

LEARNING TO EXPORT: EXPORT GROWTH AND THE DESTINATION DECISION OF FIRMS

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Abstract

In this paper, I find evidence that the geographic expansion of firm exports occurs slowly over time and that a large share of export growth is due to incumbent exporters entering new destinations. I also show that aggregated trade data can underestimate this value and hide the differing composition of export destinations by entering and incumbent exporters. New exporters enter large countries and destinations with characteristics similar to their domestic market. Less similar, distant or less developed countries are entered by firms already exporting to other destinations. I formulate a dynamic general equilibrium model to test if these patterns are due to firms learning how to export (as other recent empirical findings have suggested), or exogenous factors such as productivity growth. In this model, heterogeneous firms experience learning in the form of market entry costs that depend on export history. When calibrated to Russian firm level data, I find that learning plays a significant role in explaining the observed entry patterns, which standard trade models cannot account for. Additionally, by taking learning into account and targeting particular export destinations, governments can better assess the impact of liberalizations.

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1 Introduction

Recent evidence suggests that firms' export participation decisions are dynamic and driven by accumulation of export experience. Using data on Russian firm level exports, I show that the geographic expansion of firm exports occurs slowly, with the majority of firms initially entering just one destination, then slowly entering more. Additionally, the composition of entry destinations differs between new exporters and continuing exporters and a surprisingly large share of exports (13+%) are due to continuing exporters entering new destinations.

Current trade theories have a difficult time explaining why firms make slow and deliberate entry decisions. Because current theories don't account for geographic diffusion of firm exports, effects of trade liberalizations wrongly estimate the benefits of trade growth. To amend this, I propose a model where firms learn how to export in the setting of a Melitz (2003) model of trade with monopolistically competitive firms. Learning in my model can be thought of as learning by doing. For example, as firms enter destinations, they learn how to set up export operations and best ways to service destination groups (such as Latin American countries). The model I develop, apart from learning, includes a world with non-symmetric export destinations and heterogenous firms making export location and quantity decisions. The model provides a new margin of exports: it has the usual intensive margin of exports where a firm previously exporting to a destination exports more of their good to that existing destination, an extensive margin where new firms enter the export market, and an additional extensive margin where continuing exporters enter new locations.

The data on Russian External Economic Activities REEA (2004) is rather unique as it includes bilateral exports by firm and product (at the shipment level) over the years 2003-2004. Using the micro features of this data, I calibrate my model and show that the dynamic aspect of learning to export explains much of the observed entry patterns, while exogenous factors alone (such as productivity growth) do not.

That firms make dynamic entry decisions alters the characteristics of exporter types we would otherwise expect to observe. For example, smaller, less productive firms have greater incentive to initially enter the export market because they know they will learn how to better enter future destinations. I show that this difference in exporter characteristics greatly affects the outcome of different types of trade liberalizations for developing and transitional economies.

Failing to account for learning will lead us to overestimate the export growth that would result from a liberalization that reduces fixed entry costs. This is due to underestimating the number of firms participating in the export market, and overestimating the overall productivity of firms that do participate. Liberalizations which decrease tariffs will underestimate export growth due to ignoring the fact that higher per period profits are incentive for firms to enter the targeted destination and learn to enter additional ones. Additionally, I show by taking learning into account, destinations otherwise not targeted with liberalizations provide the largest gains to trade.

Learning by doing is widely accepted in the business management and organization literature. Wright (1963), a paper studying the airframe industry, was the first to show that unit labor inputs declined with firm output (and that this learning occurs within the bound of the firm, not industry). The learning by doing mechanism in my model is in the form of cost savings in exporting, through accumulated export experience. I call this “learning to export” in order to differentiate this class of learning from other forms of learning discussed in the literature. One type of learning studied is “learning by exporting” (Clerides et al. (1998)), refers to the question of whether higher productivity firms export due to self selection or increased productivity through exporting. Other types of learning studied are spillovers as well as learning about unknowns of firm potential or destination characteristics.

Only in the past decade has the emergence of customs data allowed trade economists to empirically analyze firm export behaviors. Additionally, panel data on firm bilateral trade has only been collected and released in the past few years. Eaton et al. (2007) analyze Colombian firm level export data over the period 1996-2005. Similar to my findings, they show that cohorts of firms entering the export market either soon exit, or expand foreign sales by expanding into additional destinations. They find that certain foreign markets tend to serve as “testing grounds” for new exporters. Neighboring markets act as stepping stones for other Latin American markets, and once firms successfully penetrate neighboring and other Latin American locations, they are more likely to reach larger OECD markets, but not vice versa.

Alvarez, Faruq, and Lopez (Alvarez et al.), using Chilean firm data, find that firms’ experience from exporting a product to a market increases the probability of the firm exporting the same product to a new market.

The contribution of this paper is in theoretically analyzing the effect of learning to export in a model reflecting real world destination choices of firms. I show that when calibrated to Russian firm level exports, this dynamic aspect allows me to better explain the patterns of entry observed in the data. Finally, I will show that by taking into account learning, governments in developing and transitional economies can target particular export destinations in order to efficiently increase export growth.

Section 2 describes the Russian firm level data, section 3 describes my model and shows the importance of including firm dynamic choice in capturing slow entry into destinations. Section 4 describes my computational strategy and method of calibration, Section 5 looks at policy implications. Finally, section 6 concludes.

2 Data

While many countries are beginning to report some details on firm export activities, currently, very few countries report destination specific firm export activities over extended periods of time. The Russian External Economic Activities (REEA), reported by Russian

customs, is an exception to this. In particular, I have reports for each shipment of exporting firms throughout 2003 and 2004. In this section, I summarize the exporting activities of firms, focusing on destination decisions. I show that conditional on firms entering new destinations, they do so slowly. The value of these new exports, I show, contributes a large amount to total exports. Additionally, I show differing composition of entry destinations between new exporters and continuing exporters.

The REEA data is shipment level customs data of uniquely identified firms over the years 2003 and 2004, providing date of shipment, value of goods shipped (in nominal USD), weight of shipment, and destination country. Goods are classified according to the Commodity Classification for Foreign Economic Activities (CC-FEA). Although I have only two years of data, it is important to recall that these are shipments, so I can track a firm's market participation by day, month, year, etc.

To overcome the time constraint, I aggregate firm shipments into monthly reports of firm bilateral exports. To overcome seasonal effects, and take advantage of the rich data, I compare export activity across months. For example, for each analysis, I compare January 2003 exports to January 2004 exports, and do so for each corresponding month. To smooth out the data, I consider an entrant to be a firm that did not export at all in 2003, but exported a positive amount in 2004. A continuing entrant must have exported a positive amount in 2003, and in 2004 exported positive amounts to destinations it never exported to in 2003. I do comparisons for each month pair, but present results from the January comparisons. (Similar results occur if I average over the 12 month pairs, or aggregate across the 12 months.)

Although very few countries report customs level data, a very rich source of data is product level bilateral trade data. I compare the firm level data to the 4 digit Standard International Trade Classification (SITC) bilateral trade data, reported by the United Nations UN (2009), in order to see what information we miss from not looking at firm level trade. Both the REEA and SITC report free on board (FOB) exports in nominal USD. (I convert all values to 2000 USD using the producer price index for finished goods.) The SITC and REEA have different sources of data. Unlike the REEA, the UN does not have customs data reported to them, but collects reports by enterprises and presents them in SITC. For both, I only look at exports of manufactured goods. While the two reports do not aggregate to the same level of exports, in 2003, firm reported total exports from the REEA accounts for 88% of SITC exports.

In order to compare the CC-FEA itemization of goods to the SITC, I create a concordance that goes from SITC4 to CC-FEA. The concordance is shown in Table 8 (appendix) and results in 56 goods. Figure 2 (appendix) shows that total exports by destination are positively correlated with number of products for both sets of data. When looking at the correlation between number of destinations exported to by number of products, there is not much relationship because my concordance is crude (though at the firm level, there is a negative correlation of -71%, and -72% at the UN product level). Hence, we see that both sets of

Table 1: Contribution of Entrant Type

Data	Entrants $\frac{\text{entrant exports}_{\text{year } b}}{\text{total exports}_{\text{year } b}}$	Continuing Entrants $\frac{\text{inc. entrant exports}_{\text{year } b}}{\text{total exports}_{\text{year } b}}$
Firm Level 2003-2004, 9474 firms	.31	.13
SITC 2003-2004, 454 products	0	.03
According to concordance, 56 products		
Sectoral (REEA) 2003-2004	0	.02
Sectoral (SITC) 2003-2004	0	.01

data display similar trends at an aggregate level.

2.1 Contribution of entrant types

In Table 1, I show the contribution of exporter entrants and continuing exporters entering new markets to total end of period exports. We see that, at the firm level, 31% of January 2004 exports consist of exporter entrants. Additionally, 13% of exports consist of exporters entering new destinations, i.e. destinations they never exported to in 2003. The second row of Table 1 looks at contributions at the product level. In 2004, 0% of exports are from products exported in only 2004, and 3% of exports are from previously exported products shipped to new destinations.

When comparing the CC-FEA and SITC data, both aggregated according to the concordance, we again see similarities between the two sets. The bottom half of Table 1, shows that, according to the concordance, there is no entry, and very little continuing entry into new destinations from both CC-FEA and SITC. What we should take from this is that the more aggregated the data, the less entry we observe. In Lande-Schmeiser (2009), I show that for developing and transitional economies, the value exported products being exported to new destinations often outweighs the value of new products being exported. Additionally, the value of this continuing entry can be upwards of 40%. If the sectoral data is in fact underestimating the value of both entry types, than this is strong motivation to understand why firms are waiting to enter what seem like profitable destinations.

2.2 Popularity of entry destinations

Table 9 (in the appendix) shows the ranking (by number of entrants) of the top 15 destinations that entrants and continuing entrants (exporters entering new destinations) enter. (The bold destinations are unique to that group.) We see that, at the firm level, firms en-

Table 2: Firms' Transition Probabilities Between # of Destinations

		Ending #					
		0	1	2	3-5	6-9	10+
Starting #	0		0.84	0.10	0.05	0	0
	1	0.57	0.34	0.06	0.02	0	0
	2	0.36	0.25	0.21	0.17	0.01	0
	3-5	0.27	0.13	0.15	0.37	0.08	0
	6-9	0.27	0.04	0.05	0.21	0.30	0.14
	10	0.30	0.06	0.03	0.02	0.12	0.47

tering the export market typically enter markets which are either very large (the US), very similar to Russia (former Soviet Union countries), or bordering nations. When entering new destinations, firms which are already exporters generally enter further, more diverse destinations. The fact that continuing exporters are entering further and poorer destinations may be a clue that exporters observe increasing productivity due to their export experience, enabling them to enter these destinations. However, Clerides et al. (1998) have shown that firms do not experience increasing productivity from exporting. Hence, a story that explains the differing compositions may be that firms are learning how to export, or that there are other exogenous factors. Notice that at the product level, this distinction is lost.

2.3 Firm transitions between number of destinations

Table 2 shows a firm's transitions between different numbers of export destinations in 2003 and 2004. From the table, we see that if a firm exports to more destinations, it does so slowly. Eaton et al. (2007) perform a similar analysis using Colombian manufacturing data, and they find an even stronger trend of firms slowly increasing the number of destinations exported to, and much lower 'exit' represented by the lower diagonal. The reason is most likely that, due to the shorter time span of the Russian data, there are more jumps in firm activities that can't be smoothed out.

Additionally, the second panel of Table 11 shows the transition probabilities for a 4 digit SITC product. Again, we see that if a product is exported to increasing numbers of destinations, it is done slowly.

In summary, there is evidence that (1) firms slowly expand the number of destinations they enter, (2) the value of exports from exporters entering new destinations is high and understated at the product level, and (3) at the firm level, entrants enter destinations that are either large or similar to the domestic market, whereas exporters entering additional destinations enter less similar, poorer destinations. Again, this distinction is lost at the

product level. However, for countries where disaggregated trade data is not available, we can still learn something about the importance of firm entry from sectoral data.

In the next section, I will construct a dynamic general equilibrium model which will test whether learning through accumulation of export knowledge can explain these patterns, or whether exogenous factors, such as productivity growth, can account for these facts.

3 Model

Consider a world with a Home country and \bar{N} Foreign destinations (in the data, $\bar{N} = 97$). Each Foreign country n is identified by GDP (Y_n), home bias (α_n), iceberg transportation cost of exports from the Home country (τ_n), and fixed entry costs of Home firms entering destination n (F_n).

Each country consumes a continuum of goods. Foreign countries each produce one good for consumption and export which is distinct from all other goods in the world. In the Home country, there is a measure of domestic firms, each producing differentiated goods. Productivities for firm in the Home country are drawn from a distribution with support $[\varphi_{Low}, \varphi_{High}]$.

3.1 Consumer's problem

Consumers in the home country consume a combination of domestic goods and goods imported from N Foreign countries. The inter-temporal C.E.S. utility function for consumers in the Home country is given by:

$$u_H = \sum_{t=0}^{\infty} \beta^t \log(C_{t,H}), \quad s.t.$$

$$C_{t,H} = \left(\alpha_H \int_{\omega} c_{t,H}(\omega)^{\rho} d\omega + (1 - \alpha_H) \sum_{n=1}^N c_{t,H,n}^{\rho} \right)^{\frac{1}{\rho}} \quad (1)$$

$$\int_{\omega} p_{t,H}(\omega) c_{t,H}(\omega) d\omega + \sum_{n=1}^N p_{t,H,n} c_{t,H,n} \leq Y_{t,H}$$

where α_H is the weight placed on consumption of Home goods (home bias), $\rho \in (0, 1)$, and $c_{t,H}(\omega)$, $c_{t,H,n}$ is consumption of the home variety ω and foreign variety n .

Consumers in Foreign country n consume a combination of their domestically produced good $c_{t,n}$ and imported goods from the Home country $c_{t,n}(\omega)$. The inter-temporal utility

function for each Foreign country n is given by:

$$u_n = \sum_{t=0}^{\infty} \beta^t \log(C_{t,n}), \quad s.t.$$

$$C_{t,n} = \left(\alpha_n c_{t,n}^\rho + (1 - \alpha_n) \int_{\omega \in \Omega_{t,n}} c_{t,n}(\omega)^\rho d\omega \right)^{\frac{1}{\rho}} \quad (2)$$

$$p_{t,n} c_{t,n} + \int_{\omega \in \Omega_{t,n}} p_{t,n}(\omega) c_{t,n}(\omega) d\omega \leq Y_{t,n}$$

where α_n again represents home bias, $\rho \in (0, 1)$. $\Omega_{t,n}$ is the set of Home goods available for consumption in country n in period t .

Notice I do not allow for any dynamics on the consumer's side and each period, all income $Y_{t,n}$ is spent on consumption.

First order necessary conditions yield per-period demand functions for Home goods, by Home and Foreign consumers respectively:

$$c_{t,H}(\omega) = Y_{t,H} \left(\frac{p_{t,H}(\omega)}{\alpha_H P_{t,H}^\rho} \right)^{\frac{1}{\rho-1}} \quad (3)$$

$$c_{t,n}(\omega) = Y_{t,n} \left(\frac{p_{t,n}(\omega)}{(1 - \alpha_n) P_{t,n}^\rho} \right)^{\frac{1}{\rho-1}}$$

Per period demand for foreign goods is given by:

$$c_{t,H,n} = Y_{t,H} \left(\frac{p_{t,H}(j)}{(1 - \alpha_H) P_{t,H}^\rho} \right)^{\frac{1}{\rho-1}} \quad (4)$$

$$c_{t,n} = Y_{t,n} \left(\frac{p_{t,n}}{\alpha_n P_{t,n}^\rho} \right)^{\frac{1}{\rho-1}}$$

where the aggregate price index in country n in each period t is given by:

$$P_{t,H} = \left((1 - \alpha_H)^{\frac{1}{1-\rho}} \sum_{n=1}^N p_{t,H,j}^{\frac{\rho}{\rho-1}} + \alpha_H^{\frac{1}{1-\rho}} \int_{\omega} p_{t,H}(\omega)^{\frac{\rho}{\rho-1}} d\omega \right)^{\frac{\rho-1}{\rho}} \quad (5)$$

$$P_{t,n} = \left(\alpha_n^{\frac{1}{1-\rho}} p_{t,n}^{\frac{\rho}{\rho-1}} + (1 - \alpha_n)^{\frac{1}{1-\rho}} \int_{\omega \in \Omega_{t,n}} p_{t,n}(\omega)^{\frac{\rho}{\rho-1}} d\omega \right)^{\frac{\rho-1}{\rho}}$$

3.2 Learning

The dynamics in this model are driven by the learning mechanism embedded in each firm's costs. Each firm will pay firm specific entry costs, which is consistent with Das et al. (2007) who showed that fixed export costs are destination and firm specific.

Learning in this model affects the initial cost of entering a foreign market, where the fixed entry cost decreases with the number of destinations previously exported to. Let I be a vector of zeros and ones, where $I(i) = 1$ if the firm previously exported to destination i . Additionally, let \hat{I} be the total number of destinations ($\hat{I} = \text{sum}(I)$) the firm has exported to. The cost of entering destination i is defined to be:

$$F_{t,i}(\cdot) = F_{0,i}e^{-\lambda\hat{I}(\cdot)} \quad (6)$$

The intuition behind the learning function is consistent with that in the trade literature (Bangs (2000), Eaton et al. (2007), Alvarez, Faruq, and Lopez (Alvarez et al.)). As a firm exports to a larger number N of locations, they gain experience in setting up foreign facilities, they may hire employees who speak a new language, giving them a fixed cost advantage of entering new locations speaking that language, etc. They learn about foreign preferences (advertising in different areas of the world) and best shipping methods.

The particular function that I use is similar to the learning functions used in the managerial literature. Wright (1963)'s paper on learning in airline production was the first empirical paper that identified learning in the production process. Studies since then, (Majd and Pindyck (1989) use the same function for decreasing costs), as reviewed in Argote et al. (1998) have shown that learning is based on lagged, not cumulative production, and that the shape of the learning curve is logarithmic. Notice that my cost function in 6 reflects the lagged number of destinations and costs decreases exponentially. I have reinterpreted production, in this case, as production of destinations, or instead of how many units produced, how many destinations entered.

In equation 6, if $\lambda = 1$, this means that the accumulated stock of export knowledge is equal to the lagged number of destinations. If $\lambda = 0$, there is no learning present. For lower levels of λ , there is little gained from learning and firms find it profitable to enter all destinations in the first few periods, whereas for λ closer to 1, firms learn more from past experiences.

3.3 Firm's problem

Firms are heterogeneous in productivity φ (which they draw once at the beginning of their lives), fixed entry cost F_i to country i , and continuation cost f_i . The fixed cost of entering a destination decreases with the number of countries previously exported to by a firm. Additionally, there is an iceberg transportation cost τ_i and exogenous firm death rate δ from the export market.

$I_{t-1}(\omega)$ is the set of countries a firm producing good ω has exported to as of $t - 1$. A firm's state variables are the export destinations the firm has exported to, I , as well as the aggregate price in each country, $P = \{P_{t,n}\}_{t,n}$. So define $s_t = \{I, P\}$.

In each period t , a firm maximizes profits in each market it participates in:

$$\begin{aligned}\pi_{t,H}(s_t, \varphi) &= p_{t,H}(s_t, \varphi)x_{t,H}(s_t, \varphi) - q_H \left(\frac{x_{t,H}(s_t, \varphi)}{\varphi} + f_H \right), \\ \pi_{t,i}(s_t, \varphi) &= p_{t,i}(s_t, \varphi)x_{t,i}(s_t, \varphi) - q_H \left(\frac{x_{t,i}(s_t, \varphi)}{\varphi} \tau_i + f_i \right),\end{aligned}\tag{7}$$

where q_H is the per-unit production cost of Home firms. A firm's per-period profits are the sum of the profits made in each market:

$$\pi_t(s_t, \varphi) = \pi_{t,H}(s_t, \varphi) + \sum_{i=1}^{\hat{I}} \pi_{t,n}(s_t, \varphi) - \sum_{i=1}^{\hat{I}} I q_{t,H} F_i(s_t, \varphi).$$

$I_{t,i} = 1$ in the initial period of entry into destination n , $I_{t,i} = 0$ otherwise. Market clearing conditions must hold at every t : $x_{t,i}(\omega) = c_{t,i}(\omega)$. Firm maximization gives per-period prices for Home consumers as:

$$p_{t,H}(s_t, \varphi) = \frac{q_H}{\varphi \rho},$$

and for Foreign consumers of Home goods:

$$p_{t,i}(s_t, \varphi) = \frac{q_H}{\varphi \rho} \tau_i.$$

Foreign firms produce with a fixed proportions technology. This guarantees that the relative prices of Foreign goods are fixed in equilibrium. The relative price is determined by balanced trade.

3.4 Aggregate variables

The aggregate price for the Home country in period t is given by:

$$\begin{aligned}P_{t,H} &= \left((1 - \alpha_H)^{\frac{1}{1-\rho}} \sum_{n=1}^N p_{t,H,i}^{\frac{\rho}{\rho-1}} + \alpha_H^{\frac{1}{1-\rho}} \int_{\omega} p_{t,H}(\omega)^{\frac{\rho}{\rho-1}} d\omega \right)^{\frac{\rho-1}{\rho}} \\ &= \left((1 - \alpha_H)^{\frac{1}{1-\rho}} \sum_{n=1}^N p_{t,H,i}^{\frac{\rho}{\rho-1}} + \alpha_H^{\frac{1}{1-\rho}} \int_{\varphi} \left(\frac{q_H}{\varphi \rho} \right)^{\frac{\rho}{\rho-1}} dG(\varphi) \right)^{\frac{\rho-1}{\rho}}\end{aligned}$$

The aggregate price for the Foreign country n in period t is given by:

$$\begin{aligned} P_{t,i} &= \left(\alpha_n^{\frac{1}{1-\rho}} p_{t,i}^{\frac{\rho}{\rho-1}} + (1 - \alpha_n)^{\frac{1}{1-\rho}} \int_{\omega \in \Omega_{t,i}} p_{t,i}(\omega)^{\frac{\rho}{\rho-1}} d\omega \right)^{\frac{\rho-1}{\rho}} \\ &= \left(\alpha_n^{\frac{1}{1-\rho}} p_{t,i}^{\frac{\rho}{\rho-1}} + (1 - \alpha_n)^{\frac{1}{1-\rho}} \int_{\varphi \in \Omega_{t,i}} \left(\frac{q_H}{\varphi \rho} \tau_n \right)^{\frac{\rho}{\rho-1}} dG(\varphi) \right)^{\frac{\rho-1}{\rho}} \end{aligned}$$

Aggregate exports to each country n are given by:

$$\begin{aligned} X_{t,n} &= \int_{\omega \in \Omega_{t,n}} p_{t,n}(\omega) x_{t,n}(\omega) d\omega = \int_{\varphi \in \Omega_{t,n}} p_{t,n}(s_t, \varphi) x_{t,n}(s_t, \varphi) dG(\varphi) \\ &= \int_{\varphi \in \Omega_{t,n}} \left(\frac{q_H}{\varphi \rho Y_{t,n}} \tau_n \right)^{\frac{\rho}{\rho-1}} (1 - \alpha_n)^{\frac{1}{1-\rho}} P_{t,n}^{\frac{\rho}{1-\rho}} dG(\varphi) \end{aligned}$$

and total exports are

$$X_t = \sum_1^N X_{t,n}$$

3.5 Dynamic equilibrium

Conditional on a firm exporting to a destination, the firm's maximization problem is static (the quantity that they choose to export to any given destination will not affect entry into additional countries). Recall, firm maximization gives prices

$$p_H(s_t, \varphi) = \frac{q_H}{\varphi \rho} \quad \text{and} \quad p_{t,i}(s_t, \varphi) = \frac{q_H}{\varphi \rho} \tau_i.$$

Maximized profits are given by:

$$\begin{aligned} \pi_H^{max}(s) &= \left(\frac{q_H}{\varphi \rho P_H} \right)^{\frac{\rho}{\rho-1}} \alpha_H^{\frac{1}{1-\rho}} Y_H - \left(\frac{q_H}{\varphi} \right)^{\frac{\rho}{\rho-1}} \rho^{\frac{1}{1-\rho}} \alpha_H^{\frac{1}{1-\rho}} P_H^{\frac{\rho}{1-\rho}} Y_H - q_H f_H \\ \pi_i^{max}(s) &= \left(\frac{q_i \tau_i}{\varphi \rho P_i} \right)^{\frac{\rho}{\rho-1}} \alpha_i^{\frac{1}{1-\rho}} Y_i - \left(\frac{q_i \tau_i}{\varphi} \right)^{\frac{\rho}{\rho-1}} \rho^{*\frac{1}{1-\rho}} \alpha_i^{\frac{1}{1-\rho}} P_i^{\frac{\rho}{1-\rho}} Y_i - q_i f_i \end{aligned}$$

Rewriting the value function,

$$V(s, \varphi) = \max_{I'} \left\{ \pi_H^{max}(s, \varphi) + \sum_{i=1 \in I'} [\pi_i^{max}(s, \varphi) - q_h I^{new} F_i(s, \varphi)] \right\}$$

$$+ \beta [(1 - \delta) E_{\delta_i}(V(s', \varphi))] \} \quad (8)$$

where $I_i = 1$ only in the entry period, 0 otherwise. In each period, there is δ chance of death in the overall export market, and δ_n chance of death in each destination. (I will expand on the expected continuation value over death rates in the calibration section.)

Definition 1 *A dynamic equilibrium in this model is value functions $V(I, P, \varphi)$ for each type of firm $\omega = (I, \varphi)$, decision rule functions $I'(I, P, \varphi)$, aggregate prices P , and distribution of firms such that for learning as defined in equation 6, the functions satisfy:*

- (a) *Home and Foreign consumer maximization problems given in (1) and (2);*
- (b) *the firms' maximization problem given in (7) and (8);*
- (c) *and the consistency of aggregate and individual decisions, given by aggregate prices in (5).*

3.6 Firm destination decisions

There are two interesting features of this model. First, this model is constructed so that firms have incentive to slowly enter destinations. Secondly, for specific sets of parameters, firms may enter destinations with negative per-period profits in order to benefit from the future reduction in fixed entry costs. Below, using simplified examples of the model, I show that each of these cases is possible.

Proposition 1 *Consider a simple world where all potential export destinations are symmetric, with potential per-period profit π . Then, a learning parameter for equation 6 that satisfies $\lambda > \frac{1}{A} \log \left(\frac{F - \pi}{\beta F} \right)$ is such that firms initially enter only a subset A of the possible N destinations. Additionally, if $\lambda = 0$, so firms don't learn, it would never be beneficial to wait to export to a profitable destination.*

This λ satisfies the following condition:

$$A \frac{\pi}{1 - \beta} - AF + \beta \left[(N - A) \left(\frac{\pi}{1 - \beta} - F e^{-\lambda A} \right) \right] > (N - A) \left(\frac{\pi}{1 - \beta} - F \right)$$

which says that it is more profitable to enter A destinations and receive the benefits of entry and lowering future fixed entry costs then it is to enter everywhere initially and benefit from higher initial period profits.

Proposition 2 *In a model with learning, it is possible for a firm to enter an unprofitable destination in order to decrease fixed entry costs for a highly profitable destination. This will occur when fixed entry costs into the profitable destination are ‘very’ high.*

Again, consider a simplified world where there are two destinations with profits $\pi_1 < 0$ and $\pi_2 > 0$. Then as long as the fixed entry cost into the 2nd destination is so high that $F_2 > \pi_1 - \pi_2 - F_1$, a λ exists such that firms enter the 1st destination, gain the experience of exporting, then drop out of the the 1st destination and continue exporting only to the 2nd. In other words,

$$\pi_1 - F_1 + \beta \left[\frac{\pi_2}{1 - \beta} - F_2 e^{-\lambda} \right] > \frac{\pi_2}{1 - \beta} - F_2$$

This occurs when $\lambda > \log \left(\frac{\pi_1 - F_1 - (\pi_2 - F_2)}{\beta F_2} \right)$ and $F_2 > \pi_1 - \pi_2 - F_1$.

3.7 Firm entry in three model variations

Why is learning important in enabling this class of model to better match patters in the data? I consider three variants of the model. The learning model presented above (L). A completely static variant of the model (S), where there is no learning ($\lambda = 0$) and no exogenous changes over time. Finally, I compare to a model with exogenous productivity growth (P).

For the static (S) variation, per period profits are the same as before and there are no dynamic decisions. For the exogenous productivity growth, per period profits for firms are given by:

$$\begin{aligned} \pi_{t,H}(s_t, \varphi) &= p_{t,H}(s_t, \varphi)x_{t,H}(s_t, \varphi) - q_H \left(\frac{x_{t,H}(s_t, \varphi)}{\gamma_t \varphi} + f_H \right), \\ \pi_{t,n}(s_t, \varphi) &= p_{t,n}(s_t, \varphi)x_{t,n}(s_t, \varphi) - q_H \left(\frac{x_{t,n}(s_t, \varphi)}{\gamma_t \varphi} \tau_n + f_n \right), \end{aligned} \quad (9)$$

where $\gamma = (1+g)^t$. The interpretation of this variation is that, while firms still draw just one productivity φ at the beginning of their lifetime, they become effectively more productive over time. Learning, again, does not occur in this variation.

In each model variation, we can find the lowest productivity firm with history N to enter the $N + 1$ destination. We do this by solving for the productivity $\hat{\varphi}_{N+1}$ such that the value of entering the destination is zero, $\pi_{N+1}(\hat{\varphi}_{N+1}) - F_{N+1}(s_t, \hat{\varphi}_{N+1}) = 0$.

For the static model (S), the productivity growth model (P), and the learning model (L),

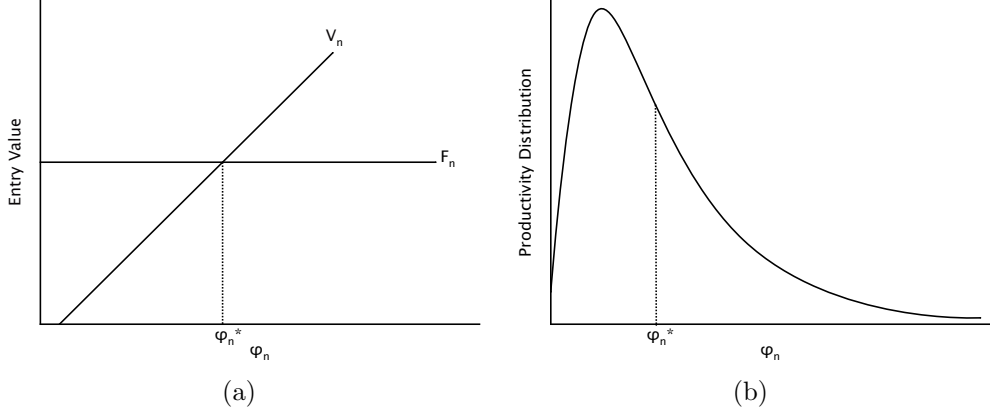


Figure 1: Finding productivity cutoffs

we find the cutoff productivity of an entrant into $N + 1$ to be:

$$\begin{aligned}
 \hat{\varphi}_{N+1}^S &= \frac{q_H \tau_{N+1}}{P_{N+1}} \left[\frac{q_H (f_{N+1} + F_{N+1})}{\left(\rho^{\frac{\rho}{1-\rho}} - \rho^{\frac{1}{1-\rho}} \right) \alpha_{N+1}^{\frac{1}{\rho}} Y_{N+1}} \right]^{\frac{1-\rho}{\rho}}, \\
 \hat{\varphi}_{N+1}^P &= \frac{q_H \tau_{N+1}}{\gamma_t P_{N+1}} \left[\frac{q_H (f_{N+1} + F_{N+1})}{\left(\rho^{\frac{\rho}{1-\rho}} - \rho^{\frac{1}{1-\rho}} \right) \alpha_{N+1}^{\frac{1}{\rho}} Y_{N+1}} \right]^{\frac{1-\rho}{\rho}}, \quad \text{and} \\
 \hat{\varphi}_{N+1}^L &= \frac{q_H \tau_{N+1}}{P_{N+1}} \left[\frac{q_H (f_{N+1} + \mathbf{F}_{N+1}(\mathbf{s}, \hat{\varphi}_{N+1}^L)) - \beta(1-\delta)V(N', P, \hat{\varphi}_{N+1}^L)}{\left(\rho^{\frac{\rho}{1-\rho}} - \rho^{\frac{1}{1-\rho}} \right) \alpha_{N+1}^{\frac{1}{\rho}} Y_{N+1}} \right]^{\frac{1-\rho}{\rho}}.
 \end{aligned} \tag{10}$$

Consider $\hat{\varphi}_{N+1}^S$ in equation 10. This shows that the lowest productivity firm (note, history here does not matter) to enter destination $N + 1$ is determined by the bilateral trade costs, the aggregate price in $N + 1$, and other exogenous parameters of the model. If fixed entry and fixed per period production costs are equal to zero, then $\hat{\varphi}_{N+1}^S = \varphi_{Low}$, the lower bound of the productivity distribution, and all firms would enter $N + 1$.

With productivity growth, in each period t lower productivity firms may enter a destination, as effective productivity grows over time (notice again that firms' export history does not matter). Because $\gamma_t \geq 1$, we have that $\hat{\varphi}_{N+1}^P \leq \hat{\varphi}_{N+1}^S$, so in any period t , with exogenous productivity growth, the cutoff productivity for each destination decreases, meaning more firms can enter each destination over time. Is exogenous productivity growth, then, enough to match the slow entry patterns observed in the data? As I will discuss later, it is not enough as long as reasonable values of productivity growth are considered.

This can be observed graphically in the first panel of Figure 1. This shows that, for

the standard no learning model, a cutoff productivity can be found, such that any firm with higher productivity than φ_n^* will export to destination n and any firm with lower productivity will not. Corresponding is the mass of firms that export to destination n which is seen in panel 2. If productivities are distributed log normal, then the mass of firms with productivities to the right of φ_n^* are exporting. In a model with productivity growth, V_n would be weakly higher, giving a lower cutoff value (so more firms will enter each destination).

With learning, what happens to the cutoff productivity is not so obvious and depends on both the export life span of individual firms as well as the destination ‘ranking’ (is it a country that firms initially always enter, or one that few firms ever export to?). For example, for a firm in the early stages of exporting, the value of entering the most profitable destination is higher (due to the benefits of learning), but fixed costs must also initially be higher (in order for each model to generate 2003 total exports). (In the next section, I find that in fact, the increase in value outweighs that of the fixed cost and you get more firms exporting – with low productivity firms initially exporting more than otherwise expected, high productivity firms less.) For a less profitable destination, firms will initially not export there because the fixed costs are so high, but the more they export, the further they decrease F_n making it eventually profitable for them.

4 Computation and calibration

In my sample of Russian exports there are 97 potential destinations. Computationally, it’s impossible to deal with 97 non-symmetric destinations in this dynamic setting. For this reason, many dynamic models (in this class of new trade theory) work only with symmetric countries. Because the new trends regarding growth of export destinations is important, I need a model that can account for 97 unique destinations, with at least some non-symmetry. I reduce the number of non-symmetric destinations firms can export to by breaking destinations into four groups: Former Soviet Union and neighbors; the largest destinations (US, UK, etc.), the European Union (excluding FSU and neighboring countries) and other close destinations (distance between major cities of less than 2000 miles); and finally the rest of the world (ROW). Table 10 in the appendix provides the complete listing of countries in each category. It is important to remember that, while each destination within a group will have the same properties (GDP and bilateral fixed costs), they are still unique destinations, and the firm still faces 97 potential export destinations.

Define $I_{j,t-1}(\omega)$ to be the set of countries within group j a firm producing good $\omega = \{I_1, I_2, I_3, I_4, \varphi\}$ has exported to in it’s lifetime. A firm’s own state variables are the number of export locations the firm has exported to within each group: $I = \{I_1, I_2, I_3, I_4\}$, and the aggregate state variables for the aggregate price in each country, $P = \{P_i\}_i$. I will be solving for a stationary equilibrium, in which $P_{t,i} = P_i$ for every period t . Define $s_t =$

$\{I_1, I_2, I_3, I_4, P\}$. Rewriting the value function, we have:

$$V(s, \varphi) = \max_{I'_1, I'_2, I'_3, I'_4} \left\{ \pi_H^{max}(s, \varphi) + \sum_{j=1}^4 \sum_{i=1}^{I'_j} [\pi_i^{max}(s, \varphi) - q_h I_j^{new} F_i(s, \varphi)] \right. \\ \left. + \beta [(1 - \delta)E(V(s', \varphi))] \right\} \quad (11)$$

where again, δ is the probability of death in the export market, and each period, there is δ_j probability of death, now from each group j . Additionally, I assume that exogenous productivity growth can occur, as defined in equation 9.

I assume that firm productivities are distributed log-normal:

$$g(\varphi) = \frac{1}{\varphi\sigma\sqrt{2\pi}} e^{-\frac{(\ln\varphi-\mu)^2}{2\sigma^2}}$$

For a stationary equilibrium, my computational algorithm amounts to the following iterative procedure: (1) Guess the aggregate price in each country. (2) Using value function iteration, solve the firm's problem, given aggregate prices, to find the optimal decision rules $I'_j(I_1, I_2, I_3, I_4, P, \varphi)$. (3) Use firms' decision rules to simulate the behavior of 2000 firms over 100 periods. (4) Use the stationary region of the simulated data to calculate the resulting aggregate price in each country. (5) If this gives an aggregate price close enough to the one guessed initially, stop, otherwise update the guess on price and go back to 2.

To calibrate the parameters of the log normal distribution, σ and μ , entry costs F_1, F_2, F_3 , and F_4 , and learning parameter λ to the Russian External Economic Activities, I simultaneously choose the parameters such that the sum of squares on data collected in my model and Russian data is minimized. For σ and μ , the parameters of the log normal distribution of productivity φ , I compare the distribution of total exports by firms in the model to that in the data. For fixed entry costs, I total exports, by destination, in the model and in the data. Learning is chosen such that the margins of entry by entrants and continuing entrants matches that in Table 1. The rest of the parameters are from the data and presented in Tables 3 and 4, except for ρ and β , which I set to parameters typically used, and the home bias parameter α which I choose in order to better represent the real world, in which Russian manufacturing goods are typically not a large portion of country imports.

To estimate transportation costs, I run a non-traditional (compared to the gravity literature) regression. I do so for two reasons: 1) I want to allow some of the heterogeneity in fixed costs to come from border effects, language, trade union, and distance effects, and don't want to control for everything in the transportation cost. Secondly, because I have data on both the value and weight of each shipment, I can potentially recover the transportation cost by looking at the differences in value/weight unit of each firm-good combination across each destination.

Table 3: Parameter Values

Variable	Description	Source
$\rho = .5 \Rightarrow \sigma = 2$	Elasticity of Substitution	Gibson (2006)
$\beta = .96$	Time Discount	Gibson (2006)
$\alpha = .98$	Home Bias	–
$\delta = .22$	Exporter Death Rate	value lost/exports ₂₀₀₃
δ_n	Death Rate from n	value lost _{n} /exports ₂₀₀₃ , Table 4
τ	Transportation Cost	Table 4
$Y_H = 306$	Russian GDP (Billions USD)	NY.GDP.MKTP.KD (WDI (2009))
Y_n	GDP in n	NY.GDP.MKTP.KD (WDI (2009))
$g = 10\%$	Productivity Growth	Firm export growth by dest.
$f_n = F_n/3.9$	Fixed Continuation Cost	Alessandria et al. (2007)
$q_H = 1$	Per Unit Production Cost	Normalized
Variable	Description	Target
F_n	Entry cost to destination n	Table 4
$\mu = .1$	Mean of Log-Normal Dist. of φ	$\mu_{exports}^{data} = 313258$
$\sigma = .09$	Std. Deviation	$\sigma_{exports}^{data} = 3253108$
$\lambda = .58$	Learning parameter	Table 5

Because shipments are reported FOB, we would assume that if costs of transportation were the same across destinations, then controlling for each firm-good combination (shipment level data is for each firm-good pair, where one firm may produce many goods), the difference in value/weight across destinations should be the same. Recall

$$p_{t,i}(s_t, \varphi) = \frac{q_{t,H}}{\rho} \underbrace{\varphi^{-1}}_{Firm} \underbrace{\tau_i}_{Destination}$$

If $\frac{TR_i(s_t, \varphi)}{Q_i(s_t, \varphi)} = \frac{TR_j(s_t, \varphi)}{Q_j(s_t, \varphi)}$, then $\tau_i = \tau_j$. In fact, running this fixed effect regression on all 97 export destinations finds large variation in the value/weight by firm/good pair, across destinations.

The fixed effects regression I run is:

$$\frac{\text{value of shipment}}{\text{weight of shipment}} = \alpha d_{destination} + \beta d_{firm} + \epsilon$$

where α is a vector of α'_i 's for each destination, and β is a vector of β'_j 's for each firm-good pair. To get the transportation cost for each destination group, I take a monotonic transformation of α_i , such that $\tau_i = f(\alpha_i)$ and then take a weighted average of each destinations' τ_i in each group j . The results are presented in Table 4.

Table 4: Foreign Country Values: $N = 4$

Destination	#	Avg. Dist.	Avg. τ	Avg. GDP (Bill. USD)	2003 exports (Mill. USD)	δ_n	$\frac{F_n}{\pi_n(\varphi_{High})}$
Largest	7	2798	1.008	3107	577	0.12	25%
FSU/Neigh.	10	1834	1.025	183	394	0.21	27%
EU/Close	31	1252	1.000	108	442	0.09	37%
ROW	49	4569	1.009	94	118	0.25	34%

The learning parameter that allows the model to best match continuing entry contributions is $\lambda = .58$. Table 5 shows the contribution of entry types to total exports. Shutting down learning, with just productivity growth of 10% per period, entry, by both entrants and continuing exporters, is underestimated. The results from the no learning model are from turning off learning ($\lambda = 0$) re-calibrating the fixed costs to match 2003 exports (results in fixed costs lower than in Table 4). In order to ‘force’ the entry in this model to come to close to that in data, $\gamma \approx 200\%$ is needed. However, different calculations of γ , looking at export growth from continuing firms among retained destinations (since I don’t have domestic production, the best proxy I have of productivity growth is to look at continued firm-destination pairs over the length of my sample), varies only between 10% and 40% (SITC). Adding learning to the model allows for entry so that entry contributions can closely be matched.

Table 11 (appendix) also shows that with $\lambda = .58$, I am able to capture some of the slow entry patterns observed in the data. A firm initially entering the export market (depending on it’s productivity) will enter 1 destination with 31% probability, and 3-5 destinations with 51% probability. Without learning, conditional on firm entry, firms initially enter all 7 of the largest (and most profitable) destinations.

5 Policy implications

In this section, I look at the implications of two types of liberalizations on export growth: decreasing fixed entry costs, and decreasing transportation costs. As show above, when firms make dynamic entry decisions as a result of learning how to export, we expect the observed characteristics of exporting firms to differ compared to a non-learning model. Specifically, lower productivity firms have an incentive to participate in the export market. I show that the difference in exporter characteristics in a learning versus no learning world greatly affects the outcome of trade liberalizations for developing and transitional economies. In particular, by taking learning into account, for different types of liberalizations targeting destinations otherwise not prioritized provides the largest gain to trade.

Table 5: Contribution of Entry Types

Data	Entrants $\frac{\text{entrant exports}_{\text{year } b}}{\text{total exports}_{\text{year } b}}$	Continuing Entrants $\frac{\text{inc. entrant exports}_{\text{year } b}}{\text{total exports}_{\text{year } b}}$
Firm Level 2003-2004, 9474 firms	.31	.13
Model: Learning	.30	.14
Model: No Learning	.18	.07
According to concordance, 56 products		
Firm 2003-2004	0	.02
SITC 2003-2004	0	.01
Model: Learning	0	0

Table 6: Policy: Decrease in Fixed Entry Cost

Policy	Export Growth	
	Learning	Productivity
10% ↓ F_{Large}	17%	11%
10% ↓ F_{FSU}	12%	45%
10% ↓ F_{EU}	3%	10%
10% ↓ F_{ROW}	5%	8%

Table 7: Policy: Decrease in Transportation Cost

Policy	Export Growth	
	Learning	Productivity
10% ↓ τ_{Large}	6%	13%
10% ↓ τ_{FSU}	57%	16%
10% ↓ τ_{EU}	4%	7%
10% ↓ τ_{ROW}	11%	39%

As before, the two models I compare are a model with exogenous productivity growth and no learning, and a model with learning and productivity growth. Recall, the two models are calibrated to match 2003 exports.

First, consider the effect on total exports of a 10% reduction in fixed entry costs, shown in Table 6. By disregarding the dynamics of firm export decisions, simulations of the cost reduction suggest exports would grow most, by 45%, when the liberalization is targeted towards the former Soviet Union and neighboring countries. However, considering firms do learn, liberalization targeted towards the largest destinations would give the greatest export growth at 17%. Why does the no learning model target the former Soviet Union and overestimate export growth?

Due to the nature of the four group breakdown and calibrated parameters, the most profitable destinations to enter are, in order: the largest countries, FSU and neighbors, EU and other close countries, and finally the rest of the world. By decreasing the entry cost into the most profitable group, a large mass of low productivity firms will enter the large destinations. (This explains why the highest expected export growth is lower than in the productivity growth model.) Additionally, because they will learn, they have the potential to enter all markets later on.

Without learning, targeting the large destinations would induce a mass of low productivity firms to enter, whereas targeting the FSU, higher productivity firms can sell to a larger, still very profitable, group of destinations. The tradeoff between mass of firms entering and productivity, as illustrated in Figure 1, is such that higher productivity entrants into a slightly less desirable group provides higher exports.

When considering liberalizations such as tariff reductions (which would affect the per unit iceberg transportation cost τ), ignoring learning will actually underestimate export growth. Tariff reduction policies in the learning model would target FSU and neighboring destinations. The benefit of higher per-period profits will promote both firm entry into the export market (with a large destination acting as a stepping stone) as well as increase per period exports to the large destinations. A model without learning would target the rest of the world (ROW) destinations because it would provide such a large influx of exporters

(only the highest productivity firms would otherwise export to the ROW).

6 Conclusion

Currently, few developing or transitional countries report panel data on bilateral firm exports. Data that is available includes Russian External Economic Activity, Colombian Bureau of Statistics–DANE (used by Eaton et al. (2007) and others), and Chilean customs (used by Alvarez, Faruq, and Lopez (Alvarez et al.)). These data exhibit a pattern of firms’ slow expansion into foreign destinations. In the Russian data, I also find that the composition of entry destinations differs between new exporters and continuing exporters and a surprisingly large share of exports are due to continuing exporters entering new destinations.

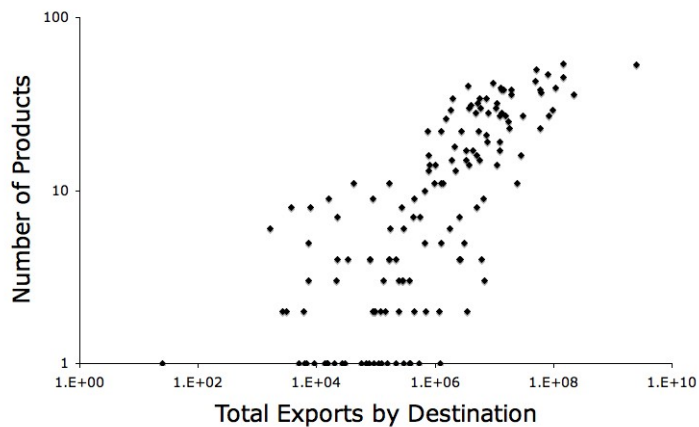
I show that a model where firms learn how to export can account for the trends observed in the data – something that standard trade models with monopolistically competitive firms cannot do. Learning provides incentive for firms to delay entry into profitable destinations in order to benefit from future reductions in entry costs.

The dynamic entry decisions of firms alters the predictions of exporter characteristics. For example, smaller, less productive firms have greater incentive to initially enter the export market, knowing they can learn how to better enter future destinations. I show that this difference in exporter characteristics greatly affects the outcome of trade liberalizations for Russia and other developing and transitional economies for which firm export behaviors are similar. In particular, taking learning into account, liberalizations should target destinations otherwise not prioritized.

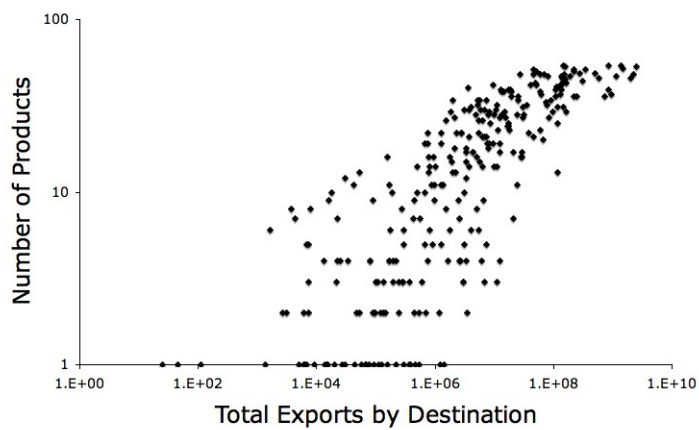
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7 Appendix



(a) Firms (according to concordance), Correlation: 0.31



(b) SITC Products (according to concordance), Correlation: 0.49

Figure 2: Relationship between number of products exporting to a destination and total exports in that destination

Table 8: Concordance: From SITC to CC-FEA

	Description	SITC	CC-FEA
1	Polymeric substances, plastic and products	893	39
2	Caoutchouc, rubber, products made of either	6210+625+628+8452	40
3	Raw Leather and fur	6113+6114+6115+6116	41
4	Leather products	6112+6118+6121+6122+6123+6129+8310	42
5	Natural and artificial fur and fur products	6131	43
6	Wood and products made of wood	634+635+81-8121-8122	44
7	Cork and products made of natural cork	633	45
8	Wickerwork made of straw, baskets, other	8997	46
9	Cellulose and paper products; Paper, paperboard and products	641	47+48
10	Books, newspapers, other products of printing industry, manuscripts and typewritten texts	6422+6423+892	49
11	Silk	6541	50
12	Wool, fine and coarse animal hair, and products made of horsehair	6542+6543	51
13	Cotton	6521+6522+6534	52
14	Other natural textile fabrics, paper yarn, fabrics	6544+6545	53
15	Fibers and microfiber of chemical origin	6531+6532+6536+6538+6539+6546+6599	54+55
16	Cotton, felt, yarn, wisp, ropes and strings	651+6571+6775	56
17	Carpets and other floor coverings	659	57
18	Special fabrics, tapestry, laces, ornamental designs, and embroidery	6574+6576+6577+6579	58
19	Absorbed, coated and processed textile products	6572+6573	59
20	Knitted Fabrics (hand or machine)	655	60
21	Knitted wear & accessories (hand or machine made)	843+8441+8459+8462	61
22	Textile wear & accessories (hand or machine made)	842+8442+8443+8451+846+847	62
23	Other products made of textile, compounds, clothing, textile products (bags, tents, sails, etc.)	658	63
24	Footwear including parts of footwear	851	64
25	Headwear including headwear made of natural fur	848	65
26	Umbrellas, walking sticks, whips, riding whips & parts	8994	66
27	Processed feather, down, products made from each, artificial flowers, products made of human hair	-	67
28	Products made of stone, plaster, cement, asbestos, foil	661+662+663	68
29	Products made of ceramic	666+8122	69
30	Glass and products made of glass	664+665	70
31	Natural and cultivated pearls, precious and semiprecious minerals, precious metals, items covered with precious metals, and articles made of them	667+681+6891+897	71
32	Ferrous metals	671+672+673+674+676+677+678+679	72
33	Products made of ferrous metals (needles, hooks, tableware, etc.)	699-6997	73
34	Copper and products made of copper	682+6931+6935+694+6974+6975+6997	74
35	Nickel and products made of nickel	683	75
36	Aluminum and products made of aluminum	684+6912+6921+6924	76
37	Lead and products made of lead	6851+6852	78
38	Zinc and products made of zinc	6861+6863	79
39	Tin and products made of tin	6871+6872	80
40	Other non-precious metals, cermets and products	6899	81
41	Tools made of non-precious metals, cutlery, forks and spoons	695+696	82
42	Other articles made of non precious metals	6911+6932+8951	83
43	Nuclear reactors, boilers, machinery and mechanical appliances and parts	6973+6978+711+712+713+714+718+741+742+743+744+745+749+751+775+8121	84
44	Electrical machines and equipment, recording devices, telephones and parts	716+72+73+76+771+772+776+778+813	85
45	Railway/tramway locomotives, rolling stock, parts	791	86
46	Overland means of transportation excluding railway or tramway rolling stock	781+782+783+784+785+786	87
47	Flying machines, spaceships and others	792	88
48	Ships, boats, other floating vessels, dinghies	793	89
49	Optical, photographic, cinematographic, measuring, medical and surgical instruments and devices	773+774+871+872+873+874+881+882+883+884+8896	90
50	All types of watches/clocks	885	91
51	Musical instruments and parts for them	898	92
52	Weapons and ammunition	-	93
53	Furniture, bedding items, mattresses, mattress supports, cushions and similar stuffed furnishings; lamps and lighting equipment	821	94
54	Toys, games and sports equipments, and parts	894	95
55	Miscellaneous ready goods	8952+8959+8991+8993+8998+8999	96
56	Works of arts, rarities and antiques	896	97

Table 9: Export Destination by Popularity

Rank	Entrants	Continuing Entrants
Firms (2003-2004)		
1	China	Switzerland
2	Netherlands	United Kingdom
3	Ukraine	Germany
4	Iran	Korea, South
5	Kazakhstan	Netherlands
6	Turkey	Iraq
7	Cyprus	Denmark
8	United States	Greece
9	Finland	Belgium
10	Sweden	Pakistan
11	Korea, South	Italy
12	Italy	Ethiopia
13	Taiwan	Spain
14	Hungary	China
15	India	Japan
4 digit SITC (2003-2004)		
1	USA	USA
2	Portugal	Portugal
3	Turkey	Turkey
4	Canada	Canada
5	Switzerland	Switzerland
6	Syria	Syria
7	India	India
8	Mexico	Mexico
9	Viet Nam	Viet Nam
10	Myanmar	Myanmar
11	Br. Virgin Isds	Br. Virgin Isds
12	Malaysia	Malaysia
13	Qatar	Qatar
14	Thailand	Thailand
15	Indonesia	Indonesia

Table 10: Description of 4 Groups: Destinations

Neighbors and FSU:

Azerbaijan, Armenia, China, Kazakhstan, Kyrgyzstan, Mongolia,
Norway, Tajikistan, Ukraine, Uzbekistan

Largest:

Canada, France, Germany, Italy, Japan, United Kingdom, United States

EU or Close:

Albania, Austria, Bulgaria, Croatia, Cyprus, Denmark, Estonia, Finland,
Greece, Hungary, Iran, Iraq, Ireland, Israel, Jordan, Lebanon, Latvia, Lithuania,
Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia,
Spain, Sweden, Switzerland, Turkey, Turkmenistan

Rest of World:

Algeria, Angola, Argentina, Australia, Bahrain,
Bangladesh, Brazil, Cambodia, Cameroon, Sri Lanka, Chile, Colombia, Cuba,
Ecuador, Equatorial Guinea, Ethiopia, Eritrea, Djibouti, Ghana, Guinea,
Iceland, India, Indonesia, Kenya, Liberia, Malaysia, Mauritania, Mexico, Morocco,
Oman, Namibia, Nepal, New Zealand, Nigeria, Pakistan, Panama, Peru, Philippines,
Saudi Arabia, Senegal, Singapore, South Africa, Sudan, Thailand,
United Arab Emirates, Tunisia, Egypt, Venezuela, Yemen

Table 11: Firms' Transition Probabilities Between # of Destinations

		Russian External Economic Activities Ending #					
		0	1	2	3-5	6-9	10+
Starting #	0		0.84	0.1	0.05	0	0
	1	0.57	0.34	0.06	0.02	0	0
	2	0.36	0.25	0.21	0.17	0.01	0
	3-5	0.27	0.13	0.15	0.37	0.08	0
	6-9	0.27	0.04	0.05	0.21	0.30	0.14
	10	0.30	0.06	0.03	0.02	0.12	0.47
		4 Digit SITC Ending State					
		0	1	2	3-5	6-9	10+
Starting State	0		1.00	0	0	0	0
	1	0.4	0.60	0	0	0	0
	2	0	0.29	0.29	0.29	0.14	0
	3-5	0.07	0	0	0.67	0.20	0.07
	6-9	0	0.05	0.13	0.26	0.33	0.23
	10+	0	0	0	0	0.03	0.97
		Learning $\lambda = .58$ Ending State					
		0	1	2	3-5	6-9	10+
Starting State	0		0.31	0.18	0.51	0	0
	1	0.22	0	0.12	0.66	0	0
	2	0.22	0	0	0.33	0.45	0
	3-5	0.26	0	0	0.07	0.56	0.11
	6-9	0.22	0	0	0	0.12	0.66
	10+	0.22	0	0	0	0	0.78
		Productivity Growth, No Learning Ending State					
		0	1	2	3-5	6-9	10+
Starting State	0		0	0	0	1.00	0
	1	0.28	0.18	0	0	0.54	0
	2	0.24	0.07	0.15	0.37	0.16	0
	3-5	0.22	0.01	0.05	0.38	0.34	0
	6-9	0.22	0	0	0.09	0.64	0.05
	10+	0.22	0	0	0	0.35	0.43