A Search and Learning Model of Export Dynamics[1]

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This draft: February 2014

[1]We gratefully acknowledge support from the National Science Foundation (Grant SES-0922358), the United States Census Bureau, and Banco de la República de Colombia. We also thank Monica Hernández, Gustavo Caballero and Camilo Acosta for excellent research assistance, as well as Enrique Montes for expert data advice. This paper was written in part by Census Bureau staff. It has undergone a more limited review than official Census Bureau publications. All results were reviewed to ensure confidentiality. Any views, findings and opinions in the paper reflect the views of the authors and do not reflect the views of the U.S. Census Bureau.

Abstract

Customs record data reveal a number of patterns in relationships Colombian firms have with their U.S. buyers. We interpret these patterns in terms of a continuous-time model in which heterogeneous sellers search for buyers in a market. Success in selling to a buyer reveals information to the seller about the appeal of her product in the market, affecting her incentive to search for more buyers. Fit using the method of simulated moments, the model replicates key patterns in the customs records and allows us quantify several types of trade costs, including the search costs of identifying potential clients and the costs of maintaining business relationships with existing clients. It also allows us to estimate the effect of previous exporting activity on the costs of meeting new clients, and to characterize the cumulative effects of learning on firms' search intensities. Finally, we use our fitted model to explore the effects of these trade costs and learning effects on aggregate export dynamics.

1 Introduction

Research on exporting has been digging deeper into microeconomics data to understand the barriers that producers face in entering foreign markets and their implications for export dynamics. Firm-level datasets have provided insights first into the costs of exporting at all, and then, as data became available, to penetrating individual markets. We take this analysis one step forward by examining exporters' relationships with individual buyers in a market, both descriptively and through the lens of a dynamic model.

1.1 Scope

We begin by summarizing patterns in a decade's worth of data on individual merchandise shipments from Colombia to the United States. First, following work by some of the authors (Eaton et al., 2008), we review patterns of entry into the U.S. market of individual Colombian exporters across different cohorts. We note that most new exporters drop out of the U.S. market within a year, but those who survive this shakedown period have much lower exit rates in the future. Indeed, surviving members of new cohorts tend to expand their sales very rapidly, causing their market shares to grow as they mature. After a decade, nearly a quarter of total Colombian exports to the U.S. originate from firms that were not supplying the U.S. market at the beginning of the period.

We then look at relationships between buyers and sellers. Colombian firms which export to the U.S. ship at least once per year to an average of 1.3 U.S. clients. In contrast, U.S. firms place at least one order per year with an average of 2.2 Colombian suppliers if they deal with Colombian firms at all. Overall, the distribution of U.S. clients across Colombian exporters is very nearly Pareto, with a handful of large sellers accounting for a substantial fraction of total shipments. Most buyer-seller matches are short-lived, lasting less than two years, on average. Matches are even less durable if they begin with a small initial shipment. But enough exporters gain buyers each period that the ergodic distribution implied by the transitions and by entry replicates closely the distribution in the cross section.

Finally, we develop a model that is consistent with these facts. It is based on the conjecture that firms' exporting behavior reflects search and learning processes in a foreign market. That is, producers who are interested in a particular market devote resources to identifying potential buyers there. When they find one, they learn something (receive a noisy signal) about the appeal of their products in this market. Taking stock of the available information, these firms update their beliefs concerning the scope for export profits, and they adjust the intensity of their search efforts accordingly, seeking to maximize their expected profit streams. At the same time, firms manage their portfolio of existing clients, investing in their profitable business relationships and letting the others expire. These features of the model are not only motivated by the exporting patterns observed in the data, but also by the exporting strategies documented by a series of interviews with Colombian exporters (Domínguez et al, 2013). Interviewed exporters described engaging in costly strategies both to search for new clients and to maintain existing relationships alive. They also frequently mentioned learning from previous relationships about the appeal of their products in a particular market, and using that information to adjust their searching behavior.

Fit to our data on shipments and business relationships, the model quantifies the role of several frictions in shaping firm-level export dynamics. We estimate that for non-exporters, the costs of maintaining low-level searches for clients in the U.S. are small, amounting to \$1,405 per year for an expected yield of one potential client every two years. However, search costs are very convex in buyer arrival hazards, rising to \$51,471 for an expected yield of one potential client per year. Both of these figures describe the search costs for a firm that has not yet established a successful business relationship abroad. But network effect are very important. We estimate that after the first relationship is formed, search costs for one client every two years drop to \$106, and \$3,898 for one client per year. Finally, once a successful match is formed, we estimate that it costs exporters \$2,855 dollars per shipment to maintain the relationship. As a benchmark, the Doing Business project of the World Bank estimates that procedures required to export a one-container shipment cost \$1,745 in Colombia in 2005. Even when a seller pays the fixed cost, her relationship dissolves with probability 0.27 per year for exogenous reasons.

In addition to trade costs, the model quantifies the effects of learning on exporter behavior. We estimate that on average, only 1 in 5 potential buyers that an exporter meets will be interested in forming a business relationship. However, this success rate varies substantially across sellers, so they adjust their search intensities dramatically as they form opinions concerning the scope of the market for their particular product. A typical firm which has met four potential buyers will choose a match hazard of 1.35 (new clients per year) if all of its encounters have led to successful business relationships, while it will choose a hazard of 0.22 if each encounter has been a failure.

This learning process, in combination with the various trade costs mentioned above, induces frictions and irreversibilities in export responses to marketwide shocks. We conclude our analysis with some experiments that quantify their implications for export dynamics. A 20 percent reduction in the cost of searching for new clients leads to an increase in total exports of around 5 percent, which takes some time to kick in. Increased exports are mostly explained by the entry of new sellers into exporting, and to a lesser extent by an increase in the mean number of clients per seller. In turn, a decrease of 20 percent in the per-shipment fixed cost leads to a much more marked increase in both the number of exporters and the mean number of clients, and also to an increase in mean sales per client. The latter occurs despite the entry into exporting of less productive sellers, and is explained by increased search by the more productive firms.

1.2 Relation to literature

While we look at the evolution of firms' sales in a particular market, our analysis is related to the literature on the dynamics of firm size in general. The model explains the size distribution of firm sales through two interacting mechanisms. One, as in Melitz (2003), Bernard et al. (2003), Luttmer (2007), and Irarrazabal and Opromolla (2006), is firm efficiency: More efficient firms sell more to a given set of buyers by having a lower price or a higher quality product. A second is that some firms have larger networks of buyers than others, as in Jackson and Rogers (2007) or Chaney (2011).

Investments in building a client base constitute a type of sunk cost, so our model also relates to the export hysteresis literature (Dixit, 1989; Baldwin and Krugman, 1989; Das, et al., 2007; Alessandria and Choi, 2007; Alessandria et al., 2010), where firms pay a one-shot start-up cost to break into new markets. But unlike these formulations, our sunk costs are incurred on the client margin rather than the country margin, and they pay off in terms of market knowledge and reputation as well as revenue streams. These features of our model allow us to explain why new exporters who don't exit tend to rapidly expand, and why established exporters' sales are relatively stable. They also explain why many firms export for short periods on a very small scale.

Our formulation is also related to the two-period learning models developed by Rauch and Watson (2003) and Albornoz et al (2012). In the former, importers experiment with foreign suppliers by placing trial orders with them, and they gain access to a supplier network if they establish a successful business relationship. In the latter, firms choose to experiment in markets with low entry costs in order to learn about their product's appeal elsewhere. Like our model, these formulations provide interpretations for the fact that when new exporters survive, their exports tend to grow rapidly.[1]

Finally, in allowing firms to attract more buyers by incurring greater costs, our analysis relates to Drozd and Nozal (2012) and Arkolakis (2009, 2010). By positing that firms face marketing costs that are convex in the number of foreign clients they service, Arkolakis also accounts for small-scale exporters and the age-dependence of export growth rates. However, since all exporting relationships last a single period in his models and learning is absent, Arkolakis's models do not explain the irreversibilities observed in firms' exporting behavior, nor do they speak to the duration of matches.

[1] Ruhl and Willis (2008) also note this pattern in plant-level export data and show that market entry costs are insufficient to explain it.

2 Firm-Level Trade: Transaction Level Evidence

2.1 Data

The empirical motivation for our model comes from a comprehensive data set that describes all imports by buyers in the United States from Colombian exporters (as well as other origins) during the period 1992-2009. The source is the U.S. Census Bureau's Longitudinal Foreign Trade Transactions Database (LFTTD). Each record includes a date, the US dollar value of the product shipped, a 6-digit harmonized system product code, a quantity index, and, critically, ID codes for both sellers and buyers. These IDs allow us to identify the formation and dissolution of business relationships between individual buyers in the U.S. and sellers in Colombia, hereafter referred to as "matches."[2]

To identify foreign exporters, the U.S. import transactions records include a manufacturer's identification code.[3] This field is an amalgamation of the manufacturer's country, company name, street address, and city. Anecdotal information from customs brokers indicates that commonly used software constructs it automatically as the name and address information is entered in other fields. So this variable is sensitive to differences in the way exporters' names and addresses are recorded as they pass through customs, and shipments from the same exporter can appear to originate from distinct Colombian firms. To gauge the importance of this problem, we have conducted various checks on the matches that are based on this

[2]There are two ways to track U.S. importers in the LFTTD: Employment Identification Numbers (EINs) and the firm identifiers in the Longitudinal Business Database ("alphas"). Though an EIN does not necessarily identify a complete firm, it is unique to a firm, and there is one associated with every import transaction. Alphas map to entire firms, but the match rate between trade transactions and alphas is only about 80 percent (Bernard, Redding, and Schott, 2009). To maximize the coverage of our sample, we use Employment Identification Numbers (EIN) to identify U.S. buyers.

[3]This variable is based on Block 13 of CBP form 7501, the import declaration form and customs brokers are required to input the data.

variable; these are explained in the Appendix.

We limit our analysis to transactions between non-affiliated trade partners, and we consider only imports of manufactured goods. The latter restriction notably excludes oil and coffee exports, which constitute the bulk of trade between the two countries and are dominated by a few Colombian sellers.[4] Our final data set of manufacturing transactions spans the years 1992-2009. It contains 26,625 unique Colombian exporters, 12,921 unique U.S. importers, and 42,767 unique trading pairs. Value data have been deflated to 1992 prices using the U.S. CPI. Since we exclude a number of large HS codes from our data, as well as affiliated trade, and because we also lose information due to disclosure restrictions, the total value covered by our data is not comparable to total Colombian exports to the U.S. Table 13 in Appendix A compares patterns in our sample to patterns in official aggregates from both the U.S. and Colombia.

In addition to U.S. customs records, we use establishment level survey data from Colombia's national statistics agency (Departmento Administrativo Nacional de Estadistica, or DANE). These data provide annual information on the sales volumes, exports, and other characteristics of all Colombian manufacturing plants with at least 10 workers. Because they have been widely analyzed, we do not discuss summary statistics for this data set herein. Later, however, when estimating our search and learning model, we use such statistics to characterize the size distribution of Colombian firms, the fraction of Colombian plants that export and, among these firms, the relationship between exports and domestic sales.

[4]Colombian commercialization of coffee is centralized to an important degree by the National Federation of Coffee Growers. A few players also dominate oil exports.

2.2 Exports and exporters

Following Brooks (2006) and Eaton et al. (2008), Tables 1-3 provide various annual measures of Colombian exports of manufactured goods to the United States for the years 1992-2009.[5] Each column follows an exporting cohort—i.e., a group of firms that began exporting in a particular year—from the year of its appearance through time. The tables report number of exporters, total exports, and exports per firm, respectively. Note that, since we don't know the history of firms before 1992, the 1992 "cohort" consists of all firms present that year, regardless of when they began exporting; given re-entry. This implies that the first few cohorts are in general overestimated in terms of their initial size. Nonetheless, the patterns highlighted below apply also to the most recent cohorts.

Consider Table 1 first. Naturally, each cohort's membership falls as it matures. But note that there is especially high attrition the first year, with more than 60 percent of firms dropping out. Conditional on making it to the second year, the survival probability is much higher, however, with an attrition rate around 40 percent the second year, and further declines occur thereafter. Thus, in terms of numbers, the most recent cohort is always larger than any previous one. Firms that were exporting to the United States in 1992 account for less than five percent of the firms exporting to the United States towards the end of the sample.

Table 2 shows that the rapid initial decline in its membership is not followed by a similar collapse of the total sales of a cohort. The decline in number of firms per cohort along with their relatively stable total sales means, of course, that sales per firm are growing substantially From the first to the second year of any cohort average sales more than double (Table 3).

[5] Similar tables for Colombian exports of all goods and to all destinations appear in Eaton, et al, 2008.

year	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	total
1992	2,232																		2,232
1993	823	1,235																	2,058
1994	583	330	1,160																2,073
1995	440	213	339	953															1,945
1996	372	163	178	255	899														1,867
1997	321	128	133	170	248	877													1,877
1998	268	104	124	132	153	256	893												1,930
1999	232	85	87	114	117	187	262	1,026											2,110
2000	203	85	79	91	103	136	170	344	1,372										2,583
2001	187	70	65	79	85	109	145	229	389	1,251									2,609
2002	173	64	62	72	68	88	112	171	242	399	1,373								2,824
2003	165	51	58	62	62	77	86	140	185	301	440	1,719							3,346
2004	150	52	41	53	63	76	80	132	164	223	327	616	1,768						3,745
2005	140	52	47	39	54	77	69	115	145	196	235	398	661	1,902					4,130
2006	122	46	44	39	44	71	65	110	131	157	168	308	410	564	1,896				4,175
2007	113	37	39	31	42	55	48	91	101	132	156	240	305	365	548	1,681			3,984
2008	93	29	30	24	38	50	45	74	90	117	130	184	198	230	331	447	1,455		3,565
2009	80	25	28	24	28	40	39	60	72	88	97	145	175	157	230	248	386	1,378	3,300

Table 1: Number of Exporting Firms, by Entry Cohort

year	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	total
1992	469																		469
1993	352	83																	435
1994	336	83	92																510
1995	313	75	102	58															549
1996	256	67	62	40	60														484
1997	247	84	43	41	48	119													581
1998	225	49	42	36	45	131	63												590
1999	207	51	49	41	39	197	74	81											739
2000	180	53	55	37	51	102	53	158	109										799
2001	150	22	51	41	28	57	36	80	101	111									677
2002	124	23	47	34	27	28	23	45	65	83	40								538
2003	147	42	51	31	42	24	22	37	71	107	50	78							702
2004	156	43	53	19	57	21	23	42	78	106	60	107	90						855
2005	150	22	75	17	52	18	23	43	78	80	58	81	75	84					855
2006	117	31	52	14	64	43	17	38	61	79	32	51	52	112	78				838
2007	103	7	18	11	67	58	19	30	28	64	22	35	33	66	67	62			689
2008	95	6	9	8	33	37	17	33	26	34	20	31	37	54	42	53	57		591
2009	68	22	7	6	13	24	10	23	16	16	14	22	41	25	39	37	36	64	485

Table 2: Value of Exports, by Entry Cohort (millions of $US)

year	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	pooled
1992	210																		210
1993	428	67																	211
1994	576	251	79																246
1995	712	353	300	61															282
1996	687	411	346	158	67														259
1997	771	652	321	241	192	136													310
1998	839	468	339	269	297	510	71												306
1999	893	601	561	361	336	1,054	281	79											350
2000	885	623	697	407	496	750	313	460	80										309
2001	801	316	783	519	329	521	251	350	259	89									260
2002	716	353	757	473	399	318	207	260	268	207	29								191
2003	891	827	870	493	677	315	257	260	385	355	114	46							210
2004	1,039	828	1,281	358	900	281	291	318	478	476	183	174	51						228
2005	1,071	413	1,593	444	967	231	326	375	535	408	248	204	113	44					207
2006	958	675	1,177	356	1,448	605	256	341	464	505	188	165	126	198	41				201
2007	915	175	466	357	1,606	1,048	391	327	278	481	140	145	108	181	123	37			173
2008	1,023	208	283	341	860	747	379	443	289	287	153	166	186	236	125	120	39		166
2009	855	864	262	266	478	607	255	389	221	176	143	152	235	162	169	151	93	47	147

Table 3: Exports per Firm, by Entry Cohort (thousands of $US)

2.3 Evidence on buyer-seller matches

We next use the data to characterize the buyer-seller matches that took place during 1992-2009.

2.3.1 Monogamous and polygamous matches

The number of Colombian exporters appearing in our sample grew from 2,232 in 1992 to 3,300 in 2009, a growth of 2 percent per annum, while the number of U.S. importing firms grew by 3 percent per annum (Table 4). The number of Colombian exporter-U.S. importer pairs (representing at least one transaction between them in a year) also grew at an annual rate of 2 percent. Roughly 80 percent of matches are monogamous in the sense that the buyer deals with only one Colombian exporter and the exporter ships to only one buyer in the United States. However, since the remainder of the matches are polygamous, the average Colombian exporter was involved in relationships with around 1.3 U.S. firms while the average U.S. buyer was involved with around 2.3 Colombian firms. Both figures declined slightly over the period.

Table 4: Size of Data Set

Year	Colombian Sellers	U.S. Importers	Pairs
1992	2,232	1,190	3,087
1993	2,058	1,183	2,824
1994	2,073	1,212	2,810
1995	1,945	1,173	2,588
1996	1,867	1,191	2,490
1997	1,877	1,208	2,480
1998	1,930	1,191	2,495
1999	2,110	1,386	2,793
2000	2,583	1,661	3,411
2001	2,609	1,698	3,483
2002	2,824	1,826	3,733
2003	3,346	2,110	4,483
2004	3,745	2,296	5,071
2005	4,130	2,457	5,552
2006	4,175	2,471	5,607
2007	3,984	2,343	5,307
2008	3,565	2,221	4,751
2009	3,300	2,079	4,467

2.3.2 Transition Probabilities

Like exporting stints (Table 1), most matches are short-lived. Of the 3,087 buyer-seller matches that existed at the beginning of the period, 70 percent didn't make it to 1993. But, of those that made it into the next year, almost 50 percent made it into the next year. Similarly, of the relationships that existed in 2005, 57 percent started that year but of those that started before, 37 percent had been around at least three years before. Of the 3,210 matches identified in 1992, less than 25 endure (are present every year) throughout the period.

Table 5 reports the probability with which a Colombian firm participating in certain number of relationships with buyers transits into a different number of relationships the following year. (Confidentiality restrictions prevent us from reporting numbers for cells that are too sparsely populated.) This table reports the annual average for 1992-2009 across all industries. A firm that stops exporting but re-appears as an exporter sometime later in our sample period is considered to have gone "dormant", while those exporters that drop to zero foreign sales for the extent of our sample are considered to have gone "out" of exporting. Those that have never been observed to export constitute the pool of potential entrants.

Among first-time exporters, 93.2 percent sell to only one firm. Of these, 62 percent don't export the next year, and only about six percent go on to establish a larger number of relationships. For firms with three relationships in a year, about twelve percent enter into a larger number of relationships the next year. Hence there is an enormous amount of churning at the lower end. Even for firms with a large number of relationships the most likely outcome is to have fewer the next year.

We can ask what this pattern of entry and growth implies about the ergodic distribution of relationships. If we assume that entrants in a year replace exiting firms, the ergodic distribution implied by this transition matrix is given by Table 6.

For purposes of comparison, the year-specific average share of Colombian firms in each group is reported as well. Note that the ergodic distribution implied by the transition matrix is very close to the cross-sectional distribution in the data, suggesting that over the period we observe the process has been quite stationary. Interestingly, both distributions are very nearly Pareto, reflecting the coexistence of many small scale exporters with a few "super-exporters."

2.3.3 Match maturation

The survival probability of new matches increases with initial sales volume. Table 7 sorts observations on matches according to their size in their first year of existence and reports year-to-year separation rates. In addition to the very low survival rates, two patterns stand out. First, those matches that begin with sales in the top quartile among all new matches are more likely to survive than matches that begin with smaller sales volumes. Second, survival probabilities improve after the initial year.

Further features of the match maturation process are evident in Figure 1, which shows the log of annual sales per match, broken down by initial size quartile. For each size quartile,

Table 5: Transition Probabilities, Number of Clients

t \t+1	Out	Dormant	1	2	3	4	5	6-10	11+
Out	.	.	0.932	0.055	0.009	0.002	0.001	0.001	0.000
Dormant	.	.	0.876	0.100	0.015	0.008	.	.	0.000
1	0.539	0.080	0.321	0.048	0.010	0.002	.	0.001	.
2	0.194	0.077	0.375	0.241	.	0.024	0.009	0.004	.
3	0.090	0.042	0.220	0.271	0.210	0.092	.	0.027	.
4	0.059	.	0.129	0.216	0.215	0.184	0.083	0.095	.
5	.	.	0.095	0.184	0.181	0.181	0.126	0.178	.
6-10	.	.	0.039	0.073	0.089	0.123	0.157	0.419	0.073
11+	.	0.000	0.000	0.000	.	.	.	0.432	0.526

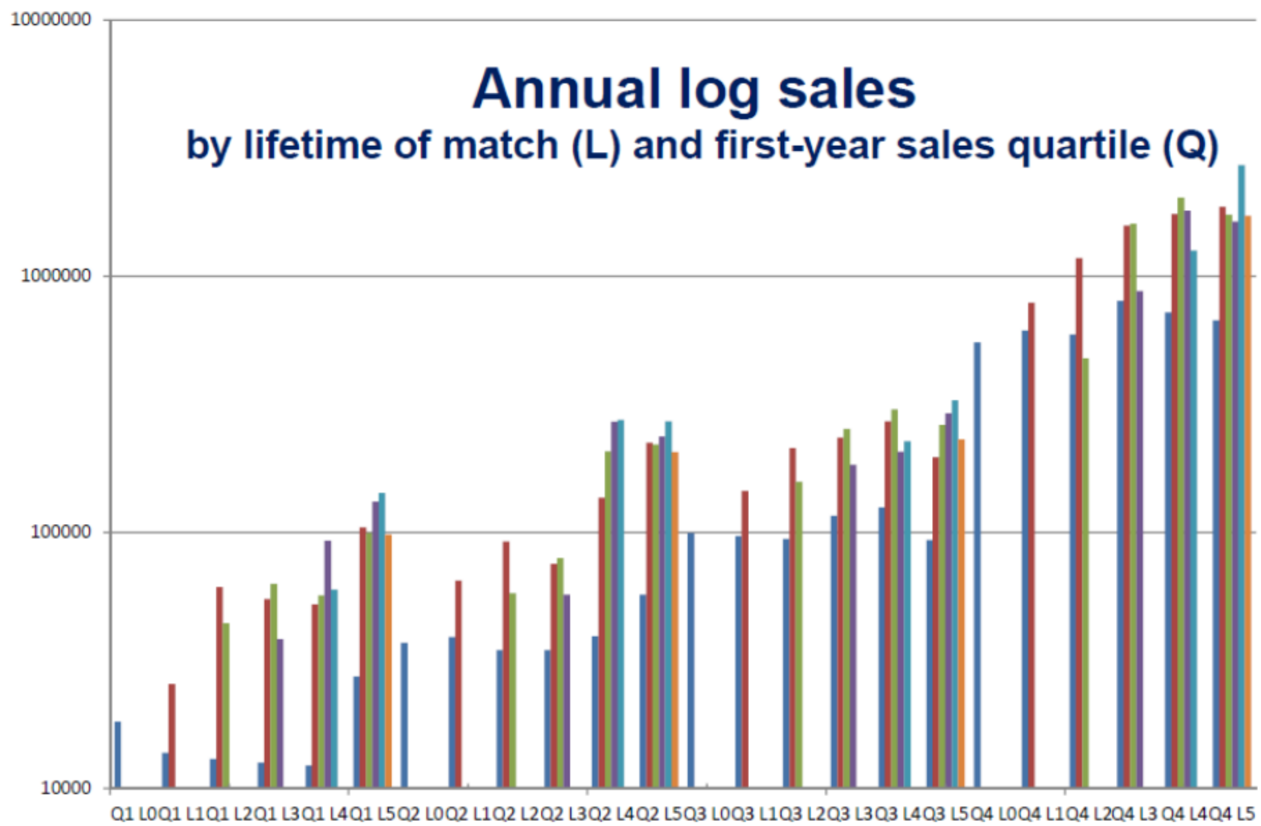


Figure 1: Log annual sales per match, by initial size quartile

matches are further distinguished according to their life span: less than one, 1 to 2 years, and so forth. And for each cluster of bars, the left-most bar corresponds to sales in the initial year of the match's existence, the next bar corresponds to sales during the second year of the match's existence, and so forth.

The first message of these graphs is that initial sales are a good predictor of sales in subsequent years, conditioning on survival. Those matches with first-year sales in the smallest

Table 6: Ergodic Client Distribution Implied by Transitions

	1	2	3	4	5	6-10	11+
Erg Distribution	0.792	0.112	0.031	0.016	0.009	0.022	0.016
Data	0.778	0.116	0.043	0.021	0.011	.	.

Table 7: Separation Rates, by Age of Match and Initial Sales

	1 year	2 years	3 years	4 years	5+ years
Quartile 1	82.9	63.2	57.3	55.0	49.7
Quartile 2	75.6	58.4	49.4	46.8	43.7
Quartile 3	67.7	52.1	44.6	40.8	37.6
Quartile 4	52.1	44.5	40.3	39.2	36.7

quartile systematically generated the lowest annual sales in subsequent years, and more generally, first-year sales are monotonically related to annual sales in subsequent years. Second, sales tend to jump from the first to the second year, in large part simply because observations on a match's first year correspond to less than a full calendar year. (There is an analogous effect at work in the final year of a match's life.) Looking at complete-year observations reveals a tendency for annual sales to grow among matches that start small and survive, but no such tendency among matches that start in the largest quartile. Finally, looking across matches with different life spans, those that survive more years tend to have higher sales in all (full) years than matches that fail relatively quickly. This pattern is robust across matches in the different quartiles for initial sales.

2.3.4 Number of clients and sales per client

Finally, firms that are successful at building a large client base also manage to sell relatively large amounts to each client. To summarize this relationship we fit the following regression:

$$\ln \overline{R}_{jt} = \phi_0^r + \phi_1^r \ln(n_{jt}^c) + \phi_2^r \ln(n_{jt}^c)^2 + \epsilon_{jt}^r$$

Here $\overline{R}_{jt}$ is exporter j's average revenue per client in year t, and n_{jt}^c is the number of clients who received shipments from j during the same year. The regression implies $\overline{R}$ is an increasing concave function of n^c: $\widehat{\phi}_1^r = 2.67$; $\widehat{\phi}_2^r = -0.14$.

3 A Model of Exporting at the Transactions Level

We now develop a model of exporter behavior consistent with the patterns reviewed above. Buyer-seller relationships form and disband at irregular intervals. Similarly, export shipments are discrete events distributed unevenly through time. To capture these features of the data, and to allow agents to update their behavior each time their circumstances change, we formulate our model in continuous time, treating all of the exogenous processes in our model as Markov jump processes.

Explaining the evolution of a firm's exports and domestic sales requires modeling both its sales to existing buyers and the evolution of its portfolio of clients. We can treat these two components sequentially. We first consider the relationship between a seller and an individual buyer. Having characterized the seller's profits from a relationship with an individual buyer, we then turn to her learning about the popularity of her product, i.e., the chance that a potential buyers likes her product. Finally, we characterize her search for buyers.

3.1 A Seller-Buyer Relationship

This section characterizes the profit streams that sellers generate from successful business relationships. The expressions we develop here describe relationships between domestic firms and foreign buyers, but with appropriate relabelling of market-wide variables they apply equally to relationships between domestic firms and domestic buyers.

3.1.1 Profits from a single shipment

Several features of our model are standard. First, at any time t seller j can hire workers at a wage w_t in real local currency units, each of whom can produce $\varphi_j \in \{\varphi^1, .., \varphi^{N_\varphi}\}$ units of output.[6] Hence seller j's unit cost in local currency is w_t/φ_j. If she sells at price p_{jt} in foreign currency her unit profit in local currency is

$$p_{jt}/e_t - w_t/\varphi_j, \tag{1}$$

where e_t is the exchange rate. Second, goods markets are monopolistically competitive and each producer supplies a unique differentiated product.

Once buyer i has agreed to form a business relationship with seller j, he periodically places sales orders with j. For j, an order from i that arrives at time t generates revenue:

$$X_{ijt} = \left(\frac{p_{jt}}{P_t}\right)^{1-\eta} y_{ijt}\overline{X}_t, \tag{2}$$

where $\eta > 1$ is buyers' elasticity of demand, p_{jt} is the price of seller j's product, $\overline{X}_t$ is the average spending level among all potential foreign buyers, P_t is the relevant price index for all competing products in the foreign market, and $y_{ijt} \in \{y^1, .., y^{N_y}\}$ is a time-varying demand shifter idiosyncratic to the ij relationship.[7]

For simplicity, and to keep the analysis as close as possible to other heterogenous firm models, we assume that the seller posts a non-negotiable price, charging the optimal markup over unit cost:[8]

$$p_{jt} = \frac{\eta}{\eta - 1}\frac{e_t w_t}{\varphi_j} \tag{3}$$

By (1), (2), and (3), an order from buyer i at time t therefore generates the following profits for seller j:

[6] We treat φ as time-invariant to facilitate model identification. Other sources of idiosyncratic temporal variation in sales will be discussed shortly.

[7] Not all buyers necessarily face the same range of goods and hence the same aggregate price index P. We treat idiosyncratic components of the price index as P as reflected in y_{ijt}.

[8] An alternative specification would introduce bilateral bargaining between buyer and seller.

$$\pi_{ijt} = \frac{1}{\eta}\frac{\overline{X}_t}{e_t}\left(\frac{e_t w_t \eta/(\eta-1)}{\varphi_j P_t}\right)^{1-\eta} y_{ijt}.$$

We can combine all the macroeconomic variables affecting the profit of any seller from this source selling in this destination, along with constants, as:

$$x_t = \frac{1}{\eta}\frac{\overline{X}_t}{e}\left(\frac{e_t w_t \eta/(\eta-1)}{P_t}\right)^{1-\eta},$$

where $x \in \{x^1, .., x^{N_x}\}$ is general to all potential buyers in the foreign market. Suppressing subscripts on state variables, this allows us to write the profits from a sale as:

$$\pi_\varphi(x, y) = x\varphi^{\eta-1}y, \tag{4}$$

In what follows, (4) is all we take from our specification of preferences and pricing behavior into the dynamic analysis. Any set of assumptions that deliver this simple multiplicative expression for a firm's profit from a sale would serve us equally well.

3.1.2 Relationship dynamics

At any point in time, each seller maintains business relationships with an endogenous number of buyers. These relationships form as a consequence of a search process that will be characterized in the following section, and they dissolve for several reasons. First, there is a constant exogenous hazard δ that any particular relationship will terminate, which could be due to the demise of the buyer or the buyer no longer finding the seller's product useful. Second, after each sale to a particular buyer, the seller evaluates whether it is worth sustaining her relationship with him. Doing so keeps the possibility of future sales to him alive, but it also means paying the fixed costs F of maintaining the account, providing technical support, and maintaining client-specific product adjustments.[9]

When deciding whether to maintain a particular business relationship, the seller knows her own type, φ, the macro state, x and profits from the current sale, $\pi_\varphi(x, y)$ to the buyer in question. She can therefore infer this buyer's current y value and calculate the value of her relationship with him to be:

$$\widetilde{\pi}_\varphi(x, y) = \pi_\varphi(x, y) + \max \left\{ \widehat{\pi}_\varphi(x, y) - F, 0 \right\}.$$

Here $\widehat{\pi}_\varphi(x, y)$ is the expected value of continuing a relationship that is currently in state (x, y). Clearly the seller terminates this relationship if $\widehat{\pi}_\varphi(x, y) < F$.

If a seller pays F to keep a relationship active, and if the relationship does not end anyway for exogenous reasons, one of several events will next affect it: with hazard λ^b the buyer will place another order, with hazard $q^X_{xx'}$ x will jump to some new marketwide state $x' \neq x$, or with hazard $q^Y_{yy'}$ y will jump to some new buyer-specific shock $y' \neq y$.[10] Let τ_b be the random time that elapses until one of these events occurs. Given that x and y are Markov jump processes, τ_b is distributed exponentially with parameter $\lambda^b + \lambda^X_x + \lambda^Y_y$, where

$$\lambda^X_x = \sum_{x' \neq x} q^X_{xx'} \tag{5}$$

and

$$\lambda^Y_y = \sum_{y' \neq y} q^Y_{yy'}, \tag{6}$$

[9] For instance, Colombian producers of construction materials interviewed for a related project (Domínguez et al, 2013) referred that it is frequent for foreign buyers to request adjustments in the specifications of products or packages. In turn, these require adjustments in the production process that are costly to maintain.

[10] Since sales in the data are discrete events rather than flows, we model the buyer's purchases accordingly. We think of the buyer not as making use of the products continually but in discrete spurts. For example, the buyer might be a producer of a product that it makes in batches. At the completion of each batch it buys inputs for the next batch.

are the hazards of transiting from x to any $x' \neq x$, and from y to any $y' \neq y$, respectively. Then assuming the seller has a discount factor ρ, the continuation value $\widehat{\pi}_\varphi(x,y)$ solves the Bellman equation:

$$\begin{aligned}
\widehat{\pi}_\varphi(x,y) &= \mathbf{E}_{\tau_b}\left[e^{-(\rho+\delta)\tau_b}\frac{1}{\lambda^b+\lambda_x^X+\lambda_y^Y}\left(\sum_{x'\neq x} q_{xx'}^X\widehat{\pi}_\varphi(x',y)+\sum_{y'\neq y} q_{yy'}^Y\widehat{\pi}_\varphi(x,y')+\lambda^b\widetilde{\pi}_\varphi(x,y)\right)\right] \\
&= \frac{1}{\rho+\delta+\lambda^b+\lambda_x^X+\lambda_y^Y}\left(\sum_{x'\neq x} q_{xx'}^X\widehat{\pi}_\varphi(x',y)+\sum_{y'\neq y} q_{yy'}^Y\widehat{\pi}_\varphi(x,y')+\lambda^b\widetilde{\pi}_\varphi(x,y)\right)
\end{aligned}$$

Before a seller has met her next buyer, she does not know what state y this buyer will happen to be in. So when choosing her search intensity for new business relationships, she must base her decisions on the ex ante expected pay-off to forming a new business relationship. Given the market state x, a type-φ seller calculates this expected value as:

$$\widetilde{\pi}_\varphi(x) = \sum_s \Pr(y^s)\widetilde{\pi}_\varphi(x,y).$$

where $\Pr(y^s)$ is the probability that a randomly selected buyer is currently in state $y^s \in \{y^1,..,y^{N_y}\}$.[11]

For the purposes of the search model that follows, all that matters about an individual relationship is $\widetilde{\pi}_\varphi(x)$, and this object can be estimated directly from data on the revenue streams generated by matches. Nonetheless, the history of a seller's interactions with a given buyer affects its overall sales trajectory and hence matters for our characterization of aggregate export dynamics.

Hereafter, we will denote the expected value of a relationship with a foreign buyer by $\widetilde{\pi}_\varphi^f(x)$ and the expected value of a relationship with a home market buyer by $\widetilde{\pi}_\varphi^h(x)$. These two objects are calculated in the same way, but since expenditure levels $(\overline{X}_t)$ and price indices (P_t) differ

[11]Here we take the probabilities $\Pr(y^m)$ to be the ergodic distribution of y implied by the transition hazards $q_{yy'}^Y$. We could assume that the distribution at the time of the first purchase is different from the ergodic one.

across markets, and no exchange rate factor e is necessary for domestic profit calculations, each has its own process for the market-wide state variable, x. These market-wide demand shifters are denoted x^f and x^h below.

3.2 Learning about Product Appeal

Sellers conduct market-specific searches for buyers. When searching in market $m \in \{h, f\}$, each recognizes that some fraction $\theta^m \in [0,1]$ of the potential buyers she meets there will be willing to do business with her. An encounter with one of these willing buyers generates an expected profit stream worth $\widetilde{\pi}^m_{\varphi,x}$, while an encounter with any of the remaining potential buyers does not generate a sale then or subsequently.

Each seller's θ^h and θ^f values are drawn before she has met any clients. These draws remain fixed through time, inducing permanent cross-market differences in her product's popularity. All θ^m draws are independently beta-distributed across sellers and markets:

$$b(\theta^m|\alpha,\beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} (\theta^m)^{\alpha-1} (1-\theta^m)^{\beta-1}, \; m \in \{h, f\},$$

where $\Gamma(\phi) = \int_0^\infty z^{\phi-1} e^{-z} dz$ is the gamma function (needed to ensure that the distribution has the proper limits). However, the independence of θ^h and θ^f does not mean sellers' domestic and foreign sales are likewise independent. Rather, cross-market correlation in sales will be induced by the firm type φ, which can be viewed as capturing aspects of product appeal that are common to both markets.[12]

[12] The firm effect is similarly interpreted to reflect both productive efficiency and product appeal in Melitz (2003) and many other papers based on CES demand systems. However in the present context, the global aspects of product appeal captured by φ are qualitatively distinct from the market-specific product appeal effects captured by θ. The former determines the amount of a product each buyer purchases, given that he is interested, while the latter determines what fraction of potential buyers are willing to place orders with the seller, should they happen to meet her.

Sellers are presumed to have already met many potential customers in the domestic market, and thus to have learned their θ^h draws. But sellers typically have far less experience abroad, so we allow them to still be learning about their θ^f draws. Specifically, each seller recognizes that for any given θ^f, the probability a random sample of n potential foreign buyers will yield a customers is binomially distributed:

$$q\left[a|n,\theta^f\right] = \binom{n}{a}\left[\theta^f\right]^a\left[1-\theta^f\right]^{n-a}.$$

So after she has met n potential buyers abroad, a of whom were willing to buy her product, a seller's posterior beliefs about her θ^f draw are distributed:

$$p(\theta^f|a,n) \propto q\left[a|n,\theta^f\right]\cdot b(\theta^f|\alpha,\beta)$$

where the factor of proportionality is the inverse of the integral of the right-hand side over the support of θ^f. Since the beta distribution is the conjugate prior for the binomial, a firm's expected success rate after a successes in n trials has a convenient closed-form representation:

$$\overline{\theta}^f_{a,n} = E\left[\theta^f|a,n\right] = \int_0^1 \theta p(\theta|a,n)d\theta = \frac{a+\alpha}{n+\alpha+\beta}. \tag{7}$$

This posterior mean converges to $p\lim\left(\frac{a}{n}\right) = \theta^f$ as n gets large.

3.3 Searching for Buyers

To complete our model we now consider sellers' search intensities in each market. Each seller continuously chooses the market-specific hazard s^m, $m \in \{h,f\}$, with which she encounters a potential buyer, recognizing that this involves the instantaneous flow cost $c(s^m,a)$, where $c(s^m,a)$ is increasing and convex in s^m.[13] Whether $c(s^m,a)$ increases or decreases in the number

[13]Interviews conducted with Colombian exporters revealed a variety of activities firms pursue to meet potential buyers abroad (Domínguez, et al, 2013). Ranked roughly in terms of decreasing cost, these included

of successful matches, a, depends upon the relative strength of several forces and will be left for the data to determine. Costs might fall with a because encounters with interested buyers increase the seller's visibility and enhance her opportunities to meet additional potential buyers. Alternatively, costs might rise if the pool of easy-to-reach buyers becomes "fished out," as in Arkolakis (2007).

We can now describe optimal search behavior, beginning with the foreign market. Recall that when the foreign market state is x^f, a type-φ seller expects the value of a new business relationship will be $\widetilde{\pi}_{\varphi}^{f}(x^f)$. Further, she believes the next match will yield such a relationship with probability $\overline{\theta}_{a,n}^{f}$. Combined with search cost function $c(s^f, a)$ and the jump process for x^f, these objects imply sellers' optimal search policy abroad.

To characterize this policy, let τ_s^f be the random time until the next foreign search event, which could be either a change in the marketwide state x^f or an encounter with a potential buyer. Then, suppressing market superscripts, the optimal search intensity s for a type-φ firm with foreign market search history (a, n) solves the following the Bellman equation:

$$V_{\varphi}(a, n, x) = \max_{s} \mathbf{E}_{\tau_s} \left[-c(s, a) \int_0^{\tau_s} e^{-\rho t} dt + \frac{e^{-\rho \tau_s}}{s + \lambda_x^X} \cdot \left(\sum_{x' \neq x} q_{xx'}^X V_{\varphi,}(a, n, x') \right.\right.$$
$$\left.\left. + \, s \left[\overline{\theta}_{a,n} (\widetilde{\pi}_{\varphi}(x) + V_{\varphi}(a+1, n+1, x) + (1 - \overline{\theta}_{a,n}) V_{\varphi}(a, n+1, x) \right] \right) \right]$$

maintaining a foreign sales office; paying the exports promotion office to organize visits with prospective clients abroad, and sending their sales representatives to those visits; sending sales representatives abroad to visit potential clients on their own; attending trade fairs; paying a researcher to search the web for foreign firms that purchase products similar to their own; paying browsers to ensure that their site appear near the top of a search for their product type; maintaining a web site in English. Interviewees also reported that relatively low-cost activities, such as traveling to trade fairs, or translating their websites to English, led to relationships with one or two clients every few years. Establishing a larger network of clients required much more costly activities.

(Recall that λ_x^X is given by (5).) Taking expectations over τ_s yields:

$$\begin{aligned} V_\varphi(a,n,x) \quad &= \quad \max_s \frac{1}{\rho + s + \lambda_x^X}\left[-c(s,a) + \sum_{x' \neq x} q_{xx'}^X V_{\varphi,}(a,n,x') \right. \\ &\left. + s\left\{ \overline{\theta}_{a,n}\left[\widetilde{\pi}_\varphi(x) + V_\varphi(a+1,n+1,x)\right] + (1-\overline{\theta}_{a,n})V_\varphi(a,n+1,x)\right\} \right] \end{aligned} \tag{8}$$

Applying the multiplication rule for differentiation and using expression (8) for $V_\varphi(a,n,x)$, the optimal search intensity s^* satisfies:

$$\frac{\partial c(s^*,a)}{\partial s} = \overline{\theta}_{a,n}\left[\widetilde{\pi}_\varphi(x) + V_\varphi(a+1,n+1,x)\right] + (1-\overline{\theta}_{a,n})V_\varphi(a,n+1,x) - V_\varphi(a,n,x) \tag{9}$$

That is, the marginal cost of search must equal the expected marginal benefit of a match, which includes the expected value of the associated profit stream, $\overline{\theta}_{a,n}\widetilde{\pi}_\varphi(x)$, and the expected value of the information generated.

Now consider the home market. Since we assume sellers have already learned their true success rates at home, θ^h, new encounters do not influence expectations, and we need not condition the value function or the expected success rate on search histories. Again suppressing market superscripts, the Bellman equation collapses to:

$$V_\varphi(x) = \max_s \frac{1}{\rho + \lambda_x^X}\left[-c(s,a) + \sum_{x' \neq x} q_{xx'}^X V_\varphi(x') + s\theta_j \widetilde{\pi}_\varphi(x) \right]$$

and the first-order condition is simply:

$$\frac{\partial c(s^*,a)}{\partial s} = \theta_j \widetilde{\pi}_\varphi(x).$$

The marginal cost of search equals the expected profit from a successful relationship times the probability of success.

4 An empirical version of the model

4.1 The search cost function

To implement our model empirically, we impose additional structure in several respects. First, we specify a functional form for our search cost function. Generalizing Arkolakis (2007) to allow for network effects, we write these costs as:

$$c(s,a)=\kappa_0\frac{[(1+s)]^{(1+1/\kappa_1)}-1}{(1+a)^{\gamma(1+1/\kappa_1)}(1+1/\kappa_1)}. \tag{10}$$

Several properties of this function merit note. First, marginal costs fall at a rate determined by γ with the number of successful matches a seller has already made, so $\gamma>0$ implies "network" effects and $\gamma<0$ implies "congestion" effects.[14] Second, a seller who is not searching in a particular market incurs no search cost: $c(0,a)=0$. Third, given the cumulative number of successful matches, a, the marginal cost of search increases with λ^s at a rate inversely related to $\kappa_1 : c_s(s,a)=\kappa_0\left[(1+s)/(1+a)^{\gamma}\right]^{1/\kappa_1}$. Finally, network effects endure, even if a firm is not actively searching.

4.2 Processes for exogenous state variables

Next we impose more structure on the exogenous state variables, φ, x^h, x^f, y^h and y^f. All are assumed to have zero means in logs, and the net effect of these normalizations is undone by introducing scalars Π^h and Π^f into the home and foreign profit functions, respectively:

$$\begin{aligned}\pi^f_{\varphi}(x^f,y^f) &= \Pi^f x^f\varphi^{\eta-1}y^f,\\ \pi^h_{\varphi}(x^h,y^h) &= \Pi^h x^f\varphi^{\eta-1}y^f\end{aligned}$$

[14]To contain the dimensionality of the computational problem we solve, we assume that firms with more than a^* buyers have (i) exhausted their learning effects, and (ii) reap no additional network effects at the margin from further matches. We choose a^* to exeed the observed maximum a for 99 percent of sellers in the foreign (United States) market. Also, we set $a=a^*$ for all sellers in their home (Colombian) market.

More substantively, we impose that the cross-firm distribution of φ is log normal with standard deviation σ_φ, and we treat all of the Markov jump processes (x^h, y^h, x^f, y^f) as independent Ehrenfest diffusion processes. The idiosyncratic match shocks, y^f and y^h, are assumed to share the same distribution, but we allow the x^f and x^h processes to differ. Among other things, the latter accommodates the fact that the exchange rate affects aggregate demand and price indices in the two markets differently.

Any variable z generated by an Ehrenfest process can be discretized into $2g+1$ possible values, $g \in I^+ : z \in \{-g\Delta, -(g-1)\Delta, .., 0, .., (g-1)\Delta, g\Delta\}$. Further, it jumps to a new value with hazard λ_z, and given that a jump occurs, it goes to z' according to:

$$z' = \begin{cases} z+\Delta \\ z-\Delta \\ \text{other} \end{cases} \text{with probability} \begin{cases} \frac{1}{2}\left(1-\frac{z}{g\Delta}\right) \\ \frac{1}{2}\left(1+\frac{z}{g\Delta}\right) \\ 0 \end{cases}.$$

Thus, given a grid size g, the intensity matrices $Q^X = \left\{q_{ij}^X\right\}_{i,j=1,N^X}$ and $Q^Y = \left\{q_{ij}^Y\right\}_{i,j=1,N^Y}$ that were introduced in section 3.1 are each block-diagonal and characterized by a single parameter, Δ.

5 Estimation

5.1 Stage 1: estimating observable jump processes

Shimer (2005) shows that if z follows a continuous time Ehrenfest diffusion process, it asymptotes to an Ornstein-Uhlenbeck process with mean zero as the fineness of the grid increases:[15]

$$dz = -\mu z dt + \sigma dW.$$

[15]Specifically, replacing the parameter vector (λ, g, Δ) with $(\lambda/\epsilon, g/\epsilon, \Delta\sqrt{\epsilon})$, $\epsilon > 0$, leaves the autocorrelation parameter μ and the instantaneous variance parameter σ unchanged. But as $\epsilon \to 0$, the innovation dW approaches normal.

Table 8: Market-wide Demand Shifters

	Parameter	*value*
home macro state jump hazard	λ^{x_h}	1.200
foreign macro state jump hazard	λ^{x_f}	1.215
home macro state jump size	Δ^{x_h}	0.003
foreign macro state jump size	Δ^{x_f}	0.053

Here $\mu = \lambda_z/g$, $\sigma = \sqrt{\lambda_z}\Delta$, and W follows a Weiner process. Accordingly, since it is possible to observe proxies for x^f and x^h, these can be viewed as discrete time observations on underlying Ornstein-Uhlenbeck processes, and the parameters of these processes can be econometrically estimated. Then, given μ and σ, estimates of Δ and λ for these processes can be inferred.

Measuring x^f as real expenditures on manufacturing goods in the U.S., and measuring x^h as real expenditures on manufacturing goods in Colombia, we obtain the results reported in Table 8.[16] They imply that x^f and x^h both jump 1.2 times per year, on average. However, jumps in the U.S. market tend to be much larger, essentially because they reflect movements in the real exchange rate as well as movement in dollar-denominated expenditures.

5.2 Stage 2: Indirect inference

Our data are relatively uninformative about the rate of time discount ρ and the demand elasticity η, so we do not attempt to estimate either one. For the former we follow convention and assume $\rho = 0.05$. For the latter, following many previous trade papers, we fix the demand elasticity at $\eta = 5$. All of the remaining parameters we estimate using the method of indirect inference (Gouriéroux and Monfort, 1996). These parameters include the exogenous match separation hazard (δ), the market size scalars ($\Pi^h, \Pi^{f\cdot}$), the fixed costs of maintaining

[16] Our foreign market size mesaure is the OECD time series on American GDP in 'Industry, including energy' adding imports and subtracting net exports of manufactures. Our home market size measure is real Colombian expenditures on manufacturing goods, taken from DANE. We converted all of the data used for the estimation into real 1992 US dollars, deflating nominal US dollars with the consumer price index available on the US Bureau of Labor Statistic website. We used an official Colombian Peso - US Dollar exchange rate time series downloaded from the Central Bank of Colombia to convert Pesos to nominal US Dollars

a match (F), the parameters of the product appeal distributions (α,β), the dispersion of the productivity distribution (σ_φ), the jump hazards for the idiosyncratic buyer shocks (λ_y), the hazard rate for shipments (λ_b), the network/congestion parameter (γ), the cost function convexity parameter (κ_1), and the cost function scaling parameter (κ_0). For notational convenience we hereafter collect these parameters in the vector Λ :

$$\Lambda = \left(\Pi^h, \Pi^{f\cdot}, \delta, F, \alpha, \beta, \sigma_\varphi, \lambda_y, \lambda_b, \gamma, \kappa_0, \kappa_1\right)$$

We seek the value of Λ that allows our model to replicate the features of the transactions-level data summarized in Section 2 above. In addition to the joint distribution of home and foreign sales across firms, these include the distribution of clients across exporters, the probabilities than a particular exporter will move up or down in this distribution, given its current position, the hazard that a given match will end, given its current age and size, the survival rates of exporting cohorts as they mature, and the distribution of shipment frequencies across matches.

The sample statistics that we use as a basis for inference are listed in Table 9. These same statistics are also repeatedly constructed using data simulated with the model at alternative candidate values for Λ. The method of indirect inference amounts to choosing the Λ value that minimizes a metric of the distance between sample and simulated statistics.[17]

[17]More precisely, our estimator for Λ is:

$$\widehat{\Lambda} = \arg\min \left[\widehat{M} - M_S(\Lambda)\right]' \widehat{W}^{-1} \left[\widehat{M} - M_S(\Lambda)\right]$$

where $\widehat{M}$ is the vector of data-based statistics listed in the right-most column of Table 9, $M_S(\Lambda)$ is their counterpart based on S simulations of our model at candidate vector Λ, and $\widehat{W}$ is a compatible matrix with $\widehat{se}(\widehat{M})$ on its diagonal and zeros elsewhere. These standard errors are constructed using the sample data. In addition to giving the greatest weight to those statistics that are most precisely estimated, W^{-1} serves to eliminate units of measurement as a factor in determining the fit. The efficient GMM estimator of ϕ would use $E\left[\widehat{M} - E(\widehat{M})\right]\left[\widehat{M} - E(\widehat{M})\right]'$ (adjusted for simulation error in $M(\Lambda)$) as its weighting matrix. But since our data on establishments and matches come from several sources, it computationally infeasible for us to

Table 9: Statistics used for Indirect Inference

Data feature	Summary method	Statistics ($\widehat{M}$)
Distribution of home and foreign sales	OLS cross-plant regression: $\ln X^f_{jt} = \phi^{hf}_0 + \phi^{hf}_1 \ln X^h_{jt} + \epsilon^{hf}_{jt}$	$\widehat{\phi}^{hf}_0$, $\widehat{\phi}^{hf}_1$, $\widehat{se}(\epsilon^{hf})$
	Cross-plant moments	$\widehat{E}(1_{X^f_{jt}>0}), \widehat{E}(\ln X^f_{jt} \mid X^f_{jt} > 0)$,
	Standard deviation of foreign sales	$se(\ln X^f_{jt})$
Distribution of clients across exporters, $\Phi(n^c)$	OLS regression for $n^c \in I^+$: $\ln[1 - \Phi(n^c)] = \phi^c \ln(n^c) + \epsilon^n$	$\widehat{\phi}^c$, $\widehat{se}(\epsilon^{n^c})$
Sales per client given number of clients	OLS cross-match regression: $\ln X^f_{ijt} = \phi^r_0 + \phi^r_1 \ln(n^c_{jt}) + \phi^r_2 \ln(n^c_{jt})^2 + \epsilon^m$	$\widehat{\phi}^r_0$, $\widehat{\phi}^r_1$, $\widehat{\phi}^r_2$, $\widehat{se}(\epsilon^r)$
Autoregression, log domestic sales	$\phi^h_0 + \phi^h_1 \ln X^h_{jt-1} + \epsilon^h$	$\widehat{\phi}^h_1$, $\widehat{se}(\epsilon^h)$
Transition probabilities, number of clients (n^c_{jt})	Cross-plant year-to-year average transition rates	$\widehat{P}[n^c_{jt+1} = m \mid n^c_{jt} = k]$, $m, k = 0, 1, 2, 3+$
Match death hazards, given match age (A^m)	Cross-match average year-to-year death rates, given age	$\widehat{E}[1_{X^f_{ijt}=0} \mid X^f_{ijt-1} > 0, A^m_{ijt-1}]$, $A^m_{ijt-1} = 0, 1, 2, 3, 4+$
Exporter exit hazard by cohort age (A^c)	Cross exporter average exit rate, given years exporting	$\widehat{E}[1_{X^f_{jt}=0} \mid A^c_{jt}]$, $A^c_{jt} = 0, 1, 2, 3, 4+$
Cohort-specific exports per plant	Cross-exporter mean log exports	$\widehat{E}(\ln X^f_{jt} \mid A^c_{jt})$, $A^c_{jt} = 1, 2, 3, 4+$
Match-specific shipments per year (n^s_{ijt})	Cross-match mean shipments per year	$\widehat{E}\,(n^s)$ (trimmed)
Autoregression, match-specific sales (X^f_{ijt})	$\ln X^f_{ijt} = \widehat{\beta}^f_0 + \widehat{\beta}^f_1 \ln X^f_{ijt-1} + \epsilon^f_{ijt}$	$\widehat{\beta}^f_1$, $\widehat{se}(\epsilon^f)$
Match death prob. and match sales	$1_{X^f_{ijt}=0} = \widehat{\beta}^d_0 + \widehat{\beta}^d_{\text{1st year}} 1_{A^m_{ijt-1}=0} + \widehat{\beta}^d_{\text{lsales}} \ln X^f_{ijt-1} + \epsilon^d_{ijt}$	$\widehat{\beta}^d_0, \widehat{\beta}^d_{\text{1st year}}, \widehat{\beta}^d_{\text{lsales}}, \widehat{se}(\epsilon^d)$

Variable definitions:
n^c_{jt}: number of foreign clients served by firm j in year t
$\Phi(n^c)$: cumulative frequency distribution of number of foreign clients in population of exporters
A^m_{ijt} : age of match (in years) between seller j and foreign buyer i in year t
A^c_{jt}: number of consecutive years exporter j has made at least one shipment abroad.

While there is no exact mapping between the statistics in the last column of Table 9 and the parameters we wish to estimate, it is possible to comment in general terms on sources of identification. First, several parameters are closely associated with sample means. Specifically, the profit function scaling parameters Π^h and Π^f are identified by average levels of sales in each market, $E(\ln X_{jt}^h)$ and $E(\ln X_{jt}^f)$, given market participation, as well as the fraction of firms that export, $E(1_{X_{jt}^f>0})$. And the shipment hazard λ_b is closely related to the average number of shipments per year, $\widehat{E}\left(n^s\right)$.

Second, the match-specific shock hazard, λ^y, the exogenous match separation hazard, δ, and the fixed costs of maintaining a match, F, are key determinants of the persistence and dispersion in client-specific sales trajectories. Accordingly, key statistics that help to identify these parameters include estimates of autoregressions for match-specific sales $\widehat{\beta}_1^f$, $s\widehat{e}(\epsilon^f)$, match death hazards by age of match, $\widehat{E}[1_{X_{ijt}^f=0}|X_{ijt-1}^f > 0, A_{ijt-1}^m]$, and parameters of the regression relating match death hazards to match size: $\widehat{\beta}_0^d, \widehat{\beta}_{\text{1st year}}^d, \widehat{\beta}_{\text{lsales}}^d, s\widehat{e}(\epsilon^d)$. Since the fixed costs of sustaining a match are incurred after each shipment, the difference in separation hazards between the first and all subsequent years helps to distinguish F from δ. Also, in the absence of shocks to market-wide conditions (x) or idiosyncratic buyer demands (y), all matches would survive A periods with probably $(1-\delta)^A$. Accordingly, the rate at which hazard rates decline with match age is informative about δ. Further identification comes from the fact that δ affects all firms equally, while the effect of F declines as $\widehat{\pi}_{\varphi,x}$ increases. This makes the association between shipment size and match longevity informative regarding the importance of F.

Third, the θ distribution parameters, α and β, determine the cross-firm joint distribution

construct this set of weights. Our weighting matrix yields a consistent estimator, provided that our model is properly specified.

of success rates in home and foreign markets and, similarly, the dispersion in firm types σ_φ helps determine the cross-distribution of domestic and foreign sales. The combined effects of these parameters is reflected in the means, variances, and covariances of foreign and domestic sales, which are implied in turn by $\widehat{\phi}_1^{hf}$, $\widehat{se}(\epsilon^{hf})$, and $se(\ln X_{jt}^f)$. Similarly, the cross-firm distribution of numbers of foreign clients, summarized by $\widehat{\phi}^c$ and $\widehat{se}(\epsilon^{n^c})$, responds to (α,β). This distribution also responds to σ_φ, since the firm effects φ strongly influence search intensities. But the role of the firm effects φ is distinct from that of the popularity indices θ^f and θ^h because φ induces correlation in sales across markets. This correlation, which is implied by $\widehat{E}(\ln X_{jt}^f|A_{jt}^c)$, $\widehat{\phi}_1^{hf}$, $\widehat{se}(\epsilon^{hf})$, and $se(\ln X_{jt}^f)$, helps to isolate the variance in firm effects, σ_φ.

Finally, the marginal cost of search and its sensitivity to previous matches are determined by γ, κ_0, and κ_1. Match rates, transition probabilities for numbers of clients, $\widehat{P}[n_{jt+1} = m|n_{jt} = k]$, and the client distribution are informative about the convexity of the matching cost function. Accordingly, $\widehat{\beta}^c$ and $\widehat{se}(\epsilon^n)$ are useful in their identification. Differences in match arrival rates among firms that have made many versus few matches help to distinguish the convexity parameter β from the network effect parameter, γ. And importantly, the shape of the client-per-seller distribution is informative about network effects, since these effects critically impact the ability of firms to sustain large client bases, and thus affect the "fatness" of the right-hand tail.

5.3 Parameter estimates

Table 11 reports estimates based on the data moments described in the previous subsection. Data-based estimates of these moments, $\widehat{M}$, are reported and juxtaposed with their simulated

Table 10: **Parameters Estimated using indirect inference (Λ)**

	Parameter	*value*	*std. error*
rate of exogenous separation	δ	0.267	0.001
domestic market size	Π^h	11.344	0.017
foreign market size	Π^f	10.675	0.017
fixed cost	F	7.957	0.018
First θ distribution parameter	α	0.716	0.007
Second θ distribution parameter	β	3.161	0.029
demand shock jump hazard	λ_y	0.532	0.001
demand shock jump size	Δ^y	0.087	0.001
shipment order arrival hazard	λ_b	8.836	0.006
std. deviation, log firm type	σ_φ	0.650	0.002
network effect parameter	γ	0.298	0.001
search cost function curvature parameter	κ_1	0.087	0.001
search cost function scale parameter	κ_0	111.499	0.512

counterparts, $M_S(\Lambda)$, in Table 11.[18] The Euclidean distance between these two vectors divided by the length of the latter vector is 0.118.

[18]The share exporters, the coefficient of log foreign sales on log domestic sales, and the AR1 coefficient for log domestic sales in Table 11 are obtained from a combination of the Colombian Annual Manufacturing Survey (AMS) and the administrative records of exports transactions. The data used cover 1993-2007. Exports from administrative records are merged into the AMS using firm identifiers. This is done because the AMS has no export information for 1993-1999, and because the dynamics of aggregate exports reported in the EAM starting in 2004 differ substantially from aggregate reports from other sources.

Table 11: Data-based and simulated statistics ($\widehat{M}$ and $M_S(\Lambda)$)

Transition probs.[19]					
No. clients (n^c)	Data	Model	**Share of firms exporting**	Data	Model
$\widehat{P}[n^c_{jt+1} = 0 \mid n^c_{jt} = 1]$	0.618	0.534	$\widehat{E}(1_{X^f_{jt}>0})$	0.299	0.351
$\widehat{P}[n^c_{jt+1} = 1 \mid n^c_{jt} = 1]$	0.321	0.358			
$\widehat{P}[n^c_{jt+1} = 2 \mid n^c_{jt} = 1]$	0.048	0.082	**Log foreign sales on**		
$\widehat{P}[n^c_{jt+1} \geq 3 \mid n^c_{jt} = 1]$	0.013	0.024	**log domestic sales**	Data	Model
$\widehat{P}[n^c_{jt+1} = 0 \mid n^c_{jt} = 2]$	0.271	0.260			
$\widehat{P}[n^c_{jt+1} = 1 \mid n^c_{jt} = 2]$	0.375	0.321	$\widehat{\beta}^{hf}_1$	0.727	0.515
$\widehat{P}[n^c_{jt+1} = 2 \mid n^c_{jt} = 2]$	0.241	0.281	$\widehat{se}(\epsilon^{hf})$	2.167	1.424
$\widehat{P}[n^c_{jt+1} \geq 3 \mid n^c_{jt} = 2]$	0.113	0.135			
Match death hazards	Data	Model	**Exporter exit hazards**	Data	Model
$\widehat{E}[1_{X^f_{ijt}=0} \mid X^f_{ijt-1} > 0, A^m_{ijt-1} = 0]$	0.694	0.857	$\widehat{E}[1_{X^f_{jt}=0} \mid A^c_{jt-1} = 0]$	0.709	0.748
$\widehat{E}[1_{X^f_{ijt}=0} \mid X^f_{ijt-1} > 0, A^m_{ijt-1} = 1]$	0.515	0.329	$\widehat{E}[1_{X^f_{jt}=0} \mid A^c_{jt-1} = 1]$	0.383	0.099
$\widehat{E}[1_{X^f_{ijt}=0} \mid X^f_{ijt-1} > 0, A^m_{ijt-1} = 2]$	0.450	0.304	$\widehat{E}[1_{X^f_{jt}=0} \mid A^c_{jt-1} = 2]$	0.300	0.121
$\widehat{E}[1_{X^f_{ijt}=0} \mid X^f_{ijt-1} > 0, A^m_{ijt-1} = 3]$	0.424	0.281	$\widehat{E}[1_{X^f_{jt}=0} \mid A^c_{jt-1} = 3]$	0.263	0.055
$\widehat{E}[1_{X^f_{ijt}=0} \mid X^f_{ijt-1} > 0, A^m_{ijt-1} = 4]$	0.389	0.305	$\widehat{E}[1_{X^f_{jt}=0} \mid A^c_{jt-1} = 4]$	0.293	0.100
Log sales per client on			**Log sales per exporter**		
client no. regression	Data	Model	**by cohort age**	Data	Model
$\widehat{\beta}^m_1$	2.677	0.842	$\widehat{E}(\ln X^f_{jt} \mid A^c_{jt} = 0)$	8.960	9.306
$\widehat{\beta}^m_2$	-0.143	0.042	$\widehat{E}(\ln X^f_{jt} \mid A^c_{jt} = 1)$	10.018	10.806
$\widehat{se}(\epsilon^m)$	2.180	1.622	$\widehat{E}(\ln X^f_{jt} \mid A^c_{jt} = 2)$	10.231	10.755
Client number inverse			$\widehat{E}(\ln X^f_{jt} \mid A^c_{jt} = 3)$	10.369	10.679
CDF regression	Data	Model	$\widehat{E}(\ln X^f_{jt} \mid A^c_{jt} \geq 4)$	10.473	10.669
$\widehat{\beta_1}^c$	-1.667	-1.587	**Log dom. sales autoreg.**	Data	Model
$\widehat{\beta_2}^c$	-0.097	-0.280	$\widehat{\beta}^h_1$	0.976	0.896
$\widehat{se}(\epsilon^{n^c})$	0.066	0.128	$\widehat{se}(\epsilon^h)$	0.462	0.683
Match shipments per year	Data	Model	**Log match sale autoreg.**	Data	Model
$\widehat{E}\,(n^s)$	4.824	3.770	$\widehat{\beta}^f_1$	0.811	0.613
Match death prob regression	Data	Model	$\beta^f_{\text{1st year}}$	0.233	0.370
$\widehat{\beta}^d_0$	1.174	1.640	$\widehat{se}(\epsilon^f)$	1.124	0.503
$\widehat{\beta}^d_{\text{1st year}}$	0.166	0.203			
$\widehat{\beta}^d_{\text{lsales}}$	-0.070	-0.100			
$\widehat{se}(\epsilon^d)$	0.453	0.395			

6 Analysis of results

6.1 Fitting the moments

Comparing the data-based moments to their simulated counterparts in Table 11, one finds the model does a reasonably good job of explaining the patterns we discussed in Section 2 above. In particular, the simulated transition probabilities for numbers of clients are close to the data, as are the match death hazards, the relationship between exit rates and cohort age, and the relationship between average exports and cohort age. The model also qualitatively (but less accurately) captures the concentration of exporters at the low end of the client count distribution and the tendency for average sales per client to co-vary positively with number of clients. Finally the model also captures the positive association between domestic and foreign sales.

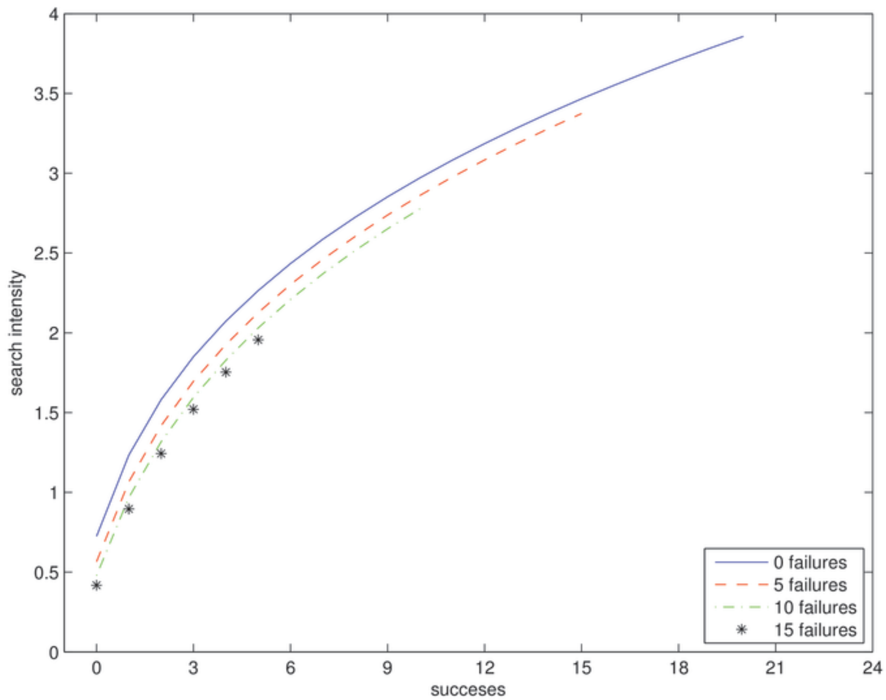
6.2 Interpreting the coefficients

Several immediate implications of the coefficient estimates merit note. First, although mature matches fail with probabilities exceeding 40 percent (Table 7), we estimate that the exogenous failure rate is only $\delta = 0.27$. Thus idiosyncratic shocks to buyer-seller matches appear to play a significant role in match survival. Second, the fixed per-shipment costs of sustaining a match are roughly $F = \exp(7.957) =$ \$US 2,855, about 70 percent higher than the per shipment costs of regulations by 2005, according to the Doing Business report. Third, the unconditional average success rate with potential U.S. buyers is $\alpha/(\alpha+\beta) \approx 0.184$, so less than one-fifth of the buyers that Colombian exporters meet are interested in establishing a business relationship. Fourth, however, success rates vary across exporters with standard deviation $\sqrt{\alpha\beta/\left[(\alpha+\beta)^2(\alpha+\beta+1)\right]} \approx 0.176$, so some firms have much higher success rates than others, and this creates considerable scope for learning. Fifth, network effects are extremely important. After a successful matches, search costs at any given s have fallen by the factor $(1+a)^{-\gamma(1+1/\kappa_1)}$ relative to the costs faced by a new exporter. Thus, for example, when a seller achieves her first successful match, her search costs for any given arrival hazard drop to 8 percent of their pre-match level, and after three success matches, they drop to 2 percent. Finally, there is considerable convexity in the search cost function ($1 + 1/\kappa_1 = 12.49$), so holding the number of successful matches constant, intensifying the search process is very costly. This is how the model explains the fact that 80 percent of exporters have a single client.

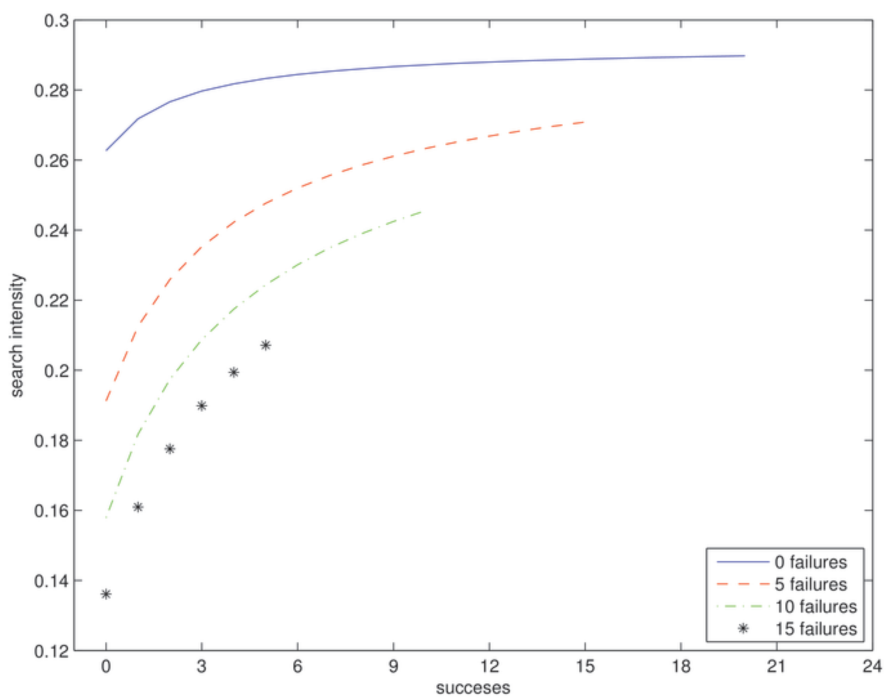
What are the combined implications of these estimates for sellers' search policy? Figure 2a below shows search intensity (s^f) as a function of number of successes (a) and failures ($n-a$), taking expectations over marketwide shocks (x) and productivity shocks (φ). For any given number of previous failures, search intensity is increasing in the number of previous successes. This reflects the fact that successes build a network and thus reduce the cost of making future matches. It is also clear that the effect of a successful match has the most dramatic effect on search intensity when firms have little experience. Partly this is due to the fact that early successes contain the most information, and thus move priors relatively more.

6.3 Resticted versions of the model

To explore identification of the learning effects and the reputation effects in our model, we consider two alternative specifications. The first, which we call the *no-learning* model, treats firms as knowing their exact θ^f draws, even before they acquire any experience in export markets. This specification involves the same set of parameters, none of which are constrained,



(a) baseline



(b) no network

Figure 2: Search policy functions by match history

Table 12: **Parameter Estimates for Alternative Models**

	Parameter	*benchmark* (Λ)	*no learning* (Λ^{NL})	*no network* (Λ^{NN})
rate of exogenous separation	δ	0.267	0.516	0.119
domestic market size	Π^h	11.344	12.670	10.884
foreign market size	Π^f	10.675	12.245	10.321
fixed cost	F	7.957	10.238	8.539
First θ distribution parameter	α	0.716	0.512	1.807
Second θ distribution parameter	β	3.161	0.351	0.963
demand shock jump hazard	λ_y	0.532	0.713	1.581
demand shock jump size	Δ^y	0.087	0.060	0.087
shipment order arrival hazard	λ_b	8.836	10.028	10.347
std. deviation, log firm type	σ_φ	0.650	1.268	1.355
network effect parameter	γ	0.298	0.112	0
search cost function curvature parameter	κ_1	0.087	0.0348	0.057
search cost function scale parameter	κ_0	111.499	234.764	175.953
fit metric	D	9.97 e+04	2.155 e+05	1.17 e+05
fit metric, no weighting	$\widetilde{D}$	0.117	0.182	0.143

so it isn't a nested version of the benchmark model. Rather it replaces one characterization of beliefs with another. The second alternative, which we call the *no-network* model, is nested by the benchmark model. It shuts down reputation effects by imposing $\gamma = 0$, but it retains the benchmark assumption that firms must learn their θ^f draws through experience. Both alternative models are calibrated to the same statistics we use for our benchmark model. The resulting parameter estimates and the associated fit metrics are reported in Table 12. Below we discuss the ability of each to fit the data.

6.3.1 No learning

Other things held fixed, the elimination of learning effects makes the rapid turnover of novice exporters less likely, both by discouraging inexperienced low-θ^f firms from exploring foreign markets and by eliminating learning-based exit. Shutting down learning effects also means that high-θ^f firms do not intensify their search efforts as they receive positive feedback about their product appeal.

With these mechanisms inoperative, the no-learning model must use other means to explain the rapid turnover of new exporters and the rapid expansion of sales per surviving exporter as young cohorts mature. To accomplish the former, lower productivity firms are induced to participate in export markets by a rightward shift in the θ^f distribution and higher values for Π^f and λ_b, while match failure rates and market exit rates are sustained by higher values for F, δ, and λ_y (Table 12, column 3 versus column 2).[20] To get sales per exporter growing with cohort age, the no-learning model relies more heavily on selection effects. Low productivity firms are enticed into the market by the bigger Π^f value and the higher average popularity of their products. But these firms tend to end their matches as soon as the fixed costs (F) come due, which–being relatively large–ensures that the surviving exporters have substantially higher sales. The relatively large value of λ_y also helps to generate growth in match sales conditioned on match survival, since buyers who draw negative shocks tend to fail, while matches with positive shocks tend to survive. Finally, the no-learning model facilitates new exporter growth by reducing the convexity of the search cost function, κ_1.

While these parameter adjustments help the no-learning model qualitatively match patterns of exporter turnover and growth, the model's overall fit metric is much worse than that of the benchmark model (Table 12, lower panel). The reason is that the no-learning model badly overstates the share of firms that export (Table 14 in Appendix B), severely understates the persistence in match-specific sales, given match continuation, overstates the relationship between sales per client and number of clients, and fails to match the Pareto shape of the

[20]Recall that $E(\theta^f) = \alpha/(\alpha+\beta)$ and $var(\theta^j) = \alpha\beta/\left[(\alpha+\beta+1)(\alpha+\beta)^2\right]$.

cross exporter client distribution

6.3.2 No network effect

Network effects mean that sellers with a history of successful matches face relatively low search costs, given search intensity. This allows firms with popular products to build larger customer bases than the sharply convex search cost function would have otherwise allowed, and thereby helps the benchmark model match the Pareto distribution of clients across sellers.

To determine the importance of this feature of the model, we set $\gamma = 0$ and re-estimated the remaining parameters, obtaining the no-network estimates reported in Table 12. Without network effects, the the model moves part way toward matching the Pareto shape by reducing the convexity of the search cost function, κ_1. But this is an imperfect fix because all exporters are equally affected by κ_1, not just the larger ones. Accordingly, various other adjustments occur, including a modest increase in F, a rightward shift in the θ distribution, an increase in the variance of φ, and an increase in the jump hazard for buyer shocks, λ_y. Interestingly, these adjustments are qualitatively similar to those that occurred when we shut down learning effects. Here, however, market sizes Π^f and Π^h shrink a bit rather than expand.

Despite these adjustments, the no-network model does signficantly worse than the benchmark model (Table 12, bottom panel). In particular, the client distribution is far from Pareto, reflecting the model's inability to explain the existance of very large exporters (Table 14 in Appendix B). The no-network model also overstates the fraction of firms that export and the average exports of surviving firms after the first year. Finally, it makes the correlation between domestic and foreign sales far too weak, and the log sales-per-client distribution far too non-linear in the log of the number of clients.

The inability of the no-network model to generate a set of super-exporters can be traced back to the search policy function this model delivers. Figure 2b summarizes its properties. Note that learning effects appear to be relatively important for the first several clients, but unlike in figure 2b, the policy function quickly flattens out as successes accumulate. So, within the general structure of our search and learning framework, sustained growth in search intensity among relatively established exporters cannot be sustained without network effects. Note also the very different scales between Figures 2a and 2b, indicating much lower search intensities when the network effect is not present.

6.4 Counterfactual experiments

It remains to use our model to explore the export dynamics in a search and learning world with network effects. These experiments will reveal the extent to which learning and network effects create deviations from the export path one would expect in a frictionless setting with the same marketwide shocks and idiosyncratic processes for buyer and seller shocks.

We graph three experiments in Figures 3-5 below. Each figure has separate panels decomposing aggregate exports into number of exporters, mean per-client exports, and mean number of clients. In Figure 3, we reduce the scalar κ_0 in the search cost function by 20% percent. In Figure 4, we decrease the fixed cost of maintaining a client relationship F by 20%, and in Figure 5, we reduce the size of foreign market jumps Δx_f by 20% percent. For all experiments, the shock takes place in 2002 and is unanticipated and permanent. The red line represents the time path that would have been observed in the absence of the shock, and the dashed blue line reflects the time path induced by the shock. We use the same draws for all stochastic processes, with and without the parameter change, so these changes are the only reason that the blue line differs from the red line after 2002. In all exercises, we take the market-wide demand shifters x_f and x_h from the data.

While the shock takes place in 2002, decreasing the cost of search has no noticeable net effect on exports until 2003. The slow reaction of firms to shocks is a theme in all of our counterfactuals. The decrease in search costs appears to mainly encourage inexperienced firms to search harder. Since exporters start small, and this is reflected in a decrease in mean sales per client, the initial effect on aggregate exports is small. Over time, however, a successful exporter will ramp up her search behavior, so that aggregate exports ultimately grow relative to the baseline.

Exporters also react slowly to the fixed cost reduction in Figure 4, and different margins react with different speeds. While the number of active exporters does most of its jumping in 2002, the mean number of clients rises more gradually as it takes all exporters time to acquire the new equilibrium collection of clients.

Somewhat surprisingly, decreasing fixed cost does not cause mean sales per client to drop. Mean sales are affected by two margins. For a particular firm, mean sales per client will decrease as poor clients that would have been let go are allowed to stick around. On the other hand, lowering fixed costs also encourages highly productive firms to search harder. Since the typical match relationship at one of the best firms is highly lucrative, a new match can cause economy-wide mean sales per client to rise. That mean sales per client rise after decreasing fixed costs suggests that productive firms gain more new clients than unproductive firms.

Both a reduction in search costs and a reduction in fixed costs per shipment could be potentially interpreted as policy experiments. For instance, Proexport, the Colombian export promotion agency, has several programs aimed at helping firms find foreign clients. These range from publishing lists of potential buyers in their website to firm-specific studies and trips organized by Proexport (some of which the firm itself pays for). The introduction of this type of programs, or subsidized prices for them could lead to reduced search costs. As for the fixed cost per shipment, regulations may also affect these costs. The World Bank, for instance, estimates that in 2005 the fees associated with procedures to export goods amounted to \$1,745 per one-container shipment.

Figure 4 shows the results of the experiment where the foreign market size suddenly increases by 20 percent. All matches become more lucrative. This mechanical rise in sales explains the sudden increase in exports and mean sales per client immediately after the shock. The gradual reaction of exports can be seen in the mean number of clients per exporter, which takes almost a decade to fully react to the shock.

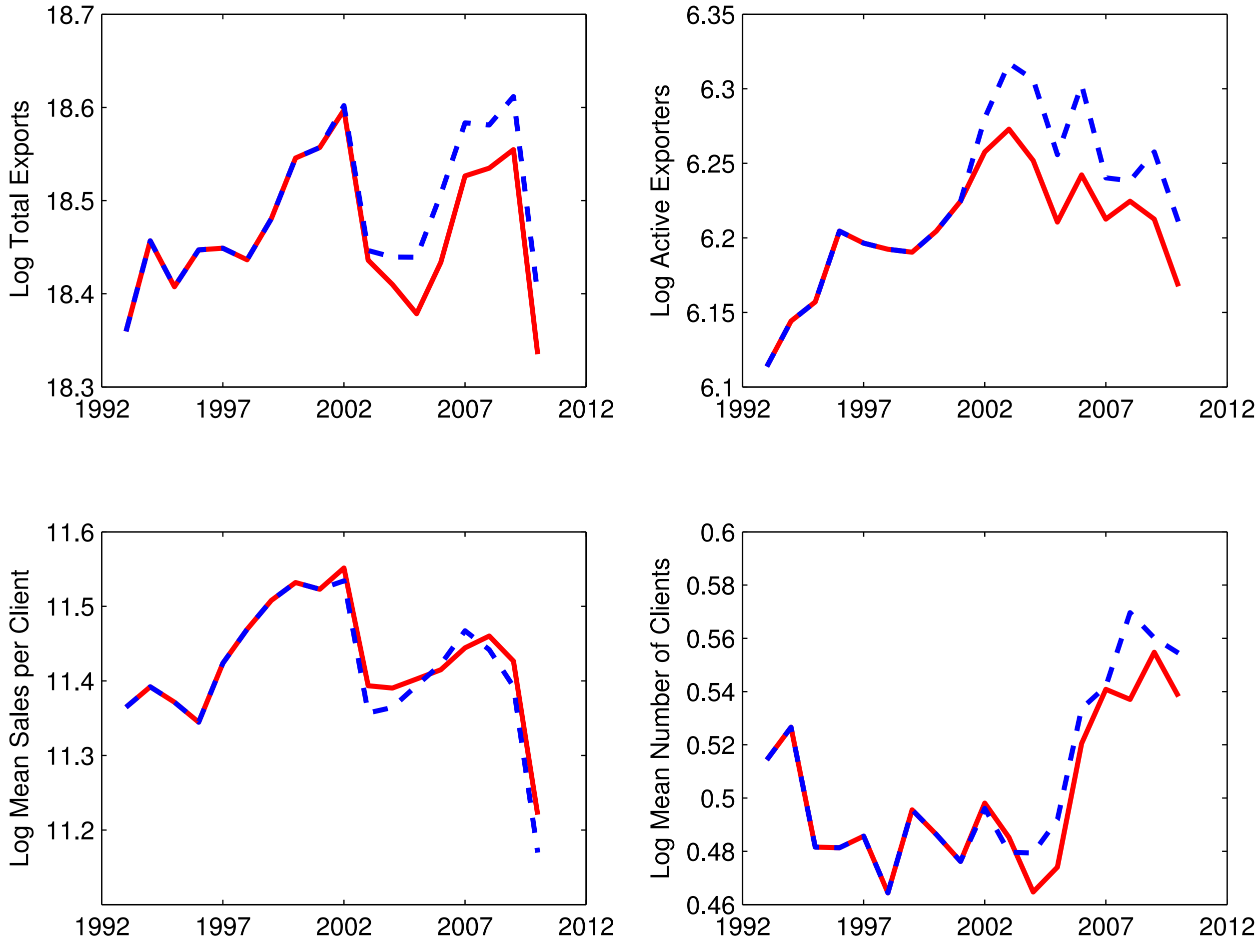


Figure 3: Time Series Effects of Search Cost Reduction

7 Summary

Customs records reveal tremendous turnover among Colombian manufacturers who export to the U.S.. In a typical year, 48 percent of these exporters are new to the U.S. market, and 81 percent of these new exporters will be gone two years hence. New exporters ship small quantities, so despite their numbers they account for only 12 percent of total Colombian exports in value terms. But each new cohort of Colombian exporters contains a small number of firms that survive and rapidly expand, growing many times faster than aggregate Colombian exports. They do so by adding U.S. clients to their customer base at a rapid rate.

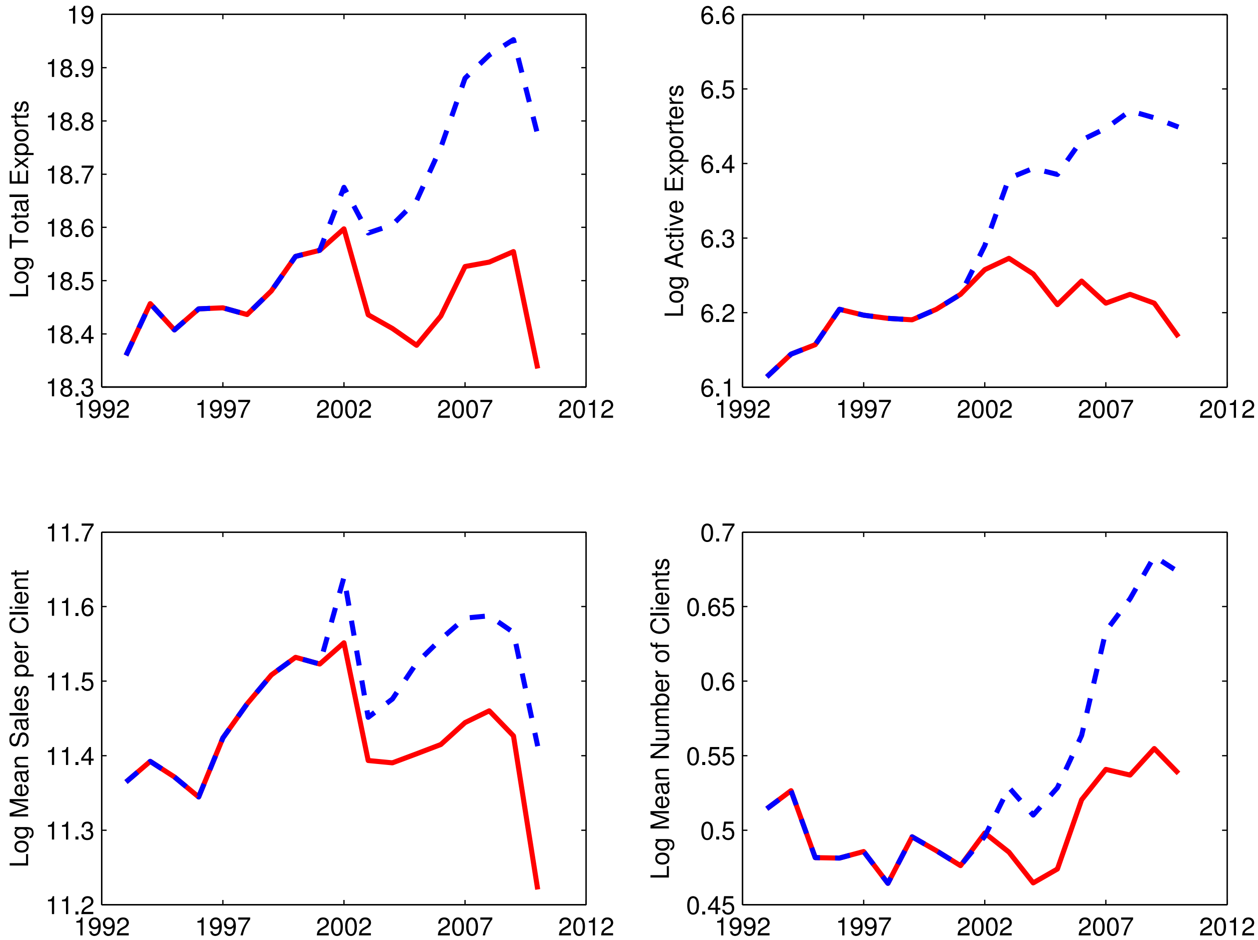


Figure 4: Time Series Effects of Fixed Cost Reduction

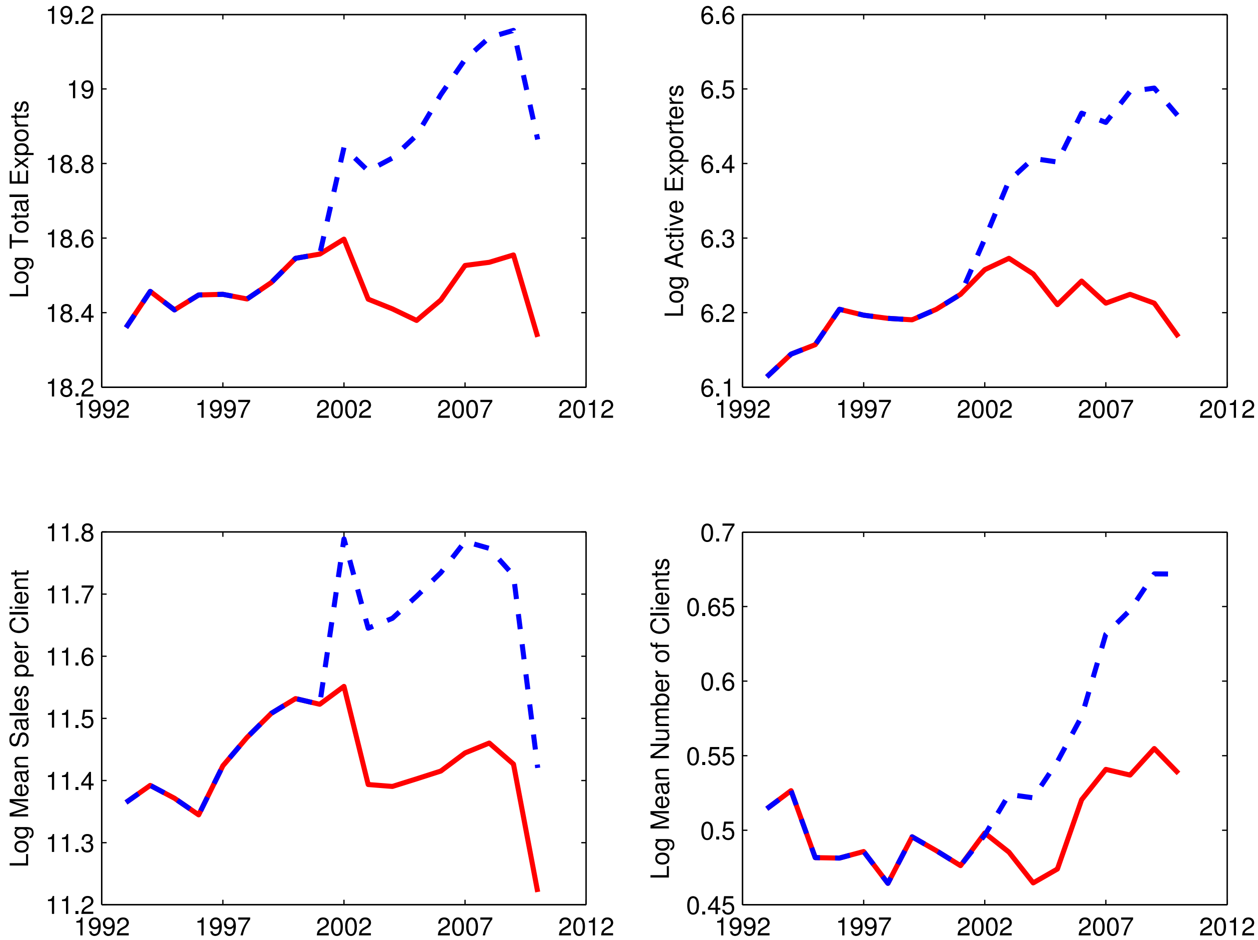


Figure 5: Time Series Effects of Positive Market-wide Shock

After documenting these patterns, we develop a continuous time model that explains them. Firms wishing to export must engage in costly search to identify potential buyers abroad. The buyers they encounter either reject their products or form finite-lived business relationships with them. Buyer who form business relationships with exporters send them favorable signals about the appeal of their products, and in doing so, encourage them to search more intensively for additional buyers. Successful business relationships also reduce search costs by improving sellers' visibility (network effects). Finally, sellers' search intensities depend upon their permanent idiosyncratic characteristics and marketwide conditions.

Fit using the method of simulated moments, the model replicates the patterns in customs records described above and allows us quantify several types of trade costs, including the search costs of identifying potential clients and the costs of maintaining business relationships with existing clients. It also allows us to estimate the network effect of previous exporting successes on the costs of meeting new clients, and to characterize the cumulative effects of learning on firms'search intensities. Both the learning effect and the network effect prove to be quantitatively important. Finally, our model provides a lens through which to view the seemingly unpredictable responses of export flows to exchange rate fluctuations.

References

Albornoz, Facundo, Hector Calvo Pardo, Gregory Corcos, and Emanuel Ornelas (2012) ”Sequential Exporting,” *Journal of International Economics* 88: 17-31.

Alessandria, George and Horag Choi (2007) ”Do Sunk Costs of Exporting Matter for Net Export Dynamics?” *Quarterly Journal of Economics*, pp. 289-336.

Alessandria, George, Joseph Kaboski and Virgiliu Midrigan (2010) ”Inventories, Lumpy Trade, and Large Devaluations,” *American Economic Review*, 100 (5) pp. 2304-39.

Arkolakis, Konstantinos (2009) “A Unified Theory of Firm Selection and Growth,” Yale University, Department of Economics, Working Paper.

Arkolakis, Konstantinos (2010) “Market Access Costs and the New Consumers Margin in International Trade,” *Journal of Political Economy*, 118(6), pp. 1151-1199.

Baldwin, Richard. E. and Paul Krugman (1989): “Persistent Trade Effects of Large Exchange Rate Changes.” *Quarterly Journal of Economics*, 104, pp. 635-654.

Bernard, Andrew and J. Bradford Jensen (1999) “Exceptional Exporter Performance: Cause, Effect, or Both?” *Journal of International Economics* , 47, pp. 1-25.

Bernard, Andrew, J. Bradford Jensen, Samuel Kortum and Jonathan Eaton (2003) “Plants and Productivity in International Trade,” *American Economic Review* 93(4), pp. 1268-1290

Bernard, Andrew, J. Bradford Jensen, J. Stephen J. Reading, and Peter K. Schott (2007) “Firms in International Trade,” *Journal of Economic Perspectives.*

Besedes, Tibor (2007). "A Search Cost Perspective on Formation and Duration of Trade," Working Paper, Department of Economics, Georgia Tech University.

Blum, Bernardo S., Sebastian Claro, and Ignatius Horstmann (2009). "Intermediation and the Nature of Trade Costs: Theory and Evidence." Working Paper, The University of Toronto.

Brooks, Eileen (2006) "Why don't firms export more? Product Quality and Colombian Plants" *Journal of Development Economics,* 80: 160-178.

Chaney, Thomas (2011) "The Network Structure of International Trade," University of Chicago.

Clerides, Sofronis, Saul Lach and James Tybout (1998) "Is Learning-by-Exporting Important? Micro-dynamic Evidence from Colombia, Mexico and Morocco," *Quarterly Journal of Economics*, pp. 903-947.

Das, Mita, Mark Roberts and James Tybout (2007) "Market Entry Costs, Producer Heterogeneity and Export Dynamics," *Econometrica* 75(3), pp. 837-874.

Domínguez, Juan Camilo, Jonathan Eaton, Marcela Eslava, and James Tybout. (2010) "Search and Learning in Export Markets: Case Studies for Colombia." Pennsylvania State University, Working Paper.

Drozd, Lukasz A. and Jaromir B. Nosal (2008) "Understanding International Prices: Customers as Capital," Working Paper, The University of Wisconsin.

Dixit, Avinish (1989), "Hysteresis, Import Penetration, and Exchange Rate Pass-Through," *Quarterly Journal of Economics*, Vol. 104, No. 2 (May), pp. 205-228.

Eaton, Jonathan, Samuel Kortum, and Francis Kramarz (2004) "Dissecting Trade: Firms, Industries, and Export Destinations," *American Economic Review Papers and Proceedings,* 94: 150-154.

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

Eaton, Jonathan, Marcela Eslava, Maurice Kugler and James Tybout (2008). "Export Dynamics in Colombia: Firm-Level Evidence," in Elhanan Helpman, Dalia Marin and Thierry Verdier, eds., T*he Organization of Firms in a Global Economy*, Cambridge, MA: Harvard U. Press.

Eslava, Marcela, John Haltiwanger, Adriana Kugler, and Maurice Kugler (2004) "The Effects of Structural Reforms on Productivity and Profitability Enhancing Reallocation: Evidence from Colombia," *Journal of Development Economics,* 75: 333-371.

Gouriéroux and Monfort, 1996. *Simulation-Based Econometric Methods.* New York: Oxford U. Press.

Irarrazabal, Alfonso A. and Luca David Opromolla (2006) "Hysteresis in Export Markets," New York University, Working Paper.

Jackson, Matthew and Brian Rogers (2007) "Meeting Strangers and Friends of Friends: How Random are Social Networks?" *American Economic Review,* 97: 890-915.

Jovanovic, Boyan (1982) “Selection and the Evolution of Industry,” *Econometrica,* 50: 649-670.

Kugler, Maurice (2006) “Spillovers from foreign direct investment: within or between industries?” *Journal of Development Economics,* 80(2): 444-477.

Luttmer, Erzo (2007) “Selection, Growth, and the Size Distribution of Firms,” *Quarterly Journal of Economics,* 122: 1103-1144.

Melitz, Marc (2003) “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity,” *Econometrica* 71, 1695-1725.

Rauch, James and Joel Watson (2003) “Starting Small in an Unfamiliar Environment,” *International Journal of Industrial Organization* 21: 1021-1042.

Roberts, Mark and James Tybout (1997a) “The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Costs,” *American Economic Review* 87(4), pp. 545-563.

Roberts, Mark and James Tybout (1997b) *What Makes Exports Boom*? Directions in Development Monograph Series, The World Bank, Washington, DC.

Ruhl, Kim and Jonathan Willis (2008) “New Exporter Dynamics,” New York University, Working Paper.

Shimer, Robert (2005) ”The Cyclical Behavior of Equilibrium Unemployment and Vacancies,” *The American Economic Review*, 95(1), pp. 25-49.

Tauchen, George (1986) “Finite State Markov-Chain Approximation to Univariate and Vector Autoregressions,” *Economics Letters,* 20.2. 177-181.

Table 13: Colombian versus U.S. Customs Records

	Colombia		United States		% difference	
Year	# exporters	value	# exporters	value	# exporters	value
2000	1775	1038	2721	1140	53%	10%
2001	2026	995	2744	1019	35%	2%
2002	2230	870	2986	855	34%	-2%
2003	2800	1113	3579	1119	28%	1%
2004	3035	1379	4002	1415	32%	3%
2005	2861	1554	4288	1438	50%	-7%
2006	2689	1665	4361	1552	62%	-7%
2007	2420	1540	4175	1496	73%	-3%
2008	2161	1570	3758	1474	74%	-6%

A Data Checks

To investigate the quality of the exporter id (manuf_id) in the U.S. import records, we ran a series of robustness checks. The Colombian and U.S. data overlap for the years 2000-2008 and both contain measures of the value of exports as well as the number of exporting firms. If the manuf_id variable is error-prone and noisy, we would expect the U.S. data to over-report the number of Colombian firms exporting to the U.S. That is, each time a customs broker wrongly enters the data in the field, a new firm would be created. Table 13 below summarizes the total value of exports to the U.S. and the number of Colombian firms, by year, for each data set.

The datasets align much more closely on value than they do on firm counts. The difference in value is never more than 10% while the firm count difference ranges from 18% to 74%. The differences are stable over time.

To look more closely at the cause of the difference in firm counts, we compared the number of firms across sources by HS2 categories. The counts in the LFTTD were higher than the Colombian data in only 28 of the 82 codes and by far the biggest differences are in HS codes

61 and 62: textiles. In these two product classes the U.S. data identifies 4025 more firms than the Colombian data. If we remove these two sectors from the list, the difference in firm counts flips and the Colombian data contain 1001 more firms than the LFTTD.

Interestingly, Title 19 of U.S. code specifically requires that the manuf_id variable for textile products represent the manufacturer of the textile products, not an intermediary. That is, for this sector in particular the manufacturer, not an intermediary must be reported on the CBP 7501 form. By contrast, prior work by several authors of this paper has shown (Marcela's 8/9/13 e-mail referenced this) that the Colombian data reports the exporter, which may or may not be the manufacturer. Given that revious research (Tybout, 2000 JEL) has shown that developing countries tend to have a disproportionately large share of small manufacturing firms, it is reasonable to assume that a large part of the reason why the U.S. data report so many more firms in the textile sector is that due to administrative reasons the U.S. data count many small manufacturers and the Colombian data are, in many cases, reporting aggregators and intermediaries.

As a final check of the integrity of the manuf_id variable - and the robustness of our main results - we experimented with a "fuzzy" version of the manuf_id variable that did not contain any street numbers in the string (a likely source of input errors). The effect of this is to reduce the number of Colombian firms in the data, an approximation of fixing any extraneous noise from data entry errors. Next we re-ran Table 7 with the fuzzy data and compared the results to the original version.

One of the key findings from Table 7 is the high match separation rates ranging from about 40% to 66%. Using the fuzzy version did not reduce the separation rates substantially and left the patterns intact. The fuzzy separation rates ranged from 26% to 62%, a drop of 6% on average. It does not appear that our results are sensitive to a modest reduction in data entry errors.

B Moments for Restricted Models

Table 14: Restricted versus Full Model Fit

	data $\widehat{M}$	*benchmark* $M_s(\Lambda)$	*no learning* $M_s(\Lambda^{NL})$	*no network* $M_s(\Lambda^{NN})$
Share of firms exporting				
$\widehat{E}(1_{X^f_{jt}>0})$	0.299	0.351	0.585	0.451
Log foreign sales on log domestic sales				
$\widehat{\beta}_1^{hf}$	0.727	0.515	0.923	0.575
$\widehat{se}(\epsilon^{hf})$	2.167	1.424	0.843	1.146
log dom. sales autoreg.				
$\widehat{\beta}_1^{h}$	0.976	0.896	0.969	0.898
$\widehat{se}(\epsilon^{h})$	0.462	0.683	0.661	0.570
exporter exit hazards				
$\widehat{E}[1_{X^f_{jt}=0} \mid A^c_{jt-1}=0]$	0.709	0.748	0.773	0.877
$\widehat{E}[1_{X^f_{jt}=0} \mid A^c_{jt-1}=1]$	0.383	0.099	0.099	0.188
$\widehat{E}[1_{X^f_{jt}=0} \mid A^c_{jt-1}=2]$	0.300	0.121	0.032	0.012
$\widehat{E}[1_{X^f_{jt}=0} \mid A^c_{jt-1}=3]$	0.263	0.055	0.056	0.198
$\widehat{E}[1_{X^f_{jt}=0} \mid A^c_{jt-1}=4]$	0.293	0.100	0.098	0.185
log sales per exporter by cohort age				
$\widehat{E}(\ln X^f_{jt} \mid A^c_{jt}=0)$	8.960	9.306	9.608	8.541
$\widehat{E}(\ln X^f_{jt} \mid A^c_{jt}=1)$	10.018	10.806	10.615	11.331
$\widehat{E}(\ln X^f_{jt} \mid A^c_{jt}=2)$	10.231	10.755	10.431	11.037
$\widehat{E}(\ln X^f_{jt} \mid A^c_{jt}=3)$	10.369	10.679	10.426	10.845
$\widehat{E}(\ln X^f_{jt} \mid A^c_{jt}\geq 4)$	10.473	10.669	10.332	11.145
Log match sale autoregression				
$\widehat{\beta}_1^{f}$	0.811	0.613	0.105	0.268
$\beta^f_{\text{1st year}}$	0.233	0.370	0.056	0.087
$\widehat{se}(\epsilon^{f})$	1.124	0.503	0.287	0.425

Match death hazards				
$\widehat{E}[1_{X^f_{ijt}=0} \mid X^f_{ijt-1} > 0, A^m_{ijt-1} = 0]$	0.694	0.857	0.943	0.879
$\widehat{E}[1_{X^f_{ijt}=0} \mid X^f_{ijt-1} > 0, A^m_{ijt-1} = 1]$	0.515	0.329	0.452	0.337
$\widehat{E}[1_{X^f_{ijt}=0} \mid X^f_{ijt-1} > 0, A^m_{ijt-1} = 2]$	0.450	0.304	0.426	0.286
$\widehat{E}[1_{X^f_{ijt}=0} \mid X^f_{ijt-1} > 0, A^m_{ijt-1} = 3]$	0.424	0.281	0.434	0.332
$\widehat{E}[1_{X^f_{ijt}=0} \mid X^f_{ijt-1} > 0, A^m_{ijt-1} = 4]$	0.389	0.305	0.398	0.226
Match death prob regression				
$\widehat{\beta}^d_0$	1.174	1.640	1.843	2.087
$\widehat{\beta}^d_{\text{1st year}}$	0.166	0.203	0.031	0.055
$\widehat{\beta}^d_{\text{lsales}}$	-0.070	-0.100	-0.092	-0.140
$\widehat{se}(\epsilon^d)$	0.453	0.395	0.266	0.343
Match shipments per year				
$\widehat{E}\,(n^s)$	4.824	3.770	2.064	4.525
Transition probabilities, No. clients (n^c)				
$\widehat{P}[n^c_{jt+1} = 0 \mid n^c_{jt} = 1]$	0.618	0.534	0.677	0.643
$\widehat{P}[n^c_{jt+1} = 1 \mid n^c_{jt} = 1]$	0.321	0.358	0.255	0.307
$\widehat{P}[n^c_{jt+1} = 2 \mid n^c_{jt} = 1]$	0.048	0.082	0.056	0.045
$\widehat{P}[n^c_{jt+1} \geq 3 \mid n^c_{jt} = 1]$	0.013	0.024	0.010	0.004
$\widehat{P}[n^c_{jt+1} = 0 \mid n^c_{jt} = 2]$	0.271	0.260	0.456	0.165
$\widehat{P}[n^c_{jt+1} = 1 \mid n^c_{jt} = 2]$	0.375	0.321	0.291	0.306
$\widehat{P}[n^c_{jt+1} = 2 \mid n^c_{jt} = 2]$	0.241	0.281	0.166	0.427
$\widehat{P}[n^c_{jt+1} \geq 3 \mid n^c_{jt} = 2]$	0.113	0.135	0.086	0.100
Log sales per client on client no. regression				
$\widehat{\beta}^m_1$	2.677	0.842	0.944	3.887
$\widehat{\beta}^m_2$	-0.143	0.042	1.049	-1.451
$\widehat{se}(\epsilon^m)$	2.180	1.622	1.893	2.067
Client number inverse CDF regression				
$\widehat{\beta_1}^c$	-1.667	-1.587	-1.395	-1.655
$\widehat{\beta_2}^c$	-0.097	-0.280	-1.184	-1.420
$\widehat{se}(\epsilon^{n^c})$	0.066	0.128	0.062	0.069