Export Market Penetration Dynamics*

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Abstract

I study how and why the microeconomic dynamics of exporting firms vary across export destinations and assess the aggregate consequences of this variation. I use Brazilian microdata to document that in smaller, poorer markets, overall turnover is higher, new exporters are larger and exit less frequently compared to incumbents, and sales grow less after entry. To account for these facts, I develop a model of exporting across multiple destinations that synthesizes two approaches: static models in which exporting costs depend on the number of customers a firm serves in each destination; and dynamic models in which these costs depend on whether a firm has exported in the past. When calibrated to match the data, the model predicts stronger and slower aggregate dynamics in smaller, poorer markets. Comparisons with existing frameworks show that the model’s novel features are important to capturing variation in exporter performance across markets, especially post-entry sales trajectories.

1 Introduction

Trade flows are driven by individual firms’ decisions: whether to start or stop exporting, whether to expand to new foreign markets, and how much to expand operations in existing markets. The static trade literature emphasizes the influence of economic geography on the distribution of exporting firms and long-run consequences of trade reforms. In smaller, poorer markets, there are fewer small exporters and sales are less concentrated among the largest ones, and consequently trade flows are more sensitive to changes in trade barriers (Arkolakis, 2010; Eaton et al., 2011; Kehoe and Ruhl, 2013). The trade dynamics literature highlights how turnover among exporters and differences in performance between new exporters and incumbents shapes transition dynamics. Export participation is highly persistent and new exporters are smaller and less likely to survive, and as a result trade adjusts slowly over time (Alessandria and Choi, 2007; Ruhl and

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Willis, 2017; Alessandria et al., 2021b). In this paper, I ask: how do the microeconomic dynamics of exporting firms vary across the markets to which they sell? What economic forces drive these differences? What are the implications for aggregate trade dynamics?

In the empirical part of the paper, I use microdata from Brazil to document new facts about exporter dynamics and how these facts vary across export destinations. The cross-sectional distribution and life-cycle dynamics of Brazilian exporters are consistent with facts that have been reported elsewhere in the literature using different data sources. Brazilian exports are highly concentrated—large firms that serve many destinations account for the bulk of export volumes—and new entrants to an export market sell less than incumbents and are more likely to exit. I use these data to analyze how exporter dynamics depend on the characteristics of the destinations that they serve. In “easy” destinations—large, rich, and/or close markets like the United States—turnover is lower and new exporters are smaller and exit more frequently relative to incumbents than in “hard” destinations—small, poor, and/or distant countries like Vietnam. Successful exporters that survive for many years in a market before exiting sell more upon entry and experience more post-entry sales growth than less successful exporters that exit quickly, and these differences, too, are more pronounced in easy destinations than in hard ones.

In the theoretical part of the paper, I develop a model of customer accumulation dynamics that can account for the full range of facts about the distribution and dynamics of exporters and how these facts vary across destinations. The model extends the endogenous market penetration framework of Arkolakis (2010) to a dynamic environment in which firms start exporting, gradually accumulate customers, and stop exporting in response to persistent idiosyncratic shocks. There is an exporting country populated by a continuum of firms and a discrete number of foreign markets that differ in population, income per capita, and trade barriers. Firms in the exporting country differ exogenously in two ways: productivity, which affects a firm’s ability to produce for all markets equally; and demand in each market, which affects the willingness of customers in that market to buy the firm’s products. Firms also differ in the number of customers they have in each market, which is endogenous. To build their foreign customer bases, firms must advertise to attract new customers and retain old ones, and greater advertising expenditures are required to reach more customers.

Three key properties allow the model to capture the patterns observed in the data. First, the marginal cost of serving even a single customer is strictly positive regardless of the size of a firm’s current customer base. As in Arkolakis (2010), this property generates the extensive margin of trade: firms with sufficiently low productivities and/or demand will choose not to serve any customers at all. In my dynamic context, however, this property generates endogenous exit as well as entry: some firms with existing customer bases accumulated through past investments will choose to stop exporting because the marginal cost of retaining the first old customer exceeds the benefit. Second, the marginal cost of reaching additional customers is decreasing in the size of a firm’s current customer base. This property implies that firms choose endogenously
to enter a market with a small number of customers and grow gradually over time. Together with the first property, it also implies that firms with smaller customer bases are more likely to exit, whereas firms with longer tenures are less likely. Third, acquiring and retaining customers is more expensive in smaller, poorer markets when measured relative to these markets’ purchasing power. This property implies that firms serve fewer customers in these markets. In combination with the first two properties, it also implies that firms are more likely to exit and experience less growth in sales over their tenures in these markets.

The model developed in this paper nests several existing models as special cases. When retaining old customers is impossible, the decision about how many customers to serve becomes static. In this case, the model is equivalent to Arkolakis (2010), or more specifically, the version analyzed in Arkolakis (2016) in which firms experience growth driven purely by exogenous productivity shocks. When the marginal cost of attracting and retaining customers is constant rather than increasing, all firms serve the same number of customers conditional on choosing to export. In this case, the model is equivalent to the sunk-cost framework of Das et al. (2007) and Alessandria and Choi (2007) in which firms pay a large up-front fixed cost to start exporting and a smaller fixed cost to continue exporting in the future. When both of these restrictions hold simultaneously, the model collapses to the seminal static framework of Melitz (2003) in which exporting simply requires a per-period fixed cost that does not depend on a firm’s current export status.

In the quantitative part of the paper, I calibrate the model so that it reproduces the facts described above. I simulate a panel of firms and choose values for the model’s parameters so that the moments computed using the simulated data match the actual moments observed in the Brazilian microdata. I then use the calibrated model to perform hypothetical trade reform exercises to investigate the implications of the theory for aggregate trade adjustment dynamics. For each of the destinations in the data, I simulate the transition dynamics that follow permanent trade reforms and temporary exchange rate shocks. I find that in harder destinations, trade flows respond more in the long run but take longer to adjust, and exhibit more pronounced hysteresis following temporary exchange rate depreciations. To corroborate these findings, I use the microdata to analyze how Brazilian bilateral trade flows responded to the large real exchange rate depreciation during 1999–2003. Consistent with the model’s predictions, I find that trade grew more—and more slowly—following this depreciation in destinations with lower export participation after controlling for changes in destinations’ price levels, incomes, and multilateral trade flows.

In addition to exploring the model’s aggregate consequences, I compare its predictions to those of several existing frameworks to evaluate the role of endogenous customer accumulation dynamics in accounting for the facts at hand. In the static market penetration model of Arkolakis (2010, 2016), turnover is too frequent; new exporters survive too often relative to incumbents; and exporters’ sales grow too much over the course of their export spells, particularly in markets with low export participation. In the sunk-cost model of Das et al. (2007) and Alessandria and Choi (2007), exports are not concentrated enough among top exporters; new exporters are too large and too likely to survive compared to incumbents; and sales actually fall with time in
The new-exporter dynamics framework of Alessandria et al. (2021b), in which exporters accumulate customers exogenously at the same rate in all markets, fares better in generating new exporters that look less like incumbents, but still fails to generate the patterns in sales growth over export spells—and the differences in these patterns across destinations—observed in the data. All of these other frameworks, however, do capture to some extent the variation across markets in sales concentration, overall turnover, and new exporters’ sizes and exit rates. This indicates that while customer accumulation is key to accounting for all of the facts at hand, the distribution and dynamics of firms’ exogenous characteristics (productivity and demand) also play important roles.

This paper makes several contributions to the literature. A number of empirical studies, such as Ottaviano and Mayer (2007), Eaton et al. (2011), and Bernard et al. (2012), have documented that export participation and the distribution of sales across exporters vary systematically with the characteristics of export destinations. Arkolakis (2010) accounts for these facts by developing a model in which exporting is more cost-effective in larger markets but that serving additional customers in a given market becomes more and more costly, which simultaneously implies that larger markets have higher export participation rates but also more small exporters. Other studies that focus on the life-cycle dynamics of exporting firms have documented that new exporters sell less than incumbents, are more likely to exit, and grow more rapidly (Bernard and Jensen, 2004; Eaton et al., 2007; Alessandria et al., 2021b; Ruhl and Willis, 2017; Fitzgerald et al., 2016). In this paper, I show that these dynamic facts vary systematically with the characteristics of export destinations, just as the cross-sectional facts do, and that a “dynamicization” of the Arkolakis (2010) model explains both sets of facts simultaneously.

In the quantitative literature, sunk-cost models in which firms face large costs of entering an export market and small costs to continue exporting are often used to study the microeconomic dynamics of export participation and analyze the macroeconomic implications of these dynamics (Das et al., 2007; Alessandria and Choi, 2007; Alessandria et al., 2021b; Ruhl and Willis, 2017). These models explain why trade flows respond less to trade reforms and other shocks in the short run than in the long run (Ruhl, 2008; Alessandria and Choi, 2016) and suggest that dynamic gains from trade policy reforms may differ substantially from the long-run gains. However, these models cannot account for the gradual growth in sales that occurs over an exporter’s tenure in a market or the fact that entrants are more likely to exit, except for variants like Ruhl and Willis (2017) and Alessandria et al. (2021b) in which demand is assumed to grow exogenously with time in a market. My model of market penetration dynamics generates this growth as an endogenous outcome, and accounts for the observed variation in this growth across firms as well as across markets. It also provides new insights about how export adjustment dynamics depend on market characteristics: in smaller, poorer markets, trade is more elastic in the long run but the transition to the long run takes longer, and exchange-rate hysteresis is more pronounced.

The most similar papers in terms of modeling approach are Fitzgerald et al. (2016) and Piveteau (2020),
both of which feature endogenous customer accumulation. The advantages of my approach are as follows. First, neither paper explains why entrants are smaller than incumbents or why the relative size of entrants varies across markets. In both papers, all entrants start exogenously with the same number of customers in all markets regardless of productivity or demand for their products. Second, both papers require sunk entry costs and fixed continuation costs on top of customer accumulation costs to generate entry and exit, and require exogenous variation in these costs across firms and across destinations to match the data. In my model, extensive-margin decisions are driven solely by the marginal cost of serving the first customer in a market, which varies endogenously across firms, over time, and across markets. Third, the parsimony of my approach makes it more amenable to quantitative analysis. In fact, it is tractable even in general equilibrium: Steinberg (2019) uses an early version of the model in a multi-country DSGE environment to study the consequences of uncertainty about Brexit. Most importantly, though, my approach accounts for variation in exporter performance dynamics across destinations—Fitzgerald et al. (2016) and Piveteau (2020) do not explore this variation at all.

Together, these contributions fill a gap highlighted by Alessandria et al. (2021a) in their recent review of the trade dynamics literature: “[T]he literature has largely avoided the treatment of a firm’s dynamic decisions across multiple destinations. The literature on (static) quantitative trade and firm heterogeneity has focused on the impact of geography on [exporting] costs. Merging these two approaches is a relatively unexplored, but promising, avenue of future research.”

2 Data

In my empirical analysis, I use Brazilian microdata to study how the distribution and dynamics of exporters vary across destinations. The data source is a record of all Brazilian firms’ monthly foreign sales from 1996 to 2008. For each transaction, the dataset includes the destination country, the value of the shipment in U.S. dollars, the year and month of the transaction, an 8-digit product code, and a unique firm identifier. I restrict attention to manufacturing industries and aggregate the data to the firm-year-destination level. I exclude destinations that are served by fewer than 20 firms per year following Fernandes et al. (2016). I combine these data with destination-level information on population, income per capita, and trade costs (measured as residuals from a standard gravity regression) from the CEPII Gravity Database.¹

First, I document the extent to which the cross-sectional distribution of exporters, the exit rate, and the performance of new exporters relative to incumbents vary across destinations, and show that this variation is systematically related to destinations’ characteristics. Second, I study how exporters’ sales and survival

¹The raw monthly data exhibit spurious exit and re-entry from one month to the next due to inventory adjustment dynamics (see, e.g., Alessandria et al., 2010); these adjustments are outside the scope of this paper. I have estimated the relationships between destination characteristics and exporter performance at the industry level, including industry effects to control for variation in the industrial composition of exports across destinations. I have also estimated specifications in which tariffs, distance, and other gravity variables are included directly as independent variables rather than indirectly through a gravity residual. The results from these alternative specifications are in line with the results reported in this paper and are available upon request.
rates grow after they enter a new destination, and how this growth varies across destinations. In appendix A, I report additional results about the differences in performance within individual exporters’ portfolios of destinations; these results are tangential to the main points of this paper but provide additional evidence on other dimensions of exporter performance that vary across markets.

The data used in these analyses cannot legally be distributed, but all programs and intermediate datasets needed to reproduce the results reported in this section are available on my website https://www.joesteinberg.com. I have also analyzed similar data on Mexican and Peruvian exporters from the World Bank’s Exporter Dynamics Database (Fernandes et al., 2016). These publicly-available datasets are of somewhat lower quality than the Brazilian data as they contain fewer firms and cover shorter time periods. Nevertheless, as appendix B shows, all of the results documented in this section (as well as the additional results reported in appendix A) about Brazilian exporters also apply to Mexican and Peruvian exporters. This corroborates my findings and indicates that they are robust to variation in conditions in the exporting country.

2.1 Variation in exporter performance across destinations

I analyze three aspects of the cross-sectional distribution of exporters: the number of firms that export to a destination; the share of sales accounted for by the top 5% of exporters in that destination; and the average number of other destinations served by firms that export to that destination. I also analyze three aspects’ of exporter dynamics: the exit rate; the average size of entrants relative to incumbents; and the exit rate of entrants relative to incumbents. In the spirit of Ruhl and Willis (2017), I use the term “new exporter dynamics” to jointly refer to the differences in entrants’ sizes and survival rates relative to incumbents.

Table 1: Summary statistics about exporter performance across destinations

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Num. exporters</th>
<th>Top-5 share</th>
<th>Avg. num. dests.</th>
<th>Exit rate</th>
<th>Entrant rel. size</th>
<th>Entrant rel. exit rate</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>(a) Data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>576</td>
<td>0.59</td>
<td>16.65</td>
<td>0.40</td>
<td>0.38</td>
<td>0.28</td>
</tr>
<tr>
<td>Min</td>
<td>30</td>
<td>0.27</td>
<td>7.77</td>
<td>0.30</td>
<td>0.09</td>
<td>0.07</td>
</tr>
<tr>
<td>Max</td>
<td>3,706</td>
<td>0.83</td>
<td>29.34</td>
<td>0.60</td>
<td>0.96</td>
<td>0.38</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>819</td>
<td>0.14</td>
<td>5.02</td>
<td>0.07</td>
<td>0.23</td>
<td>0.06</td>
</tr>
<tr>
<td><strong>(b) Model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>980</td>
<td>0.58</td>
<td>18.82</td>
<td>0.44</td>
<td>0.37</td>
<td>0.25</td>
</tr>
<tr>
<td>Min</td>
<td>42</td>
<td>0.34</td>
<td>10.67</td>
<td>0.22</td>
<td>0.09</td>
<td>0.05</td>
</tr>
<tr>
<td>Max</td>
<td>3,706</td>
<td>0.75</td>
<td>25.04</td>
<td>0.75</td>
<td>1.33</td>
<td>0.39</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>882</td>
<td>0.10</td>
<td>3.39</td>
<td>0.13</td>
<td>0.26</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Panel (a) of table 1 reports summary statistics for each of these measures. The first three columns show that the cross section of exporting firms varies widely across destinations. The most popular export destination, Argentina, has an export participation rate more than 100 times greater than the least popular
destination, Vietnam. The top-5 share ranges from 0.27 to 0.59, indicating that exports are highly concentrated among the largest exporters in some destinations and more evenly distributed in others. The average number of other destinations exporters serve varies from less than 8 to almost 30, suggesting that some destinations are served only by firms with a large portfolio of other destinations. The last three columns of the table show that exporter dynamics also vary across destinations. Exit rates range from as low as 30 percent to as high as 60 percent, and while entrants are smaller and more likely to exit than incumbents in all destinations, these differences are more pronounced in some destinations and more muted in others.

It is well-known that export participation is higher and that sales are more concentrated among top exporters in larger, richer destinations (see, e.g., Ottaviano and Mayer, 2007; Arkolakis, 2010; Eaton et al., 2011). To verify the existence of these relationships in the Brazilian data and to determine whether exporter dynamics also vary systematically across markets, I estimate regressions of the form,

\[ M_{j,t} = \alpha + \beta \log L_{j,t} + \gamma \log Y_{j,t} + \delta \log \tau_{j,t} + f_t + \epsilon_{j,t}. \]  

The dependent variable, \( M_{j,t} \), is a measure of exporter performance in destination \( j \) in year \( t \) (e.g. the top-5 share or the exit rate), the independent variables are the destination’s characteristics: population, \( L_{j,t} \); income per capita, \( Y_{j,t} \); and trade costs, \( \tau_{j,t} \). \( f_t \) is a year fixed effect that controls for multilateral trends like Brazilian business cycles and exchange rate depreciation.

| Table 2: Associations between destination characteristics and exporter performance |
|---------------------------------|----------------|----------------|----------------|----------------|-----------------|
|                                 | Num. exporters | Top-5 share | Avg. num. dests. | Exit rate | Entrant rel. size | Entrant rel. exit rate |
| (a) Data                        | 0.581          | 0.051       | -1.676           | -0.006     | -0.079           | 0.010             |
| log GDPpc                      | (0.023)§       | (0.004)§    | (0.155)§         | (0.003)†   | (0.012)§         | (0.004)‡          |
| log population                 | 0.408          | 0.047       | -1.154           | -0.010     | -0.044           | 0.004             |
|                               | (0.016)§       | (0.003)§    | (0.094)§         | (0.002)§   | (0.008)§         | (0.003)           |
| log trade barrier              | -1.098         | -0.065      | 2.677            | 0.036      | 0.096            | -0.021            |
|                               | (0.029)§       | (0.005)§    | (0.199)§         | (0.003)§   | (0.013)§         | (0.004)§          |
| Num. observations             | 568            | 568         | 568              | 568        | 568              | 568               |
| R²                             | 0.71           | 0.43        | 0.42             | 0.20       | 0.13             | 0.06              |

(b) Model

|                                 | 0.761          | 0.071       | -2.149           | -0.074     | -0.136           | 0.036             |
| log GDPpc                      | (0.022)§       | (0.005)§    | (0.199)§         | (0.003)§   | (0.013)§         | (0.004)§          |
| log population                 | 0.234          | 0.015       | -1.207           | 0.024      | -0.099           | 0.038             |
| log trade barrier              | -0.744         | -0.069      | 2.217            | 0.072      | 0.128            | -0.039            |

All specifications include year fixed effects. Robust standard errors in parentheses. §, ‡, and † denote significance at the 0.1%, 1%, and 5% levels, respectively.

Panel (a) of table 2 reports the results from these estimations. The first column shows that export participation is increasing in population and income per capita and decreasing in trade barriers. This is perhaps not terribly surprising, but it suggests that the export participation rate can be thought of as a convenient, one-dimensional summary of the difficulty of exporting to a destination, which will prove useful in the analyses that follow. The next two columns show that the cross-section of exporting firms
varies systematically across destinations as documented in other studies: in “easy” destinations with large, rich populations and/or low trade barriers, exports are more concentrated and the average exporter serves only a few other destinations. The last three columns of the table show that exporter dynamics, too, vary systematically across markets: in easier destinations, turnover is lower and new exporters are smaller and more likely to exit relative to incumbents, whereas in harder destinations, turnover is higher and new-exporter dynamics are less pronounced.

2.2 Variation in exporter performance with time in a market

To dig deeper into the differences in exporter dynamics across markets, I analyze how exporters grow over time after they enter a new market following a similar approach to Fitzgerald et al. (2016) and Fitzgerald and Priolo (2018). I group firms by the number of consecutive years that they export to a particular destination before exiting—the duration of an export “spell”—and then estimate the sales trajectories of firms in each group. Formally, I estimate the following regression:

$$\log e_{i,j,t} = \alpha + \sum_{m=1}^{6} \sum_{n=1}^{m} \beta_{m,n} \mathbb{1}_{\text{duration}_{i,j}=m} \mathbb{1}_{\text{years in market}_{i,j}=n} + f_{j,t} + \epsilon_{i,j,t},$$ (2)

where $e_{i,j,t}$ is firm $i$’s exports to destination $j$ in year $t$, duration$_{i,j}$ indicates the duration of the firm’s export spell in that destination, and years in market$_{i,j,t}$ indicates the number of years the firm has consecutively exported so far in that destination. I top-code duration at 6 years (the shortest observation window for a destination in my dataset) and include destination and year fixed effects. The reference group is the set of firms with durations of 1, i.e., firms that export for one year and then exit immediately; the coefficient $\beta_{m,n}$ captures how much more a firm with spell duration $m$ sells after exporting for $n$ periods than a firm in this group. To study how these export trajectories differ across destinations, I split the data into two subsamples: “hard” destinations below the 50th percentile of export participation; and “easy” destinations above the 50th percentile. I then estimate the above equation for each subsample separately.

Figure 1 reports the results of these estimations, with the results for hard destinations shown in panel (a) and the results for easy destinations in panel (b). Overall, the results mirror those of Fitzgerald et al. (2016). Sales tend to grow with an exporter’s tenure in a market, but this growth is strongest for exporters that ultimately achieve the longest spells (those that export for six or more consecutive years before exiting). There is substantial variation in sales upon entry: exporters with longer spells sell more in their first year in a market than exporters with shorter spells. Finally, sales tend to fall in the year before a firm exits; falling sales indicate that a firm is likely to exit in the near future. Comparing the two panels, we see that all of these findings are more pronounced in easy destinations than in hard ones: there is less growth in sales over the duration of an export spell in the former than in the latter, and the sales of new entrants conditional on spell duration are more compressed. In easy destinations, the most successful exporters more than double
Figure 1: Effects of tenure and duration on exporters’ sales

their sales over the first 6 years of their export spells, and when they enter their sales are more than 150 log points greater than those of firms that export for only 1 year. In hard destinations, on the other hand, the most successful exporters’ sales grow by less than 50 log points over the duration of their spells, and their sales upon entry are about 100 log points greater than one-year exporters’ sales. In short, these results confirm that new-exporter dynamics are more pronounced in destinations with greater export participation.

I analyze how the likelihood of continuing as an exporter depends on time in a market using a linear probability model of the form,

$$1 \{\text{exit}_{i,j,t}=1\} = \alpha + \sum_{n=1}^{6} \beta_n \{\text{years in market}_{i,j,t}=n\} + f_t + f_j + \epsilon_{i,j,t},$$

as in Ruhl and Willis (2017). Here, the reference group is new entrants, so the coefficient $\beta_n$ indicates how much more likely an exporter that has survived for $n$ years is to exit than a firm that has just begun to export. As before, I split the data into subsamples of hard and easy destinations based on export participation. The results, which are shown in figure 2, confirm findings reported elsewhere in the literature: exit becomes less likely the longer a firm has been exporting in a given market. Here, though, there is little difference between hard and easy destinations. In both groups, firms that have survived for 6 years are about 40 percentage points less likely to exit than new entrants. Note that this does not imply that firms are equally likely to exit after 6 years in hard and easy destinations, but rather that they are equally less likely to exit than new entrants after controlling for variation across destinations in entrants’ exit rates. As table 2 shows, the overall exit rate is higher in hard destinations than in easy ones. Although the difference between entrants’ and incumbents’ exit rates is smaller in easy destinations, on the whole entrants exit more frequently in easy destinations than in hard ones.

Before moving on, there is a distinction between my approach and that of Fitzgerald et al. (2016) and
Figure 2: Exit rates conditional on tenure

Fitzgerald and Priolo (2018) that is worth discussing. These studies include firm-destination fixed effects in their versions of equation (2). There are two reasons I exclude these fixed effects. The first, which is technical, stems from my goal of studying how exporter dynamics differ across destinations. There is insufficient variation within firm-destination groups to identify $\beta_{m,n}$ for hard destinations with these fixed effects because hard destinations have much lower export participation rates and higher exit rates than easy destinations.\(^2\) Fitzgerald et al. (2016) and Fitzgerald and Priolo (2018) lump all destinations together, so they don’t have this problem. The second reason is conceptual. Including firm-destination fixed effects makes the reference group the set of 1-year export spells by a specific firm in a given destination. Excluding these fixed effects makes the reference group the set of 1-year export spells by all firms in a given destination. In other words, Fitzgerald et al. (2016) and Fitzgerald and Priolo (2018) ask how much more a particular firm sells if its tenure in a market is long than if it is short, while I ask how much more a firm with a long tenure sells than other firms that have short tenures. Both questions are worth asking, but mine speaks more directly to why new exporters look more like incumbents in harder destinations as documented in section 2.1 above.

3 Model

The model economy consists of one exporting country and $J$ importing countries (a.k.a. export markets or destinations) that are indexed by $j = 1, \ldots, J$. The exporting country is populated by a continuum of firms that produce differentiated goods using constant-returns-to-scale technologies. Each export market is populated by a measure $L_j$ of identical consumers with income per capita $Y_j$ and constant-elasticity-of-substitution preferences over imported goods. Trade barriers are captured by iceberg transportation costs, $\tau_j$, which also vary across markets. As in Arkolakis (2010), firms are heterogeneous in their customer bases in

\[^2\]I can include firm and destination fixed effect separately (but not their interaction), as well as destination-industry and industry-year fixed effects. The results are similar in all of these specifications.
each market, which they can increase endogenously by advertising. The costs of retaining old customers and acquiring new ones depend on a firm’s current customer base, which leads firms to gradually accumulate foreign customers over time.

As in Arkolakis (2010) and Ruhl and Willis (2017), I assume that importing countries are large relative to the exporting country so that aggregate prices and quantities in importing countries are independent of outcomes in the exporting country. I also assume that export activities are small relative to the total size of the exporting country’s economy so that the wage in the exporting country, which I normalize to one without loss of generality, is independent of export-sector outcomes. Finally, I assume for the moment that all aggregate variables, including trade barriers and other destination characteristics, are constant to economize on notation; this section restricts attention to the model’s stationary equilibrium. In my quantitative analysis, however, I also analyze transition dynamics that follow permanent and temporary changes in trade barriers.

3.1 Firm characteristics

There is a unit measure of firms in the exporting country that produce differentiated varieties according to constant-returns-to-scale technologies. Firms are heterogeneous in productivity, \( x \in \mathbb{R}^+ \); demand in each market, \( z = (z_1, z_2, \ldots, z_J) \in \mathbb{R}^+_J \); and the fraction of consumers in each market to which they can sell, \( m = (m_1, m_2, \ldots, m_J) \in [0, 1]^J \).

Productivity is common to all markets, and evolves according to a Markov process with transition function \( G(x', x) \). Demand in each market \( j \) evolves independently according to a Markov process with transition function \( H(z_j', z_j) \). A firm’s customer base in each market is chosen endogenously in a manner that I describe below. Each period, a firm has a chance \( 1 - \delta(x) \) of dying, which I allow to depend on its productivity to capture the fact that smaller firms shut down more frequently (Alessandria et al., 2021b). When a firm dies, it is replaced by a new firm with productivity and demand shocks drawn from their respective ergodic distributions, \( \tilde{G}(x) \) and \( \tilde{H}(z_j) \). Newborn firms have zero customers in all export markets.

3.2 Export demand, pricing, and profits

Firms compete monopolistically as in Melitz (2003) and Chaney (2008). Market \( j \)'s demand for a firm’s product depends on the market’s characteristics, \( L_j \) and \( Y_j \); the firm’s price in that market, \( p \); the firm’s demand shock in that market, \( z \); and the fraction of consumers in that market to which the firm can sell, \( m \).

Conditional on purchasing the firm’s product, an individual consumer in market \( j \) has a standard downward-sloping demand function:

\[
c_j(z, p) = L_j Y_j (p / z)^{-\theta},
\]

I abstract from firm creation in this paper. My focus is on exporter performance in bilateral trade relationships, and the interpretation of this assumption is that the prospect of exporting to a single destination, even a large one, is too small to affect firm creation incentives. Studying the relationship between bilateral trade and firm creation is a promising avenue of investigation that could yield important insights, but I leave this for future research.
where the parameter $\theta$ is the elasticity of substitution between varieties. Total demand for the firm’s product in market $j$ depends on the firm’s price as well as the number of customers it can serve as in Arkolakis (2010) and Eaton et al. (2011):

$$q_j(z, m, p) = mc_j(z, p).$$

(5)

Conditional on its productivity, $x$, demand, $z$, and its customer base, $m$, a firm chooses its price in each market $j$ to maximize profits,

$$\pi_j(x, z, m) = \max_p \left\{ pq_j(z, m, p) - \frac{\tau_j q_j(z, m, p)}{x} \right\}. \tag{6}$$

The optimal price is given by the standard constant-markup solution,

$$p_j(x) = \frac{\theta}{\theta - 1} \frac{\tau_j}{x}. \tag{7}$$

The firm’s exports to market $j$ and associated profits can be written as

$$ex_j(x, z, m) = \left( \frac{\theta}{\theta - 1} \right)^{1-\theta} mL_jY_j^{1-\theta}(xz)^{\theta-1} \tag{8}$$

and

$$\pi_j(x, z, m) = \frac{1}{\theta} \left( \frac{\theta}{\theta - 1} \right)^{1-\theta} mL_jY_j^{1-\theta}(xz)^{\theta-1} \equiv \tilde{\pi}_j m(xz)^{\theta-1}, \tag{9}$$

respectively.

### 3.3 Market penetration dynamics

A firm’s customer base in each destination evolves over time as it attracts new customers and loses some of its old ones. A firm with current customer base $m$ that attracts $n \in [0, 1-m]$ new customers and retains $o \in [0, m]$ old ones will have a customer base of

$$m' = n + o \tag{10}$$

in the next period. Note that as a firm’s customer base grows, the number of potential new customers from which it can draw, $1 - m$, shrinks, while the number of customers it can potentially retain, $m$, grows. I use the term “potential entrant” to refer to a firm with $m = 0$ and the term “incumbent” to refer to a firm with $m > 0$. The terms “entrant” and “new exporter” equivalently refer to a potential entrant that chooses $m' > 0$.

4The price level in each market is normalized to one; $Y_j$ can be interpreted as purchasing power-adjusted income per capita.

5This language is somewhat imprecise. Strictly speaking, $n$ is not the number of new customers the firm attracts, but rather the fraction of the total population of customers in a market that the firm attracts as new customers. Similarly, $o$ is not the number of old customers the firm retains, but rather the fraction of the total population of customers that the firm retains as old customers. This more precise language is fairly cumbersome, however, so I opt for the more streamlined, but admittedly less precise language.
a new exporter becomes an incumbent in the next period.

Customer attraction and retention both depend on the firm’s advertising efforts. I use \( s \)—for search—to denote advertising targeted at new customers and \( r \)—for retention—to denote advertising targeted at old customers. Following Arkolakis (2010), the marginal effect of search effort on customer attraction is increasing in the total number of potential new customers, \((1 - m)L_j\), and decreasing in the fraction of potential new customers a firm successfully attracts, \( n / (1 - m) \):

\[
\frac{d}{ds} n_j(s) = \psi_n L_j^{-\alpha_n} (1 - m)^{-\beta_n} \left( \frac{1 - m - n_j(s)}{1 - m} \right)^{\gamma_n}.
\]  (11)

The parameter \( \alpha_n \) governs returns to population size in advertising to new customers. The smaller \( \alpha_n \), the easier it is to attract new customers in larger countries. Similarly, \( \beta_n \) governs the returns to scale with respect to the size of the pool of potential new customers in a particular market. The smaller \( \beta_n \), the easier it is for a firm to attract new customers when its current market penetration is low. I refer to \( \alpha_n \) and \( \beta_n \) as the macroeconomic and microeconomic returns to market size parameters, respectively. \( \gamma_n \) represents the degree of diminishing returns in advertising to new customers. The higher \( \gamma_n \), the fewer additional new customers are reached by each additional unit of search advertising. Finally, \( \psi_n \) is the efficiency of advertising to new customers. The higher \( \psi_n \), the lower the average cost of customer attraction.

Similarly, the marginal effect of retention effort is increasing in the total number of old customers, \( m L_j \), and decreasing in the fraction of old customers the firm successfully retains, \( o / m \):

\[
\frac{d}{dr} o_j(r) = \psi_o L_j^{-\alpha_o} m^{-\beta_o} \left( \frac{m - o_j(r)}{m} \right)^{\gamma_o}.
\]  (12)

The parameters \( \alpha_o, \beta_o, \gamma_o, \) and \( \psi_o \) have similar interpretations to their counterparts above. Note though, that microeconomic returns to market size wax as a firm’s customer base, and thus the pool of old customers who can be retained, grows. Differences between parameters of (11) and (12) allow for the possibility that advertising to old customers works differently than advertising to new customers. For example, it may be that the macroeconomic market size effect is less pronounced \((\alpha_o > \alpha_n)\) because advertising to current customers is more analogous to contacting them individually one after another than to mass advertising on the radio or television. It might also be the case that returns to advertising to current customers diminish less rapidly \((\gamma_o < \gamma_n)\). Indeed, when I calibrate the model’s parameters so that it matches the facts described in section 2, I find precisely these differences.

Solving the differential equations (11) and (12) yields the costs of attracting \( n \) new customers and
retaining $o$ old customers, respectively:

$$s_j(m, n) = \frac{L_j^m (1 - m)^{\delta m}}{\psi_n (1 - \gamma_n)} \left[ 1 - \left( \frac{1 - m - n}{1 - m} \right)^{1 - \gamma_n} \right],$$

(13)

$$r_j(m, o) = \frac{L_j^m m^{\delta o}}{\psi_o (1 - \gamma_o)} \left[ 1 - \left( \frac{m - o}{m} \right)^{1 - \gamma_o} \right].$$

(14)

In what follows, I use $s_j, n$ and $r_j, o$ to denote the partial derivatives of the advertising cost functions with respect to their second arguments. Although these expressions bear more than a passing resemblance to the market penetration cost function in Arkolakis (2010), they depend not only on the number of customers a firm attracts or retains, but also on the firm’s current customer base. Thus, as a firm builds its customer base over time, its search and retention costs change.

### 3.4 Market penetration cost dynamics

For a firm with current customer base $m$ that wishes to expand (or perhaps shrink) its customer base to $m'$, the total cost of customer attraction and retention—the market penetration cost in the parlance of Arkolakis (2010)—is given by the solution to the static problem,

$$f_j(m, m') = \min_{n \in [0,1-m], o \in [0,m]} \left\{ s_j(m, n) + r_j(m, o) \right\} \text{ subject to } m' = n + o. \quad (15)$$

I use $n_j(m, m')$ and $o_j(m, m')$ to denote the optimal policy functions for customer attraction and retention, respectively. The solution to this problem can be characterized as follows:

- For entrants, who have no old customers to retain, the market penetration cost is equal to the attraction cost: $f_j(0, m') = s_j(0, m')$, $n_j(0, m') = m'$, and $r_j(0, m') = 0$.

- If the firm’s customer base increases and the marginal cost of attracting the last new customer is lower than the marginal cost of retaining the first old customer, then no old customers should be retained: If $m' > m$ and $s_j(m, m') < r_j(o)(m, 0)$, then $n_j(m, m') = m'$ and $o_j(m, m') = 0$.

- If the firm’s customer base shrinks and the marginal cost of retaining the last old customer is lower than the marginal cost of attracting the first new customer, then no new customers should be attracted: If $m' < m$ and $r_j(o)(m', m') < s_j(m, 0)$, then $n_j(m, m') = 0$ and $o_j(m, m') = m'$.

- Otherwise, the marginal attraction and retention costs are equal at the optimum: $s_j, n(m, n) = r_j, o(m, o)$.

In what follows, I use $f_j, m'$ to denote the first partial derivative of (15) with respect to end-of-period market penetration, $f_j, m'm'$ to denote the second partial, and $f_j, mm'$ to denote the cross partial.
3.4.1 Key properties

The market penetration cost function (15) has several key properties that allow the model to account for both the cross-sectional and life-cycle facts about exporters documented above in section 2.

First, the marginal cost of accessing the first customer is always strictly positive, regardless of a firm’s current customer base:

\[ f_{j,m'}(m, 0) > 0, \forall m. \] (16)

This property implies that sufficiently unproductive firms may find the cost of attracting the first new customer or retaining the first old one prohibitive. As in Arkolakis (2010), this property delivers an endogenous extensive margin of trade: sufficiently unproductive potential entrants will choose not to enter. In this dynamic context, this property also delivers endogenous exit: sufficiently unproductive incumbent exporters will opt not to retain any of their old customers or attract any new ones. This is where modeling the distinction between retaining old customers and attracting new ones is especially crucial. It is possible to model market penetration dynamics without making this distinction and still match many of the facts documented in this paper, but doing so requires one to assume that exit from the export market is exogenous, or that there is an additional fixed cost of exporting on top of the market penetration costs.

Second, the marginal market penetration cost is increasing and it is impossible to saturate the market:

\[ f_{j,m'm'}(m, m') > 0, f_{j,m'm'}(m, m') \to \infty \forall m \] (17)

These properties, which are also similar to properties from Arkolakis (2010), imply that higher-productivity firms will attract more new customers and retain more of their old customers, but even the most productive firms will not fully penetrate an export market even after accumulating customers over many periods.

Third, the market penetration cost is decreasing in a firm’s current customer base, both overall and at the margin:

\[ f_{j,m}(m, m') < 0, f_{j,m'm'}(m, m') < 0 \forall m, m'. \] (18)

This property mirrors a common result in the literature on sunk-cost models, in which the cost of entering a foreign market is typically found to be higher than the cost of continuing to serve it. Here, it implies that a

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6Strictly speaking, this threshold depends on the product of a firm’s demand and its productivity. In this section, for brevity’s sake I take liberties with the terms “productivity” and “productive” to encompass the firm’s overall exogenous condition.

7Moreover, if the marginal cost of attracting the first new customer for a potential entrant, \( s_{j,n}(0, 0) \), exceeds the marginal cost of retaining the first old customer for a typical incumbent, the model will generate exporter hysteresis as in Baldwin (1992): the average entrant will be more productive than the average incumbent.

8See Steinberg (2019) for an early version of this model with no distinction between old and new customers and exogenous exit.

9This property is inherited from similar properties of the underlying attraction and retention costs, \( s_j \) and \( r_j \). Note that because it is impossible to retain all old customers—\( r_{j,\infty} \) goes to infinity as \( \sigma \) approaches 1—all firms experience customer turnover, even firms with growing customer bases.
firms derive two benefits from expanding their customer bases: increased sales in the present and reduced exporting costs in the future. This property is key to generating the new exporter dynamics documented in section 2 in which a firm’s sales and likelihood of survival increase with its tenure as an exporter in a given market. Moreover, because the marginal cost of reaching even a single customer, \( f_{j,m'}(m,0) \) is decreasing in the size of a firm’s customer base, the firm will be less likely to exit as its customer base grows.

Fourth, measured relative to purchasing power, exporting is more expensive on the whole and at the margin in smaller, poorer destinations:

\[
\frac{\partial f_j(m,m')}{\partial X_j} < 0, \quad \frac{\partial f_{j,m'}(m,m')}{\partial X_j} < 0, \quad \forall m,m', X_j \in \{L_j,Y_j\}.
\] (19)

This property implies that fewer firms will enter harder markets and those that do will accumulate fewer customers as in Arkolakis (2010). And because firms with fewer customers are more likely to exit (due to the previous property), firms in harder markets exit more often. And because they exit more often, they have less incentive to accumulate customers over time, so they grow less after the enter.

### 3.5 Optimal market penetration

Once the firm has determined the most cost-effective way to increase (or decrease) its market penetration, it chooses how much it should do so in order to maximize the present discounted value of the profits from exporting:

\[
V_j(x,z) = \max_{m' \in [0,1]} \left\{ \pi_j(z,m') - f_j(m,m') + \delta(x) \frac{1}{1+R} \mathbb{E} [V_j(x',z',m')|x,z] \right\}
\] (20)

The parameter \( R \) governs the rate at which the firm discounts future profits. This formulation of the problem is virtually identical to the Bellman equations in sunk-cost models of exporting like Das et al. (2007), Alessandria and Choi (2007), and Alessandria et al. (2021b) in which the cost of exporting depends on a firm’s current status as an exporter; the only difference is that export status is continuous, rather than binary. I use \( m_j'(x,z,m) \) to denote the optimal policy function at this stage.

Using the envelope theorem, the solution to this problem is characterized by the following inequality:

\[
f_{j,m'}(m,m') \geq \tilde{\pi}_j(xz)^{\theta-1} - \frac{\delta(x)}{1+R} \mathbb{E} [f_{j,m}(m',m'')|x,z],
\] (21)

where \( m' \) and \( m'' \) are shorthand for \( m_j'(x,z,m) \) and \( m_j'(x',z',m_j'(x,z,m)) \), respectively. The left-hand side of this expression is the marginal cost of exporting. The first term on the right-hand side is the marginal increase in flow profits the firm gains from increasing its market penetration. The second term on the right hand side is the expected change in the cost of exporting next period. Note that property (18) implies that this term is positive: increasing market penetration today reduces the cost of exporting tomorrow. If this condition holds with equality, the firm chooses \( m' \) to equate the marginal cost of exporting with the marginal benefit.
Property (17) implies that firms with higher market penetration rates at the beginning of the period will choose higher market penetration rates at the end of the period, i.e., the policy function is upward-sloping: \( m'_{j,m}(x, z, m) \geq 0 \). This implies that firms gradually build up their customer bases over time.

If, on the other hand, the marginal cost of attracting or retaining the very first customer, \( f_{j,m'}(m, 0) \), exceeds the marginal benefit, the firm will exit (if \( m > 0 \)) or not enter (if \( m = 0 \)). Entry is characterized by threshold, \( z(x) \) such that firms with demand shocks below this threshold will choose not to enter:

\[
f_{j,m'}(0, 0) \geq \tilde{\pi}_j(z(x))^{\theta - 1} - \frac{\delta(x)}{1 + \beta} \mathbb{E}[f_{j,m}(0, m'')|x, z].
\] (22)

The entry threshold is decreasing in a firm’s productivity: \( z'(x) < 0 \). Thus, high-productivity firms are more likely to enter than low-productivity firms. Exit is characterized by a threshold \( m(x, z) \) such that firms with market penetration below this threshold will choose to exit:

\[
f_{j,m'}(m(x, z), 0) \geq \tilde{\pi}_j(z(x))^{\theta - 1} - \frac{\delta(x)}{1 + \beta} \mathbb{E}[f_{j,m}(0, m'')|x, z].
\] (23)

Property (18) implies that the exit threshold is decreasing in productivity and demand: \( m_+(x, z) < 0, m_-(x, z) < 0 \). This means that firms with lower market penetration rates are more likely to exit than firms with higher market penetration rates. Because the policy function is increasing, this means that firms with shorter tenures in a market are more likely to exit as documented by Ruhl and Willis (2017), Alessandria et al. (2021b), and others. Conversely, it also means that a firm with a demand shock below the entry threshold may choose not to exit if it begins the period with a high enough market penetration rate. Thus, a firm that enters when its demand is high may accumulate a large enough customer base that it is profitable to remain in the market after receiving a poor demand shock that would have precluded it from entering initially. Also, note that although multilateral exit can also occur exogenously through death, bilateral exit only occurs endogenously because death shocks are independent of firms’ bilateral demand shocks.

Figure 3 illustrates how the features of the model work together to generate realistic exporter dynamics. Consider a potential entrant with zero customers in market \( j \) and a high enough demand shock, \( z_{hi} \), to warrant entering that market. Panel (a) shows how the firm’s optimal market penetration choice as a new entrant, \( m_1 \), is determined. It is shown in the figure as the intersection of the firm’s marginal benefit, the upper horizontal dotted line labeled \( \tilde{\pi}_j(z_{hi})^{\theta - 1} + \beta \mathbb{E}[f_{j,m}|z_{hi}], \) and the entrant’s marginal cost curve, the solid blue line labeled \( f_{j,m'}(0, \cdot) \). Panel (b) shows the firm’s policy function as the solid blue line labeled \( m'_{j}(x, z_{hi}, \cdot) \); the firm’s choice in this period is the point \( (0, m_1) \) located on this line.

In period 1, the firm’s marginal cost curve shifts outward to the dashed red line in panel (a) labeled \( f_{j,m'}(m_1, \cdot) \) due to property (18). The firm’s optimal market penetration choice in this period, \( m_2 \), is given by the intersection of this new marginal cost curve and the firm’s marginal benefit.\(^{10}\) The firm’s choice in period

\(^{10}\)The graph shows a single line for the firm’s marginal benefit, when in fact it shifts upwards over time as the firm’s rising market
Figure 3: Illustration of entry, expansion, and exit

(a) Marginal cost $f_{1,2}(m, m')$

(b) Policy function $m'_j(x, z, m)$

1 is shown in panel (b) as the point $(m_1, m_2)$ on the firm’s policy function. In period 2, the firm’s marginal cost curve shifts outward again, to the green dash-dotted line labeled $f_{j,m'}(m_2, \cdot)$ in panel (a). Suppose, however, that the firm receives a bad demand shock, $z_{lo}$, such that the marginal benefit of exporting is now lower than the marginal cost (shown by the lower horizontal dotted line in panel (a) labeled $\tilde{\pi}_j(xz_{lo})^{\theta-1} + \beta E[f_{j,m'}|z_{lo}]$). Instead of continuing to expand, the firm decides to exit. The red dashed line labeled $m'_j(x, z, m')$ in panel (b) shows the policy function associated with this lower level of demand; the firm’s decision to exit is shown as the point $(m_2, 0)$ on this curve.

Now suppose instead that the firm keeps its higher demand shock instead of receiving the bad one. In this case, its optimal market penetration choice, $m_3$, is shown in panel (a) as the intersection of its current marginal cost curve, $f_{j,m'}(m_2, \cdot)$, and its original marginal benefit. This choice is shown in panel (b) as the point $(m_2, m_3)$ on the original policy function (the solid blue line). Note that the firm’s policy function at $m_3$ is positive: this level of market penetration is high enough that the firm will no longer choose to exit if it receives the bad demand shock. This illustrates how the model generates higher exit rates among smaller, younger exporters.

### 3.6 Aggregation and equilibrium

The final piece of the model is a law of motion that describes how the distribution of exporters evolves over time. Let $\Psi_j(x, z, m)$ denote the joint distribution of productivities, demand shocks, and market penetration rates in market $j$. This distribution evolves according to the law of motion

$$\Psi'_j(\mathcal{X} \times \mathcal{Z} \times \mathcal{M}) = \int_{\mathbb{R}_+^2 \times [0,1]} Q_j(x, z, m, \mathcal{X} \times \mathcal{Z} \times \mathcal{M}) \, d\Psi_j(x, z, m),$$

penetration lowers the marginal exporting cost, again due to property (18). However, in the calibrated model these shifts are small relative to the scale of the marginal cost curve; the figure shows the actual dynamics of a firm in the calibrated model.
where $\mathcal{X}$ and $\mathcal{Z}$ denote typical subsets of $\mathbb{R}_{++}$, $\mathcal{M}$ denotes a typical subset of $[0, 1]$, and $Q_j(x, z, m, \mathcal{X} \times \mathcal{Z} \times \mathcal{M})$ is the probability that a firm with productivity $x$, demand shock $z$, and customer base $m$ transits to a state in the set $\mathcal{X} \times \mathcal{Z} \times \mathcal{M}$. This transition function is given by

$$Q_j(x, z, m, \mathcal{X} \times \mathcal{Z} \times \mathcal{M}) = \delta(x) \int_{\mathbb{R}_{++}^2} \mathbf{1}_{\{m'(x,z,n) \in \mathcal{M}\}} \, dG(x', x) dH(z', z)$$

$$+ (1 - \delta(x)) \int_{\mathbb{R}_{++}^2} \mathbf{1}_{\{0 \in \mathcal{M}\}} \, d\bar{G}(x') d\bar{H}(z').$$

The first term on the right-hand side is probability that a firm survives, chooses a new customer base in the set $\mathcal{M}$, draws a productivity shock in the set $\mathcal{X}$, and draws a demand shock in the set $\mathcal{Z}$. The second term is the probability that a firm dies and is replaced by a new firm with productivity in the set $\mathcal{X}$ and demand shock in the set $\mathcal{Z}$.

A stationary equilibrium is: (i) a collection of export cost policy functions, $(n_j(m, m'), o_j(m, m'), f_j(m, m'))_{j=1}^{J}$, that solve the cost minimization problem (15); a collection of value functions and market penetration policy functions, $(V_j(x, z, m), m'_j(x, z, m))_{j=1}^{J}$, that solve the firm’s dynamic problem (20); and (iii) a collection of distributions, $(\Psi_{j,t})_{j=1}^{J}$, that satisfy the law of motion (24). In my quantitative analysis, I solve for transition dynamics following permanent and temporary changes in trade costs as well as stationary equilibria; a transition equilibrium is a sequence of the objects described above that satisfy the relevant conditions at each point in time.

### 3.7 Relationship to other models

The model generalizes several existing export participation frameworks that are commonly used in quantitative studies. If retaining old customers is impossible ($\psi_0 = 0$), the overall market penetration cost is equal to the cost of attracting new customers, and the cost of exporting does not depend on a firm’s current customer base: $f_j(m') \equiv f_j(0, m') = s_j(0, m')$. In this case, the cost of exporting is the same as in the static model of Arkolakis (2010). Of course, even though a firm’s decision about whether to export and how many customers to serve is static, the idiosyncratic dynamics of productivity and demand still generate variation in sales and survival over firms’ life cycles. Taking these persistent shocks into account, this specification of the model in its entirety is equivalent to Arkolakis (2016), which integrates Arkolakis (2010) with a productivity-based theory of firm dynamics.

If $\gamma_0 = \gamma_o = 0$, the marginal attraction and retention costs are both constant. Because the marginal benefit of serving additional customers is also constant (equation (9) is linear in $m$), firms choose either to serve all customers in a market or none. In this case, the cost of exporting depends only on whether a firm has any current customers to retain, i.e., whether or not a firm is currently an exporter. Thus, this specification is equivalent to the sunk-cost model of Das et al. (2007); the constant marginal attraction cost can be interpreted as the sunk entry cost and the constant marginal retention cost can be interpreted as the fixed continuation.
cost. If, additionally, retaining old customers is impossible ($\varphi_0 = 0$), the export participation decision is once again static, and the model collapses to the seminal theory of Melitz (2003); the market penetration cost can be interpreted as a fixed per-period cost of exporting.

My theory of exporting costs is also similar to, but does not generalize, several other models. Ruhl and Willis (2017) extend the sunk-cost model to allow demand for exporters’ products to shift upwards exogenously over time in order to capture the fact that new exporters sell less than incumbents. Alessandria et al. (2021b) build on Ruhl and Willis (2017) by making these shifts stochastic, which allows their model to capture the fact that new exporters are also less likely to survive. One can interpret my model as an explanation for these shifts and why they are larger in some firms than others. There are several other papers that use models of endogenous customer accumulation to account for new exporter dynamics, most notably those developed by Fitzgerald et al. (2016) and Piveteau (2020). There are two key differences between these models and mine. First, they assume that all entrants start exogenously with the same number of customers in all destinations. My theory explains why new entrants have fewer customers than incumbents and generates dispersion in entrants’ sales both within and across destinations that is consistent with the data. Second, these models require sunk and fixed costs that vary exogenously across firms in order to generate realistic entry and exit patterns in addition to customer accumulation costs. In my model, extensive-margin dynamics are driven solely by the marginal cost of serving the first customer, $f_j(\cdot, 0)$, which varies endogenously across firms, across destinations, and over time.

4 Calibration

I calibrate the model’s parameters so that it matches the variation in exporter performance across destinations documented in section 2.1 using an indirect inference approach. The calibrated model succeeds in accounting for the targeted moments as well as the non-targeted facts documented in section 2.2 about how post-entry sales trajectories vary across destinations. After calibrating and validating the model, I explore how the costs of exporting that firms choose in equilibrium vary with time in a market and across destinations.

4.1 Procedure

The first step in my calibration procedure is to choose a set of destinations and assign values to their characteristics, $L_j$, $Y_j$, and $\tau_j$. I use the same 63 destinations in the Brazilian microdata that analyze in section 2; as before, their characteristics are taken from the CEPII Gravity database. The second step is to calibrate the parameters that govern the distribution of firms’ exogenous types and the cost of exporting. I assume that demand follows a standard AR(1) process in logs with persistence $\rho_z$ and innovation dispersion $\sigma^2_z$. I assume that productivity is unconditionally distributed log-normally with variance $\sigma^2_x$, and each period
firms retain their productivities with probability $\rho_x$ and draw new ones with probability $1 - \rho_x$. Following Alessandria et al. (2021b), I parameterize the death rate as $1 - \delta(x) = \max(0, \min(e^{-\delta_0 x + \delta_1}, 1))$.

With these parameterizations, there are 16 parameters that must be calibrated: $\rho_x, \sigma_x, \rho_z,$ and $\sigma_z$ govern the distributions of the exogenous state variables; $\delta_0$ and $\delta_1$ govern survival; $\alpha_n, \beta_n, \gamma_n,$ and $\psi_n$ govern the cost of attracting new customers; $\alpha_o, \beta_o, \gamma_o,$ and $\psi_o$ govern the cost of retaining old customers; $\theta$ governs the elasticity of substitution between varieties; and $R$ governs the rate at which firms discount future profits. Following Ruhl and Willis (2017) and Alessandria et al. (2021b), I set $\theta$ externally to 5, a common value in the literature that implies a trade elasticity of 4 in the absence of firm-level responses. I set the discount rate $R$ externally to match the average Brazilian real interest rate during 2000-2005 of 10%. Following Ruhl and Willis (2017) and Alessandria et al. (2021b), I set $\theta$ externally to 5, a common value in the literature that implies a trade elasticity of 4 in the absence of firm-level responses. I set the discount rate $R$ externally to match the average Brazilian real interest rate during 2000-2005 of 10%.

This leaves me with 14 parameters whose values must be jointly determined. I use an indirect inference strategy to find values of these parameters that minimize the distance between moments in the Brazilian microdata and moments in simulated data generated by the model. Specifically, for each of the six measures of exporter performance discussed in section 2.1, I target the cross-destination average shown in table 1 and the coefficients on population, income per capita, and trade barriers shown in table 2. Additionally, I target a multilateral export participation rate of 26%. For each candidate parameter vector, I use the model to simulate a panel of firms and calculate these moments by applying the same processing and analysis that I apply to the real data. I choose the number of firms in my simulation so that the most popular destination, Argentina, has the same average number of exporters as in the data (3,706). I then search over the parameter space to find the vector of parameters that minimizes the mean squared difference between the simulated moments and actual moments, where each moment is weighted by the inverse of its standard error. To ensure that the estimated parameter vector is a global minimum, I break the parameter space into increasingly small subspaces, use a stochastic population-based global optimization method in each subspace, and “polish off” each subspace’s best candidate parameter vector using a simplex-based method. Essentially, my approach follows the Subplex method (Rowan, 1990) but adds a stochastic search in each subspace. It is similar to the TikTak algorithm described in Arnoud et al. (2019).

There are a total of 25 target moments (the average and three slope coefficients for each of the six statistics from section 2.1 plus the overall export participation rate). The 14 estimated parameters are therefore overidentified, but the several of the target moments are correlated. Looking at the average number of other destinations served, for example, the cross-destination mean is negatively correlated with the three slope coefficients because exporters in the most popular markets serve only a few other destinations; increasing the magnitude of the slope coefficients because exporters in the most popular markets serve only a few other destinations; increasing the magnitude of the slope coefficients for this statistic also raises the overall mean. Consequently, an

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11 This approach is similar to a standard log-normal AR(1) process, but is more computationally tractable because an exporter’s continuation value conditional on drawing a new productivity is independent of its current productivity. It is commonly used in models with Pareto-distributed productivities (see, e.g., Buera et al., 2011)

12 Brazilian real interest rates were high and volatile during the 1980s and 1990s and then declined after the Brazilian currency was allowed to float in 1999. The 10% figure I use is almost identical to the value used by Ruhl and Willis (2017) for Colombia.

13 I do not have data on non-exporting Brazilian firms, so I rely on the estimate of Ruhl and Willis (2017) for Colombia.
exactly-identified estimation strategy would be problematic, whereas my strategy ensures there is sufficient independent variation in the target moments to pin down all of the parameters.

Each of the target moments affects some parameters more than others. The cross-destination averages of the top-5 share and the number of other destinations served pin down the variances of the productivity distribution and demand shock, $\sigma_x$ and $\sigma_z$. The overall export participation rate determines the level of the new-customer attraction cost, $\psi_n$, while the average exit rate influences the level of the old-customer retention cost, $\psi_o$, and the minimum death probability, $\delta_1$. The average exit rate of entrants relative to that of incumbents affects the persistence of the demand shock, $\rho_z$, and the sensitivity of the exit rate to productivity, $\delta_0$. The slope coefficients of the exit rate, number of other destinations served, and relative exit rate of entrants play dominant roles in identifying the returns to market size in attracting new customers and retaining old ones, $\alpha_n$ and $\alpha_o$. Finally, the average and slope coefficient of the relative entrant size and the slope coefficient of the top-5 share jointly pin down the convexity parameters of the attraction and retention costs, $\gamma_n$ and $\gamma_o$.

4.2 Parameter values

Table 3 lists the parameter estimates resulting from the procedure described above.\textsuperscript{14} Panel (a) shows the parameters that govern the distribution and evolution of firms’ exogenous characteristics. The variance of multilateral productivity shocks is somewhat lower than that estimated in models of multilateral exporter dynamics (see, e.g., Ruhl and Willis, 2017; Alessandria and Choi, 2014; Alessandria et al., 2021b), but the persistence of these shocks is higher. However, demand shocks are less persistent than productivity shocks, and the product of productivity and demand, $x \times z_j$, exhibits similar dispersion and persistence to other studies’ productivity processes. The variance of the productivity distribution on top of the variance in the demand shock process is needed to capture the high concentration of exports among the largest exporters in the average destination and the fact that most firms have relatively small portfolios of export destinations, while the lower persistence of demand helps account for variation in exit rates across destinations. The survival function parameters, shown in panel (b), are similar to the estimates of Alessandria et al. (2021b), who use business dynamics data in which firm creation and death can be directly observed.

The parameters of the advertising cost functions are shown in panels (c) and (d). The macroeconomic return to market size is significantly larger in attracting new customers than in retaining old ones: $\alpha_n < \alpha_o$. This captures the idea that advertising to current customers is more akin to contacting them individually, one by one, whereas advertising to new customers is more like advertising on the radio or television en masse. Conversely, the microeconomic return to market size is larger in advertising to old customers: $\beta_o < \beta_n$. The new-customer attraction cost function is more convex than the old-customer retention cost function: $\gamma_n > \gamma_o$. This indicates that it is harder to attract large blocks of new customers than to retain large blocks

\textsuperscript{14}Reporting standard errors is not feasible due to the computational burden of solving and simulating the model, but also due to the fact that the objective function exhibits discrete jumps and other non-differentiabilities.
Table 3: Calibrated parameter values

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Meaning</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) Distribution of firm types</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_x$</td>
<td>Variance of productivity</td>
<td>1.02</td>
</tr>
<tr>
<td>$\rho_x$</td>
<td>Persistence of productivity</td>
<td>0.98</td>
</tr>
<tr>
<td>$\sigma_z$</td>
<td>Variance of demand</td>
<td>0.44</td>
</tr>
<tr>
<td>$\rho_z$</td>
<td>Persistence of demand</td>
<td>0.60</td>
</tr>
<tr>
<td>$\delta_0$</td>
<td>Correlation of survival with productivity</td>
<td>34.7</td>
</tr>
<tr>
<td>$\delta_1$</td>
<td>Minimum death probability</td>
<td>0.03</td>
</tr>
<tr>
<td>(c) New customer attraction costs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_n$</td>
<td>Macro return to market size</td>
<td>0.51</td>
</tr>
<tr>
<td>$\beta_n$</td>
<td>Micro return to market size</td>
<td>0.94</td>
</tr>
<tr>
<td>$\gamma_n$</td>
<td>Convexity</td>
<td>6.44</td>
</tr>
<tr>
<td>$\psi_n$</td>
<td>Level</td>
<td>0.10</td>
</tr>
<tr>
<td>(d) Old customer retention costs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_o$</td>
<td>Macro return to market size</td>
<td>0.96</td>
</tr>
<tr>
<td>$\beta_o$</td>
<td>Micro return to market size</td>
<td>0.79</td>
</tr>
<tr>
<td>$\gamma_o$</td>
<td>Convexity</td>
<td>3.82</td>
</tr>
<tr>
<td>$\psi_o$</td>
<td>Level</td>
<td>0.06</td>
</tr>
</tbody>
</table>

of old ones. Finally, the level parameter is higher for customer attraction than for retention: $\psi_n > \psi_o$. Taken at face value, this would seem to suggest that acquiring new customers is cheaper than retaining old ones, which would contrast sharply with the large startup costs in standard sunk-cost models like Das et al. (2007) and Alessandria and Choi (2007) required to generate realistic export participation and turnover. However, as I show in section 4.4, when we examine more closely the exporting costs that firms choose to incur in equilibrium, we see that this is not the case.

4.3 Performance on targeted and non-targeted moments

The calibrated model closely replicates the targeted moments. The first row in panel (b) of table 1 shows the means of the 6 cross-sectional and dynamic measures of exporter performance discussed in section 2.1 in the simulated data. The mean top-5 share, average number of other destinations served, exit rate, relative entrant size, and relative entrant exit rate are all close to the means observed in the Brazilian data. The mean number of exporters is two-thirds higher in the simulated data, but this moment is weighted less than the other measures’ means due to its relatively high standard error. Panel (b) of table 2 shows the associations between destination characteristics and these measures of exporter performance in the simulated data. All coefficients but one (the effect of population size on the exit rate) have the correct sign, and of the former all but two (the effect of GDP per capita on the overall exit rate and the effect of population on the relative exit rate of entrants) have the correct magnitude.

The model also reproduces, at least qualitatively, all of the other facts documented in section 2 that were not targeted in the calibration. The last four rows in panel (b) of table 1 show how the model performs
in reproducing other summary statistics for the measures discussed in section 2.1. The model generates a similar amount of variation across destinations as in the data for the number of exporters, the top-5 share and the relative size of entrants, and about twice as much variation for the overall exit rate and the relative exit rate of entrants. Figure 1 shows that the model closely matches the facts about how sales vary with time in a market described in section 2.2. In both model and data, the most successful exporters exhibit the strongest growth in sales over the duration of their export spells and sell more upon entry than less successful exporters; sales drop in the period immediately preceding exit; and the differences in sales dynamics between more- and less-successful exporters are more pronounced in easy destinations than in hard ones. Figure 2 shows that the model qualitatively captures the fact that the likelihood of exit falls with time in a market, but does not generate as much of a decline as in the data and exhibits a larger difference between easy and hard destinations.\\footnote{This is consistent with Fitzgerald et al. (2016), who find that customer accumulation plays a key role in explaining the post-entry dynamics of export quantities, whereas slow learning about idiosyncratic demand shocks is important to matching post-entry survival dynamics; my model features the former but not the latter.}

4.4 Equilibrium exporting costs

To illustrate how exporting costs vary in equilibrium over firms’ tenures in different destinations, I estimate how time in a market affects exporting costs, both in levels and relative to profits, following the Fitzgerald et al. (2016) approach described in section 2.2:

\[
\log f_j(m_{i,j,t}, m_{i,j,t+1}) = \alpha + \sum_{m=1}^{6} \sum_{n=1}^{m-1} \beta_{m,n} \mathbb{I}\{\text{duration}_{i,j}=m\} \mathbb{I}\{\text{years in market}_{i,j}=n\} + f_j + f_t + \epsilon_{i,j,t}. \tag{26}
\]

\[
\frac{f_j(m_{i,j,t}, m_{i,j,t+1})}{\pi_j(x_{i,j,t}, z_{i,j,t}, m_{i,j,t})} = \alpha + \sum_{m=1}^{6} \sum_{n=1}^{m-1} \beta_{m,n} \mathbb{I}\{\text{duration}_{i,j}=m\} \mathbb{I}\{\text{years in market}_{i,j}=n\} + f_j + f_t + \epsilon_{i,j,t}. \tag{27}
\]

As before, I split destinations into hard and easy groups based on export participation, and the reference group is firms that export for only one year before exiting. Note though, that I exclude the last year of a firm’s export spell (i.e. when \(m = n\)) because firms that choose to exit endogenously pay zero export costs. Panels (a) and (b) of figure 4 report the estimated effects of time in a market on the level of exporting costs from specification (26). Exporting costs are approximately constant over the duration of an export spell in hard destinations, but do in fact rise with time in a market in easy destinations. Panels (c) and (d), however, which report the estimated effects of time in a market on the ratio of exporting costs to profits from specification (27), tell a different story. Measured relative to profits, exporting costs are highest at the beginning of an export spell, and decline more sharply in easy destinations than in hard ones.

Together, these results line up nicely with calibrated models of exogenous new exporter dynamics like Ruhl and Willis (2017) and Alessandria et al. (2021b), which typically feature startup costs that are similar to continuation costs when measured in levels, but substantially higher when measured relative to profits.
What’s new here is that exporting costs also vary endogenously across firms within each destination. Figure 4 shows that in both groups of destinations, more successful exporters (those with longer export spells in a given destination) pay higher exporting costs than less successful exporters, although the differences are larger in easy destinations, mirroring the results for sales shown in figure 1. In appendix A, I report additional results documenting how firms’ exporting costs vary in equilibrium across their own individual portfolios of export destinations.

5 Aggregate implications

A common theme in the trade dynamics literature is that micro matters for macro: firm-level responses drive the dynamics of aggregate trade flows in response to permanent trade policy reforms and temporary shocks. Here, I conduct two experiments using the calibrated model to study how differences in exporter dynamics across destinations generate differences in bilateral trade dynamics. First, I trace out transition dynamics in response to a permanent reduction in trade costs. Second, I analyze the transition dynamics that follow a
temporary real exchange rate shock. I corroborate the model’s aggregate implications by using the Brazilian microdata to analyze the bilateral trade dynamics that followed the depreciation of Brazil’s real exchange rate in 1999.

5.1 Permanent trade policy reforms

In my first experiment, I use the calibrated model to analyze how bilateral trade flows respond in the short and long run to a permanent, unanticipated 10% reduction in iceberg trade costs. I solve for the transition dynamics that follow this change in each of the destinations in the Brazilian customs data, and then break the resulting time series into two groups as before: destinations in the top 50% of export participation (easy destinations), and destinations on the bottom 50% (hard destinations). I adopt the following timing to make the different forces at work as transparent as possible. In period 0, the model is in its initial steady state. In period 1, trade costs fall after firms have made their market penetration decisions, so trade rises only because of the price elasticity of demand. Thus, the period-1 trade elasticity in all destinations is $\theta - 1 = 4$, the elasticity that would obtain in a model without any firm-level adjustments at all. In period 2, firms begin to adjust their market penetration rates, entering and expanding due to the increase in demand, and the trade elasticity begins to rise.

**Figure 5:** Transition dynamics following a permanent trade reform

![Graph showing transition dynamics](image)

Figure 5 shows how the number of exporters, the average market penetration rate, and total bilateral exports evolve over time in hard versus easy destinations in response to this trade reform. In the long run, export participation and market penetration both respond substantially more in hard destinations than in easy destinations. This is related to observations by Arkolakis (2010), Eaton et al. (2011), Kehoe and Ruhl (2013), and others that the least-traded products respond the most to trade reforms. Consequently, harder destinations have long-run trade elasticities more than 20 percent greater than easy destinations, consistent with the findings of Adão et al. (2020). The long-run trade elasticity in easy destinations is only slightly above $\theta - 1$. This is because exports are highly concentrated among the largest firms in these destinations,
and “the largest firms in a market grow at a positive rate that (asymptotically) depends only on the price elasticity of demand.” (Arkolakis, 2010).

In the short run, trade takes several years to converge to its new higher level as new firms enter and incumbent exporters build up their customer bases. The export participation rate converges in about 6 years, while the average market penetration rate takes about 10 years. In hard destinations, where exports are more evenly distributed across firms and these firm-level adjustments are more pronounced, the trade elasticity also takes about 10 years to converge. In easy destinations, by contrast, trade flows converge almost immediately because firm-level adjustments are quantitatively less important.

### 5.2 Temporary real exchange rate depreciation

In my second experiment, I use the calibrated model to analyze how trade responds to a temporary 10% increase in the real exchange rate that decays geometrically over time by 10% each period. Formally, the demand curve for a firm’s product in each period $t$ shifts outward to $c_{j,t}(z, p) = L_j Y_j P_t (p/z)^{-\theta}$ where $P_t = e^{0.1 \times 0.9^t}$. The timing is the same as in the previous experiment: the shock hits in period 1, and then firms start adjusting in period 2.

**Figure 6:** Transition dynamics following a temporary real exchange rate depreciation

Figure 6 shows how export participation, market penetration, and exports evolve over time in response to this shock in hard versus easy destinations. As in the previous exercise, trade rises by the same amount in all destinations on impact—the short-run trade elasticity of $\theta - 1$—because firms have not yet changed their market penetration decisions. In the following periods, export participation and market penetration respond more strongly in hard destinations than in easy destinations—the same “least-traded-products effect” that makes hard destinations respond more to permanent trade reforms. In turn, this leads to more hysteresis in hard destinations: export participation, market penetration, and overall exports are more persistent than the real exchange rate shock itself. In easy destinations, by contrast, there is little hysteresis: trade follows...
the path of the real exchange rate almost exactly.

5.3 Empirical evidence

Emerging economies, particularly those in Latin America, often experience large, persistent episodes of real exchange rate depreciation. Empirical evidence shows that exports tend to grow slowly in response to these devaluations and that the source of this sluggishness is adjustment along the extensive margin (Alessandria et al., 2013). Brazil’s 1999 depreciation, which exemplifies this pattern, provides a useful way to evaluate the model’s predictions because it can be analyzed using the same microdata from which the facts documented in section 2 were derived. As figure 7 shows, Brazil’s real exchange rate depreciated by more than 50% between 1998 and 1999, and by another 30% by 2003 before beginning to appreciate. Brazil’s aggregate exports, however, grew little until 2002, and the number of exporting firms grew gradually throughout the episode.

**Figure 7:** Real exchange rate and trade dynamics in Brazil: 1998–2006

In order to study how sales and export participation in different destinations evolved during this period, it is important to control for changes in each destination’s income, price level, and import demand. Argentina, for example, experienced an even larger devaluation than Brazil and a large drop in output when it defaulted on its sovereign debt in 2001. I use the following specification:

$$\log Y_{jt} = \alpha + \sum_{s=1998}^{2006} \mathbb{1}_{(t=s)} \left( \beta_{s,easy} \mathbb{1}_{\{\text{group}_j = \text{easy}\}} + \beta_{s,hard} \mathbb{1}_{\{\text{group}_j = \text{hard}\}} \right) + \gamma_1 \log NER_{jt} + \gamma_2 \log CPI_{jt} + \gamma_3 \log RGDP_{jt} + \gamma_4 \log IM_{jt} + f_j + e_{jt},$$

where the dependent variable $Y_{jt}$ is either the total volume of total bilateral trade in U.S. dollars or the number of exporting firms. I split destinations into two groups, “easy” and “hard,” based on their initial levels of export participation in 1998 using the same scheme as in other analyses in this paper. The nominal
exchange rate and consumer price index control for changes in each destination’s price level relative to Brazil, while real GDP and imports control for income and multilateral import demand. I also include destination fixed effects to control for the initial level of trade with Brazil in 1998.

**Figure 8:** Trade and export participation dynamics in hard vs. easy destinations in Brazil: 1998–2006

Figure 8 plots the coefficient estimates for $\beta_{s,easy}$ and $\beta_{s,hard}$. Panel (a) shows that after controlling for destinations’ changes in income, prices, and import demand during this period, exports to hard destinations grew more than exports to easy destinations, and that it took several additional years for exports to the former to reach their peak. Panel (b) shows similar results for export participation. The number of firms exporting to hard destinations grew more than the number of firms exporting to easy destinations, and this growth, too, took longer to come about. Thus, the predictions of the model described in sections 5.1–5.2 are indeed consistent with the evidence from Brazil’s 1999 real exchange rate depreciation.

This evidence is certainly not conclusive given its limited scope. However, it is consistent with findings reported in several other studies. For example, Mix (2020) shows that following the formation of free trade area, exports to minor trade partners grow more than exports to major trade partners and that this growth takes longer to materialize. For another, Boehm et al. (2020) show that when countries lower their most-favored-nation tariff rates, imports from minor trade partners in the WTO grow more than imports from major trade partners. One difference between the model and the data is that trade growth in the short run—periods immediately following a change in prices or trade costs—is larger in the former than the latter. This is a widely known issue that affects all heterogeneous-firm models of trade that are based on the Melitz (2003) framework, not just the model I have developed in this paper.\(^{16}\) Accounting for the low short-run trade elasticities observed in the data requires additional features like pricing to market (Alessandria and Choi, 2016) and adjustment costs borne by importers (Steinberg, 2020).

\(^{16}\)See footnote 34 in Boehm et al. (2020) for a detailed discussion about the challenges of generating short-run trade elasticities below one in this broad class of models.
6 Comparison to other models

As discussed in section 3.7 above, the theory of export costs developed in this paper generalizes several existing models and provides an explanation for key assumptions in others. Here, I analyze the extent to which these other models can account for the facts documented in section 2 and use these results to shed light on which of my theory’s ingredients are most important in accounting for these facts. I analyze three alternative models: Arkolakis (2016), which features a static market penetration decision rather than a dynamic one; Das et al. (2007), which features a dynamic export participation decision but no market penetration decision; and Alessandria et al. (2021b), which adds exogenous customer accumulation to Das et al. (2007). In each, I hold fixed the stochastic processes for multilateral productivity, $x$, bilateral demand, $z_j$, and survival, $\delta(x)$, at their calibrated values listed in table 3. This allows me to weigh the relative contributions of endogenous market penetration dynamics and exogenous shocks in accounting for the facts described in section 2 above. Table 4 reports cross-destination averages of exporter performance measures for these models along with the associations between these measures and destination characteristics. Figures 9–13 compare post-entry sales trajectories in these models with the baseline model’s trajectories. Figures 10–14 compare transition dynamics following permanent trade reforms in these models to the baseline model’s dynamics.\footnote{The transition dynamics following temporary real exchange rate depreciations provide no added insight into the differences between these models’ predictions and the baseline’s, so I omit them for brevity’s sake. These results are available upon request.}

| Table 4: Exporter performance across destinations in alternative models |
|---------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Statistic                  | Num. exporters | Top-5 share     | Avg. num. dests. | Exit rate | Entrant rel. size | Entrant rel. exit rate |
| (a) Cross-destination averages |
| Static mkt. pen.          | 811             | 0.57            | 14.80            | 0.55      | 0.33             | 0.11 |
| Sunk cost                 | 677             | 0.40            | 16.46            | 0.40      | 1.19             | 0.01 |
| Exog. entrant dyn.        | 520             | 0.50            | 13.41            | 0.40      | 0.38             | 0.27 |
| (c) Associations with destination characteristics: Static mkt. pen. model |
| log GDPpc                  | 0.748           | 0.063           | -1.685           | -0.071    | -0.099           | 0.028 |
| log population            | 0.357           | 0.031           | -0.836           | -0.034    | -0.047           | 0.013 |
| log trade barrier         | -0.737          | -0.062          | 1.684            | 0.071     | 0.099            | -0.028 |
| (d) Associations with destination characteristics: Sunk cost model |
| log GDPpc                  | 0.843           | 0.079           | -2.051           | -0.075    | -0.302           | 0.033 |
| log population            | 0.120           | 0.003           | -1.174           | 0.070     | -0.526           | 0.036 |
| log trade barrier         | -0.811          | -0.078          | 2.152            | 0.071     | 0.341            | -0.033 |
| (e) Associations with destination characteristics: Exog. entrant dyn. model |
| log GDPpc                  | 0.781           | 0.086           | -1.562           | -0.124    | -0.072           | 0.082 |
| log population            | 0.123           | 0.014           | -0.814           | 0.053     | -0.132           | 0.048 |
| log trade barrier         | -0.747          | -0.084          | 1.607            | 0.112     | 0.082            | -0.070 |
6.1 Static market penetration model

The first alternative model I consider is that developed by Arkolakis (2016), in which firms make static decisions about market penetration as in Arkolakis (2010) but experience sales growth and survival dynamics due to exogenous productivity shocks. This model is a special case of my model in which retaining old customers is impossible (i.e., \( \psi_0 = 0 \)), which implies that \( f_j(m') \equiv f_j(0, m') = s_j(0, m') \). In addition to exogenous shock processes, I hold fixed the relevant parameters of the customer attraction cost function \( s_j \) (the macroeconomic return to scale, \( \alpha_n \), and the degree of convexity, \( \gamma_n \); the microeconomic return to scale, \( \beta_n \), is irrelevant).\(^{18}\)

The static market penetration model is successful in generating a high level of cross-sectional sales concentration and new exporters that sell substantially less than incumbents, but it generates too much turnover on average and too little turnover among new entrants. This indicates that endogenous market penetration is an important driver of export participation dynamics. The reason is that incumbent exporters face the same export costs as entrants in this model, whereas in the baseline model export costs fall as firms accumulate customers over time. Put differently, the exit threshold in the static market penetration model—which is the same as the entry threshold—is a function solely of exogenous characteristics, whereas it also depends on a firm’s customer base in the baseline model. However, the static market penetration model is about as successful as the baseline model in capturing the associations between destination characteristics and exporter performance. This indicates that exogenous shocks to productivity, demand, and survival play important roles in generating these correlations. As we will see shortly below, this is confirmed by my analysis of other alternative models.

Figure 9: Sales trajectories in baseline model vs. static market penetration model

Figure 9 shows that although the static market penetration model captures qualitatively the differences

\(^{18}\)An alternative approach is to recalibrate \( \alpha_n \) and \( \gamma_n \), which are identified most strongly by the average number of other destinations served and the average share of exports accounted for by the top 5 percent of exporters. Choosing new values of these parameters to match these two moments does not materially alter the other results.
in sales trajectories of firms that achieve long export spells versus firms that achieve short export spells, the
most successful exporters (those that achieve the longest spells) in this version of the model sell too little
upon entry and experience too much growth over time. Additionally, the differences in sales trajectories
between hard and easy destinations are substantially smaller in this model than in the baseline model (and
in the data). This indicates that market penetration dynamics play an important role in the baseline model’s
ability to reproduce these patterns as well as match the facts targeted in the calibration.

**Figure 10:** Transition dynamics following permanent reform in baseline model vs. static market penetration
model

Figure 10 shows that the static market penetration model has similar long-run implications for bilateral
trade flows as the baseline model. In both models, trade grows more in response to a permanent trade
liberalization in hard destinations than in easy ones. This is because trade is more concentrated among
large exporters in easy destinations than hard destinations, coupled with the fact that the convex market
penetration costs that are present in both models imply that large exporters respond less to changes in trade
costs than small exporters (Arkolakis, 2010). The static market penetration model predicts slightly larger
long-run responses to trade liberalizations in all destinations (in both easy and hard destinations, the long
run trade elasticity in this model is slightly higher than in the baseline) because there is more convexity in
the cost of acquiring new customers than retaining old ones. The figure also shows, however, that there is
no gradual adjustment in trade in the static market penetration model: trade converges immediately to its
long run level. This is because the market penetration decision in this model is static, which implies that
there is no persistence at the firm-level in export participation or market penetration (after controlling for
productivity and demand; persistence in firms’ exogenous characteristics creates some persistence in export
participation). This prediction of the static market penetration model is clearly counterfactual given the
widely-documented evidence that trade adjusts gradually (see, e.g. Ruhl, 2008; Boehm et al., 2020).
6.2 Sunk cost model

The second alternative model I consider is the canonical sunk cost model of Das et al. (2007), in which firms pay a large cost to begin exporting and a smaller cost to continue exporting in the future. This model, which has been analyzed in numerous other studies such as Alessandria and Choi (2007) and Alessandria and Choi (2014), is a special case of my model in which the marginal cost of attracting/retaining customers is constant (i.e., $\gamma_0 = \gamma_1 = 0$), which implies that firms choose to either serve all customers in a given market or none. In this exercise, I recalibrate the efficiency parameters $\psi_n$ and $\psi_o$ so that this version of the model matches the overall multilateral export participation rate of 26% and the average bilateral exit rate of 40% observed in the data.\(^{19}\)

The sunk cost model generates too little concentration of exports among top exporters. Without the market penetration margin, low-productivity/low-demand exporters have the same number of customers as high-productivity/high-demand exporters, and so the former sell too much relative to the latter. This version of the model also fails to generate new exporter dynamics: entrants are too large and too likely to survive compared to incumbents. This is consistent with the findings of Ruhl and Willis (2017), who show that customer accumulation and other sources of firm-level intensive margin growth are crucial to capturing these dynamics. However, like the static market penetration model, the sunk cost model succeeds in capturing the associations between destination characteristics and exporter performance. This confirms that exogenous shocks are important to accounting for these patterns.

Figure 11: Sales trajectories in baseline model vs. sunk cost model

Figure 11 shows that the sunk cost model cannot account for post-entry sales trajectories. In fact, in

\(^{19}\)Firms’ incentives to enter and exit are different in this model due to the absence of the market penetration margin, so leaving $\psi_n$ and $\psi_o$ unchanged would lead to a different export participation rate than the baseline model (by contrast, the marginal entrant’s productivity/demand thresholds are the same in the static market penetration model as in the baseline). This approach allows me to analyze the role of the market penetration margin in accounting for the facts at hand while holding fixed the measure of exporting firms. Overall, the results are similar when leaving $\psi_n$ and $\psi_o$ fixed at their baseline values, except that the export participation rate is higher and turnover is less frequent.
this version of the model sales tend to fall after a firm enters a new export destination. This is driven by regression to the mean in productivity and demand. Firms begin exporting after they receive good shocks and do not exit until they receive sufficiently bad shocks, so new exporters tend to be more productive and have greater demand for their products than incumbents. In the absence of the customer accumulation margin, sales tend to fall post-entry as productivity and demand converge to the mean.

**Figure 12:** Transition dynamics following permanent reform in baseline model vs. sunk cost model

Figure 12 shows that trade reforms in the sunk cost model have similar effects across destinations on the extensive margin of trade as in the baseline model. In both models, the number of exporters grows more following a permanent reduction in trade costs in hard destinations than in easy ones. However, the figure also shows that there is little difference across destinations in the dynamics of aggregate bilateral trade: the long-run trade elasticity in the sunk cost model is only slightly higher in hard destinations than in easy ones. In the baseline model, by contrast, trade grows substantially more in the former than in the latter, which is inconsistent with the evidence from Brazil’s 1999 real exchange rate depreciation and the other findings in the literature discussed above in section 5.3.

### 6.3 Exogenous new exporter dynamics

The last alternative model I consider is the variant of the sunk cost model proposed by Alessandria et al. (2021b) in which export capacity grows exogenously (through customer accumulation or some other unspecified margin) over time after a firm enters a new market. Specifically, a firm enters a new market with $m_0$ customers, and each period it continues to export there is a chance $\rho_m$ its customer base will grow to $m_1 > m_0$. Once it has reached this greater level of market penetration, its customer base falls back to $m_0$ with the same probability. While this model is not a special case of the model developed in this paper, analyzing it illustrates the importance of endogenous heterogeneity in customer accumulation across firms and across destinations. As in the previous exercise, I recalculate $\psi_o$ and $\psi_n$ to match the multilateral export participation rate and average bilateral exit rate. Here, I also normalize $m_1 = 1$ and choose $m_0$ so that this version of
the model also matches the observed ratio of the average entrant’s sales to the average incumbent’s.

The exogenous new exporter dynamics model does better than the sunk cost model, but not as good as the baseline and static market penetration models, in generating concentration of sales among top exporters. It also succeeds in capturing the propensity of entrants to exit more often than incumbents. This is consistent with the findings of Alessandria et al. (2021b), who show that gradual growth in export capacity helps account for entrants’ low likelihood of survival. Like the previous two alternative models, this model, too, succeeds in capturing the associations between destination characteristics and exporter performance. This re-confirms the importance of exogenous shocks in explaining these patterns.

**Figure 13:** Sales trajectories in baseline model vs. exogenous new exporter dynamics model

Figure 13 shows that despite the exogenous new exporter dynamics model’s ability to capture many of the facts about exporter performance across destinations, it cannot account for post-entry sales trajectories. Sales grow on average for one period after entry, and then decline over time regardless of the length of an export spell as in the sunk cost model. This indicates that endogenous customer accumulation dynamics—which allows different firms choose different market penetration paths in a given destination, and the same firm to choose different paths in different destinations—is crucial to accounting for these trajectories.

Figure 14 shows that trade reforms have similar effects in the exogenous new exporter dynamics model as in the sunk cost model, except that it takes longer for the number of exporters—and thus aggregate trade flows—to converge. As before, the fact that this model predicts negligible differences across destinations in long-run trade elasticities is at odds with the data, which indicate that trade responds more to policy changes in hard destinations than in easy ones.
Figure 14: Transition dynamics following permanent reform in baseline model vs. exog. new exporter dyn. model

7 Conclusion

In this paper, I study how and why exporting firms’ performance dynamics vary across destinations and explore the aggregate implications of these patterns. I use microdata from Brazil to document that in smaller, poorer markets, overall turnover is higher, new entrants are larger and less likely to exit relative to incumbents, and successful exporters’ sales grow less dramatically over the duration of their export spells as compared to larger, richer markets.

To account for these facts, I develop a model of export market penetration dynamics that synthesizes static frameworks like Arkolakis (2010) and Eaton et al. (2011) in which firms choose how many customers to serve in each destination with dynamic frameworks like Das et al. (2007) and Alessandria and Choi (2007) in which sunk entry costs lead firms to make forward-looking export participation decisions. The cost of exporting in the model is increasing in the number of customers a firm wants to serve but decreasing in the number of customers a firm already has, and so firms choose endogenously to grow their customer bases over time. The marginal cost of serving a single customer is strictly positive regardless of the size of a firm’s current customer base, generating endogenous entry and exit. Acquiring and retaining customers is more expensive in smaller, poorer markets relative to these markets’ purchasing power, which leads exporters to exit more frequently from these markets and accumulate fewer customers over the course of their export spells.

I calibrate the model so that it reproduces a subset of the facts I document in the empirical part of the paper and validate it by demonstrating that it reproduces the remaining facts. I use the calibrated model to explore how aggregate trade dynamics differ across destinations. In response to permanent trade reforms, exports to smaller, poorer markets grow more than exports to larger, richer ones, and the former exhibit more pronounced hysteresis following temporary real exchange rate depreciations than the latter. I use the
Brazilian microdata to show that these implications are consistent with the bilateral trade dynamics that followed Brazil’s 1999 real exchange rate depreciation. To explore the role of market penetration dynamics in accounting for the facts at hand, I compare the model with several conventional alternatives that lack this feature. These alternative models can account for some of the variation across destinations in exporter performance dynamics, but market penetration dynamics are needed to capture the full range of this variation, particularly in the growth in successful exporters’ sales over the duration of their export spells.

The analysis in this paper is limited to a partial equilibrium setting in which one firm’s market penetration does not hinder or facilitate the entry and growth of other firms, and in which a firm’s performance in one market does not affect its incentives to export to other markets. Studying the interactions between firms and between markets in equilibrium would allow one to answer questions such as: What is the role of congestion (or agglomeration) externalities in shaping export participation dynamics? How does a trade reform in one market affect export participation in other markets? The model developed in this paper is tractable enough to make incorporating these kinds of interactions feasible, making it a suitable starting point for a wide range of additional research.

References


Online appendix (not for publication)

Appendix A: Variation in performance within exporters’ destination portfolios

To analyze how individual exporters’ performance varies across the destinations to which they sell, I first group firms by the number of destinations in their export “portfolios.” Figure A1 shows the distribution of exporters and their total sales across all destinations by the sizes of their portfolios. 40 percent of exporters only sell to one destination. Of the remaining 60 percent, most sell to between 2–4 destinations. Only 12 percent of firms export to 10 or more destinations, but these firms account for about 75 percent of total exports in any given year, whereas firms that export to 4 or fewer destinations account for barely 10 percent. This finding is consistent with the “superstar” phenomenon documented elsewhere in the literature (Bernard et al., 2012; Eaton et al., 2011; Ottaviano and Mayer, 2007). The distribution of exporters by destinations served in the calibrated model is close to the empirical distribution, as is the distribution of exports. This confirms that the model captures how the cross sections of exporters varies across destinations.

Figure A1: Distribution of exporters and exports by number of destinations

I then rank the destinations within each firm’s portfolio by sales and analyze how firms perform in high-vs. low-ranked destinations. Harder destinations have smaller populations with lower purchasing power and higher trade barriers, and so one would expect these destinations to be ranked lower on average in exporters’ portfolios as well as having lower export participation overall. Table A1, which reports associations between destinations’ characteristics and their average ranks within exporters’ portfolios, confirms that this is the case. The average rank of a destination within an exporter’s portfolio is decreasing in population and
income per capita, and increasing in trade barriers: firms export less to harder destinations than easy ones. The calibrated model captures these patterns.

**Table A1**: Associations between destination characteristics and average rank within exporters’ portfolios

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Baseline model</th>
</tr>
</thead>
<tbody>
<tr>
<td>log GDPpc</td>
<td>-1.280</td>
<td>-2.029</td>
</tr>
<tr>
<td></td>
<td>(0.093)§</td>
<td></td>
</tr>
<tr>
<td>log population</td>
<td>-1.140</td>
<td>-2.573</td>
</tr>
<tr>
<td></td>
<td>(0.061)§</td>
<td></td>
</tr>
<tr>
<td>log trade barrier</td>
<td>2.253</td>
<td>2.096</td>
</tr>
<tr>
<td></td>
<td>(0.124)§</td>
<td></td>
</tr>
<tr>
<td>Num. observations</td>
<td>568</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.55</td>
<td></td>
</tr>
</tbody>
</table>

All specifications control for year fixed effects. Robust standard errors in parentheses. §, †, and ‡ denote significance at the 0.1%, 1%, and 5% levels, respectively.

A.1 Turnover within exporters’ destination portfolios

Since harder destinations have higher overall exit rates, one would therefore expect that firms are more likely to exit lower-ranked destinations within their portfolios. Table A2, which lists exporters’ average exit rates broken down by portfolio size (vertical axis) and destination rank (horizontal axis), confirms that this is the case as well: exporters that serve several markets have the highest exit rates in their least important destinations. However, many-destination exporters are less likely to exit from their least important destinations than single-destination exporters are from their sole destination. The calibrated model matches the propensity of multi-destination firms to exit more frequently from their least-important destinations.

A.2 Variation in sales and survival within exporters’ destination portfolios

To analyze how the rank of a destination within a firm’s portfolio affect its sales and likelihood of exit relative to other firms that export to that destination, I estimate regressions of the form

$$\log e_{x_{i,j,t}} = \alpha + \sum_{m=1}^{10} \sum_{n=1}^{m} \beta_{m,n} I\{\text{num. dests.}_{i,j}=m\} I\{\text{dest. rank}_{i,j,t}=n\} + f_j + f_t + \epsilon_{i,j,t}$$

(29)

$$I\{\text{exit}_{i,j,t}=1\} = \alpha + \sum_{m=1}^{10} \sum_{n=1}^{m} \beta_{m,n} I\{\text{num. dests.}_{i,j}=m\} I\{\text{dest. rank}_{i,j,t}=n\} + f_j + f_t + \epsilon_{i,j,t}.$$  

(30)

Here, I top-code portfolio size and destination rank at 10. The reference group is the set of firms that serve only one destination, so the coefficient $\beta_{m,n}$ in each regression measures how much more a firm sells (in the

---

20 Estimating a Poisson or negative binomial regression on the raw firm-level data yields similar results.
Table A2: Exit rates by num. dest. and dest. rank

<table>
<thead>
<tr>
<th>Destination rank</th>
<th>Num. dest.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5-9</th>
<th>10+</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) Data</td>
<td>1</td>
<td>0.56</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.41</td>
<td>0.60</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.31</td>
<td>0.47</td>
<td>0.61</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.23</td>
<td>0.36</td>
<td>0.49</td>
<td>0.60</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>5-9</td>
<td>0.16</td>
<td>0.24</td>
<td>0.32</td>
<td>0.40</td>
<td>0.52</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>10+</td>
<td>0.06</td>
<td>0.08</td>
<td>0.10</td>
<td>0.13</td>
<td>0.21</td>
<td>0.31</td>
</tr>
<tr>
<td>(b) Model</td>
<td>1</td>
<td>0.53</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.39</td>
<td>0.53</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.30</td>
<td>0.42</td>
<td>0.52</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.24</td>
<td>0.35</td>
<td>0.43</td>
<td>0.52</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>5-9</td>
<td>0.16</td>
<td>0.24</td>
<td>0.30</td>
<td>0.35</td>
<td>0.42</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>10+</td>
<td>0.05</td>
<td>0.08</td>
<td>0.11</td>
<td>0.13</td>
<td>0.18</td>
<td>0.27</td>
</tr>
</tbody>
</table>

first specification) or how likely it is to exit (the second specification) in a given destination relative to a firm for whom this destination is its only market. Figure A2 shows the results. In panel (a), we see that firms that export to at least 2 destinations sell more in their highest-ranked destination than firms that export to that destination only. The larger a firm’s portfolio, the greater the difference: firms that sell to 2 destinations sell about twice as much in their highest-ranked market as single-destination exporters; while firms with portfolios of 10 or more destinations sell about 5 times as much. We also see, however, that sales relative to single-destination exporters fall with a destination’s rank. In fact, all firms except those with 10 or more destinations in their portfolios sell less in their lowest-ranked destinations than single-destination firms. In panel (b), we see these patterns reversed for exit rates. Multi-destination firms are less likely to exit from their most important destinations than single-destination firms—as much as 45 p.p. less likely for firms with 10 or more destinations. However, the gap shrinks as a destination’s rank with an exporter’s portfolio rises; firms that sell to 4 or fewer destinations are actually more likely to exit from their least important destinations than single-destination exporters.

The model predicts similar patterns of sales and exit rates across destinations within individual exporters’ portfolios as observed in the data. In the model, as in the data, exporters with larger portfolios sell more in their top-ranked destinations relative to single-destination exporters, but sell less in their least important destinations. Similarly, exporters with larger portfolios are less likely to exit from their most important destinations as compared to single-destination exporters, and exporters with 4 or fewer destinations have about the same exit rate in their lowest-ranked destinations as single-destination exporters. Together, these tables and figures show that the model accurately captures the facts about how export performance varies within exporters’ destination portfolios discussed above.
A.3 Variation in exporting costs within firms’ destination portfolios

To dig more deeply into cross-firm variation in exporting costs and to analyze how individual firms’ exporting costs vary across destinations, I follow the approach from section ?? and estimate the effect of a destination’s rank within an exporter’s portfolio on the cost that exporter pays to access that destination, both in levels and relative to profits:

\[
\log f(m_{i,j,t}, m_{i,j,t+1}) = \alpha + \sum_{m=1}^{10} \sum_{n=1}^{m} \beta_{m,n} \mathbb{1}\{\text{num. dests.}=m\} \mathbb{1}\{\text{dest. rank}=n\} + f_j + f_t + \epsilon_{i,j,t}, \tag{31}
\]

\[
\frac{f(m_{i,j,t}, m_{i,j,t+1})}{\pi_j(x_{ij,t}, x_{ij,t}, m_{ij,t})} = \alpha + \sum_{m=1}^{10} \sum_{n=1}^{m} \beta_{m,n} \mathbb{1}\{\text{num. dests.}=m\} \mathbb{1}\{\text{dest. rank}=n\} + f_j + f_t + \epsilon_{i,j,t}. \tag{32}
\]

Again, the reference group is the set of firms that serve only destination \(j\).

Panel (a) of figure A3 reports the estimated effects of destination rank on the level of exporting costs from specification (31). Exporters with the largest destination portfolios pay the highest exporting costs, especially in higher-ranked destinations. Firms that serve 10 or more destinations, pay about 4 times more to export to their top destinations than firms that serve those destinations only, and even firms that sell to only 2 destinations pay twice as much as single-destination exporters. Export costs fall with destination rank, however, and firms with 9 or fewer destinations in their portfolios (the vast majority) actually pay less to export to their least important destinations than firms that serve those destinations alone. Panel (b) of figure A3, which reports the results from specification (32), shows that these results reverse when export costs are measured relative to profits. Firms with larger destination portfolios have lower export cost/profit ratios, especially in their highest-ranked destinations, and these ratios rise as destination rank falls. In brief, these results show that high-productivity and/or high-demand firms pay higher costs to export, but these
costs are low relative to the large profits these firms earn from exporting.

**Appendix B: Empirical results for Mexico and Peru**

In this appendix, I report results from empirical analysis of two additional datasets on Mexican and Peruvian exporters from the World Bank’s Exporter Dynamics Database. These transaction-level customs datasets have the same structure as the Brazilian data. The Mexican dataset covers the period 2001–2006 and contains about 23,000 firms per year.\(^\text{21}\) The Peruvian dataset covers a longer time period, 1994–2008 but contains fewer firms, ranging from 2000 at the beginning of the sample to 5000 at the end. I apply exactly the same processing and analysis procedures described in section 2 to these datasets. Tables A3–A6 and figures ??–A7 show the results.

---

\(^{21}\)The dataset contains information on transactions through 2008, but there is a break in the coding of firm identifiers in 2007.
Table A3: Summary statistics of export participation and exporter dynamics across destinations (Mexico and Peru)

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Num. exporters</th>
<th>Top-5 share</th>
<th>Avg. num. dests.</th>
<th>Exit rate</th>
<th>Entrant rel. size</th>
<th>Entrant rel. exit rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) Mexico</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>661</td>
<td>0.67</td>
<td>15.09</td>
<td>0.46</td>
<td>0.37</td>
<td>0.34</td>
</tr>
<tr>
<td>Min</td>
<td>22</td>
<td>0.44</td>
<td>2.22</td>
<td>0.36</td>
<td>0.06</td>
<td>0.16</td>
</tr>
<tr>
<td>Max</td>
<td>16,908</td>
<td>0.92</td>
<td>36.50</td>
<td>0.60</td>
<td>1.13</td>
<td>0.54</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>2,162</td>
<td>0.12</td>
<td>5.94</td>
<td>0.06</td>
<td>0.27</td>
<td>0.06</td>
</tr>
<tr>
<td>(b) Peru</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>133</td>
<td>0.62</td>
<td>10.36</td>
<td>0.48</td>
<td>0.36</td>
<td>0.32</td>
</tr>
<tr>
<td>Min</td>
<td>21</td>
<td>0.31</td>
<td>3.63</td>
<td>0.35</td>
<td>0.07</td>
<td>0.16</td>
</tr>
<tr>
<td>Max</td>
<td>1,003</td>
<td>0.91</td>
<td>17.61</td>
<td>0.67</td>
<td>0.96</td>
<td>0.43</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>178</td>
<td>0.15</td>
<td>3.68</td>
<td>0.07</td>
<td>0.21</td>
<td>0.06</td>
</tr>
</tbody>
</table>

All specifications control for year fixed effects. Robust standard errors in parentheses. §, ‡, and † denote significance at the 0.1%, 1%, and 5% levels, respectively.

Table A4: Associations between destination characteristics and exporters’ behavior (Mexico and Peru)

<table>
<thead>
<tr>
<th></th>
<th>Log num. exporters</th>
<th>Top-5 share</th>
<th>Avg. num. dests.</th>
<th>Exit rate</th>
<th>Entrant rel. size</th>
<th>Entrant rel. exit rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) Mexico</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log GDPpc</td>
<td>0.308</td>
<td>0.065</td>
<td>-1.622</td>
<td>0.012</td>
<td>-0.094</td>
<td>-0.001</td>
</tr>
<tr>
<td>(0.020)§</td>
<td>(0.005)§</td>
<td>(0.127)§</td>
<td>(0.003)§</td>
<td>(0.020)§</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>log population</td>
<td>0.372</td>
<td>0.040</td>
<td>-1.278</td>
<td>-0.002</td>
<td>-0.048</td>
<td>0.006</td>
</tr>
<tr>
<td>(0.016)§</td>
<td>(0.004)§</td>
<td>(0.123)§</td>
<td>(0.002)</td>
<td>(0.013)§</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>log trade barrier</td>
<td>-0.721</td>
<td>-0.031</td>
<td>2.746</td>
<td>0.022</td>
<td>0.084</td>
<td>-0.008</td>
</tr>
<tr>
<td>(0.015)§</td>
<td>(0.004)§</td>
<td>(0.123)§</td>
<td>(0.002)</td>
<td>(0.017)§</td>
<td>(0.004)§</td>
<td></td>
</tr>
<tr>
<td>Num. observations</td>
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<td>294</td>
<td>294</td>
<td>294</td>
<td>294</td>
<td>294</td>
</tr>
<tr>
<td>R²</td>
<td>0.85</td>
<td>0.51</td>
<td>0.70</td>
<td>0.44</td>
<td>0.12</td>
<td>0.04</td>
</tr>
<tr>
<td>(b) Peru</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log GDPpc</td>
<td>0.325</td>
<td>0.077</td>
<td>-0.956</td>
<td>-0.001</td>
<td>-0.062</td>
<td>0.008</td>
</tr>
<tr>
<td>(0.027)§</td>
<td>(0.005)§</td>
<td>(0.106)§</td>
<td>(0.003)</td>
<td>(0.016)§</td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>log population</td>
<td>0.236</td>
<td>0.042</td>
<td>-0.358</td>
<td>-0.010</td>
<td>-0.058</td>
<td>0.002</td>
</tr>
<tr>
<td>(0.019)§</td>
<td>(0.005)§</td>
<td>(0.072)§</td>
<td>(0.003)</td>
<td>(0.010)§</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>log trade barrier</td>
<td>-0.575</td>
<td>-0.059</td>
<td>1.807</td>
<td>0.014</td>
<td>0.099</td>
<td>-0.013</td>
</tr>
<tr>
<td>(0.026)§</td>
<td>(0.004)§</td>
<td>(0.096)§</td>
<td>(0.003)</td>
<td>(0.018)§</td>
<td>(0.005)§</td>
<td></td>
</tr>
<tr>
<td>Num. observations</td>
<td>490</td>
<td>490</td>
<td>490</td>
<td>490</td>
<td>490</td>
<td>490</td>
</tr>
<tr>
<td>R²</td>
<td>0.64</td>
<td>0.48</td>
<td>0.48</td>
<td>0.12</td>
<td>0.14</td>
<td>0.09</td>
</tr>
</tbody>
</table>

All specifications control for year fixed effects. Robust standard errors in parentheses. §, ‡, and † denote significance at the 0.1%, 1%, and 5% levels, respectively.
### Table A5: Associations between destination characteristics and average rank within exporters’ portfolios (Mexico and Peru)

<table>
<thead>
<tr>
<th></th>
<th>Mexico</th>
<th>Peru</th>
</tr>
</thead>
<tbody>
<tr>
<td>log GDPpc</td>
<td>-0.974</td>
<td>-1.414</td>
</tr>
<tr>
<td></td>
<td>(0.196)$\dagger$</td>
<td>(0.107)$\dagger$</td>
</tr>
<tr>
<td>log population</td>
<td>-1.479</td>
<td>-0.824</td>
</tr>
<tr>
<td></td>
<td>(0.154)$\dagger$</td>
<td>(0.091)$\dagger$</td>
</tr>
<tr>
<td>log trade barrier</td>
<td>2.018</td>
<td>1.692</td>
</tr>
<tr>
<td></td>
<td>(0.175)$\dagger$</td>
<td>(0.119)$\dagger$</td>
</tr>
<tr>
<td>Num. observations</td>
<td>454</td>
<td>894</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.46</td>
<td>0.44</td>
</tr>
</tbody>
</table>

All specifications control for year fixed effects. Robust standard errors in parentheses. $\dagger$, $\ddagger$, and $\ddagger$ denote significance at the 0.1%, 1%, and 5% levels, respectively.

### Table A6: Exit rates by num. dest. and dest. rank (Mexico and Peru)

<table>
<thead>
<tr>
<th></th>
<th>Destination rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Num. dest.</td>
<td>1    2    3    4    5-9    10+</td>
</tr>
<tr>
<td>(a) Mexico</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.51</td>
</tr>
<tr>
<td>2</td>
<td>0.36</td>
</tr>
<tr>
<td>3</td>
<td>0.27</td>
</tr>
<tr>
<td>4</td>
<td>0.21</td>
</tr>
<tr>
<td>5-9</td>
<td>0.13</td>
</tr>
<tr>
<td>10+</td>
<td>0.05</td>
</tr>
<tr>
<td>(b) Peru</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.60</td>
</tr>
<tr>
<td>2</td>
<td>0.41</td>
</tr>
<tr>
<td>3</td>
<td>0.32</td>
</tr>
<tr>
<td>4</td>
<td>0.27</td>
</tr>
<tr>
<td>5-9</td>
<td>0.19</td>
</tr>
<tr>
<td>10+</td>
<td>0.08</td>
</tr>
</tbody>
</table>
Figure A4: Effects of tenure and duration on exporters’ sales (Mexico and Peru)

(a) Hard destinations

(b) Easy destinations

Figure A5: Exit rates conditional on tenure (Mexico and Peru)
Figure A6: Distribution of exporters and exports by number of destinations (Mexico and Peru)

Figure A7: Sales and exit rates by number of destinations served and destination rank (Mexico and Peru)