nu_{jk})^2] + \bar{Q}_{ijk} E[(\nu_{ijk})^2] \} - S_{jk} \\
&= \left(p_{ijk} - \frac{\tau_{jk}}{\phi_{ij}} \right) \bar{Q}_{ijk} - \frac{\tau_{jk}}{\phi_{ij}} \gamma_j \bar{Q}_{ijk} \left\{ E \left[\frac{(q_{ijk} - \bar{Q}_{ijk})}{\bar{Q}_{ijk}} (\nu_{jk})^2 \right] + E[(\nu_{ijk})^2] \right\} - S_{jk} \\
&= \left(p_{ijk} - \frac{\tau_{jk}}{\phi_{ij}} \right) \bar{Q}_{ijk} - \frac{\tau_{jk}}{\phi_{ij}} \gamma_j \bar{Q}_{ijk} [E(\nu_{jk}^3) + E(\nu_{ijk}^2)] - S_{jk}
\end{aligned}$$

The $E(\nu_{jk}^2)$ term is σ_{jk}^2 , as defined in the notes to equation (1). The $E(\nu_{jk}^3)$ term is taken as zero, as it is the third moment of the distribution of growth shocks. A plot of the the distribution of growth shocks, i.e., deviations from trend in the aggregate trade data, mimics a normal distribution - it is nearly symmetric, and centered on zero.⁵

$$E(\Pi_{ijk}) = \left[p_{ijk} - \frac{\tau_{jk}}{\phi_{ij}} (1 + \gamma_j \sigma_{jk}^2) \right] \bar{Q}_{ijk} - S_{jk} \tag{7}$$

The first term, in equation (7), the expected price, is needed for the zero profit condition. With rational risk-neutral firms that set production q^* at the profit-maximizing level:

$$\frac{dE(\Pi_{ijk})}{d\bar{Q}_{ijk}} = 0 \tag{8}$$

⁵Equation (7) can be derived for any real-valued function of growth innovation ν . For a normal distribution with mean zero, σ^2 , the second moment of ν can fully describe the terms of such a function i.e. higher order moments of ν . Growth shocks in the model represent deviations from the observed or projected trend. The same definition was used for the plot of the distribution of growth shocks observed in the data.

$$\begin{aligned}
0 &= p_{ijk} - \frac{\tau_{jk}(1 + \gamma_j \sigma_{jk}^2)}{\phi_{ij}} - q_{ijk} \left(\frac{1}{\varepsilon} \frac{p_{ijk}}{\bar{Q}_{ijk}} \right) \\
p_{ijk} &= \frac{\varepsilon}{\varepsilon - 1} \frac{\tau_{jk}(1 + \gamma_j \sigma_{jk}^2)}{\phi_{ij}}
\end{aligned} \tag{9}$$

In (9), the expected price for firm i in product-market destination jk follows the functional form in monopolistically competitive models of trade with heterogeneous firms, with one difference; unit costs include $(1 + \gamma_j \sigma_{jk}^2)$ to reflect expected production scale adjustments. Firms with high productivity ϕ_{jk} will have lower expected prices, assuming no quality differences. All firms will plan to set higher prices to cover the expected costs of production scale adjustments.

Export profits, from substituting (9) into equation (7).

$$\begin{aligned}
E(\Pi_{ijk}) &= \frac{1}{\varepsilon - 1} \frac{\tau_{jk}(1 + \gamma_j \sigma_{jk}^2)}{\phi_{ij}} \bar{Q}_{ijk} - S_{jk} \\
&= \frac{1}{\varepsilon - 1} \frac{\tau_{jk}(1 + \gamma_j \sigma_{jk}^2)}{\phi_{ij}} \left[\frac{\varepsilon}{\varepsilon - 1} \frac{\tau_{jk}(1 + \gamma_j \sigma_{jk}^2)}{\phi_{ij}} \right]^{-\varepsilon} \frac{\bar{Q}_{jk}}{P_{jk}^{1-\varepsilon}} - S_{jk} \\
E(\Pi_{ijk}) &= \frac{\bar{Q}_{jk}}{\varepsilon} \left[\frac{\varepsilon}{\varepsilon - 1} \frac{\tau_{jk}(1 + \gamma_j \sigma_{jk}^2)}{\phi_{ij}} \frac{1}{P_{jk}} \right]^{1-\varepsilon} - S_{jk}
\end{aligned} \tag{10}$$

The threshold productivity ϕ_{jk}^* for product-market destination jk , from applying the zero-profit entry condition to equation (10):

$$\phi_{jk}^* = \frac{\varepsilon}{\varepsilon - 1} \frac{\tau_{jk}(1 + \gamma_j \sigma_{jk}^2)}{P_{jk}} \left[\frac{\varepsilon S_{jk}}{\bar{Q}_{jk}} \right]^{\frac{1}{\varepsilon-1}} \tag{11}$$

Of the N_j firms producing j , only a fraction N_{jk} will export to product-market destination jk . That fraction could be as low as zero if none meets the ϕ_{jk}^* threshold. I model N_j as an exogenous variable:⁶

$$N_{jk} = N_j(1 - G(\phi_{jk}^*)) \tag{12}$$

⁶ In assuming an exogenous mass of exporters, I follow others e.g., (Chaney, 2008; Eaton et al., 2004). Here N_j is the number of firms making product j , e.g., the number of firms that make bicycles, regardless of export status or productivity. N_{jk} represents firms whose productivity exceeds the threshold for jk , given the assumed productivity distribution. Some producers of j will not export at all, if the lowest threshold ϕ^* of all possible product-market destinations is higher than firm productivity ϕ_{ij} .

$G(\cdot)$ is modeled as the Pareto distribution.⁷

$$N_{jk} = N_j[1 - (1 - (\phi_{jk}^*)^{-\theta_j})] = N_j(\phi_{jk}^*)^{-\theta_j} \quad (13)$$

θ_j is the Pareto shape parameter for product j .

The key mechanism in the model that delivers a negative relationship between export entry and demand volatility is that expected profits are lower in product-market destinations with high values of σ_{jk}^2 , even if firms plan to set higher prices to reach profitability. Equations (13) and (14) describe an unambiguous relationship between σ^2 and N_{jk} , (which supports this paper's focus on the extensive margin of trade). ϕ_{jk}^* is a function of $\tau_{jk}(1 + \gamma_j\sigma_{jk}^2)$, therefore N_{jk} is a function of σ_{jk}^2 .⁸

Substituting the threshold defined in equation (11) into (13):

$$N_{jk} = N_j \left\{ \frac{\varepsilon}{\varepsilon - 1} \frac{\tau_{jk}(1 + \gamma_j\sigma_{jk}^2)}{P_{jk}} \left(\frac{\varepsilon S_{jk}}{\bar{Q}_{jk}} \right)^{\frac{1}{\varepsilon-1}} \right\}^{-\theta_j}$$

$$\ln(N_{jk}) = \ln(N_j) - \theta_j [\ln(1 + \gamma_j\sigma_{jk}^2)] - \theta_j \left[\ln \left(\frac{\varepsilon}{\varepsilon - 1} \frac{\tau_{jk}}{P_{jk}} \right) + \frac{1}{\varepsilon - 1} \ln \left(\frac{\varepsilon S_{jk}}{\bar{Q}_{jk}} \right) \right] \quad (14)$$

Focusing on N_{jk} and σ^2

$$\frac{\partial \ln(N_{jk})}{\partial \sigma_{jk}^2} = \frac{-\theta_j \gamma_j}{1 + \gamma_j \sigma_{jk}^2} \quad (15)$$

A plot of $\ln(N_{jk})$ against σ_{jk}^2 should have a negative slope, from (14) and (15). The RHS parameters in equation (15) -the Pareto shape parameter, θ , the scaling parameter γ and demand volatility σ^2 - are all non-negative by definition:

$$\frac{\partial \ln(N_{jk})}{\partial \sigma_{jk}^2} < 0 \quad (16)$$

⁷ This choice follows Chaney (2008) and is consistent with the firm size distributions described in Hsieh and Ossa (2011) and Axtell (2001). Any of the general class of power law distributions should yield similar predictions, given reasonable assumptions about how the distribution is truncated.

The Pareto distribution function is $Pr(X < x) = 1 - \left(\frac{x_m}{x}\right)^\theta$ for $x \geq x_m$. The two parameters that characterize the distribution are x_m , the minimum productivity for a firm that produces j and θ , the shape parameter. For simplicity, I define the range of productivities on a scale $[1, \infty)$, this sets x_m equal to one, so $G(x) = Pr(X < x) = 1 - (x)^{-\theta}$.

⁸ In contrast, Section A.2.2 in the appendix models the relationship between demand volatility and trade volumes, which is not as pointed as the relationship in (13). The dominance of marginal costs' effects on the extensive margin is consistent with other papers that model the responses of heterogeneous firms to trade costs, (e.g. Crozet and Koenig, 2010; Helpman et al., 2008).

Restating equation (16):

Prediction: *Higher levels of demand volatility σ_{jk}^2 reduce the number of entrants into product-market export destinations, holding other factors constant.*

In the context of firms with heterogeneous ϕ_{ijs} , the mass of firms that find a product-market destination profitable decreases with increases in demand volatility. If demand volatility is zero, the model reverts to the form in monopolistically competitive models of trade. One way to take this prediction to the data is a linear regression of N_{jk} on σ^2 . In such a regression, the sign of the coefficient on demand volatility should be negative.

Corollary: *Holding other factors equal, the minimum productivity of entrants is higher for product-market destinations with higher levels of demand volatility.*

From equation (11):

$$\phi_{jk}^* = \frac{\tau_{jk}(1 + \gamma_j \sigma_{jk}^2)}{P_{jk}} \frac{\varepsilon}{\varepsilon - 1} \left[\frac{\varepsilon S_{jk}}{Q_{jk}} \right]^{\frac{1}{\varepsilon - 1}}$$

$$\frac{d \ln(\phi_{jk}^*)}{d \sigma_{jk}^2} > 0 \tag{17}$$

It is clear that the productivity threshold ϕ_{jk}^* for entering a product-market destination increases with demand volatility, therefore the minimum level of other proxies for productivity like exporters' share within a product category should also increase with demand volatility, all other factors being equal:

3 Empirics

This section examines the relationship between export entry and demand volatility. First, I describe data sources and key variables. Regression estimates follow the definitions, before robustness checks that address the most salient alternative explanations.

3.1 Data and Definitions

The key variables come from two trade datasets: firm-level export entry comes from the Chinese General Administration of Customs (GAC) database - the universe of Chinese export

transactions between 2000 and 2006, collapsed to firm \times HS6-product \times market \times year observations. UN COMTRADE data on imports at the HS6-product \times market \times year level provide the historical demand, size and volatility for each product-market destination. The unit of observation is a product-market destination, i.e., a unique combinations of an HS product and an importing country – say U.S. imports of bicycles (product category HS 871200). The dependent variable is *export entry* at the level of product-market destinations.

3.1.1 Export Entry

Export entry N_{jk} captures the number of unique Chinese firms that exported product j to a product-market destination jk between 2002 and 2006 — each exporter is counted only once in the entire period for the unit of observation. Only firm \times HS6-product \times country combinations first observed after December 2001 are counted. (Selecting entry after December 2001 was motivated by the fact that WTO-induced reforms eased the policy requirement that barred the majority of firms below a certain size from exporting directly (Ahn et al., 2011)). In addition to the trade reform steps, trade costs fell with China’s WTO accession.

The export entry variable reflects the equilibrium number of exporters that expected a destination to be profitable (in Section 2). The context matters. The period covered by the data captures the expansion of Chinese exports in two ways. The number of exporters expanded greatly, so that we can observe the destinations new exporters served, ostensibly because they expected export profits. More notably, Chinese exports also expanded in scope, as shown in Figure 1. Between 2001-2006, Chinese exports expanded into more than 114,000 product-market destinations with no history of Chinese exports. At that time, the exporters could have chosen any of more than 700,000 new product-market destinations. The paper rests on the argument that firms must have found those 114,000 product market destinations more profitable than the others, and that the number of unique firms that exported to the destinations in this period, (i.e. export entry) is a useful indicator of exporter responses to the zero profit condition. I use logged values of the export entry variable for the regressions that follow.⁹

The firm level trade data identifies firms, the year of each transaction, the exported product and the country to which it was shipped. The same dataset features in Manova and Zhang (2012) and Ahn et al. (2011), among others. Products are defined at the HS8

⁹Table A1 in the appendix shows the entry and exit dynamics of exporters in the years covered by the data. The table shows that exporters in 2000 represented only about a quarter of the full set of observed unique exporters. 78,700 unique exporters appear in the data before January 2002, of the 243,000 unique exporters in the database. China joined the WTO officially in December 2001.

level, which correspond to 4,903 HS6 categories — the narrowest global standard for defining exported goods. The level of detail makes it possible to identify firms and entry into product-market destinations before, or after China’s WTO accession. One observation in our analysis is U.S. imports of bicycles (HS 871200), with exports from 289 unique Chinese firms between 2002 and 2006, and another is bicycles (HS 871200) imported into Ireland, a product-market destination served by 3 Chinese exporters in the same period.

3.1.2 Demand Volatility and Size

The UN COMTRADE data show imports of each narrowly-defined HS6 product category for all countries between 1995 and 2010 for all country pairs (Gaulier and Zignago, 2010). (The Centres d’Études Prospectives et d’Information Internationales (CEPII) distributes a cleaned version of the database, branded as BACI.) Annual imports for 1995 to 2005 were collapsed to HS6-product \times importing-country \times year observations. As the data represent historical demand, 2005 was used as a reasonable cutoff. Only data from 1995 onwards was available in this database. The only other global trade database at the country-pair \times HS6 product level, the WITS database used in Kee et al. (2008) and Nicita and Olarreaga (2007) covers only a limited set of countries, compared with the ~ 200 countries in the COMTRADE database. I estimate demand volatilities using this collapsed data for all product-market destinations, including those with no observed entry by Chinese exporters.

Demand volatility is the sum of the squared deviations from a linear trend over the years 1995 to 2005 for total imports into each product-market destination from all exporting countries. (Chinese exports are excluded, to mitigate concerns about reverse causality. I did not use the Chinese firm-level export data to define volatility, for the same reason). This measure of demand volatility has the advantage of addressing the two main challenges to measuring volatility for time series: (1) making the volatility measure independent of the size of each product-market destination and (2) separating baseline growth from volatility. The measure controls for size differences by scaling all product-market destinations by the value of total imports over all periods, and controls for growth by introducing the linear trend that best fits the data. Volatility is measured as the summed squares of the shocks ϵ_{jkt} to imported demand that are not explained by the time trend in (19). Q_{jkt} in the equation represents the value of imports for the specific combination of product j and country k for

1995-2005. Formally defining volatility σ_{jk}^2 :¹⁰

$$\hat{\sigma}_{jk}^2 = \sum_t (\epsilon_{jkt})^2 \quad (18)$$

Where the residual term ϵ_{jkt} is derived from :

$$\frac{Q_{jkt}}{\sum_t Q_{jkt}} = \alpha_{jk} + \eta_{jk}t + \epsilon_{jkt} \quad (19)$$

The estimations that follow are in the cross-section of product-market destinations — demand volatility σ_{jk}^2 is destination specific and does not change over time. α_{jk} is a product-market specific scale term and t is the linear time variable. The η_{jk} term represents a secular growth trend over time t , and is captured in the size variable, as described in the last paragraph of this section. To avoid distortions due to data noise, I exclude product-market destinations with fewer than 5 years of imports of the 11 years possible. (About 708,000 active product-market destinations are eligible for analysis after this screen).¹¹

I also measure demand volatility for each product-market destination as the standard

¹⁰Defining demand volatility as deviations around a trend also helps to avoid mis-measurement when the data include instances of zero demand. The common measure of volatility as the standard deviation suffers from the problem of measuring growth from or to zero. If one uses the mid-point growth measure of Davis and Haltiwanger (1992), growth at these instances of zero will fall at the extreme values of -2 and 2. While this makes growth measurement possible, it may introduce outliers that bias the volatility measure. Demand volatility and growth measures are based on dollar values, given how quantity measures are not always comparable across products.

¹¹The demand volatility measure also corresponds to the quadratic form in equation 6). As Q_{jkt} represents the observed demand for product-market jk in a given year, and \bar{Q}_{jkt} is the predicted demand from the historical trend. The ν_{jkt} term can be reasonably represented by the residual term in equation (19).

This measure of demand volatility is one the paper's main contributions, showing for example that, at 0.90, the volatility of crude oil imports into Mozambique (one of the highest in this product category) is much higher than demand volatility in for crude oil imports into New Zealand (at 0.03). Demand volatility is generally higher for imports of crude oil than other sectors, consistent with prior papers that show sectoral differences in volatility (e.g. Koren and Tenreyro, 2007). Demand volatility is also generally higher in countries with low GDP-per-capita, as outlined in the appendix to the paper. Nevertheless, this measure makes it possible to see features of consumer taste and habits that country or product categories alone cannot explain, for example, that imports of truck tires (HS 401120) into Rwanda have lower demand volatility than US imports of electric inductors (HS850450), even if demand volatility is generally lower in the US than Rwanda, and demand volatility for truck tires as a product category is on average not much less than for electric inductors.

The alternative measure of demand volatility in this paper is the standard deviation of year-on-year growth. The two measures of demand volatility convey the same idea. In principle, volatility is the expected deviation from a variable's central moment. While the first definition directly projects product-market destination size onto a trajectory and measures deviations from that trajectory, the alternative measure abstracts from the size and growth features of demand to construct the second moment. The approximation may lead to less precision, but the estimated outcomes should be similar after adjusting for size differences.

deviation of year-on-year growth rates, to be consistent with the literature (e.g. Giovanni and Levchenko, 2009; Koren and Tenreyro, 2007). (See Appendix Section A.1.7 for how the demand volatility measure approximates this alternative measure). This alternate definition is also broadly consistent with the model. Product-market destinations in the empirics are consistent with the model.

The combined datasets represent the entry of more than 164,000 Chinese exporters into more than 310,000 product-market destinations, of the 708,000 active import destinations. Export entries are due to firms that were not observed in the first two years of the data, and represent firm-product-market destination linkages that were only observed after China joined the WTO. The scope of Chinese exports expanded from 226,000 to 340,000 product-market destinations in this period. Appendix Section A.1.1 describes the data sources further. GDP, distance and other predictors of trade come from the CEPII gravity dataset (Head et al., 2010).

Finally, I define destination size as the logged sum of imports between 1995 and 2005. In principle, this logged sum can represent projected future demand, as it captures both a baseline size and average historical growth. ($\log(\sum_t Q_{jkt}) \simeq \log(Q_{jk0}) + \log[\sum_t (1 + g_{jk}^t)]$ - the first RHS term is initial size, and the second term captures growth). This size measure offers a finer level of control for testing export destination choice than either distance or GDP, i.e. country-level measures. The regressions in this section will show that it explains more of the variation in exporter numbers than conventional gravity equation variables. (Historical demand is explained by GDP and distance, therefore, the inclusion of current GDP in an estimation exercise that includes historical demand provides little additional information).

The next sub-sections describe the key variables, outline the main results and provide robustness checks.

3.2 Results

Table 1 summarizes the key variables.

About 34 unique exporters entered the average product-market destination between 2002 and 2006. This number is highly skewed, with a median value of 4. The variation in exporter entry is large; products like buttons naturally had many producers, while airplanes had few. Country-specific variations also existed; export entry into the US and EU vastly exceeded many other economies. However, countries and products alone leave much of the variation in the data unexplained. Unreported regressions of export entry at the level of product-country product-market destinations on product and country fixed effects alone yield R^2 values of

Table 1: Summary of Key Variables

Variable	Mean	Std. Dev.	Min.	Max.	N
Export Entry	33.67	158.59	1	12,317	377,904
Entry Dummy	0.52	0.50	0	1	724,188
Demand Volatility	0.08	0.11	0	0.91	708,802
Volatility (SD)	0.93	0.53	0.02	2.19	708,802
Size	7.95	2.57	1.70	20.60	708,802

Chinese firms entered 378,000 product-market destinations between 2002 and 2006. Of the nearly 1 million product-market destinations, only 708,000 had the five or more non-zero observations required to compute demand volatility. 20,835 had no new exporters after 2001. Destination size is the log of total historical demand in the COMTRADE data.

Number of countries (237); products (5013)

0.093 and 0.096 respectively.

Demand volatility, measured as the sum of squared deviations from trend ranges from 0 to nearly 1, with a mean of 0.08 and a standard deviation of 0.11. (The distribution of this variable is also skewed). The alternative definition for demand volatility, as the standard deviation of year-on-year growth is represented in the Table as *Volatility (SD)*. The mean for *Volatility (SD)* is 0.93, near the median value, for this variable that ranges from 0.02 to 2.20. Destination size, the log of the sum of historical demand ranges from 1.7 to 20.6, with a mean of 8.

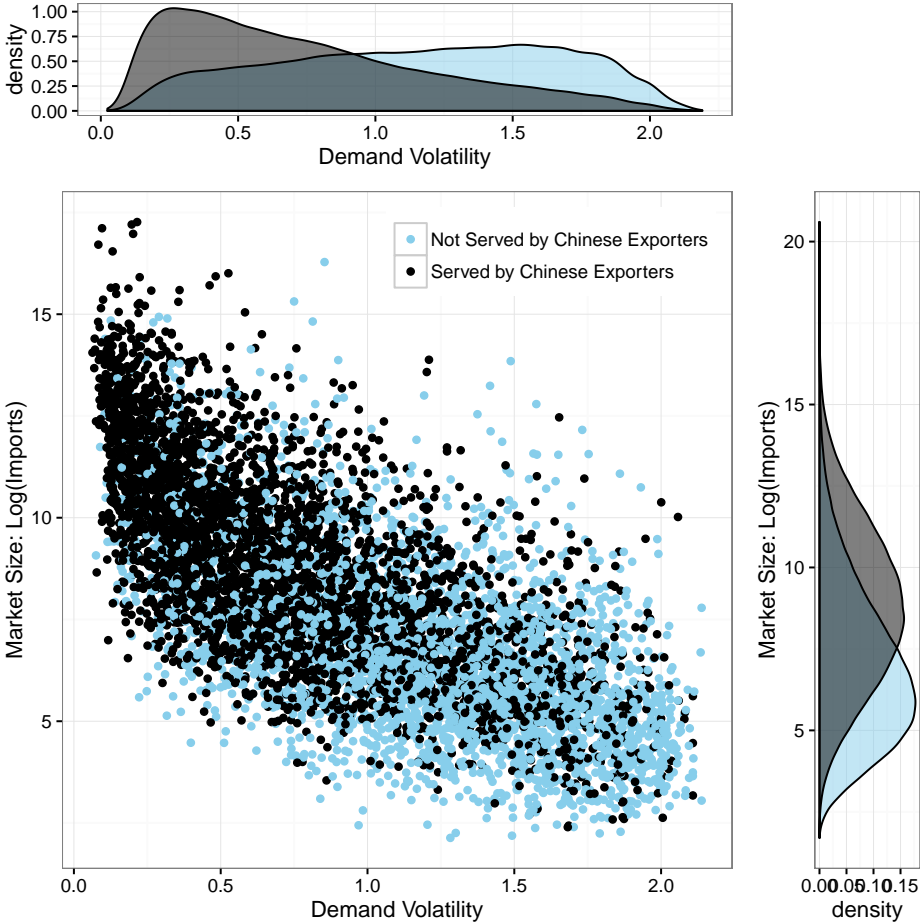
3.2.1 Demand Volatility and Destinations with Zero Exporters

More than half of the 708,000 product-market destinations in the data had zero entry by Chinese exporters. This raises the question: *do Chinese exporters avoid product-market destinations with high demand volatility?* To answer the question, Figure 2 graphs the distribution of sizes and demand volatility simultaneously for the product-market destinations, effectively comparing those served by Chinese exporters with the remainder. Figure 2 shows that Chinese exporters post-WTO are more likely to enter product-market destinations with lower demand volatility, (as well as larger product-market destinations).

To address the apparent correlation between demand volatility and size in Figure 2, equation (20) below includes controls for size and product fixed-effects. Adding this control in the regressions mitigates concerns that exporters avoid product markets are small, not necessarily because of observed demand volatility. The negative correlation observed in

the figure is consistent with previous studies on export volatility that define volatility as the standard deviation of growth (e.g. Giovanni and Levchenko, 2009; Koren and Tenreyro, 2007). The same level of growth in absolute terms in the average market corresponds to higher growth rates for small product-market destinations.

Figure 2: Destinations Served (and Not Served) by Chinese Exporters



The scatter plot only shows a random 1% sample of the more than 700,000 product-market destinations. The density plots for product-market destination size and demand volatility use the full data set. Demand volatility is the standard deviation of growth for each product-market destination. Market size is the log of the total USD value of imports into the destination between 1995 and 2005.

Data Sources: China GAC Export Data, UN COMTRADE

The density plots in Figure 2 indicate that the regression exercises that follow provide broad coverage of product-market destinations in terms of size and demand volatility. The ranges of demand volatility and destination sizes covered by the two categories are similar.

Nevertheless, from the distribution at the top of the graph, destinations served by Chinese exporters tended to have low demand volatility. The density on the right panel shows that the product-market destinations Chinese exporters serve are also on average, larger.

The following baseline regression specification, from equation (14) in Section 2, guides the rest of this section:

$$Y = \beta_0 \sigma_{jk}^2 + \beta_1 X_{jk} + \alpha_j + \alpha_k + \varepsilon_{jk} \quad (20)$$

Y = Dummy variable, 1 if at least one Chinese exporter entered a product-market destination
 $OR \log(N_{jk})$, Number of exporters to enter product-market destination

σ_{jk}^2 = demand volatility

X_{jk} = a vector of gravity model variables e.g. size, GDP, distance

α_j = product fixed effects α_k = country fixed effects

In this cross-section of product-market destinations, it is necessary to control for product-specific factors, as the number of potential entrants and the sunk costs of entry vary significantly by product. For example, between narrowly defined HS6 product categories, the number of exporting firms ranges from 1 for high-powered turbo-propeller engines (HS 841122) to more than 40,000 for miscellaneous plastic articles (HS 392690). Estimates of the Pareto distribution parameter θ_j also ranged from less than 5 to greater than 15, with varying degrees of fit for these product categories. (The parameter was estimated using total trade volumes as a proxy for size for firms; a parameter was estimated for each product category). Applying product fixed effects in the cross-section helps to address these differences.

Differences in export entry by country are expected, given factors like GDP, distance, language and currency. To ensure differences in exporter numbers due to these factors are not conflated with demand volatility at the product-country level, I introduce either country fixed effects or direct measures of these variables (for the year 2006). Product fixed effects address the fact that some items are more likely to be exported than others for time-invariant reasons outside the model, and country fixed effects or variables like GDP control for country-level factors that determine the prevalence of zeros in trade. The specifications with product fixed effects examines whether export entry differences between countries like Portugal and Greece that have similar GDP, GDP per Capita and distance from China, can be explained by demand volatility, for a narrowly defined product like bicycles. The way the data is set up makes it possible to identify which country has the higher level of demand volatility for bicycles, knowing that the similar comparisons for other products are not guaranteed to be

identical.

Table 2 reports on the estimates of whether the presence of any Chinese exporters in a product-market destination is linked to its demand volatility. The estimates, based on equation (20) represent a linear probability model with a dependent variable that is 1 if at least one Chinese firm exported to the destination between 2000 and 2006, and is 0 otherwise.

Table 2: Export Incidence and Demand Volatility:
(Dependent Variable: Dummy [$\mathbf{1}$ = At least one Chinese Exporter])

	(1)	(2)	(3)	(4)
<hr/>				
VARIABLES				
Demand Volatility	-0.34*** (0.006)	-0.26*** (0.006)		
Volatility (SD)			-0.17*** (0.002)	-0.11*** (0.002)
Destination Size		0.04*** (0.001)		0.03*** (0.001)
Observations	708,802	708,802	708,802	708,802
R-squared	0.52	0.53	0.52	0.53
Country-Year FE	Y	Y	Y	Y
Product FE	Y	Y	Y	Y

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: The units of observation are product-market destinations: unique HS6-product and country combinations, e.g., Irish imports of bicycles (HS 871200). The dependent variable is 1 if at least one Chinese firm exported to the destination between 2000 and 2006, and is 0 otherwise. Destination size is the log of total historical demand in the COMTRADE data for the product-market destination. All specifications use country fixed-effects and product fixed-effects.

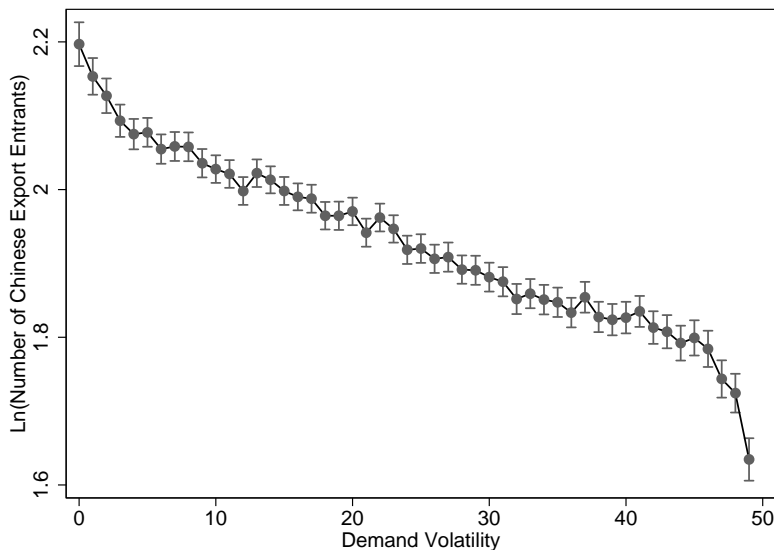
The results in Table 2 contribute another explanation for zeros in international trade, supporting notable works on the subject by papers (e.g. Baldwin and Harrigan, 2011; Helpman et al., 2008). The destinations with no entry by Chinese exporters had on average, higher demand volatility. Columns 2 and 4 control for product-market destination size to address the concern that larger destinations will generally have more exporters, as market size is correlated with demand volatility. The difference in the likelihood of having at least one Chinese exporter is about 30% on average for two otherwise identical product-market destinations with levels of demand volatility at the minimum and maximum, i.e., $0.34 \times (0.91 - 0.0)$. Increasing demand volatility by one standard deviation corresponds to a 3.7% de-

crease in the likelihood that a product-market destination is served by Chinese exporters, after controlling for destination size and country features. The standard deviation of demand volatility is 0.11 for this set of destinations. As in Figure 2, volatility in Columns 3 and 4 is defined as the standard deviation of growth. The estimated effects are almost identical to the estimates from Columns 1 and 2.

3.2.2 Demand Volatility and Export Entry

Figure 3 shows that more Chinese exporters enter product-market destinations with low demand volatility, conditional on having at least one entrant. The plot sets the number of export entrants for destinations against demand volatility. The predicted averages in the plot control for size, country features and product-fixed effects. Each average is calculated separately for 50 equal-frequency bins of demand volatility.

Figure 3: Export Entry and Demand Volatility



Note: Estimated export entry in 2002-2006 after controlling for size, Country and HS6 product fixed effects. Standard prediction errors show for each demand volatility quantile. Demand volatility grouped into 50 quantiles, least to largest.

Data Sources: China GAC Export Data (2000-2006), COMTRADE

Table 3 reports estimates for product-market destinations with at least one Chinese exporter. Destinations with high demand volatility have fewer exporters, after controlling for common predictors of exporter numbers. Columns 1 and 2 relate export entry to demand

volatility, measured as the sum of squared deviations from a growth trend. The other columns define demand volatility as the standard deviation of import growth for the destination.

Table 3: Export Entry and Demand Volatility:
(Dependent Variable: Log Export Entry in Product-Market Destination)

VARIABLES	(1)	(2)	(3)	(4)
Demand Volatility	-0.75*** (0.118)	-0.75*** (0.081)		
Volatility(SD)			-0.16*** (0.047)	-0.21*** (0.030)
Prod. Market Size	0.30*** (0.013)	0.26*** (0.009)	0.29*** (0.013)	0.25*** (0.009)
Log(GDP)	0.22*** (0.024)		0.22*** (0.024)	
Log(GDP per capita)	-0.04 (0.028)		-0.04 (0.028)	
Log(Distance)	-0.50*** (0.043)		-0.51*** (0.043)	
Observations	312,238	362,473	312,238	362,473
R-squared	0.71	0.74	0.71	0.74
Country-Year FE	N	Y	N	Y
Product FE	Y	Y	Y	Y

Two-way clustered (product-country) standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: The units of observation are product-market destinations, i.e. unique HS6-product and country combinations, e.g., Irish imports of bicycles (HS 871200). Export entry captures the number of firms that served a destination from 2000-2006, after China's WTO accession. Control variables used but not shown in the table include geographic remoteness and dummies for shared borders, common languages and WTO membership. Twoway clustered standard errors (product and country) are shown in parentheses.

A one standard deviation increase in demand volatility is expected to yield a 8% decline in the observed number of exporters. (The response is calculated as $1 - \exp(-0.75 * 0.11)$). If demand volatility was measured as the standard deviation of growth, increasing demand volatility by one standard deviation is also expected to yield a 8% decline in export entries. (The last two columns of Table 3 agree in sign and significance with the first two, with similar estimated effects). Doubling demand volatility at the mean for this measure corresponds to a decline in exporter counts of 38%. This translates to about 13 fewer exporters in the average

product-market destination, given the average exporter count of 34 and the average demand volatility of 0.93, with a standard deviation of 0.53.¹²

Other variables are well-behaved. Export entry increases with market size, GDP, and decreases with distance. Product-market destination size takes away most of the statistical significance associated with country-level variables like GDP and distance. The variable - the logged sum of imports between 1995 and 2005, represents both observed and projected demand growth, matching Q_{jk} in the model. By its definition, it also addresses concerns that historical average growth rates affect exporter numbers. The table reports two-way clustered (product and country) standard errors. I use but do not show colonial relationships, WTO membership and other gravity variables in the table to conserve space. The gravity model variables are all taken from the year 2006. (Table A2 in Appendix Section A.1.1 summarizes these additional variables).¹³

As volatility is measured using global aggregate imports into each product-market destination, the specification avoids concerns about reverse causation. Product fixed effects capture differences in the γ_j parameter, the mass and distribution of exporters N_j and θ_j , as well as the setup costs and fixed costs associated with specific products. Country fixed effects also control for factors that include exchange rates, exchange rate volatility, country size, trade costs and policies like tariffs and trade agreements. Testing in the cross-section helps to avoid concerns about other time-varying factors, as long as the variables are stable over the period under review. Column 1 allows the GDP, GDP per capita and other gravity variables to explain country-specific determinants of trade costs. The gravity model variables are either constant, e.g., distance, or highly auto-correlated, e.g., GDP. The country fixed effects eliminate the gravity model variables, as expected. Columns 2 and 4 apply both country and product fixed effects simultaneously.¹⁴

Table 5 in the robustness section links these findings to the framework in the model. The

¹²Columns 1 and 3 also have fewer observations than others because a few countries are missing GDP, distance or other control variables from the CEPII gravity dataset.

¹³A possible challenge to the definition of market size in this paper is that total absorption in each product-market destination includes imports and domestic production. That poses no real problem; the fact that imports and domestic production are generally close substitutes within the narrow product categories suggests that imports can be used as a proxy for aggregate demand.

¹⁴For computational efficiency, I follow the algorithm proposed by Guimarães and Portugal (2009) for multiple high-dimensional fixed effects. In addition to allowing for multway clustering of standard errors, just like Cameron et al. (2011), the main difference between this approach and conventional OLS estimation is that the coefficients are deduced from an iterative process, rather than directly calculating coefficients from matrix inverses and products. The coefficients are estimated simply as the vectors for the dummies and independent variables that yield the least squares, within a 1e-6 tolerance. The product and country fixed effects are not fully interacted, as that would eliminate all degrees of freedom in the data.

rationale in the model for lower export entry into destinations with high demand volatility is lower expected export profits, due to the anticipated costs of adjusting production scale. That table shows that the response of export entry to demand volatility is higher for products/sectors with historically low production scale adjustment rates.

In sum, Chinese exporters entered product-market destinations with lower demand volatility in greater numbers. This is after accounting for product characteristics, country size, distance and other determinants of the bilateral costs of exporting, or potential profits. The results hold whether demand volatility is defined as scaled deviations from growth trends or the standard deviation of demand growth. The observations capture the wave of export entry that followed China’s accession to the WTO.¹⁵

3.2.3 Demand Volatility and Exporter Selection

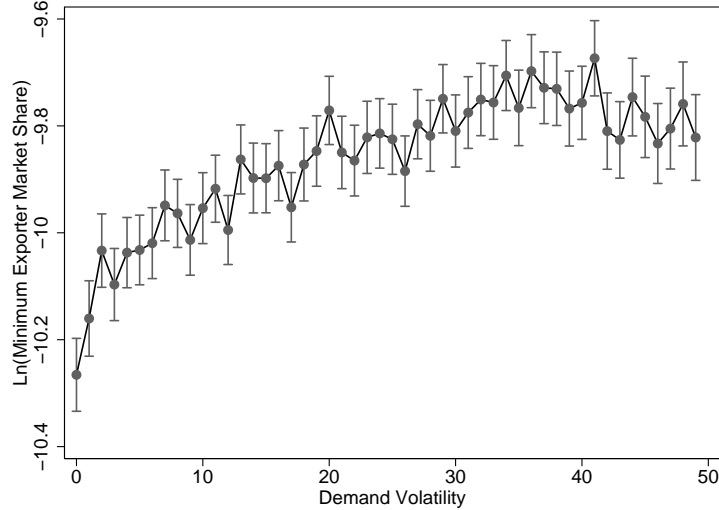
Figure 4 supports the model’s implication that demand volatility filters out producers with low productivity. The corollary prediction, equation (17) in Section 2, shows that the minimum productivity threshold should be higher for product-market destinations with high volatility. (As the data offer no direct measures of productivity, I use producers’ market shares within product categories as a proxy). To facilitate comparisons in the cross-section, I compute each exporter’s share of Chinese exports in 2006 within its HS6 category: $Share_{ij} = q_{ij} / \sum_{z \in [1, N_j]} q_{zj}$. I represent the productivity threshold ϕ_{jk}^* by the smallest market share recorded by any firm in destination jk , $\min_{jk}(Share_{ij})$. Therefore, destinations served by only the largest exporter in the product category will report a higher threshold than the destination served by both the largest and smallest exporter, (if more than one firm exports the product from China).

To see that $\min_{jk}(Share_{ij})$ is a reasonable proxy for ϕ_{jk}^* , one only needs to see that $Share_{ijk} = q_{ijk} / Q_{jk}$ is proportional to $\phi_{ij} \frac{\varepsilon - 1}{\varepsilon \tau_{jk} P_{jk}}$, from equations (3) and (9). Even after summing across countries, $Share_{ij}$ is still expected to correlate positively with ϕ_{ij} . Therefore, product-market destinations with a high $\min_{jk}(Share_{ij})$ are also expected to have a high ϕ_{jk}^* . A second proxy for productivity is the number of product-market destinations served by an exporter. This proxy relies on the argument that more productive firms have greater

¹⁵Most exporters serve more than one product-market destination – and product-market destinations are not perfectly correlated – one must consider that entering two product-market destinations simultaneously may yield a combined or portfolio volatility that is lower than what I use for the reported regression exercises. Therefore, the predicted effects of demand volatility in this paper are on the conservative side. Consider that $\beta_0 = [\log(N_{jk}) - (\beta_1 X_{jk} + \alpha_j + \alpha_k)] / \sigma_{jk}$ in equation (20); if the true volatility perceived by exporters $\sigma_{jk}^* \leq \sigma_{jk}$, then the true coefficient $|\beta_0^*| \geq |\beta_0|$

export scope, and that destinations for which the minimum observed scope for exporters is high, must have higher productivity thresholds.

Figure 4: Export Productivity Thresholds and Demand Volatility



Data Sources: China GAC Export Data (2000-2006), COMTRADE

With increasing demand volatility, the plot shows an increasing trend in the predicted minimum productivity for firms - proxied by market share within a product category. In other words, if we ranked firms by market share within each export product category, the lowest-ranked exporters are less likely to be observed in the product-market destinations with the highest demand volatility. Product fixed effects control for product-specific differences in the distributions of market shares for this graph.

Table 4 shows that the pattern in Figure 4 is statistically robust. The estimates come from equation (17), implemented as the following empirical model:

$$\hat{\phi}_{jk}^* = \beta_0 \sigma_{jk}^2 + \beta_1 X_{jk} + \alpha_j + \alpha_k + \varepsilon_{jk} \quad (21)$$

σ_{jk}^2 in equation (21) is demand volatility, as in equation (20), and X_{jk} is a vector of gravity model variables e.g., size or GDP and distance. $\hat{\phi}_{jk}^*$ is a proxy for the minimum productivity threshold for a product-market destination. The estimation uses fixed effects: α_j product fixed effects and α_k country fixed effects.

In line with the prediction of equation (17), increasing demand volatility leads to increasing export productivity thresholds, measured as either the share of exports commanded by a firm, or the number of countries served by a firm within each product category. Columns

Table 4: Exporter Size Thresholds and Demand Volatility
(Dependent Variable: Minimum Exporter Scope or Share in Destination)

VARIABLES	(1) Scope	(2) Share	(3) Scope	(4) Share
Demand Volatility	0.62** (0.270)	0.10 (0.094)		
Volat (SD)			0.14 (0.087)	0.09*** (0.026)
Destination Size	-0.41*** (0.018)	-0.19*** (0.007)	-0.41*** (0.020)	-0.18*** (0.007)
Observations	285,673	285,675	285,673	285,675
R-squared	0.24	0.60	0.24	0.60
Country-Year FE	Y	Y	Y	Y
Product FE	Y	Y	Y	Y

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: The units of observation are product-market destinations: unique HS6-product and country combinations, e.g., Irish imports of bicycles (HS 871200). Export size thresholds capture the *minimum value* within each product-market destination of [1] *Share*, each firm's export share in 2006 for the HS6 product category, and [2] *Scope*, the number of countries served by a firm within the product category. *Share* and *Scope* definitions use only 2006 data. Destination size is the log of total demand from a product-market destination between 1995 and 2005.

1 and 3 use the number of product-market destinations (i.e. countries) served within each product category as the proxy for exporter productivity. The reasoning here is that on average, a firm that is able to export to more countries should have higher productivity than the firm that is only able to export to one country. This product-market destination *Scope* variable is calculated for each firm-product combination in 2006. (To ensure fair comparisons of market share between firms, I measure *Scope* and *Share* using only one year of trade data, the most recent year, which has the largest number of exporters and product-market destinations).

The average product-market destination in 2006 had 20 exporters, and the minimum destination scope for average exporters is 3.7 countries (in the range 1 to 130). For the destination with demand volatility one standard deviation above the mean, the results in Table 4 translate to a minimum destination scope that is higher by 0.04, (i.e. 0.62×0.07). Using the results in Column 3, which use the alternative definition of demand volatility gives a comparable estimated effect of 0.06, although the latter is not statistically distinguishable from zero. Using the market share of firms (in logs) as a proxy for firm-level productivity leads to conclusions with the same sign and higher statistical significance. If demand volatility increased by one standard deviation, according to column 4 in Table 4, the minimum market share for firms serving the product-market destination is expected to increase by 4% (i.e. $exp^{(0.09 \times 0.43)} - 1$). This effect is non trivial, given how the average destination has only 20 exporters.

In sum, the evidence in Tables 3 and 4 suggests that demand volatility filters out the least productive exporters from destinations. Appendix Section A.2.2 extends the model in the previous section to derive the expected relationship between trade levels and demand volatility, as well as the expected effect of demand volatility on average exporter size (or the intensive margin). Equation (30) implies that trade should decrease marginally as demand volatility increases, but with a greater decrease in exporter numbers than average exporter size. With a sufficiently large decrease in exporter numbers, average exporter size increases with demand volatility.

What follows are robustness checks that address the following challenges and alternative explanations: [1] The OLS specification may not fully represent the relationship between export entry and volatility, given the prevalence of zero-entry observations. [2] As volatility is measured using historical demand in dollar values, it is not clear that demand volatility is not simply price volatility. [3] Volatility is measured using data that overlaps the period used to define export entry. Appendix sections A.1.3 to A.1.6 include additional tests.

3.3 Robustness Checks

3.3.1 Sectoral Differences in Scale Adjustments

This segment of the paper shows that the entry-volatility relationship is stronger for sectors which require greater relative production scale adjustments for output changes, to address concerns that the relationship between export entry and demand volatility is not related to the costs of adjusting production scale. Table 5 repeats the first two columns of Table 3, but with separate regressions for products with high or low implied adjustment costs. The implied costs of scale adjustment at the sector-level are derived from the China Annual Industrial Database, a firm-level database that shows total output, assets and employees at the firm-level. After aggregating to the sector-level, a proxy for the γ_j parameter in Section ?? was calculated for each sector by running a regression of output changes on asset changes and employment changes. (The coefficient of the asset/employee change is a proxy for γ_j because high γ_j for a sector, which implies high adjustment costs should also correspond to a high ratio for the output and input growth rates). From this firm-level output data, we know that a 1% increase in output for keyboards and other computer parts is usually associated with about a 1% increase in production assets, for example. On the contrary, large changes to the outputs of other sectors involves little change in production assets, e.g., fireworks, car parts. These differences make it possible to imply that producers of computer keyboards anticipate high adjustment costs, e.g., equipment startup and shutdown costs, while car parts producers will anticipate low adjustment costs, given markets with the same level of demand volatility.¹⁶

Table 5 matched the product-market destinations in the data to the sector-level measures of adjustment costs created from the firm-level data in the previous paragraph. (Not all HS6 products could be matched to sectors, as explained in the Appendix). For the matched product categories, the data was grouped into product-market destinations with high implied adjustment costs, and those with low implied adjustment costs. If the argument formalized in equation (14) of Section 2 is correct, then the size of the coefficient of the demand volatility variable should be higher for product-market destinations with high adjustment costs, while keeping the same sign. With high demand volatility for those destinations, export entry should be relatively lower, as fewer firms can profitably absorb the higher anticipated costs of changing production scale.

The results support the predictions of the model. Fewer exporters are observed in desti-

¹⁶Appendix section A.1.4 explains how implied adjustment costs are derived from firm-level data. Olabisi (2017) provides a detailed description for the China Annual Industrial Database.

Table 5: Exporter Entry by High and Low Adjustment Sectors
(Dependent Variable: Export Entry in Product-Market Destination)

	(1)	(2)	(3)	(4)
	Low Adjustment		High Adjustment	
VARIABLES				
Demand Volatility	-0.40** (0.159)	-0.61*** (0.108)	-0.80*** (0.159)	-1.18*** (0.110)
Prod. Market Size	0.44*** (0.021)	0.25*** (0.011)	0.44*** (0.020)	0.29*** (0.013)
Observations	87,880	87,878	86,327	86,325
R-squared	0.60	0.77	0.61	0.74
Country FE	N	Y	N	Y
Product FE	Y	Y	Y	Y

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: The units of observation are product-market destinations: unique HS6-product and country combinations, e.g., Irish imports of bicycles (HS 871200). Only HS6 products that could be matched to the Chinese industry categories were included. Adjustment represents the scale of changes over time in assets to changes in output. Export entry captures the number of firms that served a product-market destination from 2002-2006, after China's WTO accession.

nations with high demand volatility and the negative slope is even more negative for product-market destinations linked to sectors associated with costs of production scale adjustments, e.g. the manufacture of computer keyboards and accessories. These findings are consistent with the idea that when the costs of deviating from a set production scale are higher, exporters can anticipate lower export profits from destinations with high demand volatility. Consequently, fewer exporters will be observed in those destinations.

For the group of products with high implied assets adjustment costs, the coefficient of the demand volatility variable is roughly double the size, but the same sign as products with low demand volatility. The number of observations, as well as the mean values of export entry, market size and volatility are comparable for the two categories of implied adjustment costs in the data.

In sum, the evidence in Table 5 suggests that demand volatility filters out the least productive exporters from destinations, and the filter is more relevant to sectors and products with high costs of production scale adjustment, as outlined in the model of trade described by this paper. (Table A4 in the appendix also lends further support, with similar findings using implied employment adjustment costs, rather than asset adjustment costs).

3.3.2 Poisson Regressions to Include Zeros

Destinations with zero exporters were ignored in previous tables – the estimations used logarithms of a count variable. Table 6 addresses concerns of possible bias from ignoring these product-market destinations with a Poisson regression. The inclusion of observations with zero export entry after 2002 is expected to accentuate the claims made in the previous section: product-market destinations with zero entry are more likely to have high demand volatility.

The estimates using Poisson regressions with fixed effects are consistent with those from Tables 3, and larger, as expected. Interpreting the coefficients in column 2 of Table 6 suggests that a 28% decline in the number of exporters should be associated with a standard deviation increase in demand volatility from the mean, holding other factors constant. (The response is calculated as $\{-2.5 * 0.11\}$). Similarly, the estimates from columns 3 and 4 using the alternative demand volatility definition imply a 33% decline in the number of exporters with a standard deviation increase in demand volatility. These estimated effects are also, as expected, higher than the comparable numbers in Table 3. The product-market destinations excluded from previous estimates had high levels of demand volatility and zero exporters, as shown in Figure 2. The results fit expectation in terms of size, sign and significance.

Table 6: Exporter Entry and Demand Volatility - Poisson Estimates
(Dependent Variable: Export Entry in Product-Market Destination)

VARIABLES	(1)	(2)	(3)	(4)
Demand Volatility	-3.965*** (0.154)	-2.468*** (0.096)		
Demand Volatility (SD)			-0.964*** (0.027)	-0.508*** (0.021)
Prod. Market Size		0.285*** (0.006)		0.264*** (0.006)
Observations	699,402	699,402	699,402	699,402
Number of HS6 categories	4,816	4,816	4,816	4,816
Country FE	Y	Y	Y	Y
Product FE	Y	Y	Y	Y

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: The units of observation are product-market destinations: unique HS6-product and country combinations, e.g., Irish imports of bicycles (HS 871200). All 700,000+ product-market destinations with measurable demand volatility were included, the majority of which had zero Chinese exporters. Product and country-fixed effects limited the usable observations to about 699,000. Export entry captures the number of firms that served a product-market destination from 2002-2006, after China's WTO accession.

Product fixed effects and country fixed effects are applied, as in the previous tables.

3.3.3 Demand Volatility Weighted by Recency

In estimating volatility, firms may ascribe greater weight to recent information (Bloom et al., 2007). Therefore, recent shocks may carry a disproportionate share of exporter’s demand volatility estimates, (or less in times of high uncertainty). Figure 5 tests the idea by plotting the coefficient and R2 values obtained for definitions of demand volatility with different weight indices η . The weights w_t , indexed from 1 to 10 put more emphasis on recent information with higher values of η ; setting η to 1 reverts to the default scheme of equal weights. By design, the weighting scheme does not affect product-market destinations with uniform deviations from the demand trajectory in all periods. (η specifies the relative size of the first and last terms of an arithmetic series that sums to H. H is the most recent period).

$$\sigma_{jk}^2 = \sum_{t=1}^H w_t \epsilon_{jkt}^2, \quad \epsilon \text{ is the residual in equation (19):} \quad (22)$$

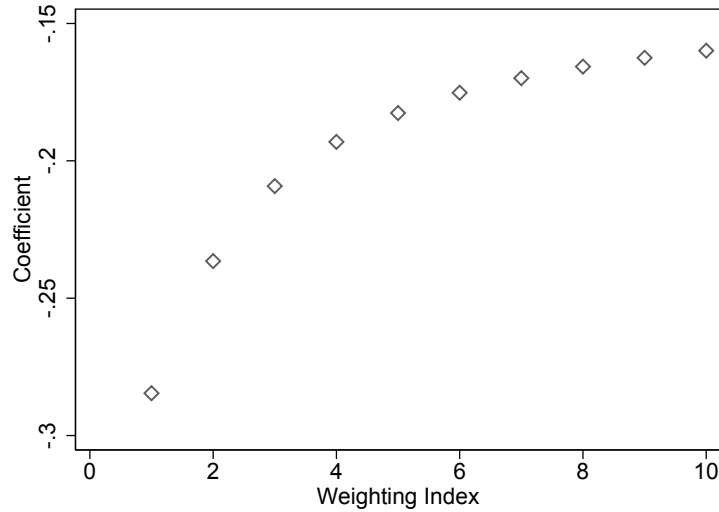
$$w_t = \frac{2}{\eta + 1} + \frac{2(t - 1)(\eta - 1)}{(H - 1)(\eta + 1)}, \quad \text{for } t \in [H, 1], \text{ with } \eta \in [1, 10] \quad (23)$$

To create the figure, I repeat the baseline regression in Table 3 for each weighted variant of σ^2 and collate the estimated coefficients and R^2 s.

Figure 5 indicates that increasing the weight of recent information in the estimation of demand volatility does not increase estimated effect of product-market destinations’ volatility on export entry, in scale. (The R^2 for the 10 sets of regressions, not shown, remains between 0.7405 and 0.7407). The estimated coefficient of demand volatility on exporter counts remains statistically significant and negative, but decreases slightly in scale from the default estimate of -0.28. to -0.15 for index 10, the volatility estimate that ascribes 10 times the weight of the first year (1995) to the most recent year of demand history (2005). These results suggest that the particular period used to estimate demand volatility does not affect the paper’s main qualitative predictions.

This exercise also helps to mitigate concerns about the absence of consistent historical demand data before 1995. If we had such data, one would simply place less weight on more recent demand data, and more weight on data from 1995 and earlier. The pattern in the figure suggests that placing greater weight on earlier information in estimating demand volatility leads to lower expected export entry. In sum, if exporters use information from

Figure 5: Estimates Using Period-Weighted Demand Volatility



Data Sources: China GAC Export Data (2000-2006), COMTRADE

prior to 1995, and the pattern in Figure 5 is unbroken, one expects the negative effect of demand volatility to be more pronounced, not less.

4 Discussion

Demand volatility's effects on trade may be robust, but this leaves the question of whether it matters for economic development unanswered. This section of the discussion will consider one mechanism through which demand volatility may affect development: fewer exporters and export varieties may mean higher prices. Higher prices for capital goods and industrial goods would be of particular concern, as imports in the categories are a channel for growth through process upgrading (Halpern et al., 2015; Goldberg et al., 2010).

Table 7 tests for a relationship between prices and demand volatility separately for each of the UN goods classifications (i.e. broad economic categories or BEC). Imports in each of the broad categories contribute differently to economic development (Jones, 2011). Imports of capital goods have been cited often as a source of productivity growth in developing economies (Eaton and Kortum, 2001; Lee, 1995). More recent papers also link increases in firm-level productivity to the onset of imports (Elliott et al., 2016).

The units of observation are unique combinations of firms, HS8 products, product-market destination countries and years, e.g., exports of bicycles (HS 871200) to Ireland in 2006 by

Table 7: Demand Volatility and Prices, by Broad Economic Categories
(Dependent Variable: Log Unit Prices)

VARIABLES	(1) Capital Goods	(2) Capital Goods	(3) Consumer Goods	(4) Consumer Goods	(5) Intermediates	(6) Intermediates
Demand Volatility	0.08*** (0.031)	0.08*** (0.030)	-0.49*** (0.027)	-0.08*** (0.024)	-0.35*** (0.016)	0.03** (0.015)
Observations	1,504,020	1,504,018	7,777,477	7,777,474	5,483,018	5,483,015
R-squared	0.94	0.94	0.88	0.88	0.86	0.86
Firm-Product-Year FE	Y	Y	Y	Y	Y	Y
Country FE		Y		Y		Y

Robust standard errors in parentheses. Errors clustered by product-year.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The units of observation are unique combinations of firms, HS8 products, product-market destination and years, e.g., exports of bicycles (HS 871200) to Ireland in 2006 by firm #311996528A. The dependent variable is the log of prices for each observation. I used the finer HS8 rather than HS6 product categorization because quantity units are consistent within HS8 but not HS6 categories. The classification into capital, consumer and intermediate goods follows the UN's correspondence between HS6 products and broad economic categories (BEC).

firm #311996528A. The specifications in this table exploit the firm-level variation in prices for each product-market destination and year. The dependent variable is the log of prices for each observation. Using the roughly 8000 HS8 product categories in this specification was necessary. Quantity units for measuring price in the firm-level data are not consistent within many HS6 categories. For example, within the 6-digit product category that cover live plants (060290), mushroom spawns (06029010) are measured by weight, while seedlings (06029091) are measured in units. Therefore, it becomes impossible to report meaningful price measures at the HS6 level. The firm \times product \times year fixed effects control simultaneously for year-to-year variations and firm-specific factors like productivity and product appeal.

The results indicate that with higher demand volatility, prices are higher for capital goods. This result holds even in the absence of explicit controls for product quality, which could matter for a category with quality differentiation potential like capital goods. Prices are lower on average with high demand volatility for consumer goods, which also tend to have quality differentiation potential but represent a larger share of exports. The estimated effect of volatility on prices is not as clear for intermediate goods and other products that do not fit into any of these three categories (like automobiles). While the findings for these other categories do not conform to the model, they could be explained by related works that

imply countries with low GDP per capita receive lower import prices (Manova and Zhang, 2012; Hummels and Klenow, 2005).

For intermediate goods, prices are higher with demand volatility after country fixed effects are introduced. Other specifications were run without country fixed effects but not shown in the table to conserve space. The coefficients in those specifications are consistent with related work on prices in international trade; prices increase with GDP per capita for the specifications that are statistically significant, increase with distance and show mixed effects with GDP.

The firm-product-year fixed effects address several potential concerns with the estimate, including possible changes in HS8 categories from one year to the next (Amiti and Freund, 2010), quality differentiation by firm (Manova and Zhang, 2012) and product differences. That prices vary by product is rudimentary, but when some HS8 products are reclassified to other categories from one year to the next, it is important to include fully-interacted HS8-year effects as a control, even if the reclassifications affect only a small share of product categories. This pair interacted with firms to create fixed effects that reflect consistent differences due to firm productivity, and investments in quality. The country fixed effects address country-specific factors that may consistently affect prices like exchange rates, but are not captured by GDP, distance or GDP per capita.

5 Conclusion

Demand volatility plays a significant role in the choices of economic agents, and international trade is no exception. This paper models a link between demand volatility, expected profits and exporters' entry decision. This approach explicitly considers the anticipated effects of costs like the overtime wages required for positive demand shocks or the deactivation costs required for negative demand shocks. In the model, exporters expect high marginal costs (and therefore lower export profits) with high demand volatility. As a result, fewer exporters would self-select into those product-market destinations. Effectively the model predicts that by reducing the expected profits for a given level of productivity, demand volatility filters out less productive potential exporters.

The main findings are consistent with the model's predictions: Fewer exporters enter product-market destinations with high demand volatility. The results are robust to how demand volatility is defined, and to several alternative empirical specifications. Furthermore, the data confirm the model's predictions about how the relationship between export

entry and demand volatility varies with implied sectoral differences in the production scale adjustments needed for demand shocks. Two rich datasets were the primary sources for this paper: UN COMTRADE data to define volatility and size for product-market destinations, and firm-level export data to identify export entry.

The predicted effects of demand volatility are statistically significant. Doubling demand volatility for the average product-market destination predicts a 38% drop in export entry in my conservative specification; (the decline is 40% in the specification that most resembles a conventional Poisson gravity model). The explained variation in exporter counts and predicted effects of this new variable are comparable to those obtained from conventional predictors of trade like GDP and distance. We also find support in the data for predictions of higher productivity thresholds in product-market destinations with high demand volatility.

Export entry is relevant to economic development: fewer exporters imply higher prices. For importing economies, higher prices for capital goods and industrial inputs prompt specific concerns about the profitability and prices of goods in sectors downstream from the imported items. Imported inputs in these categories have also been shown to stimulate process improvements in developing economies (Halpern et al., 2015; Goldberg et al., 2010; Connolly, 2003). The foregoing may with further validation, provide support for a claim that in developing economies, diversification strategies at the national level that reduce import volatility could affect the prices and varieties of imported inputs, in addition to other benefits.

These findings suggest further work to evaluate how volatility affects the development process, given how instrumental trade has been to growth in the last half-century. Empirical studies have shown that current trade models over-predict the number of exporters serving foreign markets (Arkolakis, 2010; Alessandria and Choi, 2009): a potentially interesting exercise is estimating the share that demand volatility explains of this gap between the data and models like Melitz (2003). Another possible extension is using differences in estimated labor and capital adjustment costs to explain the heterogeneity in producers' responses to demand volatility.

References

- [1] Ahn, J., Khandelwal, A. K., Wei, S.-J., 2011. The Role of Intermediaries in Facilitating Trade. *Journal of International Economics* 84 (1), 73–85.
- [2] Ahn, J., McQuoid, A. F., 2012. Capacity Constrained Exporters: Micro Evidence and Macro Implications. Working Paper.
- [3] Akhmetova, Z., Mitaritonna, C., 2012. A Model of Firm Experimentation under Demand Uncertainty with an Application to Multi-Destination Exporters. University of New South Wales, School of Economics Working Paper.
- [4] Albornoz, F., Calvo Pardo, H. e. F., Corcos, G., Ornelas, E., 2012. Sequential Exporting. *Journal of International Economics* 88 (1), 17–31.
- [5] Alessandria, G., Choi, H., 2009. Do Falling Iceberg Costs Account for Recent US Export Growth? Working Paper.
- [6] Allen, T., 2014. Information Frictions in Trade. *Econometrica* 82 (6), 2041–2083.
- [7] Allen, T., Atkin, D., 2016. Volatility and the Gains from Trade. National Bureau of Economic Research (22276).
- [8] Amiti, M., Freund, C., 2010. The Anatomy of China’s Export Growth. In: *China’s Growing Role in World Trade*. University of Chicago Press, pp. 35–56.
- [9] Arkolakis, C., 2010. Market Penetration Costs and the New Consumers Margin in International Trade. *Journal of Political Economy* 118 (6), 1151–1199.
- [10] Axtell, R. L., 2001. Zipf Distribution of US Firm Sizes. *Science* 293 (5536), 1818–1820.
- [11] Baldwin, R., Harrigan, J., 2011. Zeros, Quality, and Space: Trade Theory and Trade Evidence. *American Economic Journal-Microeconomics* 3 (2), 60–88.
- [12] Bloom, N., Bond, S., Van Reenen, J., 2007. Uncertainty and Investment Dynamics. *Review of Economic Studies* 74 (2), 391–415.
- [13] Blum, B. S., Claro, S., Horstmann, I. J., 2013. Occasional and Perennial Exporters. *Journal of International Economics* 90 (1), 65–74.
- [14] Cameron, A. C., Gelbach, J. B., Miller, D. L., 2011. Robust Inference with Multiway Clustering. *Journal of Business & Economic Statistics* 29 (2), 238–249.
- [15] Chaney, T., 2008. Distorted Gravity: The Intensive and Extensive Margins of International Trade. *American Economic Review* 98 (4), 1707–1721.
- [16] Connolly, M., 2003. The Dual Nature of Trade: Measuring its Impact on Imitation and Growth. *Journal of Development Economics* 72 (1), 31–55.

- [17] Cooper, R. W., Haltiwanger, J. C., 2006. On the Nature of Capital Adjustment Costs. *Review of Economic Studies* 73 (3), 611–633.
- [18] Crozet, M., Koenig, P., 2010. Structural Gravity Equations with Intensive and Extensive Margins. *Canadian Journal of Economics/Revue canadienne d'économique* 43 (1), 41–62.
- [19] Das, S., Roberts, M. J., Tybout, J. R., 2007. Market Entry Costs, Producer Heterogeneity, and Export Dynamics. *Econometrica* 75 (3), 837–873.
- [20] Davis, S. J., Haltiwanger, J., 1992. Gross Job Creation, Gross Job Destruction, and Employment Reallocation. *Quarterly Journal of Economics* 107 (3), 819–863.
- [21] De Sousa, J., Disdier, A.-C., Gaigné, C., 2016. Export Decision Under Risk. CESifo Working Paper Series No. 6134.
- [22] di Giovanni, J., Levchenko, A. A., 2012. Country Size, International Trade, and Aggregate Fluctuations in Granular Economies. *Journal of Political Economy* 120 (6), 1083–1132.
- [23] Dixit, A., 1989. Entry and Exit Decisions under Uncertainty. *Journal of Political Economy*, 620–638.
- [24] Eaton, J., Kortum, S., 2001. Trade in Capital Goods. *European Economic Review* 45 (7), 1195 – 1235, international Seminar On Macroeconomics.
- [25] Eaton, J., Kortum, S., Kramarz, F., 2004. Dissecting Trade: Firms, Industries, and Export Destinations. *American Economic Review* 94 (2), 150–154.
- [26] Elliott, R. J. R., Jabbour, L., Zhang, L., 2016. Firm Productivity and Importing: Evidence from Chinese Manufacturing Firms. *Canadian Journal of Economics/Revue canadienne d'économique* 49 (3), 1086–1124.
- [27] Fillat, J. L., Garetto, S., 2015. Risk, Returns, and Multinational Production. *Quarterly Journal of Economics* 130 (4), 2027–2073.
- [28] Fitzgerald, D., Haller, S., Yedid-Levi, Y., 2016. How Exporters Grow. Tech. rep., National Bureau of Economic Research.
- [29] Foster, L., Haltiwanger, J., Syverson, C., 2008. Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability? *American Economic Review* 98 (1), 394–425.
- [30] Frankel, J., Rose, A., 2002. An Estimate of the Effect of Common Currencies on Trade and Income. *Quarterly Journal of Economics*, 437–466.
- [31] Gaulier, G., Zignago, S., 2010. BACI: International Trade Database at the Product-Level. The 1994-2007 Version. CEPII Working Papers (Working Papers 2010-23).

- [32] Giovanni, J. d., Levchenko, A. A., 2009. Trade Openness and Volatility. *Review of Economics and Statistics* 91 (3), 558–585.
- [33] Glick, R., Rose, A. K., 2002. Does a Currency Union Affect Trade? The Time-Series Evidence. *European Economic Review* 46 (6), 1125–1151.
- [34] Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., Topalova, P., 2010. Imported Intermediate Inputs and Domestic Product Growth: Evidence from India. *Quarterly Journal of Economics* 125 (4), 1727–1767.
- [35] Guimarães, P., Portugal, P., 2009. A Simple Feasible Alternative Procedure to Estimate Models with High-Dimensional Fixed Effects. Tech. rep., IZA discussion papers.
- [36] Guiso, L., Parigi, G., 1999. Investment and Demand Uncertainty. *Quarterly Journal of Economics* 114 (1), 185–227.
- [37] Halpern, L., Koren, M., Szeidl, A., 2015. Imported Inputs and Productivity. *American Economic Review* 105 (12), 3660–3703.
- [38] Handley, K., Limao, N., 2012. Trade and Investment under Policy Uncertainty: Theory and Firm Evidence. NBER Working Paper.
- [39] Handley, K., Limão, N., 2013. Policy Uncertainty, Trade and Welfare: Theory and Evidence for China and the US. NBER Working Paper 19376.
- [40] Head, K., Mayer, T., Ries, J., 2010. The Erosion of Colonial Trade Linkages after Independence. *Journal of International Economics* 81 (1), 1–14.
- [41] Heiland, I., 2016. Global Risk Sharing through Trade in Goods and Assets: Theory and Evidence.
- [42] Helpman, E., Melitz, M., Rubinstein, Y., 2008. Estimating Trade Flows: Trading Partners and Trading Volumes. *Quarterly Journal of Economics* 123 (2), 441–487.
- [43] Helpman, E., Melitz, M. J., Yeaple, S. R., 2004. Export versus FDI with Heterogeneous Firms. *American Economic Review* 94 (1), 300–316.
- [44] Hsieh, C.-T., Ossa, R., 2011. A Global View of Productivity Growth in China. NBER Working Paper 16778.
- [45] Hummels, D., Klenow, P., 2005. The Quality and Variety of a Nations Trade. *American Economics Review* 95 (3), 704–723.
- [46] Impullitti, G., Irarrazabal, A. A., Oromolla, L. D., 2013. A Theory of Entry into and Exit from Export Markets. *Journal of International Economics* 90 (1), 75–90.
- [47] Jones, C. I., 2011. Intermediate Goods and Weak Links in the Theory of Economic Development. *American Economic Journal: Macroeconomics* 3 (2), 1–28.

- [48] Kee, H. L., Nicita, A., Olarreaga, M., 2008. Import Demand Elasticities and Trade Distortions. *Review of Economics and Statistics* 90 (4), 666–682.
- [49] Koren, M., Tenreyro, S., 2007. Volatility and Development. *Quarterly Journal of Economics* 122 (1), 243–287.
- [50] Kramarz, F., Martin, J., Mejean, I., 2016. Volatility in the Small and in the Large: The Lack of Diversification in International Trade.
- [51] Leahy, J. V., Whited, T. M., 1996. The Effect of Uncertainty on Investment: Some Stylized Facts. *Journal of Money, Credit and Banking* 28 (1), 64–83.
- [52] Lee, J.-W., 1995. Capital Goods Imports and Long-run Growth. *Journal of Development Economics* 48 (1), 91–110.
- [53] Manova, K., Yu, Z., 2012. Firms and Credit Constraints along the Global Value Chain: Processing Trade in China. NBER Working Paper 18561.
- [54] Manova, K., Zhang, Z., 2012. Export Prices Across Firms and Destinations. *Quarterly Journal of Economics* 127 (1), 379–436.
- [55] Melitz, M. J., 2003. The Impact Of Trade On Intra-Industry Reallocations And Aggregate Industry Productivity. *Econometrica* 71 (6), 1695–1725.
- [56] Milgrom, P., Segal, I., 2002. Envelope Theorems for Arbitrary Choice Sets. *Econometrica* 70 (2), 583–601.
- [57] Nguyen, D. X., 2011. Demand Uncertainty: Exporting Delays and Exporting Failures. *Journal of International Economics* 86 (2), 336–344.
- [58] Nicita, A., Olarreaga, M., 2007. Trade, Production, and Protection Database, 1976–2004. *World Bank Economic Review* 21 (1), 165–171.
- [59] Olabisi, M., 2017. The Impact of Exporting and Foreign Direct Investment on Product Innovation: Evidence From Chinese Manufacturers. *Contemporary Economic Policy* 35 (4), 735–750.
- [60] Pindyck, R. S., 1982. Adjustment Costs, Uncertainty, and The Behavior Of The Firm. *American Economic Review*, 415–427.
- [61] Piveteau, P., 2015. An Empirical Dynamic Model of Trade with Consumer Accumulation. Tech. rep., Working Paper, Columbia University.
- [62] Ramondo, N., Rappoport, V., 2010. The Role of Multinational Production in a Risky Environment. *Journal of International Economics* 81 (2), 240–252.
- [63] Ramondo, N., Rappoport, V., Ruhl, K. J., 2013. The Proximity-Concentration Tradeoff Under Uncertainty. *Review of Economic Studies* 80 (4), 1582–1621.

- [64] Rob, R., Vettas, N., 2003. Foreign Direct Investment and Exports with Growing Demand. *Review of Economic Studies* 70 (3), 629–648.
- [65] Soderbery, A., 2013. Market Size, Structure, and Access: Trade with Capacity Constraints. Working Paper.
- [66] Staiger, R. W., Wolak, F. A., 1992. The Effect of Domestic Antidumping Law in the Presence of Foreign Monopoly. *Journal of International Economics* 32 (3), 265–287.
- [67] Timoshenko, O. A., 2015. Product Switching in a Model of Learning. *Journal of International Economics* 95 (2), 233–249.
- [68] Viner, J., 1922. The Prevalence of Dumping In International Trade. *Journal of Political Economy* 30 (5), 655–680.

A Appendix

A.1 Empirics: Data, Variable Definitions and Supplementary Tests

A.1.1 Exporter-Level Data

Firm level export choices are taken from the universe of Chinese export transactions between 2000 and 2006, collapsed to annual values for firms in each product-market. This dataset identifies the year of trade, firms by unique IDs, the countries to which they export, and the products sent to each product-market destination. The full data set exceeds 24 million observations. The raw data report the f.o.b. value of exports in nominal U.S. dollars in an unbalanced table of more than 240,000 firms, 200 importing countries and about 4,100 HS6 product categories. This rich dataset provides no identifiers for buyers in overseas markets, unfortunately. Thus, each product-market destination conceptually stands for one representative consumer.

To link this data to the product-market destinations identified in the COMTRADE data, I match the two sources on countries and product categories. The product categories are originally reported as eight-digit HS categories in the firm-level data, of which the leading 6 digits correspond to standardized categories.¹⁷ To ensure that the product category definitions remain consistent over time, I convert all years to the 1992 HS standard using the concordances provided by the UN at <http://unstats.un.org/unsd/trade/conversions/>

¹⁷The 6-digit harmonized system (HS6) is a global standard used for reporting trade between most countries; revisions to its roughly 5,000 product categories occurred in 1996, 2002 and 2007. Each country may have more detailed HS8 or HS10 categories that further refine the HS6 product categories

`HSCorrelationandConversiontables.htm`. The product-market destination data that I describe next are reported using the 1992 HS standard. I complete the matching between the two data sources by mapping the country-codes in the export data to the standardized ISO categories used by COMTRADE.

For Chinese exporters, 2000 to 2006 was a period of notable economic growth and market entry. It spans China's entry into the WTO at the end of 2001, which lowered trade costs, reduced internally mandated barriers to trade and created export opportunities for Chinese firms. The nominal dollar value of Chinese goods exports nearly quadrupled to \$968bn in 2006 from \$250bn 2000. A large share of this growth was at the extensive margin —the number of exporters went from 62,600 to more than 170,000. (Table A1 decomposes this growth in exporter numbers into its intensive and extensive margins).¹⁸ Among firms that remained exporters, entry into new product-market destinations was pervasive. Four out of five exporters entered new product-markets in the average year.¹⁹

The first panel shows exporter numbers nearly tripled from 2000 to 2006. The last three columns in each panel break down the annual changes into entry (column C), exits (column D) and holdovers (column B). The increase in the number of exporters fits the pattern expected for trade liberalization with WTO accession.

Entry is also the dominant dynamic at the finer level of firm-destination combinations (in the second panel). Here, turnover rates are higher. The fact that many exporters exit a destination in one year only to return in a later year supports this paper's approach to defining entry over periods longer than a year.

A.1.2 Product-Country Destination Data

Global trade in nominal US dollar terms grew at an average annual rate of 7% to reach \$12tn in 2006, covering more than 220 countries and 5,000 HS6 products. Approximately 990,000 unique product-market destinations registered imports in the COMTRADE database, though many had zero demand in several years. The COMTRADE database indicates a moderate expansion from 695,000 to 738,000 between 2000 and 2006. (In the same period, product-market destinations served by Chinese exporters increased by 64% – from 179,000 to 292,000).

¹⁸See Ahn et al. (2011); Manova and Yu (2012) for fuller descriptions of how WTO accession reduced trade costs for Chinese exporters.

¹⁹The average exporter in 2000 served 28 product-market destinations - 13 countries and 7 HS6 products, while the corresponding number for 2006 was 34 (16 countries and 8 products). The distribution of Chinese exporter participation is skewed —40 firms on average served each product-market destination, but the median exporter count was 5. The reported central moments exclude product-market destinations with zero Chinese exporters.

Table A1: Exporter Dynamics in China: 2000 - 2006

Year	Exporter Count $A = B + C$	Incumbents $B = A_{t-1} - D$	Entrants C	Leavers D
2000	62,603			
2001	68,347	52,201	16,146	10,402
2002	78,567	57,263	21,304	11,084
2003	95,627	68,506	27,121	10,061
2004	120,363	82,858	37,505	12,769
2005	143,583	103,724	39,859	16,639
2006	170,642	124,419	46,223	19,164

	Exporter-Destination Count $A = B + C$	Incumbents $B = A_{t-1} - D$	Entrants C	Exits D
2000	1,782,803			
2001	2,011,808	696,379	1,315,429	1,086,424
2002	2,464,544	828,853	1,635,691	1,182,955
2003	3,076,358	1,059,347	2,017,011	1,405,197
2004	3,827,074	1,307,810	2,519,264	1,768,548
2005	4,846,699	1,593,626	3,253,073	2,233,448
2006	5,895,393	1,907,010	3,988,383	2,939,689

The original data set reports more than 63 million observations of trade at the HS6 product level for importing and exporting country-pairs in years from 1995 to 2005. (The full dataset goes to 2012, but only the first 11 years are usable as history because the firm level data stops in 2006). I collapsed this data to importing country-HS6 combinations for each of the years, noting that HS6 categories remain consistent over time. The original data reports for all years in the 1992 version of the HS6 system (Gaulier and Zignago, 2010). This collapsed form represents the history of imported demand into each product-market destination in the analysis. I expand the data to a balanced panel of 11 years for all destinations. This identifies instances of zero-demand. (Missing data is coded as zero). Market sizes and demand volatility come from this expanded data.

To facilitate replication, Table A2 shows variables used but not reported in Tables 3 and 4 to test the relationship between demand volatility and the number of Chinese exporters that enter a product-market destination. They are from Head et al. (2010).

Table A2: Additional Regression Variables

VARIABLES	N	Mean	Std. Dev.	Min.	Max.
GDP	289801	10.06095	2.438002	4.258556	16.39586
GDP per Capita	288048	8.018416	1.572457	4.634483	11.11192
Log(Distance)	346217	8.989019	.5693675	6.925665	9.857974
Log(Remoteness)	346217	-9.105768	.4982548	-10.53251	-8.298696
Contiguity	346217	.0830606	.2759742	0	1
Language	346217	.0277225	.1641769	0	1
Legal Origin	346217	.1771115	.3817636	0	1
GATT/WTO	346217	.7430744	.4369386	0	1

GDP: GDP of the importing country

GDP per Capita: of the importing country

Distance: from China to the importing country

Remoteness: Geographic remoteness, i.e. country's GDP-weighted distance from all countries

Contiguity: Dummy indicating whether country has shared borders with China

Language: Dummy indicating whether country shares ethnic or official languages with China

Legal Origin: Dummy indicating whether country shares legal origin with China

GATT/WTO: Whether importing country was a member of WTO

A.1.3 Product and Country Variation in Demand Volatility

Country-specific factors explain as much of the variation in demand volatility as product-specific factors. This is consistent with the patterns observed for output volatility (Koren and Tenreyro, 2007).

Table A3 presents linear regressions of demand volatility on product-market destination size. The first panel in the table is limited to product-market destinations with at least one Chinese exporter, while the second panel extends the regressions to include all destinations with aggregate demand volatility data. Although destination size explains a notable share of the variation in demand volatility in the first panel, it is interesting to note that country-specific factors also explain a larger share than product specific factors. This comes from a comparison of columns 1 and 2. When combined with destination size, the two sets of fixed effects explain comparable incremental shares of the variation in the dependent variable, if one compares the R^2 values in columns 4 and 5.

The second panel of Table A3 follows the same pattern as the first panel; smaller destinations tend to have higher demand volatility. (This called for the inclusion of market size as a control in the regressions that I report in the main body of the paper). Furthermore, product-fixed effects generally explain less of the variation in demand volatility if one does not control for destination size. As expected, destination size is driven in part at the

Table A3: Demand Volatility: Product and Country Fixed Effects
(Dependent Variable: Demand Volatility)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Size			-0.02*** (0.00)	-0.02*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
Constant	0.08*** (0.00)	0.08*** (0.00)	0.21*** (0.00)	0.23*** (0.00)	0.19*** (0.00)	
Observations	259,963	259,963	259,963	259,963	259,963	259,963
R-squared	0.10	0.15	0.15	0.25	0.20	0.31
Product FE	Y			Y		Y
Country FE		Y			Y	Y
For All Destinations						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Size			-0.02*** (0.00)	-0.02*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
Constant	0.08*** (0.00)	0.08*** (0.00)	0.21*** (0.00)	0.22*** (0.00)	0.19*** (0.00)	
Observations	708,802	708,802	708,802	708,802	708,802	708,802
R-squared	0.09	0.14	0.15	0.24	0.20	0.29
Product FE	Y			Y		Y
Country FE		Y			Y	Y

Robust standard errors in parentheses. Errors clustered by HS6 products.

*** p<0.01, ** p<0.05, * p<0.1

Notes: The units of observation are destinations: unique HS6-product and country combinations, e.g., Irish imports of bicycles (HS 871200). Demand volatility is the sum of the squared deviations of demand from a linear trend over the years 1995 to 2005. destination size is the sum of aggregate demand in each destination from 1995 to 2005.

country-level. Larger economies import more of most product categories.

A.1.4 Sector- and Product- Differences in Adjusting Production Scale

Deriving the implied adjustment costs for each sector called for the use of the China Annual Industrial Survey Database. This firm-level database is a census of industrial firms with sales above RMB 5 million, complemented with a random sample of firms below the threshold. (Olabisi (2017) used the same dataset, and describes in greater detail). The database provides information on the output, sales, assets, employment and sector of each firm. The dataset was collapsed to sector-year observations, so that sectors can be matched eventually to product categories in the trade data. The implied adjustment costs came from the following linear regression: $growth_{st}^{Output} = \beta_1^g growth_{st}^{assets} + \beta_2^g growth_{st}^{emp} + \epsilon^g$. s represents 4-digit sectors in the Chinese Industrial Classification scheme. I run the regressions separately for each of the approximately 400 sectors, and saved the coefficients β_1 and β_2 for each sector. The growth terms in the equation represent the mid-point year-on-year growth rate of the variable, ($growth_{st} = 2 * (Output_{st} - Output_{st-1}) / (Output_{st} + Output_{st-1})$). The β s represent the implied adjustment costs for each sector.

The regressions in Table 5 use a categorical variable from grouping products into two categories – high and low implied adjustment costs. The 4-digit sectors from the Chinese firm-level data were matched to HS6 products using a combination of HS6-ISIC concordances from the World Bank’s WITS database, and a concordance of the Chinese Industrial Classifications to ISIC.

Table A4 shows the same table, but uses categories of the implied employment adjustment measure β_2^g , (rather than assets). The pattern of coefficients is similar to Table 5. The results imply that exporters are more sensitive to demand volatility for sectors and products with high employment adjustment costs, and therefore, relatively fewer exporters will be observed to enter product-market destinations with high demand volatility for those sectors. This finding lines up with the predictions of the model of trade with stochastic demand outlined in the paper.

A.1.5 Annual Exporter Counts and Demand Volatility

To exploit the annual variations in export flows and exporter counts, Table A5 provides results of regressions structured after conventional gravity model estimations. The regressions include estimates with country-year fixed effects in the even-numbered columns.

Table A4: Exporter Entry by High and Low (Employment) Adjustment Sectors
(Dependent Variable: Export Entry in Product-Market Destination)

VARIABLES	(1)	(2)	(3)	(4)
	Low Adjustment		High Adjustment	
Demand Volatility	-0.92*** (0.171)	-1.11*** (0.131)	-0.37** (0.149)	-0.69*** (0.094)
Prod. Market Size	0.48*** (0.020)	0.28*** (0.015)	0.42*** (0.021)	0.26*** (0.010)
Observations	64,849	64,848	109,358	109,357
R-squared	0.62	0.76	0.60	0.76
Country FE	N	Y	N	Y
Product FE	Y	Y	Y	Y

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: The units of observation are product-market destinations: unique HS6-product and country combinations, e.g., Irish imports of bicycles (HS 871200). Only HS6 products that could be matched to the Chinese industry categories were included. Adjustment represents the scale of changes over time in assets to changes in output. Export entry captures the number of firms that served a product-market destination from 2002-2006, after China's WTO accession.

Table A5: Annual Trade Estimates with Demand Volatility
(Dependent Variable: Log Export Measure by Year)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Exports)		Log(Exporter Counts)		Log(Exports per Exporter)	
Demand Volatility	-2.619*** (0.084)	-2.398*** (0.083)	-1.201*** (0.040)	-0.921*** (0.041)	-1.418*** (0.056)	-1.477*** (0.054)
Log(GDP)	0.687*** (0.006)		0.343*** (0.003)		0.345*** (0.003)	
Log(GDP per Capita)	-0.095*** (0.006)		0.016*** (0.003)		-0.111*** (0.004)	
Log(GDP China)	2.983*** (0.051)		1.848*** (0.027)		1.134*** (0.034)	
Log(Distance)	-0.573*** (0.011)		-0.372*** (0.005)		-0.200*** (0.007)	
Constant	19.190*** (0.275)		8.133*** (0.127)		11.056*** (0.186)	
Observations	1,485,716	1,590,273	1,485,716	1,590,273	1,485,716	1,590,273
R-squared	0.435	0.442	0.570	0.575	0.329	0.340
Country FE		Y		Y		Y
Product FE	Y	Y	Y	Y	Y	Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The units of observation are product-market destination- years: unique year, HS6-product and country combinations, e.g., Irish imports of bicycles (HS 871200) in 2006. The dependent variable is log (the number of firms with recorded exports to a destination) in each of the years between 2000 and 2006. Size is the value of all imports into each product-market destination, for the respective year.

The results indicate that demand volatility decreases export volumes and exporter counts, just as in Table 4. Unlike Table 4, the dependent variables here measure annual export volumes and exporter numbers like most gravity model estimations.²⁰ In this table, exports per exporter decrease with increased volatility, another point of difference with the cumulative version in the main body of the paper. However, this table does not include full-fixed effects for China, only its GDP is included as an additional control for changes over time.

To address concerns about time-varying factors like exchange rate volatility, country-specific shocks or trade deals, the even-numbered columns include country-year fixed effects. These improve the estimated coefficients, usable observations and explained variation. A caveat is necessary: The demand volatility term used in this table does not change over time, nor do the country-level measures like GDP change within products for each country. In other words, the estimated variables are not well matched. (Variants of this table that include the product-market destination size term, or a measure of logged annual imports from all product-market destinations also predict smaller exporter numbers with higher demand volatility, even if they do not consistently predict lower volumes).

A.1.6 Comparing Demand Volatility with Other Predictors

Table A6 shows simple OLS regressions of exporter counts on demand volatility, GDP, distance, and product-market destination size. This regression with omitted variables provides only correlations to facilitate comparisons. The correlations suggest that analyses of trade and exporter counts could benefit from a consideration of demand volatility.

The R^2 values reported in the table alone indicate that demand volatility compares favorably with conventional predictors in explaining the variation in exporter counts. Comparing each variable's column and column 5, which includes all predictors, provides further evidence. The sign and statistical significance of demand volatility remains consistent between columns (1) and (5). Of the other variables, only product-market destination size explains as much of the variation in exporter counts.

A.1.7 Standard Deviation of Growth as a Measure of Demand Volatility

This paper's primary definition of demand volatility is:

$$\hat{\sigma}_{jk}^2 = \sum_t (\epsilon_{jkt})^2$$

²⁰ One could try to reconcile this to the model with claims that each year represents its own equilibrium; a claim that requires justification, but that may change how demand volatility should be defined.

Table A6: Comparing Demand Volatility and Conventional Predictors of Trade
(Dependent Variable: Log Number of Exporters)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Demand Volatility	-5.156*** (0.054)				-0.607*** (0.034)
Log(GDP)		-0.001 (0.001)			0.001 (0.001)
Log(Distance)			0.002 (0.005)		0.001 (0.004)
Destination Size				0.431*** (0.003)	0.421*** (0.003)
Constant	2.286*** (0.003)	1.938*** (0.011)	1.917*** (0.041)	-1.822*** (0.026)	-1.717*** (0.047)
Observations	371,531	289,801	346,217	371,531	276,459
R-squared	0.287	0.217	0.215	0.544	0.546
Product FE	Y	Y	Y	Y	Y

Robust standard errors in parentheses. Errors clustered by HS6 products.

*** p<0.01, ** p<0.05, * p<0.1

The units of observation are product-market destinations: unique HS6-product and country combinations, e.g., Irish imports of bicycles (HS 871200). The dependent variable is the log of the count of unique firms with recorded exports to a product market between 2000 and 2006. Destination size is the value of all imports into each product-market destination in 2000-2006. The other variables follow conventional definitions.

The residuals, ϵ_{jkt} come from the regression :

$$\frac{Q_{jkt}}{\sum_t Q_{jkt}} = \eta_{jkt} + \alpha_{jk} + \epsilon_{jkt}$$

The alternative definition of demand volatility *volat* is the standard deviation (or variance) of growth:

$$volat = \frac{1}{H} \sum (\hat{\nu}_{jkt} - \bar{\nu}_{jk})^2$$

$\hat{\nu}_{jkt} \simeq (Q_{jkt} - Q_{jkt-1})/Q_{jkt-1}$ is the year-to-year growth of aggregate demand for the product-market destination, and $\bar{\nu}_{jk}$ is the average growth for destination jk .

With sufficiently low growth rates, the ϵ term in equation (19) can be approximated by $\hat{\nu} - \bar{\nu}$, as the average growth term captures both the intercept and the trend term in that equation. With this assumption of low average growth rates, the two definitions of demand volatility become approximate scaled versions of one another.

A.2 Model Features

A.2.1 The Envelope Theorem Allows Optimal $\bar{Q} = E(q)$

Exporters maximize expected profits in the model by working with two parameters: [1] they set prices p , which is equivalent to setting quantities q in monopolistic competition and [2] they set production scale \bar{Q} , given that deviations of q from \bar{Q} are costly, as defined in equation (5).

The Envelope Theorem justifies the approach of treating this optimization as a one-parameter choice, with the second parameter, in this case q^* fixed at the optimal level. Formally, if profits are a function of both the production scale \bar{Q} and prices (which predicts actual quantities sold), the set of optimal profits with respect to prices should be at values of \bar{Q} that maximize profits.

Formally, one may define profits as the objective, prices as the parameter that determines profits and the production scale \bar{Q} as the maximizer. In optimizing, i.e. setting the derivative equal to zero, the derivative of the profit objective with respect to the production scale equals the partial derivative of profits with respect to prices or quantities, holding the maximizer fixed at its optimal level. Expected profits $E(\Pi)$ is a function of both p and q^* :

$$\max_p E(\Pi) = \max_{\bar{Q}} E(\Pi) \implies \frac{\delta E(\Pi)}{\delta p} = 0 \Big|_{\frac{\delta E(\Pi)}{\delta \bar{Q}} = 0} \quad (24)$$

Prices should map one-to-one to quantities, given equation (3), thus one can maximize the preceding equation with respect to q .

In the main body of the paper, I assume production scale will always be set to $E(q)$, and justify the claim with the Envelope Theorem. Here I provide the formal derivation. The optimization exercise fixes quantities and prices for trade in monopolistic competition, with the optimal exporters' production scale \bar{Q} :

$$\begin{aligned} \frac{dE(\Pi)}{d\bar{Q}} &= 0 \\ &= \frac{dE(\Pi)}{dE(a)} \frac{dE(a)}{d\bar{Q}} \end{aligned} \quad (25)$$

a is the adjustment parameter in equation (4). The next steps below show that the quadratic form in (5) is not needed to derive the argument that $\bar{Q} = E(q)$. From equation (4), $\frac{dE(\Pi)}{dE(a)} \neq 0$, therefore:

$$0 = \frac{dE(a)}{d\bar{Q}} \quad (26)$$

$$\begin{aligned} \frac{dE(a)}{d\bar{Q}} &= \frac{d[\gamma \left(\frac{E(q)-\bar{Q}}{\bar{Q}}\right)^2]}{d\bar{Q}} \\ &\implies \bar{Q} = E(q) \end{aligned} \quad (27)$$

This leaves us with a one-parameter optimization, as long as the production scale is fixed at expected quantities.

The Envelope Theorem has also been applied to the analysis of incentive constraints in contract theory and non-convex production problems (Milgrom and Segal, 2002).

A.2.2 Trade Volumes with Demand Volatility

In equilibrium, trade volumes are the integral of firm level sales over the distribution of productivities that meet the threshold ϕ_{jk}^* :

$$X_{ijk} = p_{ijk} \bar{Q}_{ijk} = p_{ijk}^{1-\varepsilon} \frac{\bar{Q}_{jk}}{P_{jk}^{1-\varepsilon}}$$

Summing across all firm varieties for product-market destination jk , where $G(\cdot) = 1 - \phi_{ij}^{-\theta_j}$.

$$\begin{aligned}
X_{jk} &= \frac{\bar{Q}_{jk}}{P_{jk}^{1-\varepsilon}} \int_{\phi_{jk}^*}^{\infty} p_{ijk}^{1-\varepsilon} dG(\phi_{ij}) \\
&= \frac{\bar{Q}_{jk}}{P_{jk}^{1-\varepsilon}} \int_{\phi_{jk}^*}^{\infty} \left[\frac{\varepsilon}{\varepsilon-1} \frac{\tau_{jk}(1 + \gamma_j \sigma_{jk}^2)}{\phi_{ij}} \right]^{1-\varepsilon} (\theta_j \phi_{ij}^{-\theta_j-1}) d\phi_{ij} \\
&= \frac{\theta_j \bar{Q}_{jk}}{P_{jk}^{1-\varepsilon}} \left[\frac{\varepsilon \tau_{jk}(1 + \gamma_j \sigma_{jk}^2)}{\varepsilon-1} \right]^{1-\varepsilon} \int_{\phi_{jk}^*}^{\infty} (\phi_{ij}^{-\theta_j-1+(\varepsilon-1)}) d\phi_{ij} \\
&= \frac{\theta_j \bar{Q}_{jk}}{P_{jk}^{1-\varepsilon}} \left[\frac{\varepsilon \tau_{jk}(1 + \gamma_j \sigma_{jk}^2)}{\varepsilon-1} \right]^{1-\varepsilon} \frac{-\phi_{jk}^{*(\varepsilon-\theta_j-1)}}{\varepsilon-\theta_j-1}
\end{aligned} \tag{28}$$

substituting ϕ_{jk}^* from equation (11):

$$X_{jk} = \frac{-\theta_j \varepsilon S_{jk} \left(\frac{\bar{Q}_{jk}}{\varepsilon S_{jk}} \right)^{\frac{\theta_j}{\varepsilon-1}} \left[\frac{\varepsilon \tau_{jk}(1 + \gamma_j \sigma_{jk}^2)}{\varepsilon-1} \right]^{-\theta_j}}{P_{jk}^{-\theta_j} (\varepsilon - \theta_j - 1)} \tag{29}$$

Taking logs, (while noting that $\varepsilon - 1 < \theta$, for sales to be finite):

$$\ln(X_{jk}) = -\theta_j \ln \left[\frac{\varepsilon \tau_{jk}(1 + \gamma_j \sigma_{jk}^2)}{\varepsilon-1} \right] + \frac{\theta_j}{\varepsilon-1} \ln \left(\frac{\bar{Q}_{jk}}{\varepsilon S_{jk}} \right) + \ln \left[\frac{-\theta_j \varepsilon S_{jk}}{P_{jk}^{-\theta_j} (\varepsilon - \theta_j - 1)} \right] \tag{30}$$

Equation (30) implies that trade should decrease with increasing demand volatility. The slope of X with respect to σ^2 in levels and logs is expected to be negative. However, the ε , Q and P , τ and S terms may lead to estimated effects that are smaller than the extensive margin. This pattern is consistent with the assertion in Chaney (2008) that if trade levels change due to changes in costs, the extensive margin dominates.

The intensive margin on the other hand, depends on the productivity distribution. In practice, it should depend on the combination of the productivity slope parameter θ_j and the elasticity of demand ε . For example, exports per exporter $\frac{X_{jk}}{N_{jk}}$ may rise if high demand volatility leads to higher prices that reduce demand, but the slope of the productivity distribution is high enough that the changing export productivity threshold leaves few exporters to meet demand, leading to higher exports per exporter. In principle, it is independent of demand volatility.

Formally;

$$\ln(X_{jk}) - \ln(N_{jk}) = \ln \left[\frac{-\theta_j \varepsilon S_{jk}}{(\varepsilon - \theta_j - 1)N_j} \right]$$

So that:

$$\frac{d \ln \left(\frac{X_{jk}}{N_{jk}} \right)}{d\sigma_{jk}^2} = 0 \quad (31)$$

The relationship in (31) is a distinctive feature of the Pareto distribution of productivity (or the class of power laws in general). For these productivity distributions, any change in the exports per exporter that would have resulted from the changes in prices due to demand volatility is perfectly offset by the change in the number of exporters. This requires the usual assumption of large numbers of atomistic exporters. In the firm level data, the average product is associated with 1300 exporters; the median has 400. In sum, deviations from a Pareto productivity distribution and a small pool of potential exporters may skew the findings away from the prediction in (31). However, it is still expected that the extensive margin dominates the intensive margin, regardless of the exact nature of the productivity distribution or the size of N_j . Chaney (2008) derived a similar relationship between trade levels and trade costs.

Total exported value to product-market destination jk is the integral over the distribution of productivities of firm-level exports, as given in equation (28). The elasticity:

$$\begin{aligned} \frac{d \ln X_{jk}}{d \ln \sigma_{jk}^2} &= \frac{dX_{jk}}{d\sigma_{jk}^2} \frac{\sigma_{jk}^2}{X_{jk}} \\ &= \frac{\int_{\phi_{jk}^*}^{\infty} \frac{dp_{ijk}^{1-\varepsilon}}{d\sigma_{jk}^2} \sigma_{jk}^2 dG(\phi_{ij})}{\int_{\phi_{jk}^*}^{\infty} p_{ijk}^{1-\varepsilon} dG(\phi_{ij})} - \frac{p_{ijk}^{1-\varepsilon}(\phi_{jk}^*) (1 + \gamma_j \sigma_{jk}^2) \frac{d\phi_{jk}^*}{d(1 + \gamma_j \sigma_{jk}^2)} dG(\phi_{ij}^*)}{\int_{\phi_{jk}^*}^{\infty} p_{ijk}^{1-\varepsilon} dG(\phi_{ij})} \end{aligned} \quad (32)$$

intensive margin extensive margin

$$= \frac{\gamma_j(1 - \varepsilon)}{(1 + \gamma_j \sigma_{jk}^2)} - \frac{\gamma_j(\theta_j - \varepsilon + 1)}{(1 + \gamma_j \sigma_{jk}^2)} \quad (33)$$

Because,

$$\frac{\int_{\phi_{jk}^*}^{\infty} \frac{dp_{ijk}^{1-\varepsilon}}{d\sigma_{jk}^2} \sigma_{jk}^2 dG(\phi_{ij})}{\int_{\phi_{jk}^*}^{\infty} p_{ijk}^{1-\varepsilon} dG(\phi_{ij})} = \frac{\gamma_j(1 - \varepsilon)}{1 + \gamma_j \sigma_{jk}^2}$$

and,

$$\frac{p_{ijk}^{1-\varepsilon}(\phi_{jk}^*)(1 + \gamma_j \sigma_{jk}^2) \frac{d\phi_{jk}^*}{d(1 + \gamma_j \sigma_{jk}^2)} dG(\phi_{ij}^*)}{\int_{\phi_{jk}^*}^{\infty} p_{ijk}^{1-\varepsilon} dG(\phi_{ij})} = \frac{\gamma_j(\theta_j - \varepsilon + 1)}{(1 + \gamma_j \sigma_{jk}^2)}$$

given that

$$\frac{d\phi_{jk}^*}{d(1 + \sigma_{jk}^2)} = \frac{\phi_{jk}^*}{(1 + \gamma_j \sigma_{jk}^2)}$$

and,

$$\frac{dp_{ijk}^{1-\varepsilon}}{d\sigma_{jk}^2} = \frac{\gamma_j(1 - \varepsilon)}{(1 + \gamma_j \sigma_{jk}^2)} p_{ijk}^{1-\varepsilon}$$

Equation 33 explains the prominence of the extensive margin.

A.2.3 Demand Volatility and Exporter Size Thresholds

One implication of the model is that product-market destinations with higher demand volatility also have higher exporter productivity thresholds.

From equation (11)

$$\phi_{ij}^* = \frac{\varepsilon}{\varepsilon - 1} \frac{\tau_{jk}(1 + \gamma_j \sigma_{jk}^2)}{P_{jk}} \left[\frac{\varepsilon S_{jk}}{\overline{Q}_{jk}} \right]^{\frac{1}{\varepsilon - 1}}$$

As demand volatility σ^2 increases, so does ϕ^* . This has two implications: first, that more volatile product-market destinations have fewer exporters, holding other factors constant, and that those exporters on average will be the most productive within their product categories. This complements a similar argument for productivity thresholds and sunk costs in related papers (Helpman et al., 2004; Melitz, 2003).

Figure 4 in the main body of the paper portrays this idea, taking the predictions of the following equation:

$$\psi_{jk} = \beta_0^\psi \hat{\sigma}_{jk}^2 + \beta_1^\psi X_{jk} + \alpha_j^\psi + \epsilon_{jk}^\psi \tag{34}$$

where $\psi_{jk} \in [1, 10]$ is defined as,

$$\psi_{jk} = \frac{1}{N_{jk}} \sum_i Rank_{ij}$$

and $Rank_{ij} \in [1, 10]$ indicates firm i 's export value decile for product j .

X_{jk} = a vector of gravity model variables e.g., GDP, distance

α_j = product fixed effects

$\hat{\sigma}_{jk}^2$ = dummy indicating one of 50 quantiles for demand volatility

The increase in ϕ^* associated with demand volatility in (11) implies that the average rank should be higher for product-market destinations with high demand volatility. The higher threshold implies a marginal increase in the average productivity, and size of observed exporters.



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