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Abstract

This dissertation consists of three chapters that attempt to understand how forward-looking firms make costly decisions and their subsequent implications for the industry's performance.

The first chapter *"Sunk Cost and Entrant's Choice of Capacity"* develops a dynamic model of strategic entry to study how the structure of sunk entry costs influences the entrant's scale decision and the long-run market outcomes. Contrary to the typical dynamic entry model, my model features that the structure of sunk costs shapes not the number of competitors but also the industry's scale distribution. I empirically assess this channel using a case study of a land-use deregulatory reform in the South Korean cinema chain industry. The deregulation is estimated to act as an entry subsidy, particularly appealing to larger-scale theaters. However, the industry suffers a 5.6 percent loss of discounted net profits due to intensified competition and increased expenses on fixed operating costs. The resulting implicit cost of the regulatory action is not uncovered by the typical model, as it obscures the shift in the distribution toward a larger scale.

The second chapter *"The Differential Effect of Exporting on Input Productivities"* examines how the firm's export decision shapes its input allocation in the long run, focusing on the non-neutral technological changes. I particularly study whether entering the export market results in differential increases in input productivities at the firm level (non-neutral change). I develop a model that distinguishes between firm-level skilled and unskilled labor-augmenting productivities and material input prices. Applying the model to data on the Colombian apparel manufacturers, I find that exporting raises the skilled labor-augmenting productivity by a 7.2-percentage point more than the unskilled counterpart. In a counterfactual simulation in which exporting raises the two productivities equally, the mean differences in skilled-to-unskilled employee ratios between exporters and non-exporters are 50 percent smaller than the data counterparts. The result suggests that non-neutral productivity gain from trade is central in shaping the input allocation differences between exporters and non-exporters.

The third chapter *"Trade Dynamics of Heterogeneous Producers under Trade Cost Complementarity"* estimates a dynamic model of the firm's joint export and import decision process. In the model, participating in trade improves within-period profits and future productivity. In addition, doing one trade activity facilitates the other by reducing the associated fixed/sunk costs. Employing a Bayesian MCMC estimator, I fit the model to Colombian chemical plant panel data from 1981 to 1985. Two findings stand out: (i) importing increases future productivity significantly while exporting does not. (ii) importing facilitates exporting by lowering the sunk costs of entering the export market, while exporting facilitates importing by decreasing the fixed continuation costs of importing. A counterfactual simulation shows that subsidizing the fixed costs of importing is the most effective among trade cost subsidy schemes in improving the average productivity and firm value.

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Chapter 1

Sunk Cost and Entrant's Choice of Capacity

1.1 Introduction

In many industries, entrants exhibit considerable heterogeneity in the scale of operation. Since their scale tends to be difficult to adjust after the entry decision has been made, entry conditions can have a profound impact on both firm's entry and scale decisions, subsequently shaping long-run market outcomes by affecting not only the number of competitors but the industry's scale distribution. Hence, in an empirical analysis of such settings, accommodating both margins of entrants' choices is central to assessing how long-run market outcomes respond to changes in entry conditions. Despite the prevalence and importance of these industries, many empirical studies on firm entry typically focus on the decision to enter a market, obscuring the role of scale distribution.[1]

This chapter studies how a particular entry condition affects long-run market outcomes through scale distribution: the structure of sunk entry costs. Although various entry conditions affect the optimal scale of operation, the cost structure can be a vital determinant of the entry scale (Collard-Wexler (2013)).[2] Sunk entry costs are of greater importance when post-entry scale adjustments incur prohibitively high costs. Understanding how sunk entry costs vary with entry scale can thus be essential to assessing the impact of entry conditions on long-run market outcomes, which may also provide a distinct implication for regulatory actions to change entry barriers. [3]

[1] Notable examples of such industries include hotels (the number of rooms), nursing homes (the number of patient beds), and dialysis centers (the number of dialysis stations).

[2] Specifically, Collard-Wexler (2013) finds that the initial size of a concrete plant is primarily dictated by the magnitude of entry and size-adjustment costs, while market demand fluctuations have a limited role in shaping the initial size of a plant.

[3] On the one hand, regulators can lower an entry barrier through direct subsidies or by removing an artificial entry barrier. For instance, Chinese governments subsidize the entry of Chinese shipyards. The

I empirically explore this channel in the South Korean cinema industry from 2010 to 2018, where three big chains (CGV, Lotte Cinema, and Megabox) operated multiple movie theaters with various scales (i.e., screens) across local markets.[4] This industry is an attractive laboratory to study the entrant's scale choice and the scale-dependent entry costs. The chains choose the screens of a new theater opening upon entry, given that post-entry screen adjustments are generally impractical. Sunk costs for opening a theater vary with the number of equipped screens. For instance, opening a theater with more screens is more costly due to increased expenses on capacity investments and a multi-story commercial building. Lastly, the 2014 land-use and construction de-regulatory reform measures and the subsequent Amendments to the Building Act provide me with a de-regulatory regime shift that my dataset spans. This structural break allows me to evaluate the policy relevance of considering scale distribution.

This chapter begins by demonstrating that the screen distribution has shifted toward mid-plex theaters, defined as theaters with 5-7 screens, following the regulatory regime shift. This descriptive analysis indicates that the industry, on average, has 0.2 more (9% more) mid-plex theaters per market than the other scales, namely mini-plex (4 or less screens) and mega-plex (8 or more screens), after the regime shift. The pattern is not explained by both observed market-level demand shifters as well as chain-market fixed effects, suggesting that the regulatory action might favor mid-plex theaters with a significant entry-cost advantage. Such a structural break at the point of the regime shift thus illustrates the need to allow the sunk entry costs to vary with the theater opening's screen counts.

To measure the scale-dependent sunk entry costs and their changes in response to the regulartory regime shift, I develop a dynamic model of chain-store (theater) entry and discrete entry scale choices (screen counts). A key feature of the model is that it allows sunk entry costs to vary with different scaled theaters. Specifically, the model features a sunk entry cost schedule over each screen count, thereby admitting both economies and diseconomies of entry scale. Given that only three chains exist, and demand for moviegoing is geographically localized, the chains' theater scale choices are specified

Federal government encourages health practitioners to enter the under-provisioned area through Health Professional Shortage Area (HPSA) program. Michael Bloomberg reformed the zoning regulations in New York City, which could act as a removal of an artificial entry barrier. On the other hand, regulators seek entry barriers. Examples can include licenses for professional occupations, such as Yellow Taxicab Medallion in New York City.

[4] Three big chains are the major players in the industry. The three chains made up 97.6% and 96.9% of theaters and screens in 2014 (KOFIC (2014)): CGV (43.8% and 45.2% of theaters and screens), Lotte Cinema (34.7% and 33.3%), and Megabox (21.5% and 21.5%).

as a dynamic game independently played across geographic markets. Every period, oligopolistic chains choose the scale of a theater opening, taking the market configuration as a given state and weigh the benefit of the scale of opening against the sunk entry costs. The chains' actions subsequently alter the market configuration in the next period.

I estimate the model using a geography-level panel of 131 municipalities from 2010H1 to 2018H2. The data tracks both the stock of different-scaled movie theaters as well as the flows of different-scaled movie theater openings and closures. In the estimation, I address a high-dimensional state space by using the two-step conditional choice probability (CCP) approach (Hotz, Miller, Sanders, and Smith (1994) and Bajari, Benkard, and Levin (2007)).[5] I start by estimating the chain's equilibrium theater-scale choice policy function. I then find the vector of model parameters at which alternative policy functions are not profitable deviations from the estimated policy function. Following the literature convention (Rust and Rothwell (1995), Ryan (2012), and Kalouptsidi (2018)), I assume the immediate transition from an old equilibrium to a new equilibrium and recover the early- and late-regime sunk entry cost parameters separately.

The central finding from the estimation is that sunk entry costs decrease following the regulatory regime shift, and the resulting reductions in the sunk costs are higher for larger-scaled movie theaters, suggesting that the regulatory action appealed to a larger-scale theater opening. In particular, the reductions in total sunk costs for mini-, mid-, and mega-plex theaters are estimated to be 14%, 32%, and 25%, respectively. However, in terms of the average *per-screen* entry costs, the reduction for mid-plex theaters is more substantial, shifting the minimum efficient entry scale from the mega-plex scale to the mid-plex scale. These disproportionate changes in *per-screen* entry costs reflect a salient increase in the number of mid-plex theaters.

Using the estimated model, I quantify the economic implications of such a disproportionate reduction in the average *per-screen* sunk entry costs via a counterfactual simulation. In particular, I simulate counterfactual chain's response as if the sunk entry cost structure remained unchanged. I compare the resulting market outcomes, such as screen distribution and industry net profit, with those implied by the baseline parameter estimates.

The counterfactual simulation reveals that the disproportionate reduction in the average per-screen entry costs, in conjunction with strategic interactions among the chains, decreases industry profit by 5.60%. In particular, more theaters and screens

[5] In practice, despite the coarsening of data, the total number of possible states is 1,259,712. Thus, a full-solution approach like the Nested Fixed Point (NFXP) is impractical in my setting.

engender tougher post-entry competitions, substantially decreasing per-screen variable profits. Thus, the industry's total variable profit merely remains unchanged (-0.26%) despite more screens in the industry. In addition, the chains are willing to open larger-scale theaters as the sunk cost schedule creates a greater cost advantage for mid-plex theaters. Hence, the industry has more screens than it would have if there was no change in the sunk cost reduction, increasing the industry's expenditures on the fixed costs of operating screens by 14.59% and thereby leading to a loss of industry operating profit. Furthermore, as the chains open movie theaters more frequently in response to lower sunk costs, the realized payments on the sunk entry costs decrease only by 12.53%, which is not sufficient to compensate for the loss of the industry's operating profits. Thus, altogethers engender a loss of industry net profit.

The primary contribution of this chapter is illustrating that a standard model without the chain's theater scale decision fails to uncover the resulting increases in industry's expenditures on fixed operating costs. A restricted model that only focuses on changes in the number of movie theaters in a market cannot capture the shift of the industry's screen distribution toward mid-plex scales. This miss leads to under-predictions over the industry's resource uses on fixed operating costs and over-predictions over the savings from the reduced sunk entry costs. Thus, the predicted loss of the industry's operating profit is small to be compensated by savings from the reduced sunk entry costs. Accordingly, the restricted model predicts that the reduced sunk entry costs can increase industry net profits by 27.3%.

Although this chapter offers a case study of the South Korean theater industry, the finding that a simple extension of the strategy space leads to a qualitatively different counterfactual can be relevant for other applied settings. In particular, an applied setting where the entrant's scale choice is important, and the regulators are interested in promoting entry would be relevant. U.S. examples may include the special nursing home industry (the number of patient beds as a unit of capacity).

I organize the rest of this chapter as follows: The next subsection reviews the related studies and discusses the main departure of this chapter. Section 1.2 describes the South Korean movie theater chain industry, data, and the observed patterns. Section 1.3 presents the empirical industry model, and Section 1.4 gives the estimation strategy. Section 1.5 reports the empirical results of the model and model fit. The counterfactual simulations are constructed in Section 1.6. Section 1.7 concludes.

1.1.1 Related Literature

My analysis belongs to ample empirical literature on discrete entry. A vast majority of works in this literature study the effect of market size, competition, entry barriers, and other factors on firm profitability with a focus on the extensive margin decision of whether or not to enter. Static analyses include Bresnahan and Reiss (1990), Bresnahan and Reiss (1991), Berry (1992), Mazzeo (2002), Seim (2006), Grieco (2014); dynamic analyses include Pakes, Ostrovsky, and Berry (2007), Aguirregabiria and Mira (2007), Pesendorfer and Schmidt-Dengler (2008). [6] One of a few exceptions is Aradillas-López and Gandhi (2016) who illustrate the identification of a static entry game with an ordered action space. I contribute to the literature by extending the spirit of Aradillas-López and Gandhi (2016) toward a dynamic game and by empirically studying the importance of the intensive margin. Specifically, I embed an ordered action space to a standard dynamic game of chain-store entry where the store entry decision is binary (Igami and Yang (2016), Arcidiacono, Bayer, Blevins, and Ellickson (2016), and Aguirregabiria and Magesan (2020)); empirically analyze how the industry's scale distribution shapes the long-run market outcomes. Since the model's features are standard in the literature and also noticeable in many modern industries, the economic channel identified by this chapter can apply to other empirical settings.

By leveraging the de-regulatory reform to conduct an empirical analysis, this chapter contributes to the literature on the impacts of regulatory actions on market structure and outcomes in a dynamic setting. Notable examples include the entry cost effects of the environmental regulation and land-use regulation ((Ryan (2012)) and Suzuki (2013), respectively), and entry subsidy in health service sectors (Dunne, Klimek, Roberts, and Xu (2013)). This chapter complements this literature in two dimensions. First, I analyze the policy impact using a model of entry and the entrant's choice of capacity. Thus, the quantified policy impact depends not on the number of competitors but also on the scale distribution, which could affect the qualitative implication of a policy of interest. Second, while previous studies tend to focus on the welfare costs of regulations, this chapter illustrates the implicit costs of deregulations in a concentrated industry, which stems from strategic interactions.

Additionally, the particular application of this chapter relates to the literature on the cinema industry. Specifically, empirical studies of the entry and exit of movie theaters thematically share the same focus as this chapter. Empirical studies in this

[6] For further studies, refer to Berry and Reiss (2007) who provide a substantial review on static entry games. For a review on dynamic games, see Aguirregabiria, Collard-Wexler, and Ryan (2021).

literature focus on each of several determinants of market structure in the movie theater industry: cannibalization between the same-chain movie theaters (Davis (2006a)), spatial competition (Davis (2006b)), strategic exits of mono-screen movie theaters (Takahashi (2015)), and preemptive entry and entry costs of drive-in movie theaters (Gil, Houde, Sun, and Takahashi (2021)). I build on this literature and develop a dynamic oligopoly model unifying these determinants. This unifying framework allows researchers to analyze each role, enriching the understanding of the turnover patterns of movie theaters in the industry.

1.2 Industry and Data

1.2.1 South Korean Movie Theater Industry

Chains: This chapter focuses on the South Korean movie theater industry from 2010 to 2018. The industry is characterized as an archetypical chain-store industry. The South Korean movie theater industry was fragmented, consisting of many independent theaters with one or two screens. According to KOFIC 2000, 83% of movie theaters had one or two screens. Even in Seoul, the capital city of South Korea, 72% of movie theaters had less than three screens.[7]

This industry structure has changed since 1998. CGV, the first multiplex theater chain in the industry, opened its first multiplex theater in Seoul in 1998. The other two chain firms, Lotte Cinema and Megabox, were established in 1999, and they opened their first multiplex theaters in Daejeon and Seoul, respectively. After the advent of chain theaters, many small-sized independent theaters were quickly replaced by chain-affiliated multiplex theaters. By 2010, the chain-affiliated multiplex theaters made up 76%, 92%, and 97% of theaters, screens, and total box office revenue (KOFIC (2010)). These shares have slowly increased over the sample period, and the chain-affiliated multiplex theaters made up 79%, 95%, and 99% of theaters, screens, and box office revenues in 2017 (KOFIC (2017)). The industry today has the characteristic of oligopolistic industry where a few firms have multiple outlets across geographic markets.

Local Oligopoly: Although the three chains own most of the industry's theaters and screens, individual movie theaters tend to compete locally because of localized demand

[7] https://www.kofic.or.kr/kofic/business/board/selectBoardDetail.do?boardNumber=2&boardSeqNumber=10486 (downloaded in July 2022).

(Davis (2006b)). Similar to the pattern in the U.S. data, I found that most municipalities are served by fewer than five movie theaters, perhaps reflecting the unwillingness of consumers to travel to further theaters (Table 1.1).

A notable feature of the South Korean cinema industry is that the ticket prices do not reflect the local market competitiveness similar to the U.S. industry. Figure 1.1 shows that the average ticket price does not vary substantially with the number of existing movie theaters within a local market (municipality).

Table 1.1. Summary of Market Structure

# of theaters	# of municipality-semester obs.	Percent
0	265	11.24%
1	721	30.58%
2	631	26.76%
3	302	12.81%
4	204	8.65%
5	120	5.09%
6 or more	115	4.88%
Total	2,358	100%

Note. The unit of measurement is market-halfyear.

Theater Size: The size (scale) of a theater in my data is measured by the number of screens. The theater scale can be affected by entry barriers. The number of screens for a new theater is determined upon entry, and it is fixed over the life cycle of the theater in most cases. This irreversible nature implies that the chain's theater size decision can carry much weight in entry decisions. Hence, entry barriers are of great importance in shaping the chain's theater size decision. Second, screen counts of a theater opening and closure are important strategic decisions for the chains. All the movie theaters provide arguably homogenous services, and ticket prices are nearly fixed, thus a movie theater differentiates itself from its local competitors by serving a variety of movies or screening a popular movie in multiple timeslots (Rao and Hartmann (2015), Orhun, Venkataraman, and Chintagunta (2016), and Yang, Anderson, and Gordon (2021)). In this light, a theater with more screens may thus easily outperforms smaller competitors (i.e., steal a greater portion of businesses from smaller competitors). These features motivate a dynamic entry model that accommodates both the decision to open a theater and the choices over screen counts.

Sunk Costs and Regulatory Regime Shift: Opening a movie theater is an expensive

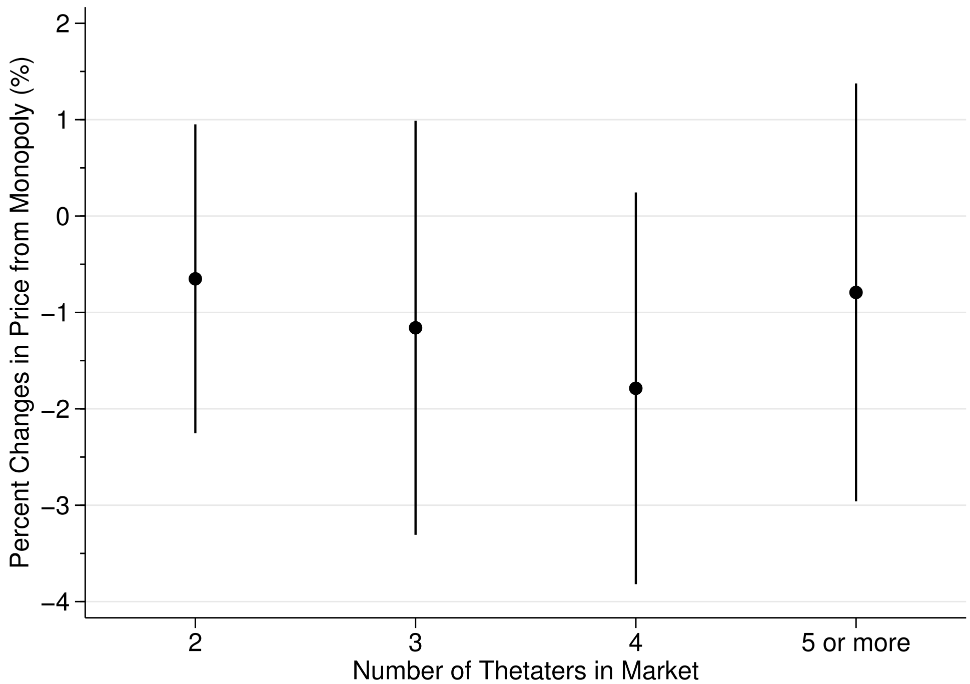

Figure 1.1. Average Ticket Price and Number of Theaters

Note. The figure depicts how the average ticket prices changes with the number of competing movie theaters.

investment in terms of accounting costs. According to a business report in 2018, the nominal capital expenditure (CAPex) for opening a 6-screen movie theater is 4.2 billion Korean Won (approximately $3.9 million).[8] In addition to monetary sunk opening costs, the chains should comply with strict guidelines about a cinema auditorium when opening a movie theater.[9] The guidelines mainly regulate a projection angle and the minimum distance between an installed screen and the first row of auditorium seating. To meet these requirements, the height of the ceiling in auditoriums tends to be higher than the counterparts of typical service businesses. Given that each auditorium accommodates one screen, the chains should build either a wider or multi-story commercial building when opening a theater with multiple auditoriums (i.e., a multiplex theater).

One complicating but attractive feature of the South Korean theater industry is that the industry underwent a series of nationwide land use regulatory reform measures and follow-up Amendments. In February and September 2014, to revitalize the urbanization

[8]https://www.thebell.co.kr/free/content/ArticleView.asp?key=201707140100027940001669&lcode=00 (lastly accessed in September 2021).

[9]Article 8, Enforcement Rule Of The Promotion Of The Motion Pictures And Video Products Act.

of disadvantaged areas, the Ministry of Land, Infrastructure and Transport announced two nationwide plans, *The Introduction of Areas under Minimal Siting Restrictions* and *Urban and Building Regulatory Reform Measures*, which primarily include plans to place more lenient administrative processes and abolish duplicated restrictions on building location and construction. After the announcement of the measures, there were subsequent changes in enforcement decrees and rules, primarily focusing on abolishing or revising stringent zoning and construction regulations. Among the follow-up regulatory actions, two primary regulatory actions could affect sunk entry costs of opening a movie theater: the Amendment to Enforcement Decree of the Building Act in November 2014 and the Amendment to the Building Act in May 2015.

The Ministry of Land, Infrastructure and Transport passed The Amendment to the Enforcement Decree of the Building Act. Since this Amendment, the Ministry has reduced the required paper works by 60% and expedited auditing processes. This regulatory action may have provided the chain firms with room to open a movie theater much easier as the chains do not have to undergo stringent administrative processes, thereby paying less bureaucratic costs associated with opening a new movie theater.

The Amendment to the Building Act in May 2015, which abolished Article 60.3, may have also changed the entry environment of the industry substantially. Article 60.3 was a setback regulation from road width. It limited the shape of buildings near roads in an urban area, thereby limiting the maximum height of a building. In the 2014 *Urban and Building Regulatory Reform Measures*, the Ministry of Land and Transportation appointed the abolishment of Article 60.3 as it had long been regarded as a primary source of inefficient building construction as well as an impediment to construction investment in urban areas. The National Assembly immediately passed the Amendment in May 2015 to boost construction investments and thus stimulate the economy. This Amendment led to considerable changes in urban structure, particularly increasing the height of commercial properties in an urban area substantially (Kim, Yoo, and Cho (2017) and Kim, Cho, and Yoo (2020)).

In this light, the regulatory regime shift may provide the theater chains with room for opening a theater with more screens much easier, suggesting that it might alter the theater opening and screen count choice behaviors. To reflect the regime shift, the empirical analysis of this chapter will estimate the sunk entry cost schedule over different-sized theaters separately for periods before and after it. The analysis then will use the estimated changes in the entry cost schedule as a guidepost for a counterfactual exercise.

1.2.2 Data

The data consist of a panel of geographic markets in South Korea observed from 2010 to 2018. I combine a series of publicly available administrative datasets to construct a panel dataset that contains the stock of chain-affiliated theaters owned and the flows of entry-exit of chain-affiliated theaters in each market.

Theater-level data. The initial data source is web-crawled from an online database archive (Korea Box Office Information System; KOBIS) administered by the Korean Film Council (KOFIC, www.kobis.or.kr). The KOFIC dataset contains the universe of movie theaters in South Korea between 2010 and 2018 at the level of the theater-screen-day-schedule. KOFIC also provides key theaters' characteristics: theater names, chain affiliations (CGV, Lotte Cinema, Megabox), opening/closure dates, number of screens (size), and geo-coordinates.

Selection of theaters. I first select a set of theaters by applying the following filters: (1) eliminating art houses that exhibited only independent or art movies and (2) eliminating movie theaters that located at the airport, apartment complexes, and the theme park. The first filter reflects the fact that art houses and commercial theaters exhibit a completely different set of movies: the commercial theaters tend to focus on showing blockbusters. So, the art houses could not be close substitutes for commercial theaters. The second filter is adopted because multiplex theaters in those locations target specific customer groups (airport or theme park visitors and residents of an apartment complex). After applying this filter, there are 543 commercial theaters that had operated during the sample period. Using the information on chain affiliation, I eliminate 99 fringe theaters that are not affiliated to the three chains. This selection reflects two institutional details of the South Korean exhibition industry. First, 50 fringe theaters were in municipalities where the chain-affiliated theaters have never entered, so they cannot be substitutes for chain-affiliated theaters. Second, though the remaining 49 fringe theaters were located close to chain-affiliated theaters, they did not have significant box office revenue.[10]. Thus, fringe theaters in the same geographic market do not appear to affect the profitability of chain-affiliated theaters and do not have significant impacts on the three chains' entry and exit decisions.

[10] Chain-affiliated movie theaters make up 97% of total box office revenue (KOFIC (2014))

Market definition and characteristics. I consider a municipality (*si-gun-gu* in Korean) as a single local market because additional data, such as population and GDP per capita, are available at the municipality-level. The municipality-level population is from the Korean Ministry of the Interior and Safety, which records at the monthly frequency. For each municipality, I keep the population in January and July of each year to make this information coincide with the KOFIC dataset. The municipality-level real GDP is from the Korean Statistical Information Service, which records at the annual frequency. Municipalities' real GDPs are expressed in 2011 Korean Wons, and I divide them by the municipality's population in July to construct the municipality's real GDP per capita. To capture the market-time level variations in fixed operating and sunk entry costs, I collect the municipality-level property values of commercial area from the Ministry of Land and Transportation. The property values of commercial area are also expressed in 2011 Korean Wons.

Among 272 municipalities, I focus on 131 municipalities where 444 chain-affiliated theaters had ever located. Table 1.2 reports the summary statistics on the characteristics of these 131 municipalities. Over the sample periods, the average population has remained unchanged. Although the average has not changed, the 95 percentile has declined by 26%. This time series pattern reflects the decline in Korean population. Meanwhile, GDP per capita and commercial property values have increased by 16% and 3.3%, respectively. At a point in time, there are substantial differences in market characteristics across the municipalities. For instance, in 2010 H1, commercial property values range from 1.77 million Korean Wons to 7.33 million Korean Wons, suggesting the possibility that the costs of operating a theater and opening a new theater are heterogeneous across the local markets.

Table 1.2. Summary Statistics on Market Characteristics of 131 Municipalities

	No. Obs.	Mean	Std. Dev	5 percentile	95 percentile
	2010 H1				
Population (thousand)	131	335.203	248.343	83.134	999.289
GDP per capita (thousand KRW)	131	31.334	38.813	9.269	77.692
Commercial property value per m^2 (million KRW)	131	2.969	1.772	1.2836	7.3311
	2018 H2				
Population (thousand)	131	348.765	211.162	82.724	733.861
GDP per capita (thousand KRW)	131	36.514	40.040	10.436	92.266
Commercial property value per m^2 (million KRW)	131	3.0689	1.8475	1.2982	7.3533

Note. Cross-sections of 131 municipalities in 2010 H1 and 2018H2. GDP per capita and commercial property values are expressed in 2011 million Korean Wons.

Measures of theater entry and exit. Following Dunne et al. (2013), a new theater opening (entry) at period t is a theater that first appears in a market in period $t+1$. Similarly, a theater closure (exit) at period t is a theater that disappears in a market in period $t+1$. Opening a new multiplex theater is an expensive investment that takes time to build, so I use the data at the half-yearly frequency rather than the daily frequency.

1.2.3 Descriptive Patterns

This section documents empirical patterns of market structure and turnover in the South Korean theater industry. I first explore the relationships between the patterns of turnover and the market characteristics. I then focus on the changes in theater opening and size decisions after the regulatory regime shift.

Table 1.3 divides market-time observations into four quartiles based on population and reports the corresponding market structure and turnover as Dunne et al. (2013). I observe that markets with larger population have more theaters and more theater openings. As population increases, the number of active theaters grows from 1.17 to 3.56, and the average number of theater openings increases from 0.08 to 0.149. The fourth column indicates that the size of theater openings increases with the market size. For instance, in the smallest group of markets, the average number of screens per entry is 5.86, whereas the counterpart of the largest group of the markets is 6.84.

Table 1.3. Market Structure and Turnover by Market Size (Population)

Market	Structure		Turnover			
Size^a	theaters	screens per theater^b	entries	screens per entry^c	exits	screens per exit^d
1	1.1780	5.7495	0.0805	5.8690	0.0233	6.3846
2	1.4904	7.5654	0.0844	6.4348	0.0395	7.1818
3	2.3746	7.5413	0.1178	7.0238	0.0308	7.9412
4	3.5586	7.5318	0.1485	6.8442	0.0376	6.7500

Note 1. ^{a} based on thousands of people. Size 1 is a group of market-semester observations with population lying in $[43.315, 195.256)$; Size 2 is a group of observations with population lying in $[195.256, 311.608)$; Size 3 is a group of observations with population lying in $[311.608, 444.282)$; and Size 4 is a group of observations with population lying in $[444.282, 1203.285]$.
Note 2. $^{b\ c\ d}$ calculated using municipalities with positive numbers of theaters, entries, and exits, respectively.

Table 1.4 reports the distributions of theater openings and closures before and after the regulatory regime shift. The distributions uncover two points. First, theater entry increases from 3.14% (=0.99 + 1.68 + 0.48) to 4.25% (= 1.09 + 2.76 + 0.40) following the regime shift, indicating the presence of high entry barriers associated with opening a new theater or low expected profit after entry. Second, the industry has experienced higher turnover rates in the later sample periods, which partly suggests a reduction in entry barriers. A lower entry barrier encourages entry of theaters, and it also increases the threat of potential entering theaters. Thus, a lower entry barrier increases both entry and exit rates.

Table 1.4. Entry and Exit of Theaters (% Of the Sample)

	2010H1-2014H2	2015H1-2018H2
Entry of megaplex (screens more than 8)	0.99%	1.09%
Entry of midplex (screens between 5 and 7)	1.68%	2.76%
Entry of miniplex (screens less than 4)	0.48%	0.40%
Unchanged	95.93%	94.51%
Exit of miniplex (screens less than 4)	0.03%	0.15%
Exit of midplex (screens between 5 and 7)	0.53%	0.51%
Exit of megaplex (screens more than 8)	0.38%	0.58%

Note. The unit of measurement is firm-market-halfyear.

Table 1.4 also decomposes the theater openings and closures into three categories based on their scale (screens). The numbers inform the importance of accommodating decisions to choose the theater opening's size when evaluating the economic implications of lowering sunk entry costs. For instance, in the later regime, chains tended to open more middle-scale movie theaters (1.68% to 2.76%), while they tended to close small-scale movie theaters (0.03% to 0.15%). The observation in Table 1.4 is not an artifact of the coarsening of theater scales. Figure 1.2 displays the histogram of annualized entry rates by screen counts under the early- and late-regime periods. Following the regulatory regime shift, the entry rates for theaters with less than four screens have decreased, while those for theaters with more than five screens have mildly increased, echoing the patterns in Table 1.4. An analysis with extensive margin entry-exit decisions alone, which is common in the literature, fails to capture the change in scale choice behaviors and could spuriously measure the overall market-structure effect of sunk entry costs.

The disproportionate changes in the size of theater openings translate into the expansion of mid-plex theaters. Table 1.5 reports the half-annual transition rates for market structure, which is described by the number of mini-, mid-, and mega-plex theaters for periods before and after the reforms. There is considerable persistence in the market structure under both regimes, reflecting the huge sunk costs of opening a new theater. In addition, the transition rates for periods after the reforms are less persistent, in line with the way that sunk entry costs have declined following the reform. Lastly, in line

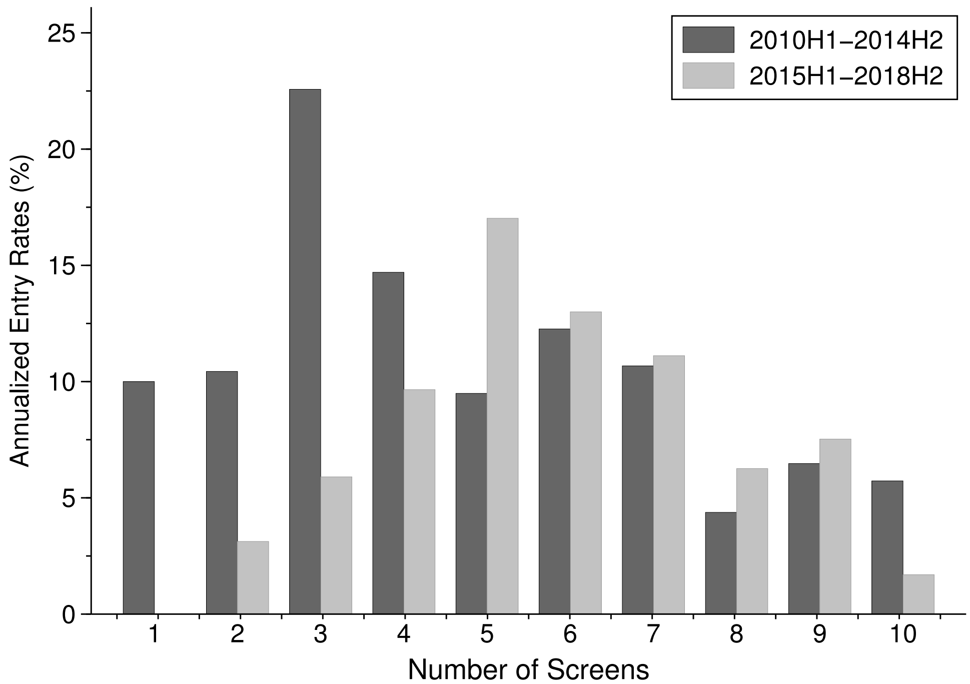

Figure 1.2. Annualized Theater Entry Rates by Screen Counts

Note. This figure displays the histograms of annualized theater entry rates by screen counts. The figure shows the entrant's screen count choices has shifted following the land-use and construction regulatory reforms.

with Table 1.4, the transition rates toward the market structure with a mid-plex theater (i.e., $n_{mid} = 1+$), have increased following the reforms, suggesting the disproportionate impacts of the reforms on the industry's sunk cost structure.

Figure 1.3 maps the mini-, mid-, and mega-plex theaters in Seoul metropolitan area (*Seoul, Incheon, and Gyeonggi-do*) in 2012 and 2018 which are three years before and after the regulatory regime shift. Two key patterns stand out from the comparison of the two maps. First, there are more movie theaters in Seoul metropolitan area as more dot points appear on the map in 2018 than in 2012. This finding indicates that the reforms may act to reduce sunk entry costs. Second and more importantly, most of the new dot points are colored green, suggesting that most of the new theater openings were mid-plex theaters. This pattern echoes the finding in Tables 1.4 and 1.5 that the chains open more mid-plex theaters after the reforms.

Besides the land-use and construction de-regulatory reforms, two alternative stories might have driven the observed shift in screen distribution. First, demand shocks or aggregate time trends in the industry would be a key factor shaping the change in the distribution. Appendix A.1 addresses these by conducting a variant of an event study, suggesting that the reforms can be the primary shock that had altered screen distribution. Another potential concern is that the chains opened theaters with more screens while reducing the size of an installed screen, indicating that the theater's relevant scale might remain unchanged. However, the national-level statistics show that such a concern would play a minor role. Specifically, the average number of seats per screen, which is a proxy of the screen size, was 174 and 153 in 2010 and 2018, respectively, which indicates that the annualized percentage change was -1.2%. In contrast, the industry has experienced relatively faster growth in screen counts. Screen counts had increased from 2003 to 2937, with an annualized growth rate of 4.6%.[11]

Table 1.5. Market Structure Transition Rates for Periods before and after the Reforms (%)

		Market Strcuture in $t+1$							
Market Structure in t		$n_{mini}=0$ $n_{mid}=0$ $n_{mega}=0$	$n_{mini}=1+$ $n_{mid}=0$ $n_{mega}=0$	$n_{mini}=0$ $n_{mid}=1+$ $n_{mega}=0$	$n_{mini}=0$ $n_{mid}=0$ $n_{mega}=1+$	$n_{mini}=1+$ $n_{mid}=1+$ $n_{mega}=0$	$n_{mini}=1+$ $n_{mid}=0$ $n_{mega}=1+$	$n_{mini}=0$ $n_{mid}=1+$ $n_{mega}=1+$	$n_{mini}=1+$ $n_{mid}=1+$ $n_{mega}=1+$
$n_{mini}=0$, $n_{mini}=0$, $n_{mini}=0$	Before	97.06	0.93	1.55	0.46	–	–	–	–
	After	90.37	2.96	5.93	0.74	–	–	–	–
$n_{mini}=1+$, $n_{mini}=0$, $n_{mini}=0$	Before	–	98.75	–	–	–	1.25	–	–
	After	–	98.25	–	–	0.87	0.87	–	–
$n_{mini}=0$, $n_{mini}=1+$, $n_{mini}=0$	Before	–	–	99.66	–	0.11	–	0.23	–
	After	–	–	99.62	–	0.13	–	0.25	–
$n_{mini}=0$, $n_{mini}=0$, $n_{mini}=1+$	Before	–	–	–	98.36	–	0.10	1.54	–
	After	–	–	–	98.13	–	–	1.68	0.19
$n_{mini}=1+$, $n_{mini}=1+$, $n_{mini}=0$	Before	–	–	–	–	96.88	–	–	3.13
	After	–	–	–	–	100.00	–	–	–
$n_{mini}=1+$, $n_{mini}=0$, $n_{mini}=1+$	Before	–	–	–	–	–	97.50	–	2.50
	After	–	–	–	–	–	96.67	–	3.33
$n_{mini}=0$, $n_{mini}=1+$, $n_{mini}=1+$	Before	–	–	0.12	0.24	–	–	98.80	0.84
	After	–	–	–	0.22	–	–	99.78	–
$n_{mini}=1+$, $n_{mini}=1+$, $n_{mini}=1+$	Before	–	–	–	–	–	–	–	100.00
	After	–	–	–	–	–	–	–	100.00

Note 1. Market structure is described by the numbers of theaters of scale categories (Miniplex, Midplex, Megaplex).
Note 2. The unit of measurement is market-halfyear.

[11] https://www.kofic.or.kr/kofic/business/board/selectBoardDetail.do?boardNumber=2&boardSeqNumber=33968 and https://www.kofic.or.kr/kofic/business/board/selectBoardDetail.do?boardNumber=2&boardSeqNumber=48560 (downloaded in February 2023).

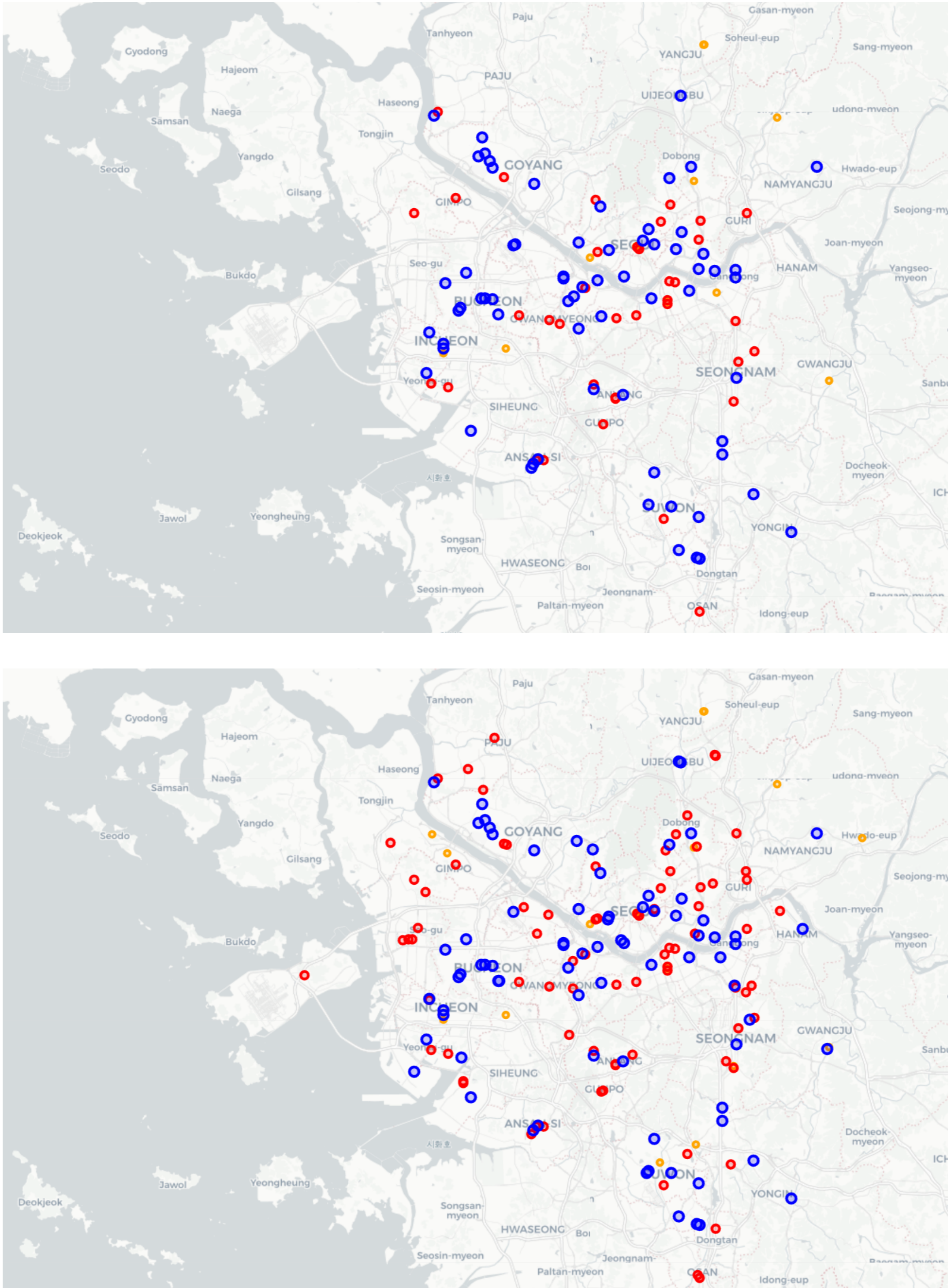

Figure 1.3. Theater Locations in 2012 and 2018

Note. The upper and lower figures map the theaters by size which located in Seoul metropolitan area in 2012 and 2018, respectively. The orange, red, and blue circles indicate miniplex, midplex, and megaplex theaters, respectively. The figures suggest that the industry had more theaters, particularly midplex theaters after the reforms.

The empirical pattern suggests that the chains began to open midplex theaters more than others after the reforms, thereby changing the entire market structure (i.e., the number of theaters and screen distribution). However, it is not sufficient to gauge the magnitude of a reduction in sunk entry costs and the resulting economic implication, such as changes in industry net profits. In addition, the pattern is insufficient to study the importance of accommodating the chain's choice of the size of a theater opening. To do so, I construct a model to identify how the cost structures changed in the later regime and examine the impact of the changes in the entry cost structures on industry net profits.

Before introducing a structural model, it is noteworthy to illustrate data features that the model should accommodate. First, population and the size of a theater opening are positively correlated. The industry model of this chapter will capture this feature by specifying *per-screen* profit as a function of population, so a theater with more screens can be more profitable in markets with larger population than less populated markets. Second, the turnover rates have increased after the reforms, suggesting a reduction in the sunk entry costs. To map this pattern to the entry cost estimates, the model will be a dynamic model which sharply distinguishes between the sunk entry costs and fixed operating costs. Lastly, chains adjust their size decisions following the regulatory regime shift, partly indicating that the reforms decrease the sunk entry costs but disproportionately affect the entry costs for midplex theaters. In that light, the model will admit a flexible specification of an entry cost schedule over the size of a theater opening.

1.3 Industry Model

This section introduces a dynamic game of chain-store entry and exit in which three oligopolistic chains decide whether to open a new theater and choose how many screens to be constructed for the theater opening. The model will allow me to recover the chains' operating profits at the screen level and the magnitude of a reduction in the sunk entry cost due to land-use and construction regulatory regime shift. These quantities will be subsequently employed in counterfactual simulations to quantify the welfare implications of the reduced sunk entry costs.

I model the chain's theater entry decision and screen counts choice as a dynamic game which is independently played in local markets. The modeling choice reflects two considerations. First, the data spans the regulatory regime shift, which might have changed the sunk entry cost. So, to appropriately address this, a structural model has to be a dynamic model which sharply distinguishes between sunk and fixed costs. Second, a model without strategic interaction among chains is not a relevant structure to study the welfare implication of lower entry barriers. In the presence of strategic interaction, a new theater can steal its competitors' business rather than expanding the market, opening the possibility that industry operating profits decrease. Thus, the economic implication of lower entry barriers becomes an empirically open question, while a single-agent model assumes away this channel and automatically produces the benefit of lower entry barriers.

1.3.1 Environment

Setting: Time is discrete with an infinite horizon, $t = 1, 2, 3, \ldots, \infty$, corresponding to six months. In the model, three cinema chains $i = 1, 2, 3$ operate multiple theaters in independent local markets $m = 1, 2, 3, \ldots, M$. Theaters differ by the number of equipped screens $j = 1, 2, \ldots, J$. In local market m, chain i decides to open or close a theater, and if it does, it chooses the number of screens of the theater opening or closure, d_{imt}. Once the number of screens is determined, the chains cannot expand or shrink it in later periods. The chains discount the future by a common discount factor β.

Market state: The industry model describes the competition among the three theater chains within a local market (municipality), which is fully characterized by market states. The market states include the chain's state variables, market demand/cost shifters, and market-specific profitability. The chain's state is a vector of the chain's theaters across the number of equipped screens. The market demand and cost shifters include population, GDP per capita, and commercial property value per meter square. The state vector in market m and period t is defined by

$$s_{mt} = (\underbrace{\{n^1_{1mt}, \ldots, n^J_{imt}\}}_{\equiv \vec{n}_{1mt}}, \{n^1_{2mt}, \ldots, n^J_{2mt}\}, \{n^1_{3mt}, \ldots, n^J_{3mt}\}, z_{1mt}, z_{2mt}, R_{mt}, \mu_m), \quad (1.1)$$

where n^j_{imt} represents the number of chain i's j-screen theaters in market m and period t. z_{1mt}, z_{2mt}, and R_{mt} represent population, GDP per capita, and commercial property value per meter square in market m and period t. μ_m is the market-specific profitability, which is observed by chains, but not by researchers.

The number of j-screen theaters operated by chain i depends on the chain's expansionsubtraction decision d_{imt}. Accordingly,

$$n_{imt+1}^{(j)} = n_{imt}^{(j)} + \mathbb{I}_{\{d_{imt}=j\}} - \mathbb{I}_{\{d_{imt}=-j\}} \qquad \text{for } j = 1, 2, \ldots, J \ . \tag{1.2}$$

This transition equation indicates that the three chains can expand or shrink the total number of own screens in a market only through opening or closing a movie theater. This restriction is indeed in line with the fact that downsizing an existing theater is extremely rare in the data. In addition, due to this restriction, a set of possible actions will depend on the chain's state $\vec{n}_{imt}$.

While the chain's state evolves deterministically, other exogenous market state variables (population, GDP per capita, and commercial property values) evolve according to a μ_m-specific first-order Markov process

$$F_{\mu_m}(z_{1mt+1}, z_{2mt+1}, R_{mt+1} | z_{1mt}, z_{2mt}, R_{mt}). \tag{1.3}$$

Timeline:

1. At the beginning of period t, each chain observes the market state s_{mt} and makes operating profits based on the current payoff-relevant market state.

2. The chains simultaneously draw a privately observed cost shock ε_{imt} from the publicly known distribution G. The chains form beliefs over their rival's decisions and then decide to open or close a movie theater and choose the number of screens for the opening or closure d_{imt}.

3. The chains pay the sunk entry costs if they decide to open a theater (i.e., $d_{imt} > 0$).

4. The dynamic decisions $(d_{1mt}, d_{2mt}, d_{3mt})$ are realized at the end of period t, and the market structure $(\vec{n}_{1mt}, \vec{n}_{2mt}, \vec{n}_{3mt})$ is updated to $(\vec{n}_{1mt+1}, \vec{n}_{2mt+1}, \vec{n}_{3mt+1})$ according to (1.2). The exogenous market state variables are updated according to (1.3).

Operating profit: Empirical studies on the dynamic chain-store oligopoly tend to specify the reduced-form *per-store* operating profit (Igami and Yang (2016), Arcidiacono et al. (2016), and Aguirregabiria and Magesan (2020)). This approach, however, assumes that the competitive effect of a store is equal regardless of the store size. To capture the size-dependent competitive effects, I instead express the operating profit in terms of *per-screen* operating profit while employing the reduced-form specification following the literature standard.

Specifically, chain i in market m and period t makes operating profit, which is given by

$$\pi_i(s_{mt}) = k_{imt} \times (-\phi_i^{FC}(\mu_m) - \phi_R^{FC} R_{mt} + \gamma_1 k_{imt} + \gamma_2 k_{-imt} + z'_{mt}\lambda), \tag{1.4}$$

where k_{imt} is the total number of own screens $k_{imt} = \sum_j j \times n^j_{imt}$; k_{-imt} is the total number of rival chains' screens $k_{-imt} = \sum_j j \times n^j_{-imt}$. The terms in bracket in equation (1.4) represent the average profit *per screen*.

$\phi_i^{FC}(\mu_m)$ is a composite of fixed operating cost and a baseline profit. A positive value of $\phi_i^{FC}(\mu_m)$ can be interpreted that a fixed operating cost overrides a baseline profit, and vice versa. Since market-specific profitability μ_m affects the baseline profit, ϕ_i depends on μ_m. For instance, higher μ_m (i.e., the higher baseline profitability) will be reflected on a lower value of $\phi_i(\mu_m)$. Commercial property value R_{mt} also constitutes a fixed operating cost as it influences the rental rate of commercial space in a local market. The equation (1.4) admits the differential competitive effects of same-chain and rival-chain screens, allowing me to distinguish between cannibalization and the business-stealing effect. Here, γ_1 captures profit cannibalization effects among same-chain screens, and γ_2 measures the competitive effect of rival screens. λ captures the effects of demand and cost shifters on the average profit per screen.

Equation (1.4) illustrates the trade-off between fixed operating costs and higher variable gross profits. If chain i owns a theater with many screens, it will gain higher variable profits $k_{imt} \times z'_{mt}\lambda$. In contrast, owning a theater with many screens will incur higher operating costs $k_{imt} \times (\phi_i(\mu_m) + \phi_R R_{mt})$.

In addition to the mechanical trade-off between fixed operating costs and higher variable profits, the strategic trade-off between cannibalization and business stealing also arises in equation (1.4). On the one hand, chains can steal higher market shares of incumbent theaters by opening a theater with many screens, which is captured by γ_2. However, this strategic benefit comes at the cost of harming the existing same-chain theaters γ_1.

Sunk costs for theater opening: After the post-entry competition, chain i draws a privately observed cost shock ε_{imt} and decides to open a new theater. The industry model of this chapter admits a flexible sunk entry cost schedule. Chain i may pay less in sunk entry costs *per screen* by constructing a movie theater with many screens (economies of entry scale). However, economies of entry scale may have limits, thereby the sunk entry costs *per screen* begin to increase as the number of added screens pass the minimum efficient entry scale (diseconomies of entry scale). To accommodate these possibilities, the sunk entry cost for entry size decision d_{imt} is given by

$$C(d_{imt}, R_{mt}, \varepsilon_{imt}) = \phi^{EC}_{d_{imt}} R_{mt} \mathbb{I}_{\{d_{imt}>0\}} + \varepsilon_{imt} d_{imt}. \tag{1.5}$$

Here, there are J total sunk entry cost schedule parameters $(\phi^{EC}_1, \ldots, \phi^{EC}_J)$. Equation (1.5) implies that the exit cost (or scrap value) is assumed to be zero, given that the entry, exit, and fixed costs of a dynamic model cannot be jointly identified. [12] Chains should pay higher sunk entry costs in markets with higher commercial property values. Thus, the entry cost depends on commercial property value R_{mt}, and this allows the sunk entry costs to differ across regional markets. A privately known cost shock ε_{imt} is assumed to be independently and identically distributed according to the normal distribution with mean zero and standard deviation $\nu \times R_{mt}$.

Collecting the operating profits and sunk entry costs for theater and screen openings, the per-period payoff function is specified as net profit:

$$\zeta_i(s_{mt}, d_{imt}, \varepsilon_{imt}) = \pi_i(s_{mt}) - C(d_{imt}, R_{mt}, \varepsilon_{imt}). \tag{1.6}$$

1.3.2 Dynamic Optimization and Equilibrium

Like most other dynamic oligopoly models, it is hard to track all the possible Nash equilibria of the model described in the previous subsection. In light of this, I analyze the chain's dynamic decision to add/subtract movie screens with a focus on pure Markovian strategies and stationary Markov Perfect Nash Equilibria (MPNEs) in the spirit of Ericson and Pakes (1995) and Maskin and Tirole (2001). In an MPNE, chians' strategies for the theater size only rely on a vector of current payoff-relevant state variables and a private cost shock.

Throughout this subsection, market and time subscripts, m and t, are suppressed, and superscript $'$ will refer to the future period in order to simplify the exposition.

Value Function: Chain i observes public state $s = (\vec{n}_i, \vec{n}_{-i}, z_1, z_2, R, \mu)$ and private cost shock ε_i. Then, chain i forms belief over the rival chains' actions d_{-i} and decides

[12] Under the normalization that the exit cost is zero, the estimates $\hat{\phi}^{FC}_d$ and $\hat{\phi}^{EC}_d$ will actually represent composites of the costs and the scrap value, namely ϕ^{SV}_d. More specifically, $\hat{\phi}^{FC}_d$ and $\hat{\phi}^{EC}_d$ can be interpreted as $\phi^{FC}_d + (1-\beta)\phi^{SV}_d$ and $\phi^{EC}_d - \phi^{SV}_d$, respectively. See Table 3 in Aguirregabiria and Suzuki (2014).

whether to open or close a theater and the number of screens for the theater opening or closure d_i in order to maximize the present value of future net profits. The corresponding Bellman equation is given by

$$V_i(s,\varepsilon_i) = \pi_i(s) + \max_{d_i \in D(\vec{n}_i)} \Bigg[-\phi^{EC}_{d_i} d_i \mathbb{I}_{\{d_i>0\}} R - d_i \times \varepsilon_i$$
$$+ \beta \sum_{\vec{n}'_{-i}} \sum_{z'_1, z'_2, R'} EV_i(\vec{n}'_i(\vec{n}_i, d_i), \vec{n}'_{-i}, z'_1, z'_2, R', \mu)\Psi_i(\vec{n}'_{-i}|s)F_\mu(z'_1, z'_2, R'|z_1, z_2, R)\Bigg], \tag{1.7}$$

where

$$EV_i(\vec{n}'_i(\vec{n}_i, d_i), \vec{n}'_{-i}, z'_1, z'_2, R', \mu) = \int_{\varepsilon'} V_i(\vec{n}'_i(\vec{n}_i, d_i), \vec{n}'_{-i}, z'_1, z'_2, R', \mu, \varepsilon')dG(\varepsilon'_i) \tag{1.8}$$

Here, $V_i(s, \varepsilon_i)$ is the chain i's value function at state (s, ε_i). $EV_i(\vec{n}'_i(\vec{n}_i, d_i), \vec{n}'_{-i}, z'_1, z'_2, R', \mu)$ is the chain i's *ex-ante* value function, the chain's valuation before observing ε_i. $\vec{n}'_i(n_i, d_i)$ is chain i's own state in the next period determined by equation (1.2). $\Psi_i(\vec{n}'_{-i}|s)$ is the chain i's belief over rival chains' states in the next period. $D(\vec{n}_i)$ is the set of feasible actions. For instance, if chain i owns 4-screen and 6-screen theaters, the chain could only close either 4-screen or 6-screen theater from the market. Thus, the corresponding $D(\vec{n}_i)$ is $\{-6, -4, 0, 1, \ldots, J\}$.

Following Nishiwaki (2016) and Caoui (2022), I consider a monotone strategy with respect to private information: the optimal policy function is expressed in terms of the cutoff strategy; the corresponding cutoff points are characterized by differences between two choice-specific value functions.[13]

I first define the chain i's choice-specific value function of taking action d_i

$$W_i(d_i|s) \equiv \beta \sum_{\vec{n}'_{-i}} \sum_{z'_1, z'_2, R'} EV_i(\vec{n}'_i(\vec{n}_i, d_i), \vec{n}'_{-i}, z'_1, z'_2, R', \mu)\Psi_i(\vec{n}'_{-i}|s)F_\mu(z'_1, z'_2, R'|z_1, z_2, R).$$

To derive a cutoff point, consider $d_i+1, d_i, d_i-1 \in D(\vec{n}_i)$. Let $\bar{\varepsilon}_{d_i, d_i-1}$ be the cutoff point at which actions d_i and d_i-1 are indifferent. Thus,

$$W_i(d_i-1|s) - \phi^{EC}_{d_i-1}R - (d_i-1)\bar{\varepsilon}_{d_i,d_i-1}R = W_i(d_i|s) - \phi^{EC}_{d_i}R - d_i\bar{\varepsilon}_{d_i,d_i-1}R \tag{1.9}$$

[13] The conditions under which a monotone strategy Markov Perfect Equilibrium exists are satisfied in my model. Specifically, the payoff function (1.6) satisfies the *decreasing difference* restriction. See Srisuma (2013).

$$\Rightarrow \bar{\varepsilon}_{d_i,d_i-1}(s) = \frac{W_i(d_i|s) - W_i(d_i-1|s)}{R} - \frac{\phi^{EC}_{d_i-1}}{d_i-1} - d_i(\frac{\phi^{EC}_{d_i}}{d_i} - \frac{\phi^{EC}_{d_i-1}}{d_i-1})$$

The cutoff point at which actions d_i+1 and d_i are indifferent is characterized analogously

$$\bar{\varepsilon}_{d_i+1,d_i}(s) = \frac{W_i(d_i+1|s) - W_i(d_i|s)}{R} - \frac{\phi^{EC}_{d_i}}{d_i} - (d_i+1)(\frac{\phi^{EC}_{d_i+1}}{d_i+1} - \frac{\phi^{EC}_{d_i}}{d_i}). \tag{1.10}$$

Thus, chain i in state s with realized private cost shock ε_i open a d_i-screen theater if

$$\bar{\varepsilon}_{d_i+1,d_i}(s) < \varepsilon_i < \bar{\varepsilon}_{d_i,d_i-1}(s). \tag{1.11}$$

Cutoff points (1.9) and (1.10), and decision rule (1.11) show the role of economies (diseconomies) of entry scale in shaping the chain's choice of the number of screens upon theater entry. For instance, if there are entry scale economies from d_i-1 to d_i (i.e., $\frac{\phi^{EC}_{d_i}}{d_i} < \frac{\phi^{EC}_{d_i-1}}{d_i-1}$), chain i would enjoy an additional margin, $-d_i(\frac{\phi^{EC}_{d_i}}{d_i} - \frac{\phi^{EC}_{d_i-1}}{d_i-1})$, from choosing d_i against d_i-1. This additional margin is reflected on a larger value of $\bar{\varepsilon}_{d_i,d_i-1}(s)$ (Equation (1.9)), increasing the likelihood that chain i to choose d_i (Equation (1.11)). The opposite case (diseconomies of entry scale) can be established analogously.

Taken together, the optimal decision rule for the new theater's screen counts is given by

$$d_i = \begin{cases} J & \text{if } \varepsilon_i < \bar{\varepsilon}_{J,\max J-1}(s) \\ \underline{d}_i < d < J & \text{if } \bar{\varepsilon}_{d+1,d}(s) < \varepsilon_i < \bar{\varepsilon}_{d,d-1}(s) \\ \underline{d}_i & \text{if } \varepsilon_i > \bar{\varepsilon}_{\underline{d}_i+1,\underline{d}_i}(s) \end{cases}, \tag{1.12}$$

where $\underline{d}_i = \min D(\vec{n}_i)$. Note that the maximum number of screens to be subtracted depends on the chain's configuration since shrinking the total number of screens can only occur through closing an existing theater. For instance, if chain i owns 3-screen and 4-screen theaters in a market, $\underline{d}_i = -4$.

Assuming that ε_i is drawn from a Normal distribution with standard deviation νR, the chain i's optimal decision rule can be expressed as conditional choice probabilities (CCPs) $P_i(d_i|s)$:

$$P_i(d_i|s) = \begin{cases} \Phi(\frac{\bar{\varepsilon}_{J,J-1}(s)}{\nu R}), & \text{if} \quad d_i = J \\ \Phi(\frac{\bar{\varepsilon}_{d,d-1}(s)}{\nu R}) - \Phi(\frac{\bar{\varepsilon}_{d+1,d}(s)}{\nu R}) & \text{if} \quad \underline{d}_i < d_i < J \\ 1 - \Phi(\frac{\bar{\varepsilon}_{\underline{d}_i+1,\underline{d}_i(s)}}{\nu R}), & \text{if} \quad d_i = \underline{d}_i, \end{cases} \tag{1.13}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function.

Markov Perfect Nash Equilibrium: A Markov-perfect Nash equilibrium constitutes the chains' screen adding/subtracting strategy profile and beliefs (σ^*, Ψ^*) such that

1. Given belief Ψ^*, $\sigma_i^*(s, \varepsilon_i)$ is optimal at all states

$$V_i(s, \varepsilon_i; \sigma_i^*, \sigma_{-i}^*) \geq V_i(s, \varepsilon_i; \tilde{\sigma}_i, \sigma_{-i}^*), \qquad \forall s, i, \tilde{\sigma}_i.$$

2. Belief Ψ_i^* is consistent with conditional choice probabilities (1.13)

$$\Psi_i^*(x'_{-i}|s) = \prod_{l \neq i} P_l^*(\sigma_l^*|s).$$

The existence of an MPNE of the game follows from Doraszelski and Satterthwaite (2010) and Srisuma (2013).

1.4 Estimation

This section describes the estimation of the industry model in Section 1.3. The key objects of interest are the competitive effects of the same-chain screens and rival-chain screens, γ_1 and γ_2, and two different sunk entry costs schedules, $(\phi_1^{EC}, \ldots, \phi_J^{EC})$, under the early- and late-regimes.

Solving the model repeatedly for any candidate of the structural parameters is impractical, hindering a nested-fixed point algorithm for the estimation. [14] I circumvent the issue regarding a high-dimensional state-space by following two-step approach proposed by Bajari et al. (2007). The approach allows me to estimate the structural parameters without solving the model. The estimation of the structural parameters is divided into two stages. In the first stage, I estimate the chain's equilibrium conditional choice probabilities (1.13) for the number of screens for a theater opening or closure before and after the regulatory regime shift. These estimates are complete descriptions of how chains will choose the size of their theater opening or closure in a geographic market. In the second stage, I search the structural parameters at which the estimated CCPs weakly dominate possible alternative strategies.

[14] For instance, assuming the maximum number of screens to be added is 10 (i.e., $J = 10$), and chains can open at most one theater for each size, the total number of states is 1,073,741,824.

To recognize the impact of the regulatory regime shift, I allow the fixed operating costs (or baseline profit) and the sunk entry costs to differ before and after 2014. Identifying changes in the fixed operating and sunk entry costs relies on two key assumptions. First, following the spirit of Rust and Rothwell (1995), Ryan (2012), and Kalouptsidi (2018), I assume that the regulatory regime shift were unexpected; firms believed that the reforms would be permanent; and they immediately switch from the old equilibrium to the new one. Thus, the identification of the cost impact of the regime shift relies on a comparison between the firms' behaviors before and after the regime shift.[15] Second, I assume that the other profit function parameters, such as competitive effects of the same-chain and rival-chain screens and the effect of the demand shifters, have remained unchanged after the regime shift. Given that the goal of the reforms is to relax land-use regulations involved in opening a new business, the reforms most likely affected the sunk entry costs, while retaining the nature of competition among theaters.

I also allow the fixed operating costs (or baseline profit) to differ before and after the regulatory regime shift because of the following reason. In response to the relaxation of land-use regulations, other service businesses would have entered a local market, which could increase the baseline profit of a theater. This change would be reflected in a decrease in the fixed operating costs in the model of this chapter. Thus, assuming fixed costs to be the same before and after the regime shift would obscure positive spillover effects on the entry of theaters, which translates into a considerable reduction in sunk entry costs, biasing the counterfactual predictions.

1.4.1 First Stage: Estimating Conditional Choice Probabilities

In the first stage, I estimate an ordered probit regression of the size (screen) of a theater opening or closure which is implied by equation (1.13). Similar to Caoui (2022), I coarsen the size of a theater opening or closure into three scale categories to bypass the high-dimensionality of state space. Specifically, theaters with four screens or less are assumed to be 3-screen theaters, and theaters with five, six, or seven screens are treated as 6-screen theaters. Theaters with eight screens or more are set to be 9-screen theaters. Such a coarsening is sufficient to study the importance of intensive margin entry decisions

[15] Of course, firms might have slowly adjusted their behaviors after the regulatory reforms due to uncertainty about their rivals' behaviors. In this regards, accommodating the learning process regarding the competitors' new strategies might be appealing, such as Doraszelski, Lewis, and Pakes (2018) who estimate the learning processes of firms in the UK frequency response market after the deregulation. However, the periods that my dataset spans are too short to pursue this avenue.

while controlling the size of the state space.[16]

I approximate cutoff point $\bar{\varepsilon}_{d_i,d_i-1}(s)$ as a function of the number of same-chain screens, the number of rival-chain screens, population, GDP per capita, commercial property value per m^2, and market dummies. The first five variables are the payoff-relevant state variables, while market dummies are introduced to capture the unobserved market-specific profitability μ_m. To capture the impact of the regulatory regime shift on the chain's theater opening/closure's size decisions, I allow for cutpoints in an ordered probit regression to differ across the chains and before and after 2014H2. Thus, the probability of observing chain i adding or subtracting a j-screen theater at state s_{mt} and in policy regime $r \in \{before, after\}$ is given by

$$\begin{aligned} P(d_{imt} = j | s_{imt}, r) &= P(\kappa_{irj-1} < d^*_{imt} + u_{imt} < \kappa_{irj}) \\ &= \Phi(\kappa_{irj} - d^*_{imt}) - \Phi(\kappa_{irj-1} - d^*_{imt}), \end{aligned} \tag{1.14}$$

where κ_{irj} is a chain i's cutpoint at policy regime r corresponding to opening j-screen theater (if $j > 0$) or closing j-screen theater (if $j < 0$), and u_{imt} is drawn from standard normal. As discussed, I specify the latent variable d^*_{imt} as

$$d^*_{imt} = \alpha_1 k_{imt} + \alpha_2 k_{-imt} + z_{mt}\alpha_3 + \alpha_4 R_{mt} + \delta_m, \tag{1.15}$$

where k_{imt} and k_{-imt} are the total numbers of own and rival screens in market m at point in time t; δ_m is market dummies. The main parameters of interest are α_1, α_2 and the collection of cutpoints κ_{irj}.

α_1 and α_2 in equation (1.15) are informative about the strategic interactions among the chains. If there is strong business stealing, the entry of rival chain's screens reduces the profitability of chain i's theater, so chain i is unwilling to open a theater or would like to close the existing theater. This effect turns in a decrease in latent variable d^*_{imt}. Thus, one would expect $\alpha_2 < 0$. An analogous argument can be made for α_1. When cannibalization among same-chain theaters exists, the entry of same-chain screens reduces the profit of the other same-chain theater, so α_1 is expected to be negative.

The estimates of cutpoints will inform the fixed operating costs and sunk entry costs. As well documented by Dunne et al. (2013), the fixed operating costs govern the decision to close a theater (exit), while the sunk entry costs shape the decision to open a theater (entry). All else equal, a higher cutpoint for $j > 0$ translates into a decrease in the

[16]Indeed, the coarsening reduces the number of possible market configurations substantially from 1,073,741,824 to 19,683.

probability of observing chain i opening a theater as $P(d_{imt} > 0|s_{imt}, r) = 1-\Phi(\kappa_{ir0}-d^*_{imt})$. Hence, a higher cutoff will suggest higher sunk entry costs. Similarly, a higher cutpoint $j < 0$ would reflect the higher fixed operating costs since it implies an increase in the probability of a theater closure ($P(d_{imt} < 0|s_{imt}, r) = \Phi(\kappa_{ir,-3} - d^*_{imt})$). In addition, the differences between cutpoints further reflect how the sunk entry costs vary with the size of a theater opening. As shown in equation (1.14), the larger difference between κ_{irj} and κ_{irj-1} implies that chain i is more likely to open a j-screen theater than a theater with a different number of screens, making the sunk entry cost estimates for a j-screen theater smaller than those for other theaters.

I estimate (1.14) via the method of maximum likelihood using a panel at the firm-market-time level. Note that firms cannot have a negative number of j-screen theaters, thereby making the feasible action space depend on own configurations. For instance, if firm i has only owned a 3-screen theater in m, the set of possible choices $D(\vec{n}_i)$ would not contain -9 and -6. When constructing the likelihood function, such a state-dependency is taken into account.

Coarsening of Data: Before proceeding to the second stage, I discretize the data to facilitate the structural estimation. First, I discretize estimated market dummies into three categories based on their 33rd and 66th percentiles in order to control market-level profitability μ_m. Accordingly, 131 markets are grouped into the three categories, and the fixed operating costs (or baseline profits) are separately estimated for each category. Second, for each market category, I divide population, GDP per capita, and commercial property values into their respective quartiles. Thus, for each market-type category, markets will fall into 64 possible combinations ($4 \times 4 \times 4$). Using a bin estimator, I separately estimate transition matrices for population, GDP per capita, and commercial property values. That is, $F(z'_1, z'_2, R'|z_1, z_2, R) = F_{z_1}(z'_1|z_1)F_{z_2}(z'_2|z_2)F_R(R'|R)$. The transition matrices are also estimated separately for time periods before and after the regime shift. Since the regulatory regime shift may also alter the dynamics of exogenous market state variables, particularly commercial property values. Estimating the transitions separately for periods before and after the regime shift may capture such a change.

1.4.2 Second Stage: Recovering the structural parameters

Although the estimated CCPs characterize how chains choose the size of theater opening and closure in any state before and after the regime shift, they are not sufficient to study how chains adjust their decisions in response to an exogenous reduction in the sunk entry costs and measure the welfare implications. Doing so requires the estimates of the operating profits and sunk entry costs.

The industry model is characterized by a vector of the structural parameters $\Theta = (\vec{\phi}^{FC}, \gamma_1, \gamma_2, \lambda, \vec{\phi}^{EC}, \nu)$, where $\vec{\phi}^{FC}$ and $\vec{\phi}^{EC}$ are vectors of fixed and sunk cost parameters. Solving for equation (2.5) at every guess of Θ is computationally impractical due to a high-dimensional state space. In the spirit of Hotz et al. (1994) and Bajari et al. (2007), I sidestep this computational challenge. Specifically, I approximate the *ex-ante* value function $EV_i(s_m; \sigma_i, \sigma_{-i})$ via Monte Carlo simulation.

Note that the *ex-ante* value function (1.8) is the discounted sum of flows of per-period payoffs:

$$EV_i(s_m; \sigma_i, \sigma_{-i}, \Theta) = \mathbb{E}\left[\sum_{\tau=0}^{\infty} \beta^\tau \zeta_i(s_{m\tau}, d_{im\tau}, \varepsilon_{im\tau}; \Theta) | s_{m0} = s_m, \sigma_i, \sigma_{-i}\right], \tag{1.16}$$

where $\mathbb{E}$ are taken conditional on own and rivals' strategies σ_i and σ_{-i}.

Given initial state s, I can simulate NS paths of firms' actions, industry states, and the corresponding per-period payoffs forward using $\hat{\sigma}$ and the estimated transition matrices $\hat{F}_\mu(z'|z)$. For each simulated path, I can calculate the discounted sum of flows of per-period payoffs and then approximate (1.16) by averaging the NS discounted sums:[17]

$$\hat{EV}_i(s_m; \hat{\sigma}_i, \hat{\sigma}_{-i}, \Theta) = \frac{1}{NS} \sum_{ns=1}^{NS} \left[\sum_{\tau=0}^{T} \beta^\tau \zeta_i(ns; s_{m\tau}, d_{im\tau}, \varepsilon_{im\tau}; \Theta) | s_{m0} = s_m, \hat{\sigma}_i, \hat{\sigma}_{-i}\right]. \tag{1.17}$$

Following Srisuma (2013), I construct a set of alternative strategies by perturbing the estimated equilibrium cutoffs using the first stage estimates of CCPs. To do so, I first derive the normalized cutoffs by inverting equation (1.13) in the spirit of Hotz and Miller (1993):

$$P(d_{imt} \leq d | s_{mt}) = 1 - \Phi(\frac{\bar{\varepsilon}_{d+1,d}(s_{mt})}{\nu R}), \qquad \text{for } d < \max D_i(\vec{n}_{imt}). \tag{1.18}$$

Since the left-hand side of equation (1.18) is obtained from the first stage estimates of

[17] Following Bajari et al. (2007) and subsequent empirical applications, I leverage the fact that payoff function $\zeta_i(s, d_i, \varepsilon_i)$ is linear in vector of parameters Θ to avoid repeated calculations of (1.17) when iterating Θ.

CCPs, I obtain the normalized cutoff values which is given by

$$\frac{\bar{\varepsilon}_{d+1,d}(s_{mt})}{\nu R} = \Phi^{-1}(1 - P(d_{imt} \leq d|s_{mt})). \tag{1.19}$$

I construct NP perturbed normalized cutoff values (1.19) by adding small random numbers: $\Phi^{-1}(1-\hat{P}(d_{imt} \leq d|s_{imt})+\xi_i$, where ξ_i is drawn from a normal distribution with zero mean and 0.1 standard deviation. For each perturbation $np = 1, 2, \ldots, NP$, I use a perturbed cutoff values to compute perturbed CCPs $\tilde{\sigma}_{i,np}$. I use the perturbed CCPs to calculate the alternative *ex-ante* value function $\hat{EV}_i(s_m; \tilde{\sigma}_{i,np}, \hat{\sigma}_{-i}, \Theta)$ as equation (1.17). For perturbation np, the penalty of deviating from an equilibrium is given by

$$g_{i,np}(s_m; \Theta) = \hat{EV}_i(s_m; \hat{\sigma}_i, \hat{\sigma}_{-i}, \Theta) - \hat{EV}_i(s_m; \tilde{\sigma}_{i,np}, \hat{\sigma}_{-i}, \Theta). \tag{1.20}$$

Since chains face different fixed and sunk entry costs and play the different strategies for periods before and after the regulatory regime shift, I do the jobs described above separately for the estimated MPNE cutoffs for periods before and after the regime shift as Ryan (2012). Thus, $g_{i,np}(s_m; \Theta)$ is essentially policy-regime specific: $g_{i,np,r}(s_m; \Theta_r)$, where r is the index of regulatory regime.

For each regime, I search for a vector of the structural parameters at which the observed strategies weakly dominate the perturbed strategies. Thus, the estimated vector of the structural parameters $\hat{\Theta}_r$ is the minimizer of the following objective function. [18]

$$Q_r(\Theta_r) = \frac{1}{M \times I \times NP} \sum_{m,i,np} (\min\{0, g_{i,np,r}(s_m; \Theta)\})^2. \tag{1.21}$$

Implementation and Calibration: I use $NS = 2,000$ and $T = 80$ to approximate the ex-ante value function (1.17). I draw 500 perturbed strategies ($NP = 500$) to construct objective function (1.21).

Since the data contain only the market structure and the theater entry-exit patterns

[18] I can also jointly estimate the pre- and post-reforms parameters by minimizing the following objective function:

$$Q(\Theta_1, \Theta_2) = \frac{1}{M \times I \times NP \times 2} \sum_{m,i,np,r} (\min\{0, g_{i,np,r}(s_m; \Theta_r)\})^2.$$

The estimation results are qualitatively similar, but the estimated reduction in the sunk entry costs resulting from the regime shift is unreasonably large (a reduction of 40%).

along with their size, the estimated structural parameters will be expressed in units of standard deviation. To interpret the parameters in money units, I calibrate the sunk entry cost parameter for a 6-screen theater in the early-regime periods, $\phi^{EC}_{6,1}$, to 1,800 million KRW. In doing so, the sunk entry cost in the municipality of *Gyeong-ju* can be 3.6 billion KRW, in line with an engineering estimate quoted from a business report.

I choose half-year discount factor β to 0.963, matching the average annual real interest rates of 7.8% in South Korea from 2010 to 2018.[19]

1.5 Empirical Results

1.5.1 CCP Estimates

Table 1.6 presents estimated coefficients of the policy function for the screens of a theater opening or closure (1.14). Column (1) in Table 1.6 reports the result of an estimation that has market dummies, while Column (2) does not.

The results suggest that the presence of competing theaters (screens) lowers a propensity to open a theater. The competitive effect of own screens is -0.1013; the effect of rival chains' screens is -0.0739. The magnitude of the effect of same chain theaters is slightly larger than the rival chains' counterpart, despite the difference not being statistically significant. Yet, this finding suggests cannibalization among theaters within the same chain would be a concern for a chain-store firms in the South Korean movie theater industry.

Contrasting the estimates in Column (1) with those in Column (2), I observe introducing market dummies, which control for the unobserved market-specific profitability μ_m, is crucial to obtaining correct estimates for the competitive effect. Since chains may prefer to open a theater in markets with higher μ_m, markets with higher μ_m can attract more theaters and screens. Thus, chains appear to enter markets with more rivals without control for the unobserved market-specific profitability (Igami and Yang (2016)). Indeed, without the market dummies, the effect of the number of rival-chain screens on the entry and size decisions is positive. In addition, the effect of same-chain screens substantially increases from -0.1013 to -0.0260. Overall, the absence of market dummies spuriously suggests that a chain favors the presence of competing theaters and is less concerned about cannibalization. These biased estimates will result in an incorrect prediction of the welfare implications of the reduced sunk entry costs.

[19] $0.963 \approx (\frac{1}{1+0.078})^2$.

Table 1.6. Ordered Probit on Intensive Marginal Theater Entry-Exit Decision: Coefficients

Covariates	(1)	(2)
# own chain screens	-0.1013^{***}	-0.0260^{***}
	(0.0129)	(0.0094)
# rival chain screens	-0.0739^{***}	0.0022
	(0.0082)	(0.0034)
population (thousand people)	0.0084^{***}	0.0008^{***}
	(0.0014)	(0.0001)
GDP per capita (thousand KRW)	0.0057	0.0013
	(0.0048)	(0.0007)
Property value per m^2 (million KRW)	-0.3692^{*}	-0.0250
	(0.2067)	(0.0160)
Market Dummies	✓	
Log likelihood	-1456.33	-1551.38
Observations	6,681	

Note. Estimated using a strongly balanced panel of the chain-market-time level. Standard errors are in parenthesis. Asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All units are expressed in one standard deviation of the standard Normal distribution.

Addressing market-specific the unobserved market-specific profitability is also vital to accurately measure the effect of commercial property values on the chain's theater opening decisions, which is informative about the fixed cost of operating screens. Since markets with higher μ_m would attract several service establishments, they are more likely to have a higher demand for commercial space, leading to higher commercial property values. Thus, without control for the unobserved market profitability, the CCP estimates suggest an implausible pattern that the chains do not respond to changes in property values (Column (2) in Table 1.6). In contrast, I obtain the significantly negative effect of property values on the chain's decision after including market dummies (Column (1) in Table 1.6).

Table 1.7 presents estimated cutpoints of theater entry-exit policy function (1.14). For the exposition purpose, I report only the estimated cutpoints when chain firms do not have any theater in a local market at a point in time (i.e., $\vec{n}_{imt} = \{0, 0, 0\}$).

The result shows that the cutpoints for all the chain firms have decreased after the regime shift, suggesting a possible reduction in sunk entry costs. For instance, the cutpoints for an entry of a CGV's 3-,6-, and 9-screen theaters decrease from 3.1500, 3.2563, and 3.7141 to 2.6105, 2.6788, and 3.3317, respectively. Such a decrease implies that moving CGV from the early-regime periods to the late-regime periods increases the probability of observing an entering CGV theater.

Table 1.7. Ordered Probit on Intensive Marginal Theater Entry-Exit Decision: Cutpoints

Cutpoints	2010H1-2014H2	2015H1-2018H2
	CGV	
κ_3	3.1500	2.6105
κ_6	3.2563	2.6788
κ_9	3.7141	3.3317
	Lotte Cinema	
κ_3	3.0476	2.7593
κ_6	3.1540	2.8276
κ_9	3.6118	3.4805
	Megabox	
κ_3	3.4949	2.6464
κ_6	3.6012	2.7148
κ_9	4.0590	3.3676
Log likelihood	-1456.33	
Observations	6,681	

Note. Estimated cutoffs for $\vec{n}_{imt} = (0, 0, 0)$ are reported. $\vec{n}_{imt}$ is a vector of own state, which collects the number of theaters by size: $\vec{n}_{imt} = (n_{imt}^{(3)}, n_{imt}^{(6)}, n_{imt}^{(9)})$. Estimated cutpoints for other own states are suppressed for the expositional purpose and available upon request. All units are expressed in one standard deviation of the standard Normal distribution.

In addition, the cutpoints do not decrease uniformly: the difference between the first two cutpoints decreases from 0.1063 to 0.0683, whereas the difference between the last two cutpoints increases from 0.4573 to 0.6563. The probability of observing an entering 3-screen CGV theater increases in the first difference, while the probability of observing an entering 6-screen CGV theater increases in the second difference. Thus, the estimation result implies that conditioning on opening, the probability of observing a 3-screen theater opening decreases and that of observing a 6-screen theater opening increases when moving CGV from the early-regime periods to the later-regime periods.

Note that all the parameter estimates are expressed in units of one standard deviation of the Normal distribution. To interpret the results as changes in the probabilities of entry, I calculate the corresponding probabilities at the median of all the other explanatory variables and tabulate them in Table 1.8. In line with the summary statistic in Table 1.4, the chains open a theater more frequently in the late-regime. For instance, the probability of CGV not opening a theater decreases from 98% to 93.85%. Similar patterns stand out for the other two chains. Put differently, the probabilities of CGV, Lotte Cinema, and Megabox opening a theater increase by 4.28 percentage points, 2.15 percentage points, and 4.97 percentage points, respectively. The reforms also alter the chains' decisions to choose the size of a theater opening. The probability of observing an entry of CGV's 3-screen theater has increased only by 75%, from 0.44% to 0.79%. In contrast, I find that the conditional probability of observing an entry of CGV's 6-screen theater has increased by 400%, from 1.03% to 4.18%. A similar pattern also holds for the other two chain firms. Overall, the estimation results highlight the chain's theater size decisions.

Table 1.8. Predicted Probabilities at Median of Explanatory Variables

Predicted Probs.	2010H1-2014H2	2015H1-2018H2
	CGV	
$P(d=0\|s)$	0.9813	0.9385
$P(d=3\|s)$	0.0044	0.0079
$P(d=6\|s)$	0.0103	0.0418
$P(d=9\|s)$	0.0041	0.0118
	Lotte Cinema	
$P(d=0\|s)$	0.9761	0.9546
$P(d=3\|s)$	0.0054	0.0062
$P(d=6\|s)$	0.0130	0.0313
$P(d=9\|s)$	0.0055	0.0079
	Megabox	
$P(d=0\|s)$	0.9924	0.9427
$P(d=3\|s)$	0.0020	0.0074
$P(d=6\|s)$	0.0043	0.0391
$P(d=9\|s)$	0.0014	0.0107

Note. Predicted probabilities for $\vec{n}_{imt} = (0, 0, 0)$ at the median of explanatory variables are tabulated.

Goodness of the fit of the CCP: Before proceeding to estimating the model parameters, I assess the overall performance of the estimated policy functions for theater opening's screen counts (CCPs) in matching the industry dynamics. Since the technique of Bajari et al. (2007) relies on the value functions simulated by the CCPs, the accuracy of the CCPs is crucial in obtaining the correct model parameters (Collard-Wexler (2013)).

I take the initial period's configuration of 131 markets as given and simulate the market structures from 2010H2 to 2014H2 using the CCPs and transition matrices for the pre-reform periods. Taking the simulated market structure in 2014H2 as given, I then simulate the market structures from 2015H1 ot 2018H2 using the CCPs and transition matrices for the post-reform periods. Table 1.9 compares the moments of raw data with the simulated counterparts.

The estimated CCPs predict the distribution of theater size (Panel A) and the market

Table 1.9. Goodness-of-Fit: Conditional Choice Probabilities

Moments	Real Data (2010H1-2018H2)	Simulated Data Using CCPs
	Panel A. Chain-Level Moments	
Share of 3-screen theaters: CGV	8.23%	9.76%
Share of 6-screen theaters: CGV	37.82%	39.87%
Share of 9-screen theaters: CGV	53.95%	50.37%
Share of 3-screen theaters: Lotte Cinema	9.03%	8.31%
Share of 6-screen theaters: Lotte Cinema	48.35%	45.18%
Share of 9-screen theaters: Lotte Cinema	42.62%	46.52%
Share of 3-screen theaters: Megabox	7.65%	7.31%
Share of 6-screen theaters: Megabox	41.38%	42.64%
Share of 9-screen theaters: Megabox	50.96%	50.06%
	Panel B. Market-Level Moments	
# Theaters per Market (All)	2.150	2.208
# Theaters per Market (Category 1)	2.321	2.442
# Theaters per Market (Category 2)	1.841	1.860
# Theaters per Market (Category 3)	2.282	2.315
	Panel C. Correlations	
Avg Screen per Theater & Population	0.3521	0.3270
Avg Screen per Theater & GDP	-0.0258	-0.0349
Avg Screen per Theater & Property value	0.3359	0.0585
# Theater & Population	0.5528	0.7503
# Theater & GDP	0.0642	0.0078
# Theater & Property value	0.2003	0.0359
	Panel D. Profitability	
Avg annual operating margins: CGV	8.448%	7.1022%

Note. Data are simulated using computed CCPs and market type-specific demand process D^{μ}. The predicted moments are obtained by averaging 500 simulations.

structure (Panel B) precisely. Although the model underpredicts the share of 9-screen theaters, the deviations are small. The calculated CCPs do a good job of predicting the correlations between demand shifters and the market structure, though they overpredict the correlation between a population and the total number of theaters in a market (Panel C).

The CCPs do not fit the correlation between commercial property values and market structure (Panel C). For instance, the correlation between the number of theaters and property values is 0.2 in the realized data, while the simulated counterpart is only 0.0359. However, this discrepancy between the realized and simulated data may not harm the structural estimates and counterfactual outcomes. The high correlation in the realized data may reflect the positive correlation between unobserved market-level profitability and commercial property values, as discussed in Section 1.5.1. In contrast, the CCPs accurately obtain the negative effect of property values on the chain's theater opening decision by including market dummies (Table 1.6), so the simulated data produce a much weaker correlation between commercial property values and market structure. Overall, the discrepancy between the realized and simulated data indicates that the CCPs obtain the plausible relationship between the chain's theater opening decision and commercial property values rather than evidence of the poor predictive performance of the CCPs.

In Appendix A.2, I further examine the performance of the estimated CCPs in describing the industry dynamics. The CCPs closely match the trend in theater counts and their average number of screens. In addition, the CCPs replicate the considerable persistence of screen transition.

1.5.2 Model Parameters

Variable profit parameters: Table 1.10 displays estimates of variable profit function per screen. In line with the policy function estimates in Table 1.6, both same-chain and rival-chain screens reduce the profit of an incumbent theater by a equal amount. For instance, the entry of a same-chain theater with six screens will reduce a incumbent same-chain theater's profit by 22.8 million KRW (6×3.8). A rival-chain theater with six screens has the similar competitive effect by decreasing the incumbent's per-screen profit by 20.88 million KRW (6×3.48). The parameter estimates further suggest the size-dependent business effects, which govern strategic motives of the three theater chains. By opening 3-screen, 6-screen, and 9-screen theaters in a local market, a chain can steal business of rival chains by 10.44, 20.88, and 31.32 million KRW.

More screens do not necessarily translate into the higher chain's variable profits because of profit cannibalization. Figure 1.4 plots the chain's variable profit function in a median market with median population and GDP per capita over the numbers of own screens and rival screens. Indeed, the variable profit function is concave in the number of screens. In addition, as rival screens increase, the chain's variable profits decrease, capturing the business-stealing effect. The figure thus suggests that the industry's variable profits can diminish, even though there are more theaters/screens due to tougher within- and between-chain competition.

Table 1.10. Estimates of Variable Profits per Screen (In Millions of 2011 Korean Won)

	Estimates	SEs
Competitive Effects: γ		
Cannibalization	-3.8228	0.2392
Rival competition	-3.4897	0.3130
Demand Shifters: λ		
Population (thousands)	0.3676	0.0241
GDP per capita (thousand 2011 KRW)	0.0964	0.0402

Note. The sunk entry cost parameter for a 6-screen theater is calibrated to 1,800 million KRW, which is quoted from a business report. All units of the other estimates are expressed in millions of 2011 constant KRW. Standard errors are calculated via subsampling.

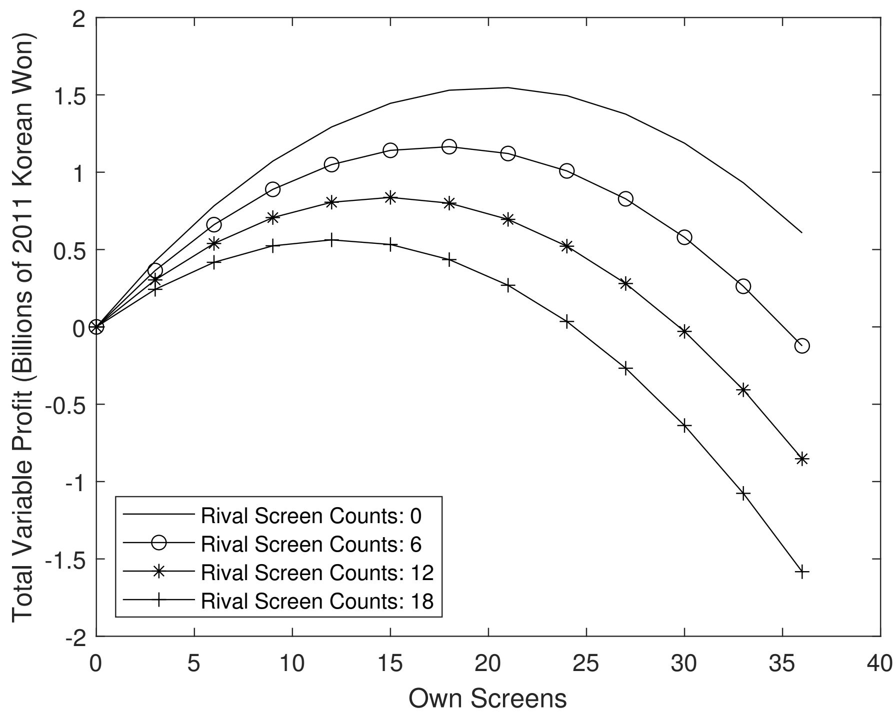

Figure 1.4. Chain's Variable Profits

Note. The figure displays chain's variable profits over the numbers of own screens and rival screens in a market with median population and median GDP per capita, calculated using the estimated parameters (Table 1.10). The variable profit function is concave in the number of own screens, suggesting that more screens do not necessarily translate into higher variable profits.

Fixed operating cost parameters: The estimates of the fixed operating cost (or baseline profit) parameters before and after 2014 are tabulated in the first and second panels in Table 1.11. There is considerable heterogeneity $\phi_i^{FC}(\mu_m)$ across chains and market types, reflecting the dispersion in market profitability. Furthermore, the positive sign of ϕ_R^{FC} suggests that the chains will pay higher fixed operating costs in markets with higher commercial property values. This finding is consistent with the fact that the rental rates of commercial buildings, which could account for considerable parts of operating fixed costs, tend to increase as commercial property values increase.

Table 1.11. Estimates of Fixed Operating and Sunk Entry Costs (In Millions of 2011 Korean Won)

	2010H1-2014H2		2015H1-2018H2	
	Estimates	SEs	Estimates	SEs
Fixed Cost Parameters:$\phi_i^{FC}(\mu_m)$				
CGV in market category 1	53.4994	5.0688	56.2970	5.3429
CGV in market category 2	6.2942	3.4670	-12.2008	2.9616
CGV in market category 3	-34.1934	5.5993	-52.6255	6.5957
Lottecinema in market category 1	49.9761	4.6929	45.7212	4.9224
Lottecinema in market category 2	9.6216	3.6917	-7.8857	3.0319
Lottecinema in market category 3	-43.6061	4.4018	-56.2455	5.8793
Megabox in market category 1	69.6435	5.7576	47.7503	4.9274
Megabox in market category 2	15.2166	3.5697	-10.7940	3.0788
Megabox in market category 3	-26.6932	4.5031	-64.4234	6.7935
Fixed Cost Parameters:ϕ_R^{FC}				
Property Values per m^2 (million 2011 KRW)	12.7179	1.6744	15.4969	1.5118
Sunk entry cost parameters				
3-screen (ϕ_3^{EC})	1573.375	43.9893	1318.671	102.1674
6-screen (ϕ_6^{EC})	*1800.00*	N/A	1217.902	60.5988
9-screen (ϕ_9^{EC})	2587.919	44.6247	1982.5209	115.6194
standard deviation (ν)	64.6319	3.3262	-	-

Note. This table displays the sunk entry cost parameters. The sunk entry cost parameter for a 6-screen theater is calibrated to 1,800 million KRW, which is quoted from a business report. All units of the other estimates are expressed in millions of 2011 constant KRW. Standard errors are calculated via subsampling.

Fixed operating cost (or baseline profit) parameters have decreased (increased) after 2014. These results suggest that the 2014 land-use regulatory reforms might have a positive effect on the underlying profitability, perhaps reflecting the positive spillover effect from the entry of other service businesses after the reforms. For instance, the per-screen fixed operating cost parameter for Megabox in market category 1 decreases by 46% from 69.64 million KRW to 47.75 million KRW; the baseline profit for CGV in market category 3 increases by 54% from 34.19 million KRW to 52.63 million KRW. Although the percentage changes in the fixed cost operating parameters after the reforms are substantial, changes in magnitudes are small compared to the per-screen entry cost parameter for 6-screen (300 million KRW). For instance, the per-screen fixed cost operating parameter for Megabox in market category 1 decreases by only 7.2% of the per-screen entry cost parameter for 6-screen ((69.64-47.75)/300). This change thus may not be large enough to rationalize the increases in the theater entry, suggesting a considerable reduction in the sunk entry costs.

Sunk entry cost parameters: The last panel in Table 1.11 displays the sunk entry cost parameters for early- and late-regimes. In periods before the regime shift, the sunk entry cost structure exhibits economies of scale: the average *per-screen* entry cost declines as a chain opens a larger-scaled theater. Thus, a 9-screen is the minimum efficient entry scale before the reforms. After the shift, the average *per-screen* entry costs for 3-, 6-, and 9-screen theaters decreases by 14% (84 million KRW), 32% (97 million KRW), and 25% (67 million KRW) respectively, and thus a 6-screen becomes the minimum efficient entry scale. This disproportionate shift increases the relative benefit of opening a 6-screen theater to other scales, which is characterized in equations (1.9) and (1.10), leading the chains to open a theater more frequently and more likely to choose the scale of 6-screen when opening a theater.

The disproportionate changes in the *per-screen* sunk entry cost schedule do not imply that the *total* sunk entry costs for 6-screen theaters decrease more than those for other scales. After the reforms, the total sunk entry costs for 3-, 6-, and 9-screen theaters have declined from 1,572M KRW, 1,800M KRW, and 2,583M KRW to 1,317M KRW, 1,217M KRW, and 1,982M KRW, respectively. These decreases indicate that the reforms actually have decreased the total sunk entry costs for 6- and 9-screen theaters equally by 600M KRW, even though 6-screen In contrast, the total sunk entry costs for 3-screen theaters have decreased by smaller amounts of 250M KRW. One possible explanation for the cost advantage for larger-scaled theaters is that the Amendment to the Building Act indeed relaxed restrictions on the maximum height of a building, thereby benefiting chains with cheaper economic costs for constructing a larger commercial property.

Assessing the relevance of the model and calibration: Using the estimated parameters of the variable profit function and fixed operating costs, I can calculate the operating margins of each chain and compare them with the actual margins in the chains' financial statement. In doing so, I can assess the relevance of the structural model and calibration. Figure 1.5 plots the realized annual operating margins for CGV and the predicted counterparts implied by the structural parameter estimates and the estimated CCPs. According to the financial statement of CGV from 2010 to 2018, the average operating profit margin at CGV is 8.4%. The average CCP-predicted operating profit margins over the same periods is 7.10%. Furthermore, as shown in Figure 1.5, the model predicts the downward trend in operating profit margins. Given that the estimated profits are inferred without exploiting any direct observation of theater-level revenues or operating profits, these findings support the validity of the model and calibration.

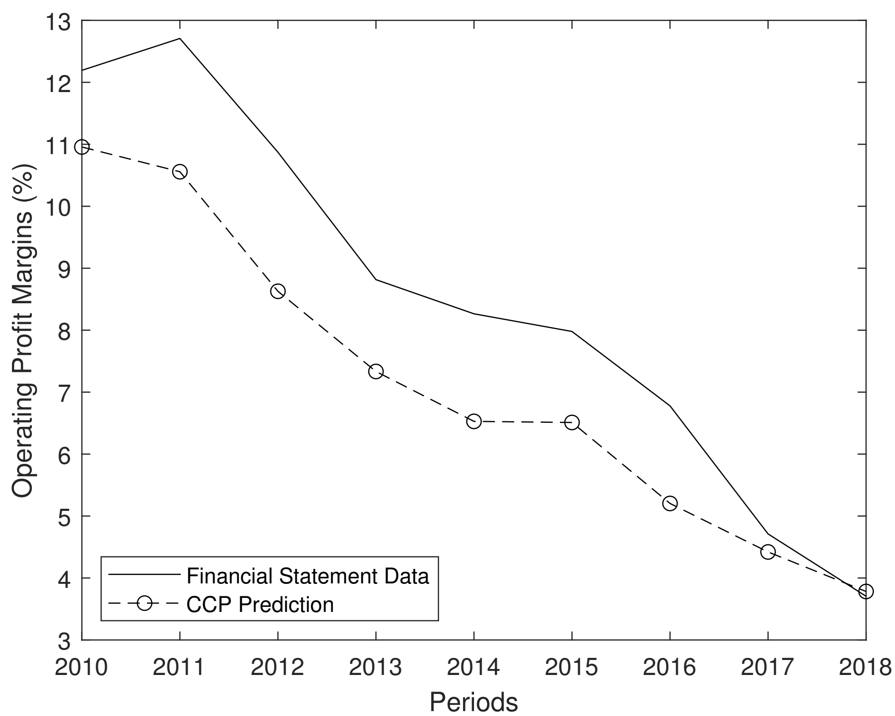

Figure 1.5. Trend in Operating Margins: CGV

Note 1. Model-implied annual operating profit margins are calculated using the estimated parameters (Tables 1.10 and 1.11) and the estimated conditional choice probabilities (Table 1.6). The predicted operating profit margins are obtained by averaging 500 simulations.

Note 2. Realized annual operating profit margins of CGV are downloaded from Repository of Korea's Corporate Filings, DART, in February 2022.

1.6 Counterfactual Analysis

This section explores the economic implications of the reduction in the *per-screen* sunk entry costs resulting from the land-use regulatory reforms. Following the literature standard (Ryan (2012), Dunne et al. (2013), and Kalouptsidi (2018)), I employ the estimated reduction in the sunk cost parameters (Table 1.11) as a guideline for a policy counterfactual.

The exercise in this section narrowly focuses on how the reduced sunk entry costs, in conjunction with strategic interactions among the chains, influence the chain's behaviors and industry net profits rather than measuring the overall impacts of the reforms. To do so, fixed operating costs, variable profit function, and transition matrices are held fixed at the post-reform estimates, and I solve the dynamic model with the pre-reform entry cost schedule. That is, I re-solve the model with $\vec{\phi}^{EC'} = (1.16\phi^{EC}_{3,2}, 1.47\phi^{EC}_{6,2}, 1.33\phi^{EC}_{9,2})$ for a counterfactual MPNE policy functions for each market type.[20] I then use the calculated counterfactual MPNE policy function to simulate the market structure dynamics 2,000 times and average them for each municipality. I compare the resulting dynamics to those implied by the estimated CCPs for periods after the reforms following Arcidiacono et al. (2016). Specifically, I measure the effects as $\Delta Q = \frac{Q(\vec{\phi}^{EC}_2) - Q(\vec{\phi}^{EC'})}{Q(\vec{\phi}^{EC'})}$, where $Q(.)$ is a counterfactual market structure: the number of all movie theaters, 3-screen, 6-screen, and 9-screen movie theaters in the industry.

Table 1.12 tabulates counterfactual changes in market composition for years 1, 3, 5, and 7. I particularly focus on changes in the number of theaters and proportions of 3-screen, 6-screen, and 9-screen theaters. The top panel shows that the reduced sunk entry costs raise the number of theaters in the industry. The number of theaters increases by 7.51% immediately. In addition, the number of theaters gradually increases over time. After seven years, the number of theaters is higher by 21.04%.

A key finding is that the reduction in sunk entry costs shifts the theater size distribu-

[20]Specifically, following Igami and Yang (2016), I parameterize the MPNE CCPs and iterate the parameters until the implied CCPs for the three chains are mutually best responses to each other in the spirit of Pakes and McGuire (1994). As discussed in Igami and Yang (2016), a dynamic oligopoly model of chain-store entry can possess multiple equilibria. However, without using a state-of-art algorithm, finding the possible equilibria is infeasible. In addition, this task is beyond the scope of this chapter. The reported results in this section are based on an MPNE that the proposed algorithm has encountered. The results thus only suggest the existence of an MPNE in which the main qualitative message in this section arises and do not guarantee the non-existence of other equilibria. An analogous argument of Suzuki (2013) can be applied to my setting to address a concern about the presence of an equilibrium whose qualitative implications are considerably different from my finding. Since the chains' theater size decisions are strategic substitutes, the industry's total numbers of mini-, mid-, and mega-plex theaters might be similar across equilibria, which implies a similar effect on industry profits and costs.

Table 1.12. Reduced Sunk Entry Costs and Industry Composition

	Year			
	1	3	5	7
Changes in the number of movie theaters				
Percent	7.51	17.95	20.33	21.04
Changes in the number of 3-screen theaters				
Percent	-1.62	-7.11	-14.24	-20.29
Changes in the number of 6-screen theaters				
Percent	12.49	34.74	45.26	52.93
Changes in the number of 9-screen theaters				
Percent	5.15	8.97	6.79	3.58

Note. The table tabulates the percent and percentage-point differences in market structure variables between baseline and counterfactual MPNEs. The first stage CCPs for periods after 2015H1 are used as the baseline MPNE following Arcidiacono et al. (2016). The predicted differences are obtained by averaging 2,000 simulations.

tion toward mid-plex scales. This is mainly driven by the fact that 6-screen becomes the minimum entry scale after the reforms. Thus, the chains open more 6-screen movie theaters, resulting in a substantial increase in the proportions of 6-screen theaters and a reduction in the proportions of other theaters. The last three panels in Table 1.12 show that the number of 6-screen and 9-screen theaters in the industry are higher by 52.93% and 3.58% after seven years, respectively. In contrast, the number of 3-screen theaters in the industry decreases by 20.29% in response to the changes in sunk cost schedules. As opening a 6-screen theater becomes cheaper, chains might find it is more profitable to close an existing 3-screen theater and open a new 6-screen theater.

I further investigate how these changes in industry composition translate into industry performance. Note that having knowledge of the parameter values and the corresponding MPNE policy functions, the NPVs of variable profit and costs are easily computed through forward-simulation. In this counterfactual exercise, I calculate changes in industry performance as the aggregate differences between counterfactual quantities under the two different cost structures:

$$\Delta\Pi = \frac{\sum_i \sum_m \left(\Pi_i(s_m; \vec{\phi}_2^{EC}) - \Pi_i(s_m; \vec{\phi}^{EC'}) \right)}{\sum_i \sum_m \Pi_i(s_m; \vec{\phi}^{EC'})},$$

where $\Pi_i(s_m; \vec{\phi}^{EC'})$ and $\Pi_i(s_m; \vec{\phi}_2^{EC})$ are counterfactual quantities evaluated at market state s_m under pre-reform and post-reform cost structures, respectively: NPV of net profit (chain value), NPV of variable profit, NPV of fixed costs, NPV of sunk costs.

Table 1.13 reports the impact of a disproportionate reduction in the average *per-screen* entry costs on chain value and the NPV of variable profit, fixed operating costs, and sunk entry costs. As displayed in the first panel, the lower sunk entry costs reduce the total chain values by 5.60% (77.35 billion KRW). The loss of industry net profits primarily comes from tougher competition. The second panel shows industry variable profit does not change, suggesting that additional theaters make their profit primarily by stealing business from incumbents, not expanding the market. As shown in Figure 1.4, more screens can result in a reduction in the industry variable profits. Thus, the shift of the theater size distribution toward mid- and mega-plex scales translates into less variable profits at the industry level.

No surprisingly, the third panel of Table 1.13 shows that a substantial increase in theaters, particularly 6-screen theaters, incur much higher fixed operating costs by 14.59% (367.26 billion KRW), reducing industry operating profits substantially. In addition, as shown in the last panel, even though the three chains pay less sunk entry costs, the total expenses on the sunk costs decreases only by 12.53% (95.68 billion KRW) as the chains open larger-sized movie theaters in response to the disproportionate reduction in the sunk costs. These savings thus are not sufficient to compensate for the substantial decreases in operating profits, resulting in a reduction in net profits. Overall, the reduced sunk entry costs engender competition externalities in the industry.

Although industry net profits decrease substantially, not all three chains experience the loss of their net profits. Following the reduction in sunk entry costs, the net profit of Megabox increased by 16% (57.31 billion KRW) at the expense of the other two chains. Since Megabox had the smallest market share of theaters and screens in 2015H1, the reduction in sunk entry costs provides it with an opportunity for expansion. Specifically, Megabox has a larger pool of business stealing while being less concerned about profit cannibalization. Indeed, as shown in the second panel in Table 1.13, the other two chains make much fewer variable profits due to tougher competition, and their loss is transferred to the variable profits of Megbox. Thus, there is almost no change in total industry variable profits. Megabox expands its business more rapidly, paying more expenses on fixed operating and sunk entry costs. Thus, the industry's payments on fixed costs increase, and those on sunk costs do not decrease as much to compensate for increases in fixed costs.

Table 1.13. Reduced Sunk Entry Costs and Industry Performance

	Percent	billions in KRW
Δ NPV of net profits (Chain value)		
Industry Total	-5.60	-77.35
CGV	-16.07	-81.68
Lotte Cinema	-10.25	-52.98
Megabox	16.06	57.31
Δ NPV of variable profits		
Industry Total	-0.26	-10.79
CGV	-3.39	-57.57
Lotte Cinema	-23.76	-395.61
Megabox	59.00	442.39
Δ NPV of fixed operating costs		
Industry Total	14.59	367.26
CGV	11.96	134.65
Lotte Cinema	-13.58	-137.43
Megabox	97.62	370.04
Δ NPV of sunk entry costs∗		
Industry Total	-12.53	-95.68
CGV	-15.23	-42.65
Lotte Cinema	-44.81	-149.11
Megabox	63.67	96.08

Note 1. All the Net Present Values (NPV) are evaluated at the observed state in 2015H1.
Note 2. Caculated by excluding the NPV of expected scrap shocks $\mathbb{E}(\varepsilon|d<0,s)$.

Are the resulting welfare penalty to the chains indeed socially undesirable? Despite a considerable loss of industry net profits, consumers may derive welfare gains from more movie theaters in the market. For example, new movie theaters provide consumers with easier access to the theaters, and thus the consumer demand for moviegoing can increase, improving consumer welfare. However, the aggregate trend in demand for moviegoing in South Korea suggests that such a welfare-enhancing channel may not be the case. Figure 1.6 shows that the number of movie attendees began to grow more slowly after 2014, indicating that the consumer welfare gains from easier access to movie theaters are expected to be limited in the current empirical setting.

Abstracting away the chain's theater scale decision influences how researchers interpret

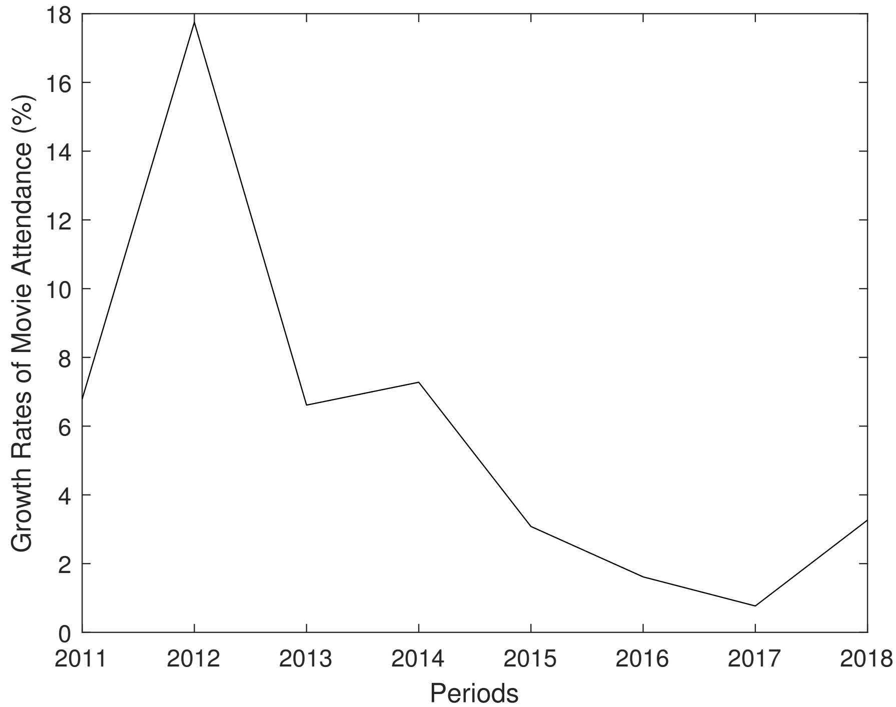

Figure 1.6. Growth Rates of Movie Attendance

Note. The figure depicts the time series of the annual growth rates of movie attendance.

Source. Korea Film Council (downloaded in December 2021).

the impacts of the reduced sunk entry costs. Table 1.14 displays the industry outcomes under the model without the chain's theater scale decision.[21] When researchers ignore the theater scale decision, they miss the shift of the industry screen distribution toward mid-plex scales. Such a miss in turn results in (i) under-predictions over increases in fixed operating costs and (ii) over-predictions over savings from the reduced sunk entry costs as researchers predict the increases by merely comparing the number of theaters. The third panel in Table 1.14 indeed confirms this conjecture: the restricted model predicts a mild increase of 2.77% (120.83 billion KRW) in industry fixed operating costs, which is 66% lower than those predicted by the baseline model. In addition, the restricted model predicts that the inudstry saves 23.1% of resource uses on sunk entry costs (-169.95 billion KRW) due to the reduction in sunk entry costs. Thus, additional resource uses on fixed operating costs are outweighed by the savings from the reduced sunk entry costs, resulting in increases of 27.3% in industry net profit.

[21] The estimation results of the restricted model are reported in Appendix A.3.

Table 1.14. When Screen Count Choices Are Ignored

	Percent	billions in KRW
Δ NPV of net profits (Chain value)		
Industry Total	27.3	311.51
CGV	25.9	129.58
Lotte Cinema	15.3	64.96
Megabox	47.1	137.02
Δ NPV of variable profits		
Industry Total	-0.00	-0.908
CGV	-4.24	-100.31
Lotte Cinema	0.71	12.78
Megabox	5.05	86.62
Δ NPV of fixed operating costs		
Industry Total	2.77	120.83
CGV	-3.21	-56.22
Lotte Cinema	4.08	55.24
Megabox	9.77	121.33
Δ NPV of sunk entry costs∗		
Industry Total	-23.1	-169.95
CGV	-5.50	-11.52
Lotte Cinema	-28.9	-64.20
Megabox	-30.9	-94.23

Note 1. All the Net Present Values (NPV) are evaluated at the observed state in 2015H1.
Note 2. * Caculated by excluding the NPV of expected scrap shocks $\mathbb{E}(\varepsilon|d < 0, s)$.

1.7 Conclusion

Despite the prominence of industries where entrants are heterogeneous in the scale of operation, studies on the entrant's scale decision are limited. This chapter has empirically investigated the implications of such a size decision upon entry with a focus on the role of scale-dependent sunk entry costs. In particular, I studied how the entrant's scale decision, in conjunction with lower sunk costs, shapes market structure and the industry's profit and expenditures.

Employing the South Korean cinema industry as an empirical case, I have estimated the dynamic game in which sunk entry costs vary with the scale, the number of screens, of theater openings. I found that sunk entry costs shape the optimal scale of a theater opening since post-entry screen adjustments are almost infeasible. Regarding the 2014 land-use regulatory reform measure and the following amendments as a reduction in sunk entry costs, I have recognized the regulatory regime shift favored mid-plex theaters with a greater *per-screen* sunk-cost advantage, expanding the number of mid-size theaters, which were defined as theaters with 5-7 screens, across South Korea. Simulation exercise has established that the shift of screen distribution toward mid-plex scales engenders a substantial increase in fixed operating costs. In contrast, I have found that the model without the scale decisions did not capture the shift of screen distribution, underpredicting an increase in fixed operating costs.

Chapter 2

The Differential Effect of Exporting on Input Productivities

2.1 Introduction

[1] Many empirical studies document that exporting raises the firm-level future productivity, which is oftentimes labeled 'learning-by-exporting'.[2] Firms who enter the export market can improve their productivity through technical support from trading partners, adopting a newly innovated technology abroad, or upgrading product quality. Previous studies confirm the productivity effect of exporting by documenting that exporting raises the firm's total factor productivity (TFP). However, the papers do not consider the possibility that such a mechanism could enhance the firm's productivities in a biased way: a particular factor-augmenting productivity increases more than others in response to the past export experience. The goals of this chapter are to (i) provide micro evidence on biased productivity gains from exporting in the context of skilled and unskilled labor-augmenting productivities and (ii) quantify the contribution of biased gains to the differences in skill intensity (skilled-to-unskilled ratios) between exporters and non-exporters.

Exploring the bias in productivity gains from exposure to the export market is important to understand how the exposure shapes the differences in input allocation between exporters and non-exporters. Suppose exporting raises a particular input-augmenting productivity more than others. All else equal, exporters and non-exporters

[1] I am grateful to Mark Roberts and James Tybout for providing the Colombian manufacturing survey data used in this chapter.

[2] See Tybout (2003) and Greenaway and Kneller (2007) for the review of literature on the positive productivity effect of exporting at the firm level.

differ in relative productivity. Due to the different relative productivity, exporters would have a higher marginal product of the input whose productivity increases more from exporting. Thus, exporters demand that input more (less) than non-exporters when inputs are gross substitutes (complements). In this way, exporters and non-exporters make different input allocation decisions. In this way, exploring whether productivity gains from exporting are biased has a direct implication to input allocation differentials between exporters and non-exporters.

My motivation for a focus on skilled and unskilled labor-augmenting productivities improvements from exporting comes from the two stylized facts in the Colombian apparel industry. First, plant-level skilled-to-unskilled ratios largely deviate from predicted ratios by a model with neutral productivity alone. Such large deviations suggest the existence of skilled and unskilled labor-augmenting productivities within a simple framework with CES production function. Second, I further document that large deviations are strongly connected to export status in the previous period even after controlling for plant-level fixed effects and the possible persistence of the deviations. The result suggests evidence that exporting raises particular productivity more than the other- biased productivity gains from exporting.

This chapter measures the effects of exporting on skilled and unskilled labor-augmenting productivities as well as the elasticity of substitutions between skilled and unskilled workers. I document that skilled labor-augmenting productivity increases a 7.2-percentage pooint more than the unskilled one in response to export market exposure. The estimated elasticity of substitutions between skilled and unskilled workers is 2.6, which indicates skilled and unskilled workers are gross substitutes, which echoes the findings in the labor economics literature (Acemoglu and Autor (2011)). Thus, all else equal, exporters become more skill-intensive than non-exporters. I further show that biased gains from exporting are quantitatively important in shaping the differences in skill intensity between exporters and non-exporters in the Colombian apparel industry.

I recover skilled and unskilled labor-augmenting productivities using data on skilled and unskilled wage rates and the number of skilled and unskilled workers. Observing expenditures and quantities for skilled and unskilled workers separately establishes the identifiability of skilled and unskilled labor-augmenting productivities. The optimality conditions of the plant's optimization problem show that skilled-to-unskilled expenditure ratios depend on skilled-to-unskilled worker ratios and relative productivity. Since I can observe the expenditure ratios and the worker ratios, I recover the relative skilled (or unskilled) productivity through the optimality conditions of the plant's optimization problem. I recover the remaining labor-augmenting productivity by inverting the first-order condition,[3] and then retrieve all the labor-augmenting productivities.

Since the bias of productivity gains from exporting toward a particular factor hinges on whether inputs of interest are substitutes or complements, the precise estimate of the substitution patterns between skilled and unskilled workers is crucial. Yet, the failure to control for input prices leads to downwardly biased estimates of the elasticity of substitutions between inputs (Grieco, Li, and Zhang (2016)), which generate an incorrect conclusion on the substitution patterns. Since the input prices are not observable in the data, I address this concern by leveraging the parametric inversion of the first-order conditions in the spirit of Grieco et al. (2016) and Grieco et al. (2022).

The empirical finding that export market exposure disproportionately improves skilled-labor augmenting productivity reflects the combined effect of several mechanisms proposed by the international trade literature. Exporters should serve consumers in foreign markets who prefer skill-intensive products (i.e., higher quality) than their domestic counterparts (Verhoogen (2008)). To meet such needs of foreign markets, exporters thus adopt advanced technology to upgrade their product quality (Lileeva and Trefler (2010) and Bustos (2011)). Reflecting the possibility that skilled workers have a comparative advantage in exploiting such technology (Yeaple (2005)), the measured firm-level skilled-labor augmenting productivity increases more than unskilled-labor augmenting productivity.

To quantify the relevance of skilled-biased productivity gains from exporting (skilled-biased learning-by-exporting), I simulate a counterfactual scenario in which skilled and unskilled-labor augmenting productivities increase equally in response to the past export status. By comparing the differences in skill intensity between exporters and non-exporters in real and counterfactual worlds, I find that the skilled-biased productivity gains explain 50 percent to 80 percent of the observed differences between exporters and non-exporters. In addition, I find that the skilled-biased productivity gains have a long-run impact on the differences in skill intensity between exporters and non-exporters due to the high persistence of skilled-labor augmenting productivity.

This chapter contributes to the strand of literature studying the link between firm-level export and the firm's future performance. Specifically, I extend this strand by

[3]This strategy is different from Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015) who use proxy variables such as investment or material expenditures to control for unobserved productivity. To follow, I need enough observations reporting positive investment. However, in the Colombian apparel industry, about 40 percent of observations report zero or negative investment. Thus, the investment policy function would not be invertible. Given this data feature, I exploit the parametric inversion of first-order conditions in the spirit of Doraszelski and Jaumandreu (2013).

providing micro evidence that productivity gains from exporting could be biased. Several recent empirical studies report the positive effect of exporting on firm-level productivity. [4] However, all these studies look at the relationship between past exporting experience and total factor productivity (TFP) and thus do not deliver the implication to the relationship between export status and future input allocations. I contribute to the literature by documenting that export status alters future input allocations via a skilled-biased learning-by-exporting channel.

This chapter is related to the recent two studies on the relationship between firm-level trade status and factor-augmenting productivities. Balat, Brambilla, and Sasaki (2016) show that exporters in Chile are more skilled labor efficient than non-exporters. Imbruno and Ketterer (2018) show manufacturing plants in Indonesia become more energy-efficient when they start importing foreign material goods within a reduced-form framework. My empirical results complement Balat et al. (2016) by further exploring the quantitative implication of the biased gains from exporting to the skill intensity differences between exporters and non-exporters. Besides, my work complements Imbruno and Ketterer (2018) by structurally recovering factor-augmenting productivities and then measuring their responses of them to export status in the previous period.

This chapter also joins the strand of literature that estimates factor-augmenting productivities. Though many studies in the productivity literature focus on measuring neutral productivity due to the scarcity of data, recent studies such as Doraszelski and Jaumandreu (2018), Zhang (2019), and Raval (2019) estimate factor-augmenting productivities by using the first-order conditions of the firm optimization problem. However, the methodology requires researchers to observe firm-level material prices to tease out labor-augmenting productivity from other factor-augmenting productivities. However, a widely used manufacturing survey typically does not record firm-level material prices and quantities separately. [5] My work thus complements these studies by augmenting the spirit of Grieco et al. (2016) so that a researcher can control for unobserved material prices and recover a particular factor-augmenting productivity such as skilled (or unskilled) labor-augmenting or energy-augmenting productivity.

The chapter is organized as follows. Section 2.2 describes the data and presents the motivating facts. Section 2.3 lays out the model providing the first-order conditions

[4] Examples are as follows: Aw et al. (2000) for Korean and Taiwanese manufacturers, Van Biesebroeck (2005) for African manufacturers, De Loecker (2007), De Loecker (2013) for Slovenian manufacturers, Aw et al. (2011) for Taiwanese electronic manufacturers, and Bai et al. (2017) for Chinese manufacturers

[5] For instance, widely used manufacturing datasets such as Chilean, Chinese, Colombian, and Slovenian manufacturing survey data record firm-level revenues and material expenditures. Few datasets, such as the Spanish or Indian manufacturing datasets, record output and material input prices.

used for identifying non-Hicks-neutral productivity. Section 2.4 describes the estimation strategy. Section 2.5 presents and discusses the empirical results. Section 2.6 conducts the counterfactual exercise to quantify the role of non-Hicks-neutral productivity gains from exporting in explaining the skilled labor demand of exporters. Section 2.7 concludes the chapter.

2.2 Data and Suggestive Evidence

2.2.1 Data

For the empirical analysis, I employ the Colombian manufacturing survey from the Departamento Administrativo Nacional de Estadistica (DANE), which spans from 1977 to 1991. This panel dataset allows me to track each manufacturing plant's detailed information about domestic and export sales, material expenditures, the number of workers, employee payments (salaries + benefits), investment, and capital stock. Since export sales are available for periods since 1981, I restrict my attention to periods from 1981 to 1991. For a more detailed discussion of the data, refer to Roberts (1996).

The notable feature of the survey is that the surveyed plants report the number of workers and the corresponding payments by type of workers. This information allows me to measure the plant-level average wage rates for skilled workers and unskilled workers, which are crucial for the identification of skilled and unskilled labor-augmenting productivities. I measure the number of skilled workers as the sum of variables labeled as "management", "technicians", and "skilled workers". Similarly, I measure the number of unskilled workers as variables labeled as "unskilled workers". I measure the total payments to skilled and unskilled workers as the sum of the corresponding payments to each category. The wage rates for skilled workers are computed by the ratio of the total payments to the number of workers. The wage rates for unskilled workers are measured by the same manner.

I particularly focus on the plants in the apparel industry who operated at least two years consecutively. The choice of the industry reflects several considerations. First, in the apparel industry, logged skilled-to-unskilled ratios and logged capital stock are weakly correlated (0.08). This features capital-skill complementarity channel would not be enough to explain the relative skilled labor demand of the plants in this industry. Thus, I can focus on the role of skilled and unskilled labor-augmenting productivities in explaining the relative skilled labor demand. Second, during the sample period, when a plant participates in trade activities, it usually does exporting only. Hence, I can rule out the possibility that increases in productivities due to exporting are driven by the spurious correlation with productivities gains from importing.

To simplify empirical analysis, I restrict the sample to plants who always hired both skilled and unskilled workers during the sample period. That is, I assume away any non-convex costs associated with labor choices, and treat skilled and unskilled workers as flexibly adjusted inputs. By doing so, I can resort to first order conditions with respect to skilled and unskilled workers to recover skilled and unskilled labor-augmenting productivities. This simplification is a reasonable starting point because of two reasons. First, of the sample observations, about nine percent of total reports either zero skilled workers or zero unskilled workers. Second, most exports in the Colombian apparel industry were driven by plants who hire skilled workers during the sample period. I clean the data following the way described by Roberts (1996). The cleaning process leaves 7,620 plant-year observations in the apparel industry.

2.2.2 Facts

This section describes motivating reduced form evidence. In Section 2.2.2.1, I document that the observed skilled-to-unskilled ratios in the data largely deviate from the skilled-to-unskilled ratios predicted by the model without skilled and unskilled labor-augmenting productivities. If a production function of plants is described by only neutral productivity, variations in relative wage rates for skilled workers can explain most of variations in skilled-to-unskilled ratios. Therefore, if the deviations are significantly large, it suggests the existence of skilled and unskilled labor-augmenting productivities. In Section 2.2.2.2, I show that those deviations are tightly linked to plants' export status in the previous period. In simple CES framework, the deviations are proxy for relative productivity of unskilled workers scaled up by the elasticity of substitution. If exporting raises a particular productivity higher than the other, the deviations are more likely to be explained by plants' export status in the previous period.

2.2.2.1 Evidence of Factor-augmenting Productivities

To illustrate the intuition for why deviations from prediction by first order conditions are evidence for skilled and unskilled labor productivities, I consider a widely accepted CES production function. Assume that skilled and unskilled workers are flexibly chosen by plants, skilled-to-unskilled ratios and the relative wage rates are in the following simple log-linear relationship.

$$\ln \frac{L_{jt}^S}{L_{jt}^U} = -\sigma \ln \frac{W_{jt}^S}{W_{jt}^U} + (1-\sigma)(a_{jt}^U - a_{jt}^S). \tag{2.1}$$

Here, σ is the elasticity of substitution between skilled and unskilled workers. L_{jt}^S and L_{jt}^U are the number of skilled and unskilled workers, respectively. W_{jt}^S and W_{jt}^U are the corresponding wage rates. Finally a_{jt}^S, a_{jt}^U are skilled and unskilled labor-augmenting productivities, respectively. If plant-level productivity is neutral, the last term in equation (2.1) will be omitted and thus the skilled-to-unskilled ratios are entirely explained by variations in relative wage rates. Thus, if I observe that the relative wage rates can explain only a small portion of skilled-to-unskilled ratios, I could use that result as evidence of skilled and unskilled labor-augmenting productivities.

Table 2.1 displays a series of regression of logged skilled-to-unskilled ratios on logged relative wage rates. I also employ year dummies, ownership dummies, location dummies, logged capital, and its squared as control covariates. I include the logged capital to rule out the possibility that capital-skill complementarity plays a dominant role in explaining the skilled labor demand in the Colombian apparel industry. Regression results suggest strong evidence of skilled and unskilled labor-augmenting productivities. From the sixth column of Table 2.1, we see that logged relative wage rates and all the covariates can only explain at most 8.4% of the variations in skilled-to-unskilled ratios.

Figure 2.1 further provides evidence of skilled and unskilled labor-augmenting productivities. In Figure 2.1, I plot the skilled-to-unskilled ratios predicted by first order conditions and the data counterpart with the value of the year 1981 normalized to be one. Following Zhang (2019), I compute predicted skilled-to-unskilled ratios by using relative wage variations and the estimates of the elasticity of substitutions reported in Table 2.1. Note that while skilled-to-unskilled ratios increase by around 70%, the simulated ratios increase by only 20% during the sample period. This picture thus reinforces the argument that relative wage rates are insufficient to explain skilled-to-unskilled ratios, and indicate the evidence of skilled and unskilled labor-augmenting productivities.

2.2.2.2 Evidence of Biased Productivity Gains from Exporting

Let $\hat{\xi}_{jt}$ be the residuals from the regression in sixth column of Table 2.1. The residuals are capturing the deviations of skilled-to-unskilled ratios from the prediction by the model with only neutral productivity. Then by equation (2.1), the residuals $\hat{\xi}_{jt}$ are proxy for $(1-\sigma)(a_{jt}^U - a_{jt}^S)$. Thus, I can draw suggestive evidence of biased productivity gains

Table 2.1. Skilled-to-Unskilled Ratios and Relative Wage

	OLS	OLS	OLS	OLS	OLS	OLS	Panel FE
σ	0.2214	0.2193	0.2139	0.2602	0.2915	0.2955	0.2751
	(0.0276)	(0.0266)	(0.0276)	(0.0279)	(0.0285)	(0.0285)	(0.0337)
$\ln K_{jt}$					0.0532	−0.2730	−0.2854
					(0.007)	(0.0712)	(0.1507)
$(\ln K_{jt})^2$						0.0117	0.0110
						(0.0026)	(0.0055)
Constant	✓	✓	✓	✓	✓	✓	✓
Year		✓	✓	✓	✓	✓	✓
Location			✓	✓	✓	✓	
Ownership				✓	✓	✓	✓
R^2	0.0105	0.0248	0.0471	0.0744	0.0818	0.0842	0.0462

Note. The table displays the estimates of the regression equation $\ln \frac{L^S_{jt}}{L^U_{jt}} = \delta_0 + \delta_j + \delta_t + \beta_1 \ln K_{jt} + \beta_2(\ln K_{jt})^2 - \sigma \ln \frac{W^S_{jt}}{W^U_{jt}} + \xi_{jt}$. Robust standard errors for OLS and plant-clustered standard errors for FE are in parenthesis. R^2 values for panel FE model are overall R^2.

from exporting by regressing $\hat{\xi}_{jt}$ on lagged indicator of exporting. If exporting raises both productivities equally, the improvement of a^S_{jt} due to exporting would cancel out the improvement of a^U_{jt} due to exporting. In this case, we would not see the significant link between the residuals and lagged indicator of exporting.

However, regressing $\hat{\xi}_{jt}$ on lagged indicator of exporting through OLS would be clouded by endogeneity of exporting decision: It is probable that plants whose productivities are combined in a way of generating higher skilled-to-unskilled ratios (higher $\hat{\xi}_{jt}$) would more likely to enter the foreign market. In this case, OLS would be upwardly biased. To bypass the endogeneity issue, I employ a dynamic panel approach which controls for plant-level unobserved fixed effects and a lagged dependent variable (Arellano and Bond (1991) and Blundell and Bond (1998)).

Table 2.2 provides evidence for biased productivity gains from exporting. In Table 2.2, I report the estimation results from OLS, Arellano and Bond (1991), and Blundell and Bond (1998). I find that even after controlling for unobserved plant-level fixed effects and $\hat{\xi}_{j,t-1}$, exporting is associated with the residuals which are proxy for $(1-\sigma)(a^U_{jt} - a^S_{jt})$. The estimates of the coefficient to lagged indicator of exporting drawn from Arellano and Bond (1991), and Blundell and Bond (1998) are statistically significant at 10% and 5% significance levels, respectively. Furthermore, exporting is positively correlated with $\hat{\xi}_{jt}$. These results indicate that it is more likely that productivity gains from exporting is

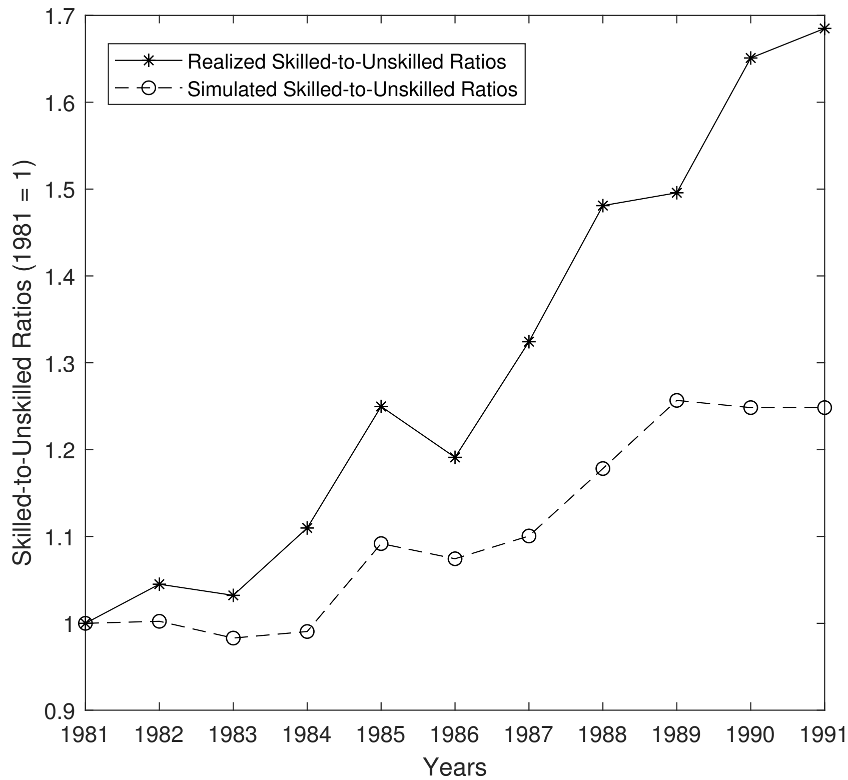

Figure 2.1. Skilled-to-Unskilled Ratios: Data vs. Simulated

Note. The Figure plots the time evolution of data and simulated skilled-to-unskilled ratios. The solid line displays the realized skilled-to-unskilled ratios and the dashed line displays the simulated counterpart with $\sigma = 0.2955$.

non-neutral and favor skilled over unskilled workers.

Table 2.2. Exporting and Non-neutral Productivities

	OLS	Arellano-Bond	Blundell-Bond
Lagged Export	0.1401	0.0805	0.1001
	(0.0428)	(0.0485)	(0.0503)
$\hat{\xi}_{j,t-1}$		0.5650	0.6679
		(0.0519)	(0.0356)

Note. The table reports the estimation results of OLS, Arellano and Bond (1991) dynamic panel approach, and Blundell and Bond (1998) dynamic panel approach. Robust standard errors are in parenthesis. Dependent variable is the residuals from the regression in Table 2.1, namely $\hat{\xi}_{jt}$.

Figure 2.2 also suggests evidence of biased productivity gains from exporting. Note that, as Table 2.2 indicates, exporters would gain skill-biased productivity and thus their skilled-to-unskilled ratios become more deviated from the predicted ratios by the model without non-neutral productivities. Figure 2.2 confirms this conjecture. In Figure 2.2, I display the time evolution of the deviations obtained in Figure 2.1 for exporters and non-exporters. While the deviations of exporters have increased by five to nine times during the sample period, the non-exporters' counterpart have increased pretty moderately.

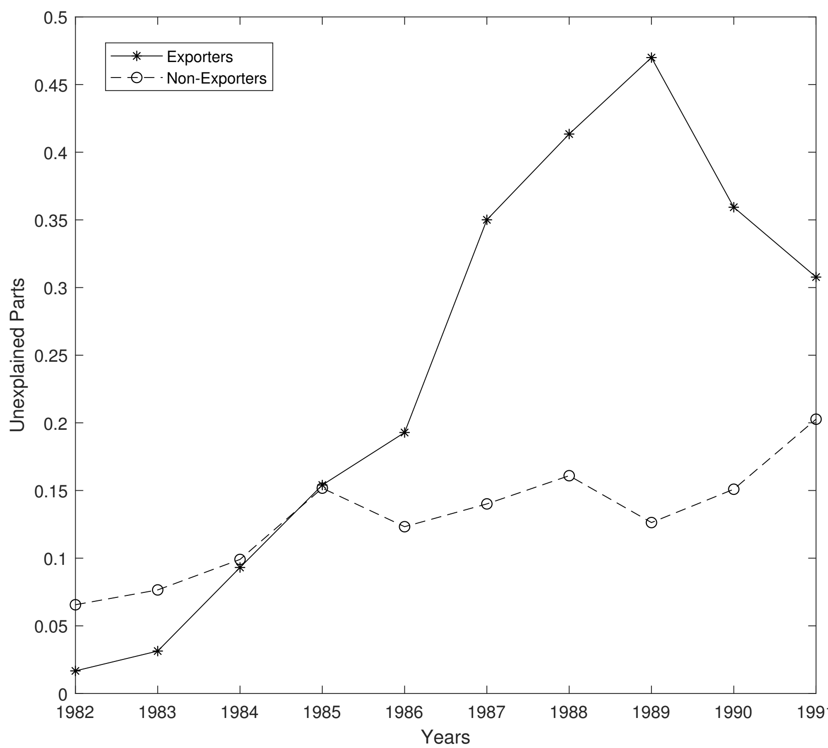

Figure 2.2. Deviations: Exporter vs. Non-exporters

Note. The Figure plots the time evolution of the deviations computed in Figure 2.1 for exporters and non-exporters. The solid line displays the series for exporters and the dashed line displays the non-exporters counterparts.

Although the results in Table 2.2 and Figure 2.2 indicate that exporting raises productivities biased toward skilled workers, I cannot answer the question which labor-augmenting productivity improves more than the other. To answer this question, I need to estimate the elasticity of substitutions between skilled and unskilled workers, and this motivates the structural model discussed in the next section.

2.3 Model

In this section, I model plants' production and input choice decisions. Specifically, I embed factor-augmenting productivities (Doraszelski and Jaumandreu (2018)) to the model of firms that can serve multiple markets (Grieco et al. (2022)). In Section 2.3.1, I lay out the model ingredients including demand and production functions, and transition process of skilled and unskilled labor-augmenting productivities. Section 2.3.2 describes plants' optimization problem. The optimality conditions from the optimization problem will be employed to identify skilled and unskilled labor-augmenting productivities along with the elasticity of substitution between skilled and unskilled workers.

2.3.1 Model Ingredients

2.3.1.1 Demand and Production

At the beginning of period t, plant j faces constant elastic inverse demand curves in domestic (D) and export (X) markets, which are assumed to be monopolistically competitive: $P_{jt}^m = \kappa_m \Phi_t^m (Q_{jt}^m)^{1/\eta_m}$, where $m = D, X$. Here, Q_{jt}^m is the quantity demanded in market m and P_{jt}^m is the price firm j set in market m at time t. I allow for different demand elasticities to capture the possibility that plants have different market power in the domestic (η_D) and export markets (η_X). Φ_t^m is an aggregate time-variant demand shifter in market m. Finally κ_m captures time-invariant size of market m. I normalize size of the domestic market to one and let $\kappa = \kappa_X$. Thus, κ essentially captures the time-invariant size difference between the domestic and export markets.

Plant j produces output $Q_{jt} = Q_{jt}^D + e_{jt} Q_{jt}^X$ through the following CES function nesting a CES aggregation of skilled and unskilled workers with factor-augmenting productivities.

$$Q_{jt} = [\alpha_L \tilde{L}_{jt}^\gamma + \alpha_M (\exp(a_{jt}^M) M_{jt})^\gamma + \alpha_K (\exp(a_{jt}^K) K_{jt})^\gamma]^{\frac{1}{\gamma}},$$
$$\tilde{L}_{jt} = [(\exp(a_{jt}^U) L_{jt}^U)^\rho + (\exp(a_{jt}^S) L_{jt}^S)^\rho]^{\frac{1}{\rho}},$$

where M_{jt} and K_{jt} are material and capital, respectively, and $\tilde{L}_{jt}$ is a composite basket of unskilled worker L_{jt}^U and skilled workers L_{jt}^S. The elasticity of substitutions among labor, material, and capital is governed by γ, and the elasticity of substitutions between skilled and unskilled workers is governed by ρ. α_L, α_M, and α_K are the distribution parameters for labor, material, and capital. a_{jt}^f is a factor f-augmenting productivity, where $f = S, U, L, K$.

I cannot identify all the four factor-augmenting productivities together because the Colombian manufacturing survey does not record plant-level output and material prices which can be other independent variations to identify material- and capital-augmenting productivities. Thus, in practice, for the sake of identification, I assume that skilled labor-, material- and capital-augmenting productivities are the same: $a^S_{jt} = a^M_{jt} = a^K_{jt}$. Then, the production function that I estimate is

$$Q_{jt} = \exp(a^S_{jt})[\alpha_L L^\gamma_{jt} + \alpha_M M^\gamma_{jt} + \alpha_K K^\gamma_{jt}]^{\frac{1}{\gamma}}, \tag{2.2}$$

$$\tilde{L}_{jt} = [(\exp(\tilde{a}^U_{jt}) L^U_{jt})^\rho + (L^S_{jt})^\rho]^{\frac{1}{\rho}}, \tag{2.3}$$

where $\tilde{a}^U_{jt} = a^U_{jt} - a^S_{jt}$ is relative unskilled labor-augmenting productivity.

2.3.1.2 Transition Process

I model the transition process of skilled and unskilled labor-augmenting productivities as well as logged material prices p^m_{jt} as the following controlled Markov process:

$$\begin{bmatrix} a^S_{jt} \\ a^U_{jt} \\ p^m_{jt} \end{bmatrix} = g\left(\begin{bmatrix} a^S_{j,t-1} \\ a^U_{j,t-1} \\ p^m_{j,t-1} \end{bmatrix} \right) + \begin{bmatrix} g^s_e \\ g^u_e \\ g^m_e \end{bmatrix} e_{j,t-1} + \begin{bmatrix} \varepsilon^s_{jt} \\ \varepsilon^u_{jt} \\ \varepsilon^m_{jt} \end{bmatrix}, \tag{2.4}$$

where $e_{j,t-1}$ is an indicator whether or not the firm j was an exporter at time $t-1$, ε^s_{jt}, ε^u_{jt}, and ε^m_{jt} are unexpected productivity shocks which are $i.i.d.$ across firms and over time. The specification incorporates empirical findings that exporting raises plant's future productivity (Van Biesebroeck (2005), De Loecker (2007), Aw et al. (2011), De Loecker (2013)). These productivity gains could be due to technical support from a trading partner, technology adoption, or access to knowledge on product innovation, quality upgrading, or the preference of foreign consumers. The productivity changes induced by these activities can improve a particular factor-augmenting productivity more than the others. This biased change is captured by the differences between g^s_e and g^u_e. Allowing material prices to have impact on the other productivities is motivated by empirical findings of Kugler and Verhoogen (2012) that material input quality complements plant/firm-level productivity. Here, based on the empirical findings that more qualified materials are more expensive , I use the recovered material prices as measure of material input quality.

2.3.2 Plant Optimization

At the beginning of period t, plants take their productivities (a^S_{jt}, a^U_{jt}), capital K_{jt}, export status e_{jt}, wages and material prices $(W^S_{jt}, W^U_{jt}, P^M_{jt})$, and aggregate demand shifters (Φ^D_t, Φ^X_t) as their state variables. Plants then optimally choose $(L^S_{jt}, L^U_{jt}, M_{jt})$, allocate (Q^D_{jt}, Q^X_{jt}), and decide whether or not to export in the next period $(e_{j,t+1})$ to maximize their expected discounted sum of future operating profits. Let Σ_{jt} be a state vector of the firm j at the beginning of the period t and $V(.)$ denote the value function. The corresponding Bellman equation is

$$
\begin{aligned}
V(\Sigma_{jt}) = \max_{L^U_{jt}, L^S_{jt}, M_{jt}, Q^D_{jt}, Q^X_{jt}, e_{j,t+1}} & \{P^D_{jt}Q^D_{jt} + e_{jt}P^X_{jt}Q^X_{jt} - W^U_{jt}L^U_{jt} - W^S_{jt}L^S_{jt} - P^M_{jt}M_{jt} \\
& - C(e_{jt}, e_{j,t+1}) + \beta E(V(\Sigma_{j,t+1})|\Sigma_{jt}, e_{j,t+1})\}, \\
& \text{subject to (2.2), (2.3), (2.4)}, Q^D_{jt} + e_{jt}Q^X_{jt} = Q_{jt}, \\
& \text{and } P^D_{jt} = \Phi^D_t (Q^D_{jt})^{1/\eta_D}, P^X_{jt} = \kappa \Phi^X_t (Q^X_{jt})^{1/\eta_X}
\end{aligned} \tag{2.5}
$$

where $C(.,.)$ is the non-convex export cost. The problem provides the optimality conditions concerning inputs $(L^S_{jt}, L^U_{jt}, M_{jt})$. These conditions are employed to identify skilled and unskilled labor-augmenting productivities while controlling for unobserved material prices.

2.4 Estimation

Following Grieco et al. (2022), I estimate the model through two-stage approach. In the first stage, I estimate the demand and production function parameters and recover skilled and unskilled labor-augmenting productivities. I then estimate the transition process parameters and document which productivity increases more in response to export status in the previous period.

2.4.1 Stage 1. Demand and Production Parameters

In this section, I recover the demand elasticities in both markets (η_D, η_X), the export market size κ, aggregate market demand shifters (Φ^D_t, Φ^X_t), and the production function parameters $(\gamma, \rho, \alpha_L, \alpha_M, \alpha_K)$ using the data on plant-level revenues, input and input expenditure. Throughout this section, I assume that econometricians observe both domestic and export revenues (R^D_{jt}, R^X_{jt}) with measurement errors (u^D_{jt}, u^X_{jt}) and these measurement errors are unobserved to plants when they make decisions.

$$R_{jt}^D = \Phi_t^D (Q_{jt}^D)^{\frac{\eta_D+1}{\eta_D}} \exp(u_{jt}^D) \tag{2.6}$$

$$R_{jt}^X = \kappa \Phi_t^X (Q_{jt}^X)^{\frac{\eta_X+1}{\eta_X}} \exp(u_{jt}^X) \tag{2.7}$$

The main challenge of estimating the production function parameters is that I need control for three latent plant-year specific variables: skilled and unskilled labor-augmenting productivities, and material prices. Following Doraszelski and Jaumandreu (2013), Doraszelski and Jaumandreu (2018) and Grieco et al. (2016), I parametrically invert the first-order conditions of the short-run profit maximization problem in order to control for the unobservables. More detailed derivation appears in Appendix B.1.

I first recover the closed form equation mapping the observables to relative unskilled labor productivity $\tilde{a}_{jt}^U$. By taking the ratios of the first-order conditions with respect to skilled labor and unskilled labor, I arrive at

$$\tilde{a}_{jt}^U = \frac{1}{\rho} \ln \frac{E_{jt}^U}{E_{jt}^S} + \ln \frac{L_{jt}^S}{L_{jt}^U}, \tag{2.8}$$

where E_{jt}^U is $W_{jt}^U L_{jt}^U$ and $E_{jt}^S = W_{jt}^S L_{jt}^S$. Besides, by substituting this term back into (2.3), I represent L_{jt} as a closed form function of observed variables.

$$L_{jt} = (\frac{E_{jt}^L}{E_{jt}^S})^{\frac{1}{\rho}} L_{jt}^S, \tag{2.9}$$

where $E_{jt}^L = E_{jt}^S + E_{jt}^U$.

Using the first-order conditions concerning skilled labor and material, M_{jt} is also linear in L_{jt}^S.

$$M_{jt} = (\frac{\alpha_L}{\alpha_M} \frac{E_{jt}^M}{E_{jt}^L})^{\frac{1}{\gamma}} (\frac{E_{jt}^L}{E_{jt}^S})^{\frac{1}{\rho}} L_{jt}^S, \tag{2.10}$$

where $E_{jt}^M = P_{jt}^M M_{jt}$. Therefore, upon recovering the production function parameters, I retrieve the material inputs employed by plant j in period t.

Substituting (2.9) and (2.10) back into the domestic revenue equation, I arrive at the following estimating equation.

$$\ln R_{jt}^D = \ln \frac{\eta_D}{\eta_D + 1} + \ln [E_{jt}^M + E_{jt}^L (1 + \frac{\alpha_K}{\alpha_L} (\frac{K_{jt}}{L_{jt}^S})^{\gamma} (\frac{E_{jt}^S}{E_{jt}^L})^{\frac{\gamma}{\rho}})] + u_{jt}^D, \tag{2.11}$$

where u_{jt}^D is measurement errors to domestic revenues. To identify all the parameters, I need to impose restrictions on the distribution parameters. Equation (2.10), in conjunction with the normalization restriction that the geometric mean of inputs is one, provides a restriction for identification of α_M.

$$\frac{\alpha_M}{\alpha_L} = \frac{\bar{E}^M}{\bar{E}^L}(\frac{\bar{E}^L}{\bar{E}^S})^{\frac{\gamma}{\rho}},$$

where $\bar{E}$ refers to the geometric mean of expenditures. To identify α_K, I follow Grieco et al. (2016) and Grieco et al. (2022) and restrict the sum of distribution parameters to be one.

$$\alpha_L + \alpha_M + \alpha_K = 1$$

I estimate equation (2.11) through nonlinear least squared (NLLS) subject to the two additional restrictions using the observations serving the domestic market only.

The remaining parameters to be estimated are $(\eta_X, \kappa, \Phi_t^D, \Phi_t^X)$. Using from the first-order conditions concerning Q_{jt}^D and Q_{jt}^X, I derive the following linear relation between R_{jt}^D and R_{jt}^X

$$\ln R_{jt}^X = -\eta_X \ln \kappa + (\eta_X + 1) \ln (\frac{\eta_X}{\eta_D}\frac{\eta_D + 1}{\eta_X + 1}) + \frac{\eta_X + 1}{\eta_D + 1} \ln R_{jt}^D + \delta_t + \underbrace{u_{jt}^X - \frac{\eta_X + 1}{\eta_D + 1} u_{jt}^D}_{u_{jt}}, \tag{2.12}$$

where $\delta_t = (\eta_X + 1)[\frac{\eta_D}{\eta_D+1} \ln \Phi_t^D - \frac{\eta_X}{\eta_X+1} \ln \Phi_t^X]$. By construction, $\ln R_{jt}^D$ is correlated with error term u_{jt} in equation (2.12). I estimate the η_X, κ, and δ_t through generalized method of moments (GMM) with instrumental variables for $\ln R_{jt}^D$: $(\ln K_{jt}, \ln L_{jt}^U, \ln L_{jt}^S, \ln E_{jt})$. The instruments are valid given the assumption that plants do not observe u_{jt}^D and u_{jt}^X when making a decision on inputs.

I identify Φ_t^D by using the CES functional form: $\Phi_t^D = P_t^D (Q_t^D)^{-\frac{1}{\eta_D}}$. The Colombian dataset provides implicit industry-level price index and I measure P_t^D as this index. I measure Q_t^D as share-weighted domestic revenues following Klette and Griliches (1996). Upon recovering Φ_t^D, I identify Φ_t^X through the relationship $\delta_t = (\eta_X + 1)[\frac{\eta_D}{\eta_D+1} \ln \Phi_t^D - \frac{\eta_X}{\eta_X+1} \ln \Phi_t^X]$.

2.4.2 Stage 2. Estimating Process Parameters

Given structural parameters estimated in Stage 1, I recover skilled and unskilled labor-augmenting productivities (a^S_{jt}, a^U_{jt}) as well as logged material prices p^m_{jt} numerically.[6] I estimate the parameters of controlled Markov process (2.4) by imposing the model restrictions: innovations to productivities in period t are uncorrelated with the inputs chosen by plants in period $t-1$. Specifically, I approximate the Markov process as a VAR(1) process and estimate parameters via two-step GMM with the following two sets of moment restrictions.

$$E\left(Z^1_{jt} \otimes \begin{bmatrix} \varepsilon^s_{jt} \\ \varepsilon^u_{jt} \\ \varepsilon^m_{jt} \end{bmatrix}\right) = 0, \tag{2.13}$$

$$E\left(Z^2_{jt} \otimes \begin{bmatrix} \varepsilon^s_{jt} \\ \varepsilon^u_{jt} \\ \varepsilon^m_{jt} \end{bmatrix}\right) = 0, \tag{2.14}$$

, where $Z^1_{jt} = (1, a^S_{j,t-1}, a^U_{j,t-1}, p^m_{j,t-1}, e_{j,t-1})$ and $Z^2_{jt} = (\ln K_{jt}, \ln L^U_{j,t-1}, \ln L^S_{j,t-1}, \ln E^M_{j,t-1})$. The first set of moment restrictions (2.13) comprises typical VAR orthogonality conditions and the second set (2.14) comprises the timing assumption of the model.

2.5 Results

In this section, I report the estimates of demand and production parameters as well as transition parameters of skilled and unskilled labor-augmenting productivities. I then briefly discuss the relationship among recovered productivities and other observed variables such as revenues and skilled-to-unskilled ratios.

2.5.1 Production and Demand Parameters

The key parameter of interest is the elasticity of substitutions between skilled and unskilled workers $(\frac{1}{1-\rho})$ because it is central to understand how productivity improvements shape skilled-to-unskilled ratios. The estimated elasticity of substitutions between skilled and unskilled workers equals 2.64 as the first column of Table 2.3 shows. This value is higher than most estimates obtained by using aggregate data. For instance, since Katz and

[6] See Appendix B.2 for the detailed procedure.

Murphy (1992) estimated the elasticity at 1.4, the following works have estimated the elasticity at values ranging from 1.4 to 2 (See Acemoglu and Autor (2011) and the reference therein). Besides, Fieler, Eslava, and Xu (2018) calibrate the elasticity at 1.6 to 1.8 using the Colombian manufacturing sector spanning from 1982 to 1988. However, my estimate is higher than the values obtained in the previous works because it is possible that the apparel industry which could not be representative to reflect the aggregate manufacturing sector in Colombia. The elasticity greater than one indicates that, all else equal, increases in skilled labor-augmenting productivities result in replacing unskilled workers with skilled workers and that plants with higher skilled labor-augmenting productivities tend to have higher skilled-to-unskilled ratios.

Table 2.3. Estimates of Production and Demand Parameters

Parameters	Estimates	Parameters	Estimates	Parameters	Estimates
γ	0.5332	α_L	0.1229	η_D	-5.7816
	(0.0881)		(0.0234)		(0.1383)
ρ	0.6221	α_M	0.8364	η_X	-4.4716
	(0.1050)		(0.0266)		(0.1092)
		α_K	0.0407	κ	2.3162
			(0.0054)		(0.2754)

Note. The table displays the estimates of the production and demand parameters. Standard errors are in parenthesis. Implied elasticity of substitution across labor, material, and capital is $\frac{1}{1-\gamma} = 2.1422$. The implied elasticity of substitution between skilled and unskilled workers is $\frac{1}{1-\rho} = 2.6460$.

The third column of Table 2.3 reports the demand elasticities for both domestic and export markets as well as the relative export market size. The estimation results show exporters enjoy two benefits from exporting which induce higher operating profits. First, exporters can charge higher markups for export sales. While the demand elasticity of the domestic market being -5.78, the counterpart of the export market is -4.47. These values imply that plants in the apparel industry in Colombia charge markups over marginal cost by 20.9 percent in the domestic market and 28.8 percent in the export market. Second, exporters face higher demand in the export market. The estimate of κ is 2.3, which suggests *cetris paribus* exporters can earn 2.3 higher revenues.

2.5.2 Transition Process Parameters

Table 2.4 reports the estimates of transition process parameters. The skilled and unskilled labor-augmenting improvements due to exporting are reported in the last column of Table

2.4. Both estimates are positive and statistically significant but the effect of exporting on skilled labor-augmenting productivities is larger than that on the unskilled counterpart. While exporting raising skilled labor-augmenting productivity by 21.8 percent, it raises unskilled labor-augmenting productivity by 15.4 percent.

Table 2.4. Estimates of Transition Process

	$a^S_{j,t-1}$	$a^U_{j,t-1}$	$p^m_{j,t-1}$	$e_{j,t-1}$
a^S_{jt}	0.8193	0.0934	-0.0359	0.2180
	(0.0101)	(0.0125)	(0.0074)	(0.0245)
a^U_{jt}	-0.0195	0.7104	0.0663	0.1538
	(0.0064)	(0.0100)	(0.048)	(0.0193)
p^m_{jt}	-0.1461	0.1259	0.9223	0.2190
	(0.0156)	(0.0156)	(0.0142)	(0.0281)

Note. The table displays the estimates of the Markov process parameters in equation (2.4). Standard errors are in parenthesis. The Markov process is approximated as a VAR(1) process. Constant terms are suppressed.

Why does skilled labor-augmenting productivity increases more? Notice that there are several mechanisms whereby exporting has impact on plant-level productivity pointed by De Loecker (2013). The mechanisms involve not only cost-reducing improvements such as production process innovation but demand-inducing improvements such as product innovation, quality upgrading, or learning the demand appeal to the export market.[7] In these cases, exporters are willing to upgrade their technology for better product quality (Lileeva and Trefler (2010) and Bustos (2011)). Skilled workers can have a comparative advantage in the usage of newly innovated technology (Yeaple (2005)). In this way, skilled labor-augmenting productivity could increase more than unskilled labor-augmenting productivity in response to export market exposure.

In the first three columns of Table 2.4 display the estimates of effect of $a^S_{j,t-1}$, $a^U_{j,t-1}$, and $p^m_{j,t-1}$ on a^S_{jt}, a^U_{jt}, and p^m_{jt}. They show that both productivities are highly persistent over time. The persistence indicates that changes in skilled and unskilled labor-augmenting productivities influence plant's decision on hiring skilled and unskilled workers persistently. In addition, the persistence can have a significant impact on skill intensity differences between exporters and non-exporters in the long-run. Given that exporting raises skilled labor-augmenting productivity more and skilled labor-augmenting productivity is more persistent, the skilled productivity gains from exporting do not

[7]This feature arises because researchers typically use deflated revenues as proxy for output. The measured plant/firm-level productivity reflects not only firm-specific cost-reducing technology but firm-specific demand-shifters.

disappear quickly, while unskilled productivity gains doing so. Overall, higher persistence of skilled labor-augmenting productivities generates the large differences in relative skilled labor productivities between exporters and non-exporters.

2.6 Quantitative Implication of Biased Gains from Exporting

This section explores what would have been mean-differences between exporters and non-exporters in skill intensity if exporting raises both productivities equally. For the sake of simplicity and highlight the role of biased productivity gains from exporting, I hold wage rates for skilled and unskilled workers (W_{jt}^S, W_{jt}^U), the innovation terms $(\epsilon_{jt}^s, \epsilon_{jt}^u)$, and plants' export status e_{jt} at the realized values in the counterfactual exercise.[8]

In my counterfactual exercise, I equalize the effect of exporting on skilled and unskilled labor-augmenting productivities: $g_e^s = g_e^u = 0.15$ - productivity gains from exporting are neutral. Then, using the parameter estimates and the innovations, I create the counterfactual skilled and unskilled labor-augmenting productivities $\bar{a}_{jt}^S, \bar{a}_{jt}^U$ for each plant-year observation. I then construct counterfactual relative skilled labor demand $\frac{\bar{L_{jt}^S}}{L_{jt}^U}$ through first order conditions with respect to skilled and unskilled labors and compute the mean difference in skilled-to-unskilled ratios between exporters and non-exporters. In the first row of Table 2.5,I tabulate the counterfactual and data-driven mean-differences in skill intensity between exporters and non-exporters. Overall, the intensity is lower by 50 percent in the absence of the biased productivity gains from exporting. This considerable drop suggests that the biased productivity gains from exporting are quantitatively important in generating the large differences between exporters and non-exporters. A qualitatively similar results arise when it comes to the median-differences (The second row of Table 2.5).

Figure 2.3 further examines the path of skill intensity differences between exporters and non-exporters from 1982 to 1991 under neutral improvements from exporting. The picture indicates that biased productivity gains from exporting are more quantitative important in shaping the differences between exporters and non-exporters in the later

[8]This exercise thus does not consider the feedback effect as Aw et al. (2011). Specifically, in the absence of the non-neutral productivity effect of exporting, firms might adjust their export decisions. These adjusted export status then shapes the evolution of input productivities, and this change alters the next period's probabilities of export decisions. Capturing such a reinforcing process necessitates a fully dynamic structural model of exporting, which is beyond the scope of this chapter.

Table 2.5. Quantitative Importance of Non-neutral Productivity Improvement from Exporting

	Data: non-Neutral	Counterfactual: Neutral
Mean Differences	0.3420	0.1795 (52.5%)
Median Differences	0.2528	0.0669 (26.4%)

Note. The table displays the observed/counterfactual logged differences between exporters' skilled-to-unskilled ratios and non-exporters' one. In the counterfactual world, skilled and unskilled labor-augmenting productivities respond to the firm's previous export status equally.

years. Notice that because the skilled labor-augmenting productivity is more persistent than unskilled labor-augmenting productivity, the biased gains from exporting persist in the long-run, generating exporters become more skill intensive in the later years. In contrast, in the counterfactual exercise with the restriction that the effects of exporting on both productivities are the same, exporters have not become more skill intensive over time. Thus, the quantitative importance of biased productivity gains from exporting in shaping skill intensity differences between exporters and non-exporters is larger in the later years.

2.7 Conclusion

I study the biased productivity gains from exporting in the context of skilled and unskilled labor-augmenting productivities. Skilled and unskilled labor-augmenting productivities drive the plant-level heterogeneity in skill intensity. Therefore, to understand the relationship between exporting and future skilled-unskilled allocation at the plant level, documenting whether exporting raises one of the productivities more is a reasonable starting point. In this chapter, I measured the effects of exporting on future skilled and unskilled labor-augmenting productivities and quantified the importance of the biased gains in producing the skill intensity differences between exporters and non-exporters.

Using data on the Colombian apparel manufacturers, I first documented that skilled-to-unskilled ratios in the data largely deviate from the predictions by the model without factor-augmenting productivities. I further showed that the plant's export status in the previous period is tightly associated with the deviations, which suggests evidence of biased productivity gains from exporting.

Structural estimation in this chapter showed that exporting raises future skilled labor-augmenting productivities by 21 percent while unskilled ones by 15 percent. The estimate of the elasticity of substitutions between skilled and unskilled workers is 2.6,

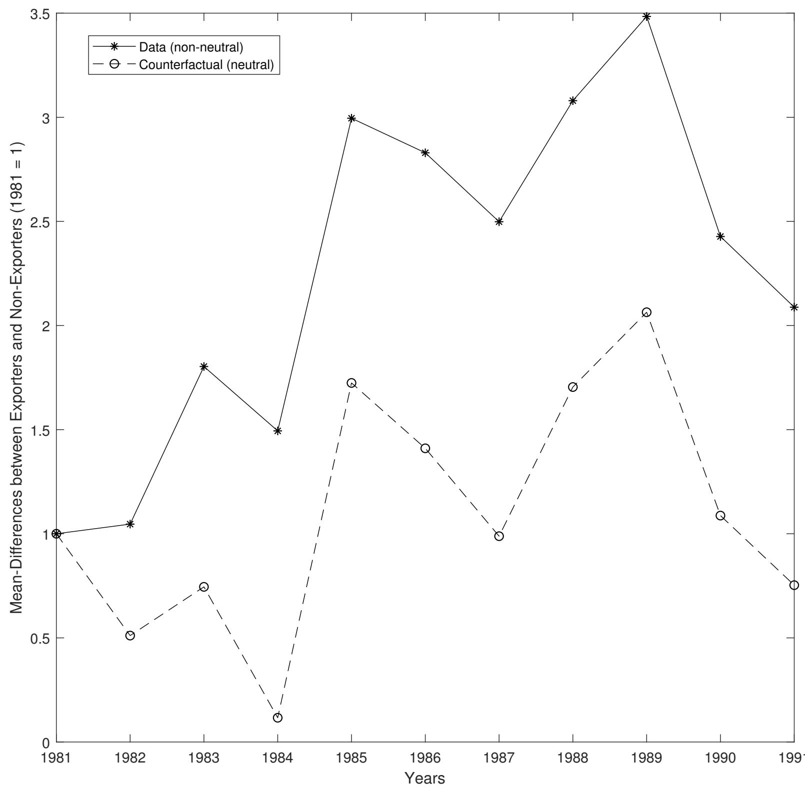

Figure 2.3. Realized vs. Counterfactual Skill Intensity Differences

Note. The Figure plots the time evolution of the realized and counterfacutal skilled intensity differences between exporters and non-exporters.

implying two types are gross substitutes. Thus, a plant that began exporting in the previous period would likely have higher skill intensity in the following period. When evaluating the quantitative relevance of the biased gains, I find the biased effects of exporting on plant-level productivities explain 51.5 percent of skill intensity differences between exporters and non-exporters.

Chapter 3

Trade Dynamics of Heterogeneous Producers under Trade Cost Complementarity

3.1 Introduction

[1] A vast literature at the intersection of industrial organization and international trade documents the short-run and long-run benefits of trade participation at the firm level. First, by serving the foreign market (exporting), firms can make additional profits from the foreign market (Das, Roberts, and Tybout (2007), Li (2018)). Second, importers can access a broader selection of high-quality inputs at lower prices (Grieco, Li, and Zhang (2022), Halpern, Koren, and Szeidl (2015)). In addition, firms can improve their productivity in the long run via technical support or expertise from their foreign buyers, which is known as "learning-by-exporting" and "learning-by-importing" (Aw, Roberts, and Xu (2011), Bai, Krishna, and Ma (2017), Grieco, Li, and Zhang (2022), Kasahara and Rodrigue (2008), Zhang (2017)).

However, the evaluation of the benefits of exporting and importing is potentially biased when a researcher does not consider both activities. For instance, exporting and importing might be interdependent: participating in one activity alters the incentive to engage in the other activity. Hence, models ignoring either exporting or importing can incorrectly measure the benefits of trade participation and the impacts of hypothetical trade subsidy schemes. Yet, to the best of my knowledge, except for Grieco et al. (2022), empirical studies tend to analyze these two trade activities individually.

Having this gap in mind, I build a structural model for the joint import and export

[1] I am grateful to Mark Roberts and James Tybout for providing the Colombian manufacturing survey data used in this chapter.

decision process by augmenting the dynamic model of Aw et al. (2011) with the production function of Halpern et al. (2015). As well established by earlier studies, there are both static and dynamic gains from trade in the model of this chapter. Firms can enjoy higher profits and boost their future productivity by importing and exporting. Besides these standard gains, I add one more potential gain from trade: if a firm participates in one trade activity, it will pay different (potentially cheaper) start-up or continuation costs for the other trade activity. Allowing for the dependence of sunk start-up and fixed continuation costs of trading on the trade status is motivated by the two observed transition patterns: (i) a firm doing one activity is more likely to start the other activity than its counterpart; (ii) 92% of firms doing both in current period continue doing both activities in next period (Table 3.1).

Table 3.1. Transition Rates for Trade Status: 1981-1985

Trade Status in Year t	Trade Status in Year $t+1$			
	Both	Only Export	Only Import	Neither
Both	0.9258	0.0156	0.0547	0.0039
Only Export	0.1818	0.5758	0.0303	0.2121
Only Import	0.0479	0.0056	0.8212	0.1257
Neither	0.0067	0.0101	0.1145	0.8687

I take the model to panel data of Colombian chemical plants that continuously operated from 1981 to 1985 to back out relevant structural parameters. Since the parameters of the model are too many and constructed likelihood function involves the simulation, the likelihood function is not globally concave. A conventional optimization algorithm is thus inappropriate for estimating the model. I bypass such a non-global concavity by using the Bayesian Markov Chain Monte Carlo (MCMC) method to characterize the posterior distribution of the structural parameters.

I use the estimated model to conduct two counterfactual simulations: (1) I quantify the three proposed gains from trade; (2) I evaluate the anticipated performance and efficiency of policies that subsidize start-up/continuation costs of importing and exporting.

My empirical results reveal several aspects of international trade in the Colombian chemical industry. First, productivity is endogenously determined; using imported material purchases enhance future productivity. However, serving the export market does not improve future productivity significantly. Notably, in the specification with learning-by-exporting alone, I observe that researchers may incorrectly interpret the productivity effects of trading as if Chemical plants in Colombia enjoyed the substantial learning-by-exporting effect. This biased positive productivity effect of exporting thus reflects a spurious correlation with importing. Second, there are substantial sunk start-up costs for undertaking exporting and importing. Third, one trading decision facilitates the other decision by reducing start-up/continuation costs: exporting decreases the continuation costs of importing, while importing reduces the start-up costs of exporting.

The first counterfactual exercise shows that static gains from exporting contribute to 80% of total gains from export, while dynamic gains from importing contribute to 85% of total gains from import. However, gains from the complementarity in costs are not playing a crucial role in shaping total gains from export or import. For export, gains from facilitating importing only account for about 1.8% of total gains, and for import, gains from facilitating exporting account for about 3.78%.

The second counterfactual exercise shows that amongst four possible subsidy policies, subsidizing the continuation costs of importing is the most effective. The simulation result indicates that ten years after the policy, subsidizing the continuation costs of importing increases the average productivity by 0.8% while subsidizing export fixed costs raises the average productivity by 0.2%. The other two policies do not increase productivity. For analyzing the cost and benefit of each policy, I divide the increases in the total values of firms due to a policy by the total subsidy costs paid by the government. Ten years after the policy was implemented, subsidizing import fixed costs outperforms all the other policies. The measured efficiency of subsidizing the continuation costs of importing is about 16, while those of subsidizing the start-up costs of importing, the continuation costs of exporting, and the start-up costs of exporting are one, nine, and 0.5, respectively.

Section 3.2 develops the theoretical framework of the firm's joint decision of export and import. Section 3.3 describes a two-step estimation strategy for the model. Section 3.4 reports estimates of structural parameters of the model and Section 3.5 summarizes the counterfactual results. Finally, Section 3.6 concludes.

3.2 Model

This section constructs a dynamic model of the firm's joint export and import decision process. Specifically, I expand upon Aw et al. (2011) by incorporating the production function of Halpern et al. (2015) in the spirit of Zhang (2017). Firms produce outputs using labor, domestic and imported materials, and capital and sell their outputs to the domestic and export markets, which are monopolistically competitive. Firms make two dynamic discrete choices: importing and exporting.[2] In addition, I introduce trade cost complementarity between these two activities: the fixed continuation and sunk start-up cost parameters depend on the firm's current trade status. For instance, if an importer would like to start exporting, then it would face the lower start-up costs of exporting than the one that its counterpart would have to pay. This feature embodies the possibility that one trade activity could facilitate other activity. Then, armed with the model, I can quantify the three channels through which current trade status improves the values of firms: (i) improving the future productivity, (ii) improving per-period profits, and (iii) reducing the fixed/sunk costs that a firm should pay to undertake the other activity.

3.2.1 Timeline

Times are discrete, and firms seek to maximize its present value of future profits, discounted with common discount factor δ, by choosing the sequence of the optimal trading decisions. The timeline of the production and trading decision processes is as follow:

1. At the beginning of period t, firm j takes its state vector s_{jt} as given:

$$s_{jt} = (e_{jt}, d_{jt}, k_{jt}, x_{jt}, z_{jt}),$$

   where (e_{jt}, d_{jt}) indicates the firm's export and import status, k_{jt} is the logged amount of capital, x_{jt} is the logged productivity, and z_{jt} is the logged foreign market demand shifter.

2. The firm makes the inputs decision for production and earns variable profits by selling their products to the domestic and export markets.

3. The firm draws the start-up (continuation) costs of importing C^M_{jt} from the distribution $F_M(\cdot|s_{jt})$ and then decides whether or not to start (continue) importing in the next period (d_{jt+1}).

4. The firm subsequently draws the start-up (continuation) costs of exporting C^X_{jt} from the distribution $F_X(\cdot|s_{jt})$ and decides to start (continute) exporting in the next period (e_{jt+1}).

[2] I abstract away the decision to invest in physical capital following Aw et al. (2011), Zhang (2017), and Grieco et al. (2022). This abstraction is justified by the fact that my empirical analysis utilizes a short panel. Since the decisions to invest in the capital are lumpy, it is unlikely that there would be a rapid change in the firm's stock of capital within the sample periods.

It is noteworthy to point out the crucial assumptions in the model of this chapter. First, I assume that one time period is required for making a trade contract with foreigners. These assumptions embody the fact that trade agreement could proceed with the product inspections, search frictions, and negotiations. Second, I abstract from the firm's lumpy investment decision given that the data spans five years.

3.2.2 Technology

The first building block of the model is a production function that converts labors, capital, and material purchases (domestic and imported) to outputs. Following Halpern et al. (2015) and Zhang (2017), I consider the following Cobb-Douglas production function with a nested CES basket which aggregates domestic and imported materials:

$$\begin{aligned} Q_{jt} &= \exp(x_{jt}) L_{jt}^{\alpha_l} M_{jt}^{1-\alpha_l} K_{jt}^{\alpha_k}, \\ M_{jt} &= [(M_{jt}^d)^{\frac{\theta-1}{\theta}} + (A_t M_{jt}^f)^{\frac{\theta-1}{\theta}}]^{\frac{\theta}{\theta-1}},\ \theta > 0 \end{aligned} \tag{3.1}$$

where L_{jt}, K_{jt} are labor and capital inputs, and M_{jt} is the composite basket of domestic materials M_{jt}^d and imported materials M_{jt}^f. θ is the elasticity of substitution between domestic and imported materials. A_t represents the time-varying relative physical quality measures of imported materials. Note that I assume that the production function is characterized by a constant return to scale (CRS) technology *in the short-run.* Under this assumption, the short-run marginal cost function is invariant in the amount of produced quantities Q_{jt}.

All firms are a short-run cost minimizer and behave competitively in the factor market. Thus, they take the technology constraint (3.1) and the prices of composite materials $P_{M,t}$ and the wage rates W_t as given. If a firm is not an importer, then it optimally chooses L_{jt} and M_{jt} to minimize the short-run total costs. If a firm is an importer, it optimally chooses L_{jt} and M_{jt}, and then optimally allocates M_{jt} into M_{jt}^d and M_{jt}^f.

The first order conditions of the short-run cost minimization problem imply the following marginal cost functions:

$$C_{import} = B(\alpha_l) W_t^{\alpha_l} (P_{M,t}^d)^{1-\alpha_l} K_{jt}^{-\alpha_k} \exp(-x_{jt}) (1 + (A_t \frac{P_{M,t}^d}{P_{M,t}^f})^{\theta-1})^{\frac{1-\alpha_l}{1-\theta}}, \tag{3.2}$$

$$C_{non-import} = B(\alpha_l) W_t^{\alpha_l} (P_{M,t}^d)^{1-\alpha_l} K_{jt}^{-\alpha_k} \exp(-x_{jt}), \tag{3.3}$$

where

$$B(\alpha_l) = [(\frac{\alpha_l}{1-\alpha_l})^{1-\alpha_l} + (\frac{1-\alpha_l}{\alpha_l})^{1-\alpha_l}] \tag{3.4}$$

Note that the cost shifting effect of importing is captured by $(1 + (A_t \frac{P^d_{M,t}}{P^f_{M,t}})^{\theta-1})^{(1-\alpha_l)/(1-\theta)}$ in (3.2) and this is the only one shifting effect of importing. One can see that when importer and non-importer are with the same level of productivity and capital, the ratio of marginal costs of them is exactly equal to $(1 + (A_t \frac{P^d_{M,t}}{P^f_{M,t}})^{\theta-1})^{\frac{1-\alpha}{1-\theta}}$. This result allows me to specify the logged marginal cost c_{jt} as a linear function of logged level of productivity and capital, and import dummy.

$$c_{jt} = \beta_0 + \alpha_l w_t + (1-\alpha)p^d_{m,t} + \beta_{m,t}d_{jt} + \beta_k k_{jt} - x_{jt} \tag{3.5}$$

where $w_t, p^d_{m,t}$ are logged wage rates and domestic material prices, k_{jt} is a firm j's logged level of capital at time t, $\beta_k = -\alpha_k$, and $\beta_{m,t}$ is $\frac{1-\alpha_l}{1-\theta} \log{(1 + (A_t \frac{P^d_{M,t}}{P^f_{M,t}})^{\theta-1})}$.

Note that $\beta_{m,t}$ is time-varying as the relative material price and physical relative quality of imported materials are time-varying. However, in this chapter, I strictly focus on the average advantage of importing due to the reduction in marginal cost. Thus, I simplify $\beta_{m,t}$ as time-invariant parameter β_m by assuming that the price-adjusted quality of imported materials $A_t \frac{P^d_{M,t}}{P^f_{M,t}}$ has a constant value, namely κ: $\beta_m \equiv (1 + (\kappa)^{\theta-1})^{\frac{1-\alpha}{1-\theta}}$.

Thus, the logged marginal cost to be used hereafter and to be estimated is as the following:

$$c_{jt} = \beta_0 + \beta_t + \beta_m d_{jt} + \beta_k k_{jt} - x_{jt}, \tag{3.6}$$

where β_t captures any time-varying marginal cost shifters including the factor prices and the time-varying components associated with $\beta_{m,t}$ which is abstracted in this specification. This specification is analogous to the marginal cost specification of Aw et al. (2011), except for the inclusion of an indicator of import status as a cost shifter.

Two features of β_m merits comments. First, the impact of importing on short-run marginal costs hinges on the substitutability between domestic and imported materials. For instance, when imported materials are substitutes for domestic counterparts ($\theta > 1$), importers can enjoy lower short-run marginal costs than non-importers. In addition, imported materials with better quality (i.e., $\kappa > 0$) amplify such a cost-reduction effect of importing.

3.2.3 Demand and Static Profits

In the domestic and export markets, each firm faces iso-elastic demand curves:

$$Q_{jt}^D = \Phi_t^D (P_{jt}^D)^{\eta_D}, \tag{3.7}$$
$$Q_{jt}^X = \Phi_t^X (P_{jt}^X)^{\eta_X} \exp(z_{jt}), \tag{3.8}$$

where Q_{jt}^m are the amount of demanded goods in market m; P_{jt}^m is market m's prices set by firm j; Φ_t^m represents the time-varying aggregate industry demand shifter for market m; and η_m represents the demand elasticity of market m. Note that for the export demand, I incorporate export market demand shifter z_{jt} which varies across firms and periods. Here, z_{jt} essentially captures the relative differences between domestic and foreign market demand shifters.

The domestic and export markets are assumed to be monopolistically competitive. Thus, firm j charges constant mark-up $\frac{\eta_m}{1+\eta_m}$, and the logged revenue functions are given by

$$r_{jt}^D = (\eta_D + 1)\log\frac{\eta_D}{1+\eta_D} + \log\Phi_t^D + (\eta_D+1)(\beta_t + \beta_m d_{jt} + \beta_k k_{jt} - x_{jt}), \tag{3.9}$$
$$r_{jt}^X = (\eta_X + 1)\log\frac{\eta_X}{1+\eta_X} + \log\Phi_t^X + (\eta_X+1)(\beta_t + \beta_m d_{jt} + \beta_k k_{jt} - x_{jt}) + z_{jt}. \tag{3.10}$$

In addition, operating profits of each market are proportional to revenues:

$$\pi_{jt}^D = -\frac{1}{\eta_D}\exp(r_{jt}^D) = \Pi_D(k_{jt}, x_{jt}, d_{jt}), \tag{3.11}$$
$$\pi_{jt}^X = -\frac{1}{\eta_X}\exp(r_{jt}^X) = \Pi_X(k_{jt}, x_{jt}, d_{jt}, z_{jt}). \tag{3.12}$$

Two important features of the model need to be pointed out. First, importers would make higher domestic and export profits than non-importers if domestic and imported materials are substitutes (i.e., $\beta_m < 0$), capturing the cost-reduction effect of importing. Second, export market demand shifter z_{jt} is the only firm-level heterogeneity that shapes between-exporter variations in revenues. That is z_{jt} will capture differences in revenues across exporters which are unexplained by capital, productivity, and import status. In addition, this feature allows me to distinguish between productivity x_{jt} and export market demand shifter z_{jt}, which prevents from conflating "learning-by-exporting" effect and export market specific shocks (Aw et al. (2011)).

3.2.4 Evolution of Productivity and Export Market Demand Shifter

Firm's productivity x_{jt} evolves according to a stationary Markov process depending on the firm's trade participation status in the previous period. Specifically, the productivity x_{jt} evolves as the following:

$$x_{jt} = \rho_0 + \sum_{p=1}^{3} \rho_p x_{jt-1}^p + g_e e_{jt-1} + g_m d_{jt-1} + u_{jt}, \tag{3.13}$$

where e_{jt-1} and d_{jt-1} are indicating whether a firm j was a exporter and an importer in period $t-1$, respectively. The specification allows for the possibility of learning-by-trading. For instance, a firm could access to technical support from trading partners or improve the quality of their product from an interaction with their partners.

Export market demand shifter z_{jt} follows a stationary AR(1) process:

$$z_{jt} = \rho_z z_{jt-1} + \epsilon_{jt}. \tag{3.14}$$

The persistence of z is capturing all the other possible driving forces associated with exporting such as the quality of product or the contractual relationship between foreign importers.

3.2.5 Trading Decisions

When deciding whether or not to partake in trade activities (exporting & importing), a firm seeks to maximize its presented discounted values of future domestic and export profits after observing realized continuation and start-up costs. However, it is probable that each firm faces heterogeneous continuation and start-up costs of partaking in trade. For instance, firms can be different in trade experience or a connection to a foreign partner. I capture this potential heterogeneity by assuming that costs of importing and exporting C_{jt}^M and C_{jt}^X are identically and independently drawn from exponential distributions whose scale parameters depend on the trade status:

$$C_{jt}^M | s_{jt} \sim iid\ Exp(\lambda_M(e_{jt}, d_{jt}))$$
$$C_{jt}^X | s_{jt} \sim iid\ Exp(\lambda_X(e_{jt}, d_{jt}))$$

where

$$\lambda_M(e_{jt}, d_{jt}) = (1-d_{jt})(1-e_{jt})\gamma^{SM} + (1-d_{jt})e_{jt}\nu^{SM} + d_{jt}(1-e_{jt})\gamma^{FM} + d_{jt}e_{jt}\nu^{FM}$$
$$\lambda_X(e_{jt}, d_{jt}) = (1-d_{jt})(1-e_{jt})\gamma^{SX} + (1-d_{jt})e_{jt}\gamma^{FX} + d_{jt}(1-e_{jt})\nu^{SX} + d_{jt}e_{jt}\nu^{FX}.$$

Note that the trade status in current period affects the cost distribution that a firm will face. First, if firm j is an exporter ($e_{jt} = 1$), it would pay only the continuation costs of exporting (ν^{FX} or γ^{FX}) to become an exporter in the next period, and so is it for the case of importing. Second, the model allows for the potential cost complementarity between two trade activities. For instance, if firm j is an importer but not an exporter in time t, the firm's export start-up costs would be drawn from $Exp(\nu^{SX})$. Meanwhile, if it has not participated in any trade activity, it's start-up costs of exporting would be drawn from $Exp(\gamma^{SX})$. If there is the cost complementarity, the estimation results would indicate that $\gamma^{SX} < \nu^{SX}$.

Given state vector s_{jt}, the firm's value before the realization of trade costs is given by

$$\begin{aligned} V(s_{jt}) =& \Pi_D(k_{jt}, x_{jt}, d_{jt}) + e_{jt}\Pi_X(k_{jt}, x_{jt}, d_{jt}, z_{jt}) \\ &+ \int \max_{d_{jt+1}}\{V_M(s_{jt}) - C^M_{jt}, V_{NM}(s_{jt})\}dF_M(C^M_{jt}|s_{jt}) \end{aligned} \tag{3.15}$$

where V_M is the value of an importer given the optimal choice for its export status and V_{NM} is the value of a non-importer given the optimal choice for its export status. The optimal values of an importer and non-importer are given by

$$V_M(s_{jt}) = \int \max_{e_{jt+1}} \left\{ \begin{aligned} &\delta EV(e_{jt+1} = 1, d_{jt+1} = 1|s_{jt}) - C^X_{jt}, \\ &\delta EV(e_{jt+1} = 0, d_{jt+1} = 1)|s_{jt}) \end{aligned} \right\} dF_X(C^X_{jt}|s_{jt}) \tag{3.16}$$

$$V_{NM}(s_{jt}) = \int \max_{e_{jt+1}} \left\{ \begin{aligned} &\delta EV(e_{jt+1} = 1, d_{jt+1} = 0|s_{jt}) - C^X_{jt}, \\ &\delta EV(e_{jt+1} = 0, d_{jt+1} = 0)|s_{jt}) \end{aligned} \right\} dF_X(C^X_{jt}|s_{jt}) \tag{3.17}$$

Note that depending on the current trade status, the firm's future productivity would change in way characterized by (3.13). Thus, the future value of firms will be depending on both future and current trade status. Finally, the expected future value conditional on the trade status is defined as following:

$$EV(e_{jt+1}, d_{jt+1}|s_{jt}) = \int V(e_{jt+1}, d_{jt+1}, k_j, x_{jt+1}, z_{jt+1}) dF_x(x_{jt+1}|x_{jt}, e_{jt}, d_{jt}) dF_z(z_{jt+1}|z_{jt}). \tag{3.18}$$

In this framework, the marginal returns to exporting is depending on the future import status due to the assumption on timeline. Thus, the margin is defined as following:

$$MBX_{jt}(d_{jt+1}, s_{jt}) = \delta[EV(e_{jt+1} = 1, d_{jt+1}|e_{jt}, d_{jt}) - EV(e_{jt+1} = 0, d_{jt+1}|e_{jt}, d_{jt})]. \tag{3.19}$$

However, the margin on importing is only relying on the current state vector s_{jt} and it is defined by

$$MBM_{jt}(s_{jt}) = V_M(s_{jt}) - V_{NM}(s_{jt}). \tag{3.20}$$

Hence, a given state s_{jt}, a firm decides to import if and only if $MBM_{jt}(s_{jt}) \leq C^M_{jt}$, and then given s_{jt} and d_{jt+1}, the firm decides to export if and only if $MBX_{jt}(d_{jt+1}, s_{jt}) \leq C^X_{jt}$.

3.3 Estimation Strategy

I estimate the structural model described in the previous section through the two step approach. In the model, the structural parameters include the demand elasticities (η_D, η_X), the cost shifters (β_k, β_m), the productivity parameters ($\rho_0, \rho_1, g_e, g_m, \sigma_u$), the foreign market demand parameters (ρ_z, σ_z), the average logged export revenue Φ^X_0, and the parameters on the sunk and fixed costs (γ, ν).

3.3.1 Static Parameters

I start with recovering the parameters involved in firm's static decision. Augmenting the domestic revenue function (3.9) with measurement error ξ_{jt}, I obtain

$$\begin{aligned} r^D_{jt} &= (\eta_D + 1)\log\frac{\eta_D}{1+\eta_D} + \log\Phi^D_t + (\eta_D + 1)(\beta_t + \beta_k k_{jt} + \beta_m d_{jt} - x_{jt}) + \xi_{jt} \\ &= \tilde{\Phi}^D_t + (\eta_D + 1)(\beta_k k_{jt} + \beta_m d_{jt} - x_{jt}) + \xi_{jt}. \end{aligned} \tag{3.21}$$

Here, ξ_{jt} is not correlated with the explanatory variables. Note that I abandon identifying the time shifts in the revenue and cost functions separately for the sake of a simplified estimation procedure. Thus, the composite term of time variations in revenues and costs is captured by $\tilde{\Phi}_t^D$.

Equation (3.21) cannot be consistently estimated through ordinary least squares. The error term in this regression equation is the composite of unobserved productivity x_{jt} and measurement error ξ_{jt}. By (3.13), x_{jt} is correlated with x_{jt-1} and d_{jt} is also correlated with x_{jt-1} because d_{jt} is determined in the previous period. Therefore, a typical simultaneity problem arises if one does not control for x_{jt}.

I address the simultaneity problem emerging in (3.21) by following Olley and Pakes (1996), Levinsohn and Petrin (2003), and Aw et al. (2011)'s proxy approach. In the theoretical model, the factor demand for composite of domestic and imported materials M_{jt} is monotone in productivity x_{jt}. In addition, with the assumption that the price-adjusted relative quality of imported materials is constant, the factor demand for domestic material M_{jt}^d is constantly proportional to the composite of materials. Therefore, conditional on the level of capital and the import status, I can utilize the logged domestic material expenditure m_{jt}^d as a control function for the firm's productivity: $\tilde{h}(k_{jt}, d_{jt}, m_{jt}^d)$. Hence, equation (3.21) can be written by

$$\begin{aligned} r_{jt}^D &= \Phi_t^D + (\eta_D + 1)(\beta_t + \beta_k k_{jt} + \beta_m d_{jt} - \tilde{h}(k_{jt}, d_{jt}, m_{jt}^d)) + \xi_{jt} \\ &= m_0 + m_t + h(k_{jt}, d_{jt}, m_{jt}^d) + v_{jt}. \end{aligned} \tag{3.22}$$

where the function h is a complex unknown function of capital, import status, and domestic material purchases. Following Aw et al. (2011), I approximate h as a cubic polynomial and conduct ordinary least squares to estimate (3.22). Let $\hat{h}_{jt}$ be the fitted values of h. This term is estimates of $(\eta_D + 1)(\beta_k k_{jt} + \beta_m d_{jt} - x_{jt})$. Given the cost parameters (β_k, β_m), the productivity is defined by the following: $x_{jt} = -\frac{1}{1+\eta_D}\hat{h}_{jt} + \beta_k k_{jt} + \beta_m d_{jt}$. Plugging this term into (3.13), I obtain the nonlinear equation characterizing the productivity evolution.

$$\begin{aligned} \hat{h}_{jt} = &-(\eta_D + 1)\rho_0 \\ &+ \rho_1(\hat{h}_{jt} - (\eta_D + 1)\beta_k k_{jt-1} - (\eta_D + 1)\beta_m d_{jt-1}) \\ &- (\rho_2/(\eta_D + 1))(\hat{h}_{jt-1} - (\eta_D + 1)\beta_k k_{jt-1} - (\eta_D + 1)\beta_m d_{jt-1})^2 \\ &+ (\rho_3/(\eta_D + 1)^2)(\hat{h}_{jt-1} - (\eta_D + 1)\beta_k k_{jt-1} - (\eta_D + 1)\beta_m d_{jt-1})^3 \\ &+ (\eta_D + 1)\beta_k k_{jt} + (\eta_D + 1)\beta_m d_{jt} \\ &- (\eta_D + 1)g_e e_{jt-1} - (\eta_D + 1)g_m d_{jt-1} \end{aligned}$$

$$- (\eta_D + 1)u_{jt} \tag{3.23}$$

Equation (3.23) can be consistently estimated through nonlinear least squares. By the timeline of the model, all the explanatory variables in the right-hand side are uncorrelated with the innovation in the firm's productivity. k_{jt} is subsumed to be constant over time and d_{jt} is determined in the previous period. Also, the variables with subscript $t-1$ are obviously uncorrelated with the innovation occurring at time t.

Upon recovering the demand elasticity of domestic market η_D, I can identify the whole structural parameters associated with marginal cost and the productivity evolution path. One can be doubt about identifying β_m and g_m separately because both are associated with d_{jt-1} in the equation because the effect of d_{jt-1} on $\hat{h}_{jt}$ is the composite of three parameters: $(g_m + \rho_1\beta_m)$. However, since the correlation between $\hat{h}_{jt}$ and $\hat{h}_{jt-1}$ pins down ρ_1 and the response of $\hat{h}_{jt}$ to d_{jt} pins down β_m, I could separately identify g_m. That is, I could tease out the learning-by-importing effect from the cost reduction effect of importing.

The remaining first stage parameters are the demand elasticities of domestic and foreign markets (η_D, η_X). To back out the elasticities, I follow Aw et al. (2011). Notice that the demands are CES and the marginal cost does not depend on the amount of quantities produced. Thus, the total variable costs TVC_{jt} are the weighted sum of domestic and foreign market revenues:

$$TVC_{jt} = (1 + \frac{1}{\eta_D})R^D_{jt} + (1 + \frac{1}{\eta_X})R^X_{jt} + \zeta_{jt},$$

where ζ_{jt} is the associated measurement error. I regress this equation by ordinary least squares to obtain the estimates of η_D and η_X.

3.3.2 Identification of Dynamic Parameters and Associated Issues

The remaining parameters are the ones associated with the firm's dynamic decision of importing and exporting. I exploit the time variations in the trade participation rates and the transition patterns of the firm's trade status to identify the fixed and sunk cost parameters (ν, γ). For example, the transition rates from the trade status $(e_{jt} = 1, d_{jt} = 0)$ to the status $(e_{jt} = 0, d_{jt} = 1)$, and the transition rates from $(e_{jt} = 1, d_{jt} = 0)$ to $(e_{jt} = 1, d_{jt} = 1)$ will be involved in identifying the ν^{SM}. Furthermore, conditioning on the firm's export status, the observed variations in the export revenues can provide me with the information on the parameters Φ_0^X, ρ_z and σ_z.

Estimating dynamic parameters is not a trivial problem. The associated numerical issues in estimating the dynamic parameters of the model are in order. First, while foreign market demand shifter z_{jt} is observed by firms, it is not observed by the researcher. Second, the conditional choice probabilities based on the equations (3.19) and (3.20) are not relevant to the initial period trade status because there is no information on the previous trade status. Third, the likelihood function would be subject to non-global concavity problem. I will discuss these issues and the methodologies employed to tackle them in the following three subsections.

3.3.3 Dealing with Unobserved z_{jt}: Das, Roberts, and Tybout (2007)

To estimation the structural parameters, I maximize the likelihood for the observed trade participation and the logged level of export revenues $\{(e_{jt+1}, d_{jt+1}, r^X_{jt+1})\}_{j=1,t=1}^{N,T-1}$. The likelihood that I have to construct is as the following.

$$\prod_{j=1}^{N}\prod_{t=1}^{T-1} f(e_{jt+1}, d_{jt+1}, r^X_{jt+1}|x_{jt}, k_j, e_{jt}, d_{jt}, r^X_{jt}).$$

By the construction of the model of this chapter, conditioning on x_{jt}, k_j, e_{jt}, d_{jt}, and r^X_{jt}, the variations in r^X_{jt+1} is only governed by z_{jt+1}. Also, the conditional choice probabilities of (e_{jt+1}, d_{jt+1}) are depending on the state vector at time t: s_{jt}. Thus, the likelihood value of firm j at time $t+1$ can be represented as the following.

$$\begin{aligned} &P(e_{jt+1}, d_{jt+1}|x_{jt}, k_j, e_{jt}, d_{jt}, z_{jt}) f(z_{jt+1}|z_{jt}). \\ =&P(e_{jt+1}, d_{jt+1}|s_{jt}) f(z_{jt+1}|z_{jt}) \end{aligned} \tag{3.24}$$

This likelihood cannot be evaluated immediately given that only exporters report r^X_{jt}, which turns in that econometricians can only observe z_{jt} of exporters. However, it is true that even non-exporting firms also observes z_{jt} and then decides whether or not to export. Thus, to construct the likelihood function, I need to back out latent z_{jt} for non-exporting firms. To do so, I follow Das et al. (2007)'s simulation approach. More specifically, given the observed z_{jt} and the parameters Φ_0^X, ρ_z, and σ_z, I can simulate K's many time series datasets of foreign market demand shifter $\{z^k_{jt}\}_{j,t,k}^{N,T,K}$ which is serially correlated in a manner of the AR(1) process characterized by the equation (3.14):

1. Notice that given marginal cost parameters and firm-specific productivity, I attain the adjusted exported revenues for exporters.

$$\tilde{r}^X_{jt} = r^X_{jt} - (\hat{\eta}_X + 1)\hat{\beta}_k k_{jt} - (\hat{\eta_X} + 1)\hat{\beta_m} d_{jt} + (\hat{\eta_X} + 1)\hat{x}_{jt}.$$

2. Next, given $(\Phi^X_0, \rho_z, \sigma_z)$, I can back out observed z_{jt} for exporters through the following equation

$$z_{jt} = \tilde{r}^X_{jt} - \Phi^X_0.$$

3. For firm j who at least has served the foreign market at once, define $z^+_j = \{z_{jt} : \tilde{r}^X_{jt} \text{ is observed}\}$ and let $q_j = \sum_{t=1}^T e_{jt}$. Then, q_j is the number of periods in that firm j exports and z^+_j is a $q_j \times 1$ vector. With the assumption that z_{jt} is in the long-run stationary process, I obtain

$$z^+_j \sim N(0, \Sigma_+),$$

   where the diagonal components of Σ_+ are $v_z \equiv \frac{\sigma^2_z}{1-\rho^2_z}$ and off-diagonal components are $\rho^{|p|}_z v_z$ for $p \neq 0$.

4. Note that z^+_j and $\mathbf{z}_j = (z_{j1}, z_{j2}, \cdots, z_{jT})'$ are both normal random vectors. By using the property of Normal random vector, I can represent $\mathbf{z}_j$ as a linear combination of z^+_j and some normal random vector:

$$\mathbf{z}_j = Az^+_j + B\epsilon_j,$$

   where ϵ_j is T by 1 standard Normal random vector, $A = \Sigma_{z+}\Sigma^{-1}_+$, and B satisfies $BB' = \Sigma_{zz} - \Sigma_{z+}\Sigma^{-1}_+\Sigma'_{z+}$. Here, Σ_{z+} is a T by q_j matrix $E[\mathbf{z}_j z^{+'}_j]$ and Σ_{zz} is T by T matrix $E[\mathbf{z}_j \mathbf{z}'_j]$.

5. Draw $\{\epsilon^k_j\}^K_{k=1}$ from standard Normal distribution. Then, given observed z_{jt}, (ρ_z, σ_z), I can simulate $\{\mathbf{z}^k_j\}^K_{k=1}$ by following the linear representation:

$$\mathbf{z}^k_j = Az^+_j + B\epsilon^k_j.$$

6. For firm j who has never exported during the sample period, I simulate $\{\mathbf{z}^k_j\}^K_{k=1}$

from the long-run stationary distribution of z_{jt}. That is,

$$\mathbf{z}_j^k = chol(\Sigma_{zz})\epsilon_j^k,$$

where $chol(\cdot)$ refers to the Cholesky decomposition of a positive semi-definite matrix.

There are two important features of this method. First, as the first term Az_j^+ implies, the simulation method exploits the entire information in the periods in which firm j exports, which incorporates the fact that z_{jt} is serially correlated stochastic process. Furthermore, by the construction of A, a row of A corresponding to the period in which firm j exports is a row vector that consists of one and $q_j - 1$'s many zeros so that A can always pick up the observed z_{jt} for exporting periods. Second, the dimension of kernel (or null space) of BB' is q_i, thus B contains q_i's many zero rows. These rows are corresponding to the periods in which the firm j exports. Therefore, ϵ_j is not involved in constructing z_{jt} for exporting periods. Given these, one can see that (i) simulated shifters can be serially correlated with observed demand shifters and (ii) the elements of $\mathbf{z}_j$ in rows corresponding to exporting periods do not vary across simulations. [3]

For each simulation $k = 1, 2, \cdots, K$, I can observe state vector $s_{jt}^k = (x_{jt}, k_j, e_{jt}, d_{jt}, z_{jt}^k)$, and then construct the conditional choice probabilities of exporting and importing:

$$P(e_{jt+1}, d_{jt+1}|s_{jt}^k) = P(e_{jt+1}|d_{jt+1}, e_{jt}, d_{jt}, k_j, x_{jt}, z_{jt}^k)P(d_{jt+1}|e_{jt}, d_{jt}, k_j, x_{jt}, z_{jt}^k), \quad (3.25)$$

where

$$P(e_{jt+1}|d_{jt+1}, e_{jt}, d_{jt}, k_j, x_{jt}, z_{jt}^k) = P(C_{jt}^X \leq MBX_{jt}(d_{jt+1}, s_{jt}^k)|s_{jt}^k), \quad (3.26)$$
$$P(d_{jt+1}|e_{jt}, d_{jt}, k_j, x_{jt}, z_{jt}^k) = P(C_{jt}^M \leq MBM_{jt}(s_{jt}^k)|s_{jt}^k). \quad (3.27)$$

The conditional choice probabilities are depending on the continuation values driven from the fixed point problem characterized by (3.15), (3.16), (3.17), and (3.18). Given the candidate dynamic parameters, I can compute the continuation values by iterating the equations (3.15), (3.16), (3.17), and (3.18) backward and then evaluate the likelihood value.

[3] Appendix C.1 describes how the method works with a simple example.

Given the specification that z_{jt} follows AR(1) process as (3.14), I have

$$f(z^k_{jt+1}|z^k_{jt}) = \frac{1}{\sigma_z}\phi(\frac{z^k_{jt+1} - \rho_z z^k_{jt}}{\sigma_z}), \tag{3.28}$$

for $k = 1, 2, \cdots, K$. Here ϕ refers to the pdf of standard Normal distribution.

Using (3.25) and (3.28), I construct the individual contribution to the full likelihood:

$$\prod_{t=1}^{T-1} P(e_{jt+1}, d_{jt+1}|s^k_{jt}) f(z^k_{jt+1}|z^k_{jt}) \tag{3.29}$$

in each simulation k. Note that the equation (3.29) conveys the information for the years $(2, 3, \ldots, T)$ so this formula is not a complete form of the individual likelihood function.

3.3.4 Constructing the Likelihood of the Initial Period: Heckman (1981)

I need $P(e_{j1}, d_{j1}) f(z^k_{j1})$ to complete the individual likelihood function. Incorporating the likelihood of the initial period is essential. Notice that z^k_{jt} and x_{jt} are evolving over time. Thus, z^k_{j1} and x_{j1} are correlated with the variations in s^k_{jt} in the subsequent periods. Given this feature, I cannot treat the choice behavior in the initial period as exogenous process. This is so-called "Initial Period Problem" raised by Heckman (1981). I follow the method proposed by Heckmann. Specifically, I approximate the expected margins of exporting and importing at the initial period as the following representations:

$$\text{Export: } w^{'}_{j1}\alpha_e - \zeta^X_j,$$
$$\text{Import: } w^{'}_{j1}\alpha_m - \zeta^M_j,$$

where ζ^X_j and ζ^M_j are mutually independent standard Normal distributed random variables. Thus, I obtain the choice probabilities of exporting and importing at the initial period:

$$P(e_{j1}, d_{j1}) = G(w^{'}_{j1}\alpha_e) G(w^{'}_{j1}\alpha_m), \tag{3.30}$$

where G is a cdf of the standard Normal distribution. The crucial job done for correcting initial period problem is that when I approximate the margins of exporting and importing at the initial period, I should include the variations correlated with the variations in every subsequent periods. By doing so, I can treat the initial period choices as endogenous process. Hence, w_{j1} includes constant, z_{j1}, x_{j1}, and k_j.

The initial period density of z_{j1}^k is simply defined as the following:

$$f(z_{j1}^k) = \frac{1}{v_z} g(\frac{z_{j1}^k}{v_z}), \tag{3.31}$$

where g is a pdf of the standard Normal distribution, and $v_z = \sqrt{\frac{\sigma_z}{1-\rho_z^2}}$. Thus, by multiplying $P(e_{j1}, d_{j1}) f(z_{j1}^k)$ and (3.29), I complete the individual likelihood in generic k-th simulation:

$$P(e_j, d_j | s_j^k) f(z_j^k), \tag{3.32}$$

where $e_j = (e_{j1}, e_{j2}, \cdots, e_{jT})$, $d_j = (d_{j1}, d_{j2}, \cdots, d_{jT})$, and $z_j^k = (z_{j1}^k, z_{j2}^k, \cdots, z_{jT}^k)$.

Finally, by averaging out (3.32) over the K simulations, I obtain the final individual contribution to the full likelihood. By multiplying these contributions across all the firms, I construct the full likelihood function:

$$\mathcal{L}(\Theta_D | D) = \prod_{j=1}^{N} \frac{1}{K} [\sum_{k=1}^{K} P(e_j, d_j | s_j^k) f(z_j^k)], \tag{3.33}$$

where $\Theta_D = (\Phi_0^X, \rho_z, \sigma_z, \gamma, \nu, \alpha_e, \alpha_m)$ and D is the dataset in my hand. In practice, I choose $K = 10$ to simulate z_{jt}.

3.3.5 Non-Global Concavity of Likelihood: Bayesian MCMC

Since the likelihood function is not globally concave, a conventional algorithm would have difficulty in finding the global maximum. Following Das et al. (2007) and Aw et al. (2011), I address this issue using Bayesian Markov Chain Monte Carlo (MCMC). Specifically, I construct the random-walk Metropolis-Hastings Markov chain to draw the samples from the posterior distribution of the dynamic parameters. When characterizing a posterior distribution, I use the diffuse prior distribution to prevent the estimates from being influenced by an arbitrary choice of prior distributions.[4]

The main goal of Bayesian MCMC is to characterize the posterior distributions of model parameters. Using the random-walk Metropolis-Hastings chain, I draw B's many dynamic parameter vectors $(\Theta_{D,1}, \Theta_{D,2}, \cdots, \Theta_{D,b}, \cdots, \Theta_{D,B})$ from the posterior distribution $\pi(\Theta_D | D) = \mathcal{L}(\Theta | D) p(\Theta)$. Then I construct the mean and 95% credible

[4] A posterior distribution, through Bayes' rule, boils down to the scaled likelihood function when the prior distribution is diffuse. Thus, the mean or mode of the posterior distributions drawn from MCMC is numerically not different from the maximum likelihood estimates.

intervals as $\bar{\Theta}_D = \frac{1}{B}\sum_{b=1}^{B}\Theta_{D,b}$ and the corresponding percentiles of MCMC draws.[5]

One crucial issue is the choice of initial parameter vector to generate the chain. If one chooses initial parameter which is too far away from the posterior maximizer, she would generate many draws for being confident that the chain has converged to a stationary region. I search over the parameter space using Simulated Annealing algorithm to find a point which is close to the posterior maximizer. Start with that point, I draw 60,000 MCMC draws and burn-in the first 10,000 draws to annihilate the initial choice effect.[6]

3.4 Empirical Results

This section first describes the dataset used for the empirical analysis and then reports the estimates of demand, marginal cost, productivity dynamics, and trade costs in the Colombian chemical industry.

3.4.1 Data

I estimate the model using a firm-level panel dataset, collected by the Colombian manufacturing plant survey which is collected by Colombia Departamento Administrativo Nacional de Estadistica (DANE) for periods from 1977 to 1991. The dataset contains detailed information about both domestic and export sales, domestic and imported materials, the number of employees, book values of plants' fixed properties such as land or building, investments, and any other plant's characteristics. I clean the data and construct the capital using perpetual inventory approach which is described in Roberts (1996). I focus on periods after 1981 because DANE began to track export sales since then.

I look at 236 chemical plants (SIC codes are 351 and 352) that continuously operated in the domestic market from 1981 to 1985, reflecting two considerations. First, the industry is trade-oriented as shown in Table 3.2. During the sample periods, approximately 61% of plants purchased imported materials, and 30% of of plants sold their products to the export market. Second, the stringent import tariffs of Colombia were liberalized in 1985, which might affect the margins of trading decisions (Roberts (1996)). Hence, I focus on periods from 1981 to 1985 to avoid a potential bias in structural estimates due to this regime shift.

[5] Appendix C.2 describes the details about the random-walk Metropolis-Hastings algorithm.
[6] Appendix C.3 reports the MCMC diagnostics.

Table 3.2. Trade Participation Rates: 1982-1985

1982	1983	1984	1985
Export Participation Rates			
0.3008	0.3136	0.3093	0.3051
Import Participation Rates			
0.6186	0.6483	0.6568	0.6398

Table 3.3 provides summary statistics of firm sales. The upper panel reports the median sales of plants in each year and the lower panel summarizes the average sales of plants in each year. Notice that regardless of the export status, importers enjoy larger domestic sales. While the median domestic sales of firms doing neither are around 20,000 Million in 1981 Pesos, the median domestic sales of firms doing only import increases from 62,000 Million to 106,000 Million. Similarly, the median sales of firms doing only export are substantially smaller than those of firms doing both. Similar patterns stand out when it comes to average sales. This pattern indicates that even after controlling for the firm size, any possible time-varying factors, and self-selection, there could be a systematic difference between non-importers and importers, which indicates the possibility of learning-by-importing. A similar pattern arises when I compare sales of non-exporters and exporters, suggesting the possibility of learning-by-exporting. The empirical model of this chapter allows me to disentangle such effects of learning-by-trading from other factors shaping the trading decisions: firm size, productivity, and trade costs.

3.4.2 Demand, Cost, and Productivity Dynamics

Tables 3.4 reports the parameter estimates of the demand, cost, and productivity dynamics in equations (3.22) and (3.23). I add dummies of SIC 4-digit industry codes to control for 4-digit industry-specific effects on the firm's domestic revenues. For the robustness check, I also estimate the productivity dynamics with a variety of specifications. The estimates from the benchmark specification are reported in the first column of Table 3.4 and the estimates from the other specifications are reported in the remaining columns. I will use the estimates of the parameters and estimated productivity from the benchmark specification in the second stage. The estimation results are summarized as follows.

First, the estimates of demand elasticities imply that an exporter could enjoy a larger market power than its counterpart. Notice that the demand elasticities of the domestic and export markets are approximately -6.47 and -4.72, respectively. The estimates imply

Table 3.3. Median and Mean Sales: 1981-1985

		1981	1982	1983	1984	1985
		Median Sales				
Neither	Domestic	21.4	24.6	20.0	22.3	26.1
Only Import	Domestic	62.9	79.9	93.7	115	106
Only Export	Domestic	75.1	87.4	90.5	58.6	41.8
	Export	11.5	24.7	3.84	2.09	3.64
Both	Domestic	508	500	514	496	512
	Export	14.3	11.3	10.5	12.0	13.3
		Mean Sales				
Neither	Domestic	37.3	43.6	39.4	39.1	52.8
Only Import	Domestic	211	211	209	277	286
Only Export	Domestic	195	200	178	66	234
	Export	38.5	40.9	34.3	3.65	30.5
Both	Domestic	896	885	908	959	1021
	Export	49.6	47.8	64.1	65.0	84.3

Note. Units are in 100 Millons of 1981 Pesos

that a plant in the Colombian chemical industry charges about 18% and 26% markups over marginal costs for domestic and foreign markets, respectively.

Second, both capital and import status decrease the marginal cost that a firm should pay and this result is consistent with the prediction drawn from the theoretical framework that I discussed in Section 3.2. In equation (3.6), the sign of the parameters associated with import status and the level of capital is expected to be negative. The estimation results confirm this theoretical prediction, indicating that (i) as the level of capital increases by 1%, a firm could produce a good by paying 5.26% lower marginal costs than its counterpart, and (ii) an importer would face the 6.8% lower marginal costs than a firm who is using only domestic materials.

Third, firm-specific productivity evolves and is highly persistent. The estimated coefficient on the lagged productivity is 0.9155 and this implies that one deviation increase in the productivity innovation term u_{jt} will persistently affect the future productivity path for about 50 years. Furthermore, there is a strong nonlinear relationship between the current and past productivities. Notice that both coefficients on the squared and cubic terms of x_{jt-1} are statistically significant and quantitatively large.

Fourth, the experience in trade improves upon the current level of productivity but the learning-by-importing is about five times larger than learning-by-exporting. In particular, holding everything, the productivity of a firm that has exported is about 0.45% higher than the counterpart's one. However, this is not statistically significant. In contrast, the

Table 3.4. Estimated Static Parameters

Parameters	Benchmark	No Learning-by-Importing	No Cost Reduction	$d_{jt} = \frac{M^f_{jt}}{M_{jt}}$	Linear
η_D	-6.4738^{***} (0.1403)	-6.4738^{***} (0.1403)	-6.4738^{***} (0.1403)	-6.4738^{***} (0.1403)	-6.4738^{***} (0.1403)
η_X	-4.7286^{***} (0.7869)	-4.7286^{***} (0.7869)	-4.7286^{***} (0.7869)	-4.7286^{***} (0.7869)	-4.7286^{***} (0.7869)
const.	0.001 (0.0036)	0.0091^{**} (0.0028)	0.0074^{**} (0.0036)	0.0177^{**} (0.0080)	0.0080^{**} (0.0036)
x_{jt-1}	0.9155^{***} (0.0290)	0.9533^{***} (0.0107)	0.9295^{***} (0.0310)	0.9215^{***} (0.0619)	0.9341^{***} (0.0107)
x^2_{jt-1}	0.2702^{**} (0.1146)	0.1984^{*} (0.1121)	0.2667^{***} (0.1067)	0.1298 (0.1361)	–
x^3_{jt-1}	-0.4047^{***} (0.1129)	-0.3553^{***} (0.1129)	-0.3589^{***} (0.0956)	-0.0974 (0.0868)	–
g_m	0.0201^{***} (0.0045)	–	0.0032 (0.0049)	0.0259^{***} (0.0076)	0.0216^{***} (0.0045)
g_e	0.0045 (0.0044)	0.0083^{**} (0.0043)	0.0091^{**} (0.0046)	0.0038 (0.0044)	0.0080^{*} (0.0045)
β_k	-0.0526^{***} (0.0065)	-0.0543^{***} (0.0069)	-0.0543^{***} (0.0094)	-0.0365^{***} (0.0083)	-0.0326^{***} (0.0094)
β_m	-0.0679^{***} (0.0061)	-0.0589^{***} (0.0058)	–	-0.0739^{***} (0.0134)	-0.0689^{***} (0.0062)

Note. Standard errors are in parenthesis. Asterisks mark rejection at the 1%(***), 5%(**), and 10%(*) significant level, respectively.

gains from importing are about 2% and these are significantly larger than the gains from exporting. This result indicates that when a firm has participated in both activities, it would enjoy much larger productivity in the current period. Furthermore, due to the high persistence in the productivity dynamics, the long-run impacts of exporting and importing become substantially large. Relative to a firm that will never do trading, a firm that will continuously do both exporting and importing will have long-run mean productivity that is about 35% higher. However, this long-run gain is mostly accounted for by learning-by-importing. Notice that a firm always participating in exporting will be only 5% more productive, while an always importer becomes 29% more productive in the long run.

3.4.3 Fixed and Sunk Costs, and Foreign Market Demand

Given the first stage estimates, I recover the remaining dynamic parameters through the method of MCMC. Table 3.5 reports the means and 95% credible intervals of the dynamic parameters. Since the 95% credible intervals never cover zero, I can conclude that the posterior distribution is quite tight and consider the means of the posterior distributions as credible estimates of the dynamic parameters. The estimation results are summarized as follows.

Table 3.5. Estimated Dynamic Parameters

Parameters	Mean	95% Credible Interval	Prior Dist.
γ^{FM}	0.8959	[0.897, 1.0108]	$N(0, 500^2)$
γ^{SM}	6.1272	[4.1943, 8.8647]	$N(0, 500^2)$
ν^{FM}	0.6648	[0.5992, 0.7359]	$N(0, 500^2)$
ν^{SM}	6.5011	[3.051, 10.2651]	$N(0, 500^2)$
γ^{FX}	0.6931	[0.5868, 0.8079]	$N(0, 500^2)$
γ^{SX}	64.2326	[62.2998, 66.9702]	$N(0, 500^2)$
ν^{FX}	0.7642	[0.6986, 0.8353]	$N(0, 500^2)$
ν^{SX}	25.4269	[22.8308, 29.1909]	$N(0, 500^2)$
Φ_0^X	0.5107	[0.4821, 0.5405]	$N(0, 100^2)$
ρ_z	0.9029	[0.8926, 0.9117]	$U[-1, 1]$
$\log \sigma_z$	0.2153	[0.2050, 0.2241]	$N(0, 10^2)$

Note. Mean and 95% Credible interval of parameters are drawn from the posterior distribution. I draw 60,000 parameters through Metropolis-Hastings random walk chain, and burn-in the first 10,000 draws to rule out the effect of the starting value. MCMC diagnostics are reported in Appendix C.3. The starting point of an MCMC is the maximizer of log kernel, which was found by Simulated Annealing algorithm.

First, the estimate of the average export market revenue Φ_0^X is substantially lower than the estimate of the average domestic market revenue (0.5107 and 3.12, respectively. The average domestic market revenue is not reported in any table). This difference indicates that Colombian chemical exporters sell less in the foreign market than they do in the domestic market.

Second, the foreign market demand shifter is highly persistent and it is highly volatile. The autoregressive coefficient is 0.9029 and the standard deviation σ_z is $\exp(0.2153) = 1.15$. These estimates are quite larger than the estimates from the previous studies but qualitatively in line with them. Aw et al. (2011) report that the estimates of these parameters are 0.77 and -0.287, respectively, and Bai et al. (2017) report that they are 0.83 and -0.176, respectively. The persistence in z_{jt} also contributes to the persistence in export status and export revenues.

Finally, the implications from the estimates of the cost parameters are summarized as follows.

Import Costs. Both exporters and non-exporters will draw similar sunk costs for importing, while a firm doing both activities can continue importing more easily than only importers. These estimates imply that exporting seems to facilitate importing through the reduction in the fixed costs for importing. Note that the estimates of γ^{FM} and ν^{FM} are substantially different: the 95% credible intervals for both parameters never overlap each other. One can see that the lower bound of the 95% credible interval for γ^{FM} is larger than the upper bound of 95% credible interval for ν^{FM}. That is, to continue importing, a firm that is doing both is likely to draw smaller fixed costs associated with import than its counterparts. In contrast, the estimates of γ^{SM} and ν^{SM} are also similar and the 95% credible interval for γ^{SM} is nested to the one for ν^{SM}. This result indicates that a firm doing neither and a firm doing only exporting are supposed to pay a similar amount of money to start importing foreign materials.

Export Costs. In contrast to the case of import costs, an importer is likely to pay less money to start serving the foreign market than a domestic counterpart does. Note that though both firms are expected to pay high entry costs for exporting (ν^{SX} and γ^{SX} are 25.42 and 64.23, respectively), an importer would pay about 3.5 times smaller entry costs to enter the foreign market. The substantial difference in sunk costs for exporting is intuitive: an importer has experienced the foreign market by interacting with foreign exporters, and they learned the foreign customs, which reduces the startup costs that the importer should have to pay. But doing importing does not complement continuing firms' foreign business. Note that the estimates of ν^{FX} and γ^{FX} are not much different and surprisingly the ν^{FX} is larger than γ^{FX}. One possible explanation is that firms participating in both activities are way larger than their counterparts in terms of the level of capital.[7] Aw et al. (2011) show that large firms in the Taiwanese electric industry would like to pay larger fixed and sunk costs for exporting than the smaller ones due to the larger scale of operation for larger firms. This story could also be the case in the Colombian chemical industry. Thus, I expect that I could get the more intuitive estimates of ν^{FX} and γ^{FX} if I control for the size of capital in estimating the fixed and sunk cost parameters. However, due to the computational burden, I do not take it into account in this chapter.

3.4.4 Model Fit

Armed with the estimates in Tables 3.4 and 3.5, I assess the model's in-sample fitting power. To do so, I start with the year 1981's the firms' productivity and trade status, and then simulate the firms' productivity and trade status in the subsequent years. Since the dynamics of a firm's productivity are endogenously determined by the firm's dynamic decision, it is necessary to check whether the simulated trajectory tracks the realized average productivity well. Table 3.6 compares the realized moments and the model moments. Though it underpredicts the import participation rates in the first few years, the model tracks the overall trend well.

Table 3.7 summarizes the transition patterns from the data and the model. The simulated data performs quite well in matching the transition patterns of firms engaging in both or engaging in nothing, while it does not do a good job at tracking the transition patterns of firms doing only one activity. In particular, the model overpredicts the transition from only export to both (35% vs 18%). The model captures, however, the interdependence between exporting and importing. In the data, a firm undertaking at least one activity is more likely to start the other activity than a firm that does not undertake anything. For example, in the model, a firm doing neither at the current period would translate to an exporter in the next period with a probability of 0.0054, while an importer would start exporting with a probability of 0.0640. These patterns are similar to the observations in the data.

[7] In the Colombian chemical industry, firms doing both activities are almost six to seven times larger than firms participating in only one activity in terms of the level of capital. Also, those firms are 24 times larger than firms serving only the domestic market without using imported materials.

Table 3.6. In-Sample Model Fits: Productivity and Trade Participation Rates

	1982	1983	1984	1985
	Productivity			
Data	0.2985	0.2944	0.3086	0.3220
Model	0.2989	0.2957	0.2929	0.2931
	Export Participation Rates			
Data	0.3008	0.3136	0.3093	0.3051
Model	0.3008	0.3016	0.3045	0.3101
	Import Participation Rates			
Data	0.6186	0.6483	0.6568	0.6398
Model	0.6220	0.6136	0.6094	0.6161

Note. Simulation reports average results from fifty simulations.

Table 3.7. In-Sample Model Fits: Transition Rates for Trade Status

Trade Status in Year t	Trade Status in Year $t+1$				
		Both	Only Export	Only Import	Neither
Both	Data	0.9258	0.0156	0.0547	0.0039
	Model	0.9203	0.0057	0.0676	0.0064
Only Export	Data	0.1818	0.5758	0.0303	0.2121
	Model	0.3497	0.4931	0.0200	0.1372
Only Import	Data	0.0479	0.0056	0.8212	0.1257
	Model	0.0640	0.0038	0.7528	0.1794
Neither	Data	0.0067	0.0101	0.1145	0.8687
	Model	0.0026	0.0054	0.1245	0.8675

Note. Simulation reports average results from fifty simulations.

3.5 Counterfactuals

3.5.1 Quantifying Benefits from Trade

This section quantifies the impacts of importing and exporting in the Colombian chemical industry. The model of this chapter is constructed to quantify the three possible channels through which import and export can boost the firm's performance. For importing, the proposed three channels are (i) improving future productivity, (ii) reducing the current short-run marginal cost, and (iii) reducing the sunk costs that a firm should pay to start serving the foreign market. For exporting, there are analogous three channels: (i) improving future productivity, (ii) earning additional profits from the foreign market, and (iii) reducing the fixed costs that a firm should pay to continue importing foreign materials. To quantify the impact of each channel, I follow the decomposition exercise conducted by Zhang (2017). This exercise allows me to isolate the contribution of each channel to the industry average of the firm values in 1981 Colombian Pesos.

3.5.1.1 Gains from Importing

I begin with defining the total gains from importing. Let $V(s_{jt})$ be the simulated industry average of the firm values in the benchmark specification and $V_{No-Import}(s_{jt})$ be the simulated industry average of the firm in the economy where importing is not allowed. Then, the gains from importing in the model are defined by the difference between $V(s_{jt})$ and $V_{No-Import}(s_{jt})$:

$$\text{Gains from importing} = V(s_{jt}) - V_{No-Import}(s_{jt})$$

Following Zhang (2017), I compute $V_{No-Import}$ by letting $\gamma^{SM} = \gamma^{FM} = \nu^{SM} = \nu^{FM} = \infty$.

The gains from importing can be exactly decomposed into three parts: gains from learning-by-importing, gains from facilitating export, and gains from reducing the short-run marginal costs. First, the gains from learning-by-importing can be computed by the difference between $V(s_{jt})$ and $V(s_{jt}|g_m = 0)$:

$$\text{Gains from learning-by-importing} = V(s_{jt}) - V(s_{jt}|g_m = 0),$$

where $V(s_{jt}|g_m = 0)$ is the simulated industry average of the firms in the economy where there is no learning-by-importing channel. Second, I compute the gains from facilitating exporting by the difference between $V(s_{jt}|g_m = 0)$ and $V(s_{jt}|g_m = 0, \nu^{SX} = \gamma^{SX})$:

$$\text{Gains from facilitating exporting} = V(s_{jt}|g_m = 0) - V(s_{jt}|g_m = 0, \nu^{SX} = \gamma^{SX}),$$

where $V(s_{jt}|g_m = 0, \nu^{SX} = \gamma^{SX})$ is the simulated industry average of the firms in the economy where there are no learning-by-importing and facilitating exporting channels. Finally, the remaining term would account for the gains from reducing the short-run marginal costs:

$$\text{Gains from reducing marginal costs} = V(s_{jt}|g_m = 0, \nu^{SX} = \gamma^{SX}) - V_{No-Import}(s_{jt}).$$

Table 3.8 displays the gains from importing, and the gains from three channels spanning from 1982 to 1985. The first panel reports the total gains from importing.

All units are expressed in 100 million of 1981 Colombian Pesos. The second to fourth panels report the gains from (i) learning-by-importing, (ii) facilitating exporting, and (iii) reducing short-run marginal costs, respectively. Notice that the learning-by-importing channel accounts for about over 80% of the gains from importing. In the year 1985, the total gains are 383 million of 1981 Pesos and 85% of the gains are attributed to the impact of learning-by-importing. This result is not surprising because as shown in Table 3.4, importing was playing a crucial role in boosting the future level of productivity, which translates to the larger values of firms. Also, 13% of the gains are explained by the reduction in short-run marginal costs. This result is also consistent with the static estimates indicating that an importer could enjoy higher profits than its counterpart as it can produce a product with cheaper costs. However, the facilitating exporting channel does not attribute to the total gains from importing. The channel only accounts for 1.8% of the total gains. That is, even though an importer could access the export market easily, it does not translate to an increase in the firm values.

Table 3.8. Accounting for Benefits from Importing

	1982	1983	1984	1985
	Total Benefits			
Firm Values	3.2939	3.4843	3.7381	3.8321
	Long-run Benefits			
Firm Values	2.6846	2.8951	3.1321	3.2654
%	(81.50)	(83.09)	(83.79)	(85.21)
	Benefits from Complementarity			
Firm Values	0.0594	0.0628	0.0656	0.0681
%	(1.80)	(1.80)	(1.75)	(1.78)
	Short-run Benefits			
Firm Values	0.5499	0.5264	0.5404	0.4986
%	(16.69)	(15.11)	(14.46)	(13.01)

Note. Simulation reports average results from fifty simulations. Firm values are in 100 millions of 1981 Pesos. The numbers in brackets are the percentage ratio of each gains to the total gains. Long-run Benefits are the gains from learning-by-importing; Benefits from Complementarity are the gains from reducing the costs of exporting; and Short-run Benefits are the gains from reducing short-run marginal costs.

3.5.1.2 Gains from Exporting

I decompose the total gains from exporting in the same manner. Again, let $V(s_{jt})$ be the simulated industry average of the firm values in the benchmark specification and

$V_{No-Export}(s_{jt})$ be the simulated industry average of the firm in the economy where exporting is not allowed. The value can be computed by letting $\gamma^{FX} = \gamma^{SX} = \nu^{FX} = \nu^{SX} = \infty$. I also define the firm values used to isolate the effect of each channel: $V(s_{jt}|g_e = 0)$ is the simulated industry average of firms in the economy where no learning-by-exporting channel exists, and $V(s_{jt}|g_e = 0, \nu^{FM} = \gamma^{FM})$ is the simulated average in the economy where there are no learning-by-exporting and facilitating importing channels. Thus, the total gains of exporting can be decomposed analogously:

$$\begin{aligned}
\text{Gains from learning-by-importing} &= V(s_{jt}) - V(s_{jt}|g_e = 0),\\
\text{Gains from facilitating exporting} &= V(s_{jt}|g_m = 0) - V(s_{jt}|g_e = 0, \nu^{FM} = \gamma^{FM}),\\
\text{Gains from making an export profit} &= V(s_{jt}|g_e = 0, \nu^{FM} = \gamma^{FM}) - V_{No-Export}(s_{jt}).
\end{aligned}$$

Table 3.9 reports the decomposition of the gains from exporting. The first panel displays the total gains from exporting. The second to fourth panels display the gains from the three channels. Notice that in the year 1985, unlike the case of importing, the impact of learning-by-exporting only accounts for 18% of the total gains. In contrast, the gains from short-run export profits are central to shaping the total gains from exporting. This short-run gain explains about 79% of the total gains from exporting. In line with the case of importing, facilitating the other activity plays a minor role in accounting for the total gains. The gains account for only about 3% of the total gains.

3.5.2 Policy Counterfactual

Using the estimated model, I conduct counterfactual experiments to evaluate trade-cost subsidy schemes, which are typical policy instruments to encourage firms' international trade activities. In this exercise, I consider four possible subsidy plans: subsidizing (1) import fixed, (2) export fixed, (3) import sunk, and (4) export sunk costs. I choose subsidy rates of each policy such that the firm's expected subsidized grants are equal to 1,500,000 1981 Colombian Pesos.[8] To quantify the effects, I simulate the model for 10 years and report the differences between the outcomes from the counterfactual world and the benchmark. I particularly investigate differences in (i) the industry average of productivity, (ii) import participation rates, (iii) export participation rates, and (iv) the industry average of firm values.

Figures 3.1 to 3.3 display the results of all four policies. Amongst all the four

[8]This amount is equivalent to about 10% subsidy of export fixed costs.

Table 3.9. Accounting for Benefits from Exporting

	1982	1983	1984	1985
	Total Gains			
Firm Values	3.2304	3.4686	3.8278	3.9018
	Long-run Benefits			
Firm Values	0.5400	0.5858	0.6420	0.6729
%	(16.72)	(16.89)	(16.77)	(17.25)
	Benefits from Complementarity			
Firm Values	0.1347	0.1404	0.1456	0.1475
%	(4.17)	(4.05)	(3.80)	(3.78)
	Short-run Benefits			
Firm Values	2.5557	2.7424	3.0402	3.0814
%	(79.11)	(79.06)	(79.42)	(78.97)

Note. Simulation reports average results from fifty simulations. Firm values are in 100 millions of 1981 Pesos. The numbers in brackets are the percentage ratio of each gains to the total gains. Long-run Benefits are the gains from learning-by-exporting; Benefits from Complementarity are the gains from reducing the costs of importing; and Short-run Benefits are the gains from making short-run profits in the foreign market.

policies, subsidizing import fixed costs is the most effective to boost the industry average productivity. Ten years after the import fixed cost subsidy policy, the average productivity is about 0.4% higher than the benchmark case. This result reflects the fact that import fixed cost subsidy could boost the import participation rates dramatically (Figure 3.2) and the learning-by-importing effect is significant. Notice that in the long run, subsidizing export/import sunk costs will not increase the average productivity. Given that learning-by-importing is crucial and subsidizing export/import sunk costs would not boost the import participation rate in the long run, the decrease in the average productivity is not a surprising result. Subsidizing export fixed costs also improves the average productivity but the improvement is quantitatively small.

Subsidizing fixed trade costs is expected to promote trade participation rates (Figure 3.2 and 3.3). First, not surprisingly, subsidizing import fixed costs improves import participation rates by 4% points ten years after the policy, and a similar result emerges in the case of export fixed cost subsidy. Second, along with the estimation result that export and import facilitate each other, I find that subsidizing import/export fixed costs also promotes other activity participation rates. In particular, subsidizing import fixed costs would increase the export participation rates by 1.5% points, and subsidizing export fixed costs encourages more firms to engage in using foreign intermediate inputs.

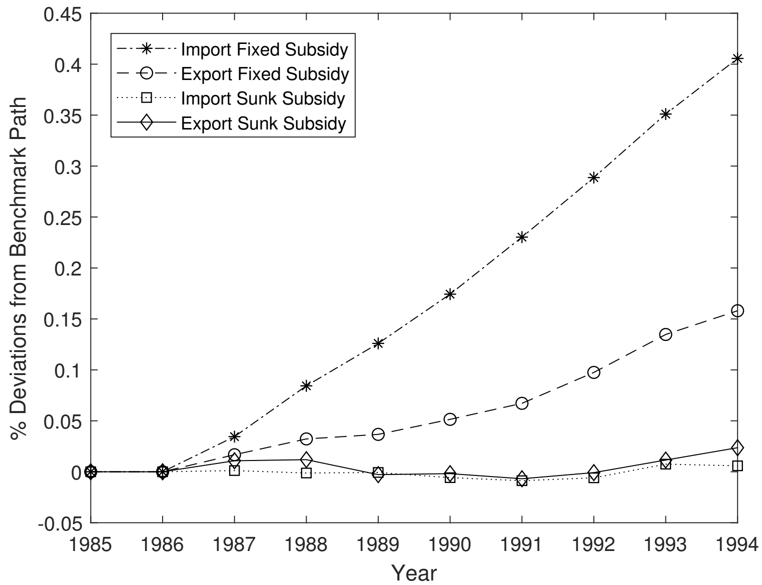

Figure 3.1. Effect of Trade Cost Subsidy Schemes: Productivity

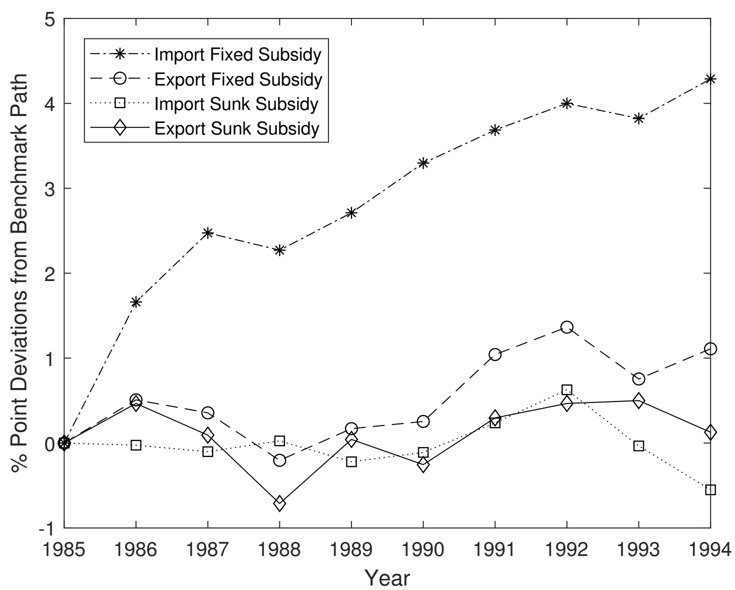

Figure 3.2. Effect of Trade Cost Subsidy Schemes: Import Participations

Contrary to the fixed cost subsidy case, subsidizing sunk costs, which is equivalent to encouraging non-trade participants to engage in international trade, is not a good policy plan in terms of improving productivity and trade participation rates. This result is similar to Peters, Roberts, Vuong, and Fryges (2017) and Peters, Roberts, and Vuong (2022), who document that subsidizing R&D startup costs is not helpful for both

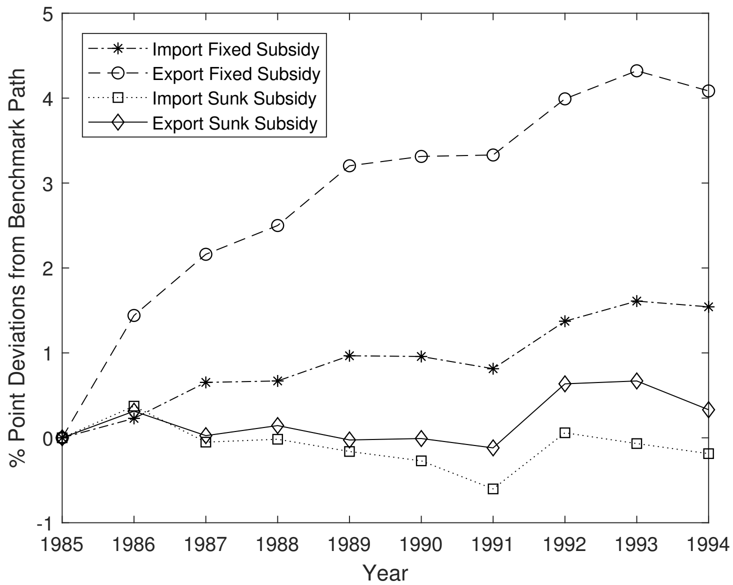

Figure 3.3. Effect of Trade Cost Subsidy Schemes: Export Participations

German high- and low-tech industries. Of course, a domestic firm could start exporting or importing at cheaper costs, and it will raise participation rates. However, the policy also could encourage firms who are currently doing export or import to stop now and plant to restart the activity later. Under the parameter values in Tables 3.4 and 3.5, the latter offsets the former one and thus the participation rates remain unchanged or changed very slightly. This result also translates to no change in average productivity.

Finally, subsidizing import fixed costs is the most effective among the proposed subsidy plans according to the cost-benefit analysis displayed in Figure 3.4. The figure displays the gains from the subsidy. Ten years after the policies, the gains from the policy subsidizing import fixed costs are about 5,300 million of 1981 Pesos which is the largest one amongst the gains from other policies. This is because subsidizing import fixed costs improves the industry average productivity, and this large improvement translates into an increase in the average firm values. Export fixed cost subsidy is also beneficial to Colombian chemical firms, but the benefits are not as large as the ones from import fixed cost subsidy. Given that sunk cost subsidy plans do a poor job at promoting productivity and trade participation rates, the benefits of sunk cost subsidy plans are quite small: 150 and 70 million of 1981 Pesos from import and export sunk cost subsidies, respectively.

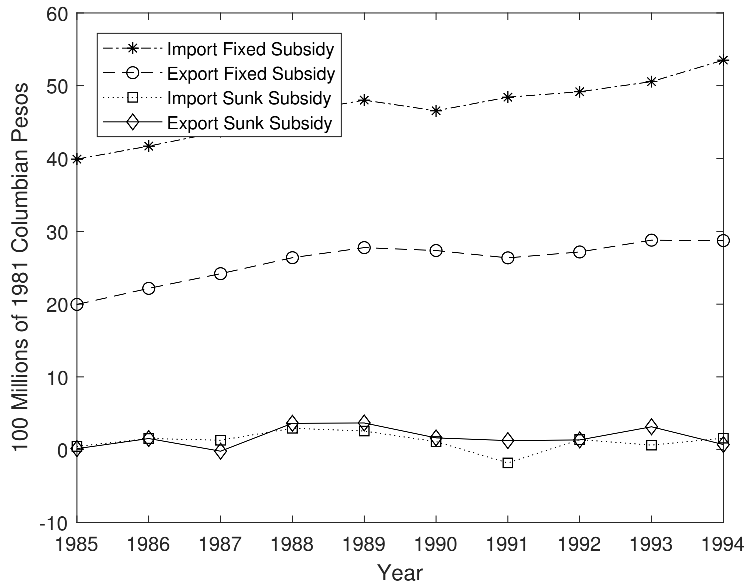

Figure 3.4. Effect of Trade Cost Subsidy Schemes: Ratio of Benefits to Costs

3.6 Conclusion

I propose a dynamic model of the joint decisions to export and import to quantify the gains from partaking in trade activities. Using the model, I decompose the gains from partaking in trade activities into the gains from three channels: (i) learning-by-trading, (ii) increasing the short-run profits, and (iii) trade cost complementarity. In addition, I use the model to evaluate trade cost subsidy schemes, which are common policy instruments in many developing countries.

Estimation results drawn from the Colombian chemical industry indicate that a firm has the incentive to import because it will face the lower marginal cost and boost its productivity through the learning-by-importing channel. A firm also has the incentive to export as it will enjoy more profits from the foreign market but exporting does not affect the future level of productivity as much as importing does. In line with the previous studies, startup costs for both importing and exporting are significantly larger than continuation costs for trade. A novel result is that an importer could access the foreign market more easily than a domestic firm due to the reduction in sunk costs for exporting, and an exporter can pay less money in order to continue its import status due to the reduction in fixed costs for importing.

Decomposition of the gains from trade implies that the most of gains from importing are explained by the gains from learning-by-importing, while the gains from exporting are mostly explained by the static gains from earning more profits from the foreign market. Learning-by-importing effects explain about 85% of the total gains from importing in the year 1985. In the same year, static gains from earning more profits account for 80% of the total gains from exporting.

Counterfactual results indicate that subsidizing the import fixed costs is the most efficient policy plan among the four proposed plans. The gains from this policy are about 16 times larger than the subsidy costs that the Colombian government should pay. In contrast, no matter what the trading activity is, subsidizing sunk costs is not a good way to promote international trade participation and improve the firm values.

Appendix A

Appendix of Chapter 1

A.1 Structural Break in Market Structure Dynamics

The shift of the screen distribution toward mid-plex theaters suggests that the chains have altered their size decisions. However, this change might be driven by local market characteristics or aggregate time trends. In this appendix, I alleviate this concern by estimating the following regression:

$$n_{mt}^{(j)} = \theta_j + \theta_m + \theta_t + \sum_{k=-1}^{-8} \tau_k T_k D_j + \sum_{k=1}^{8} \tau_k T_k D_j + W'_{mt-1}\theta_w + u_{mt}^{(j)}, \tag{A.1}$$

where $j \in \{\text{others}, \text{midplex}\}$, $n_{mt}^{(j)}$ is the number of j-type theaters in market m and in period t, and θ_j, θ_m, and θ_t are market, size, and time fixed effects, respectively. D_j is an indicator of whether or not j is midplex. T_k is a dummy whether time t relative to 2014H2 is the same with k. W_{mt-1} is a vector of lagged market characteristics, including population, GDP per capita, and commercial property values. The key parameters are τ_k with $k > 0$. These coefficients capture the structural break at a point of the regime shift in the relative changes in the number of midplex theaters to the others. I omit T_0 by using it as a reference group.

Figure A.1 displays the estimates of τ_k in equation (A.1) and the corresponding 95-percent confidence intervals. The early-regime coefficients are statistically indistinguishable from zero, suggesting that the numbers of midplex theaters and the other share a parallel trend before the regime shift.

The regulatory regime shift had a disproportionate impact on the size of movie

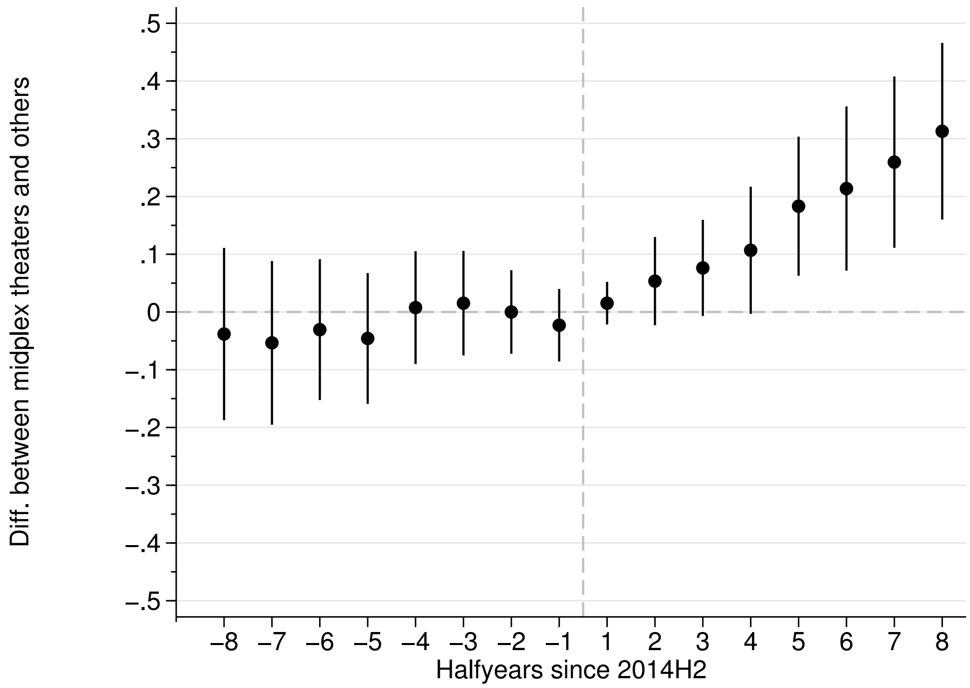

Figure A.1. Effect of Regulatory Regime Shift

Note. The figure depicts the effects the land use regulatory regime shift on the number of midplex theaters. It plots the point estimates of τ_k in equation (A.1).

theaters. Following the shift, the number of midplex theaters per market gradually increased. During the first two years, the number of midplex theaters per market increased by 0.05. However, during the last two years, that increased by 0.25. This gradual transition suggests the presence of the sunk entry costs that impedes an immediate response of the chains to the changes in the profit and cost structures.

A.2 CCP's Goodness of Fits

In this appendix, I report the performance of the first stage CCPs in describing the industry dynamics.

Market Structure Dynamics The estimated CCPs track the trends in theater counts and their average number of screens well. Figure A.2 plots the evolution of the number of CGV, Lotte Cinema, and Megabox theaters, and Tables A.1 tabulates the time evolution of the average number of screens per theater by chains. Note that the predictions of the number of theaters are smoother than the actual trends, and the predicted average number of screens is lower than the data counterpart. Despite these discrepancies, the model MPNEs capture the main trends in the data well.

Transitions of Screens Lastly, I evaluate the performance of the model in matching the transition patterns of the number of screens. Table A.2 tabulates screen transition. The calculated MPNEs do a good job of replicating a considerable persistence of screen transition, suggesting a considerable sunk opening cost. Also, the MPNEs predict a higher transition rate from k to $k+6$ than those to $k+3$ and $k+9$. This pattern means that the sunk cost of opening a 6-screen theater is lower than those of opening 3-screen and 9-screen theaters.

The calculated MPNEs show a poor performance in matching screen transition when the number of screens is higher than 21. In particular, the MPNEs underpredict the persistence of screen transition. However, this finding is likely driven by rare observations with screens of more than 21.

Table A.1. Trends in Average Number of Screens per Theater

	CGV		Lotte Cinema		Megabox	
	Real Data	Simulated Data	Real Data	Simulated Data	Real Data	Simulated Data
2010H1	7.8041	7.4842	7.5273	7.5818	7.7885	7.6731
2010H2	7.7822	7.4469	7.4000	7.4992	7.7843	7.6064
2011H1	7.7885	7.4092	7.3770	7.4048	7.7255	7.5574
2011H2	7.7273	7.3679	7.3636	7.3362	7.6981	7.5143
2012H1	7.7431	7.3375	7.2143	7.2772	7.7321	7.4729
2012H2	7.7143	7.3059	7.0513	7.2319	7.6909	7.4345
2013H1	7.7436	7.2769	6.9639	7.1891	7.7636	7.3999
2013H2	7.7692	7.2462	6.8571	7.1480	7.6552	7.3614
2014H1	7.7845	7.2233	6.8351	7.1138	7.6491	7.3270
2014H2	7.6000	7.2018	7.0000	7.0839	7.5082	7.2906
2015H1	7.6290	7.1807	7.0481	7.0579	7.4355	7.2593
2015H2	7.6429	7.1442	6.9083	7.0291	7.1714	7.1725
2016H1	7.6349	7.1147	6.9455	7.0026	7.1081	7.1024
2016H2	7.5769	7.0860	6.9561	6.9772	7.1358	7.0540
2017H1	7.5259	7.0597	6.9569	6.9554	7.0920	7.0125
2017H2	7.5106	7.0351	6.9407	6.9355	6.9677	6.9772
2018H1	7.4257	7.0142	6.9661	6.9128	6.9565	6.9486
2018H2	7.3775	6.9934	6.9918	6.8974	6.9388	6.9210

Note. Data are simulated using the estimated CCPs and market type-specific demand process D^{μ}. The predicted evolutions are obtained by averaging 500 simulations.

Table A.2. Half-Annual Predicted Transition Rates (%)

Screens at t		Screens at $t+1$												
		0	3	6	9	12	15	18	21	24	27	30	33	36
0	Predicted	95.53	0.65	2.45	1.36	0	0	0	0	0	0	0	0	0
	Actual	96.30	0.59	2.16	0.96	0	0	0	0	0	0	0	0	0
3	Predicted	0.79	95.67	0.4q	1.8t	1.29	0	0	0	0	0	0	0	0
	Actual	0.41	96.75	0.41	1.63	0.81	0	0	0	0	0	0	0	0
6	Predicted	3.20	0.01	92.72	0.26	2.55	1.26	0	0	0	0	0	0	0
	Actual	1.83	0.00	95.25	0.27	2.01	0.64	0	0	0	0	0	0	0
9	Predicted	2.77	0.04	0.11	92.33	0.19	2.49	2.07	0	0	0	0	0	0
	Actual	1.40	0.00	0.17	94.42	0.17	2.27	1.57	0	0	0	0	0	0
12	Predicted	0	0.18	2.20	0.55	94.73	0.49	0.45	1.40	0	0	0	0	0
	Actual	0	0	3.11	0.44	94.67	0.00	0.44	1.33	0	0	0	0	0
15	Predicted	0	0	2.73	2.42	0.18	90.51	1.06	1.75	1.36	0	0	0	0
	Actual	0	0	1.71	2.05	0	93.15	1.03	1.37	0.68	0	0	0	0
18	Predicted	0	0	0	3.24	0.15	0.33	93.40	0.27	2.50	0.10	0	0	0
	Actual	0	0	0	2.03	0	0.29	95.64	0.29	1.45	0.29	0	0	0
21	Predicted	0	0	0	0	3.82	2.37	1.11	90.76	0.58	0.39 3	0.97	0	0
	Actual	0	0	0	0	0	3.57	0	96.43	0	0	0	0	0
24	Predicted	0	0	0	0	0	3.08	2.35	0.26	91.58	1.10	1.58	0.05	0
	Actual	0	0	0	0	0	3.92	1.96	0	90.20	1.96	1.96	0	0
27	Predicted	0	0	0	0	0	0	4.90	2.97	8.23	80.77	0.72	2.40	0
	Actual	0	0	0	0	0	0	0	0	16.67	66.67	0	16.67	0
30	Predicted	0	0	0	0	0	0	0	8.22	7.32	0.52	83.22	0.67	0.05
	Actual	0	0	0	0	0	0	0	0	0	0	100	0	0
33	Predicted	0	0	0	0	0	0	0	0	16.14	6.89	15.44	61.16	0.38
	Actual	0	0	0	0	0	0	0	0	0	0	0	100	0
36	Predicted	0	0	0	0	0	0	0	0	0	0	8.33	2.27	89.39
	Actual	na	na	na	na	na	na	na	na	na	na	na	na	na

Note. The unit of measurement is firm-market-halfyer. Data are simulated using the estimated CCPs and market type-specific demand process D^{μ}. The predicted moments are obtained by averaging 500 simulations.

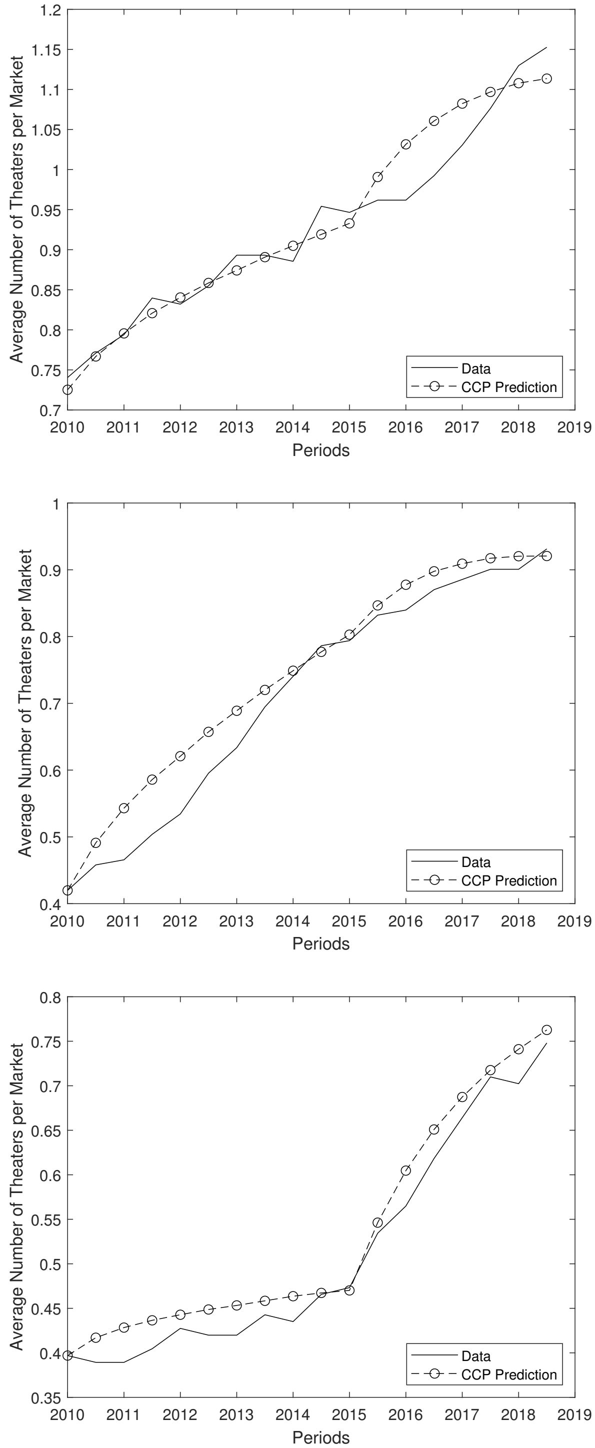

Figure A.2. The Average Number of Theaters per Market

Note. Data are simulated using the estimated CCPs and market type-specific demand process D^{μ}. The predicted moments are obtained by averaging 500 simulations.

A.3 Estimates of model with only theater entry decision

This appendix estimates a typical dynamic entry model in which the corresponding action space is $\{-1, 0, 1\}$, where -1 indicates an exit of a theater, whereas 1 indicates an entrant. Similar to the equilibrium policy function of the benchmark model, I can characterize the equilibrium policy function of this model as an ordered probit regression. Using the estimated policy function, I perform a forward simulation method to estimate the underlying structural parameters. Upon the estimation of the model, I perform the same counterfactual exercise to quantify the effect of lowering entry barriers on the producer surplus.

Tables A.3, A.4, and A.5 report the estimated CCP coefficients, variable profit parameters, and fixed- and sunk-cost parameters, respectively.

Table A.3. Ordered Probit on Extensive Marginal Theater Entry-Exit Decision

Covariates	(1)
# own chain theaters	-0.7449^{***}
	(0.0858)
# rival chain theaters	-0.5137^{***}
	(0.0535)
population (thousand people)	0.0098^{***}
	(0.0014)
GDP per capita (thousand KRW)	0.0057
	(0.0050)
Property value per m^2 (million KRW)	-0.4707^{**}
	(0.2183)
Market Dummies	✓
Log likelihood	-1204.93
Observations	6,681

Note. Estimated using a strongly balanced panel of the chain-market-time level. Standard errors are in parenthesis. Asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All units are expressed in one standard deviation of the standard Normal distribution.

Table A.4. Restricted Model: Estimates of Variable Profits per Theater

	Estimates	SEs
Competitive Effects: γ		
Cannibalization	-119.2102	11.9863
Rival competition	-135.2731	19.1731
Demand Shifters: λ		
Population (thousands)	2.5474	0.2632
GDP per capita (thousand 2011 KRW)	1.2615	0.2408

Note. Early-regime sunk entry cost parameter is calibrated to 1,800 million KRWs, which is quoted from a business report. All units of the other estimates are expressed in millions of 2011 constant KRW. Standard errors are calculated via subsampling.

Table A.5. Restricted Model: Estimates of Fixed Operating and Sunk Entry Costs

	2010H1-2014H2		2015H1-2018H2	
	Estimates	SEs	Estimates	SEs
Fixed Cost Parameters:$\phi_i^{FC}(\mu_m)$				
CGV in market category 1	-625.6663	59.1033	-567.4308	52.8206
CGV in market category 2	-214.9851	29.8943	-155.7225	18.4651
CGV in market category 3	133.5679	19.6595	163.9915	23.6065
Lottecinema in market category 1	-595.2884	67.2614	-597.5310	55.3321
Lottecinema in market category 2	-211.8450	30.1368	-180.4478	15.6520
Lottecinema in market category 3	164.1895	18.5007	135.8644	26.5437
Megabox in market category 1	-667.5595	66.8960	-580.2130	57.9888
Megabox in market category 2	-263.7131	27.6147	-170.6763	16.5021
Megabox in market category 3	67.3320	18.5322	153.5719	25.5545
Fixed Cost Parameters:ϕ_R^{FC}				
Property Values per m^2 (million 2011 KRW)	-87.2158	12.8121	-	-
Sunk entry cost parameters				
6-screen (ϕ^{EC})	*1,800.00*	N/A	1221.87	58.5511
standard deviation (ν)	405.810	–	-	-

Note. This table displays the fixed operating and sunk entry cost parameters. Early-regime sunk entry cost parameter is calibrated to 1,800 million KRWs, which is quoted from a business report. All units of the other estimates are expressed in millions of 2011 constant KRW. Standard errors are calculated via subsampling.

Appendix B

Appendix of Chapter 2

B.1 Derivation of Estimating Equations

The first-order conditions of the maximization problem in (2.5) with respect to skilled labor, unskilled labor, material, output for the domestic market, and output for the export market are as follows:

$$W_{jt}^S = \mu_{jt} \exp(a_{jt}^S)[\alpha_L L_{jt}^\gamma + \alpha_M M_{jt}^\gamma + \alpha_K K_{jt}^\gamma]^{\frac{1}{\gamma}-1} \alpha_L (L_{jt})^{\gamma-\rho} (L_{jt}^S)^{\rho-1} \tag{B.1}$$

$$W_{jt}^U = \mu_{jt} \exp(a_{jt}^S)[\alpha_L L_{jt}^\gamma + \alpha_M M_{jt}^\gamma + \alpha_K K_{jt}^\gamma]^{\frac{1}{\gamma}-1} \alpha_L (L_{jt})^{\gamma-\rho} \exp(\rho \tilde{a}_{jt}^U)(L_{jt}^U)^{\rho-1} \tag{B.2}$$

$$P_{jt}^M = \mu_{jt} \exp(a_{jt}^S)[\alpha_L L_{jt}^\gamma + \alpha_M M_{jt}^\gamma + \alpha_K K_{jt}^\gamma]^{\frac{1}{\gamma}-1} \alpha_M (M_{jt}^U)^{\gamma-1} \tag{B.3}$$

$$(\frac{\eta_D + 1}{\eta_D}) \Phi_t^D (Q_{jt}^D)^{\frac{1}{\eta_D}} = \mu_{jt} \tag{B.4}$$

$$\kappa(\frac{\eta_X + 1}{\eta_X}) \Phi_t^X (Q_{jt}^X)^{\frac{1}{\eta_X}} = \mu_{jt}, \text{ provided } e_{jt} = 1 \tag{B.5}$$

where μ_{jt} is the Lagrange multiplier corresponding to the production restriction ($Q_{jt}^D + e_{jt} Q_{jt}^X = Q_{jt}$).

I first recover the equation mapping the observables to relative unskilled labor efficiency $\tilde{\nu}_{jt}$. Take ratio with respect to (B.2) and (B.1), I recover $\tilde{a}_{jt}^U$ as a function of observables displayed in (2.8). Plug back this term into a CES aggregator of skilled and unskilled labors, I arrive at the following equation

$$L_{jt} = (\frac{E_{jt}^L}{E_{jt}^S})^{\frac{1}{\rho}} L_{jt}^S, \tag{B.6}$$

where $E_{jt}^S = W_{jt}^S L_{jt}^S$, $E_{jt}^U = W_{jt}^U L_{jt}^U$, and $E_{jt}^L = E_{jt}^U + E_{jt}^S$.

Second, I can control for unobserved material prices using (B.1), (B.3), and (B.6). Take the ratio with respect to (B.1) and (B.3), and replace L_{jt} with (B.6), I obtain a closed form of M_{jt} as a function of observables.

$$M_{jt} = (\frac{\alpha_L}{\alpha_M}\frac{E^M_{jt}}{E^L_{jt}})^{\frac{1}{\gamma}}(\frac{E^L_{jt}}{E^S_{jt}})^{\frac{1}{\rho}}L^S_{jt}. \tag{B.7}$$

Finally, for plants serving the domestic market only, (B.1) and (B.4) imply

$$\exp(\frac{\eta_D+1}{\eta_D}a^S_{jt}) = (\Phi^D_t)^{-1}[\alpha_L L^\gamma_{jt} + \alpha_M M^\gamma_{jt} + \alpha_K K^\gamma_{jt}]^{1-\frac{1}{\gamma}\frac{\eta_D+1}{\eta_D}}(L_{jt})^{\rho-\gamma}E^S_{jt}(L^S_{jt})^{-\rho}. \tag{B.8}$$

Then, observed domestic revenue R^D_{jt} is

$$\begin{aligned} R^D_{jt} &= \Phi^D_t(Q^D_{jt})^{\frac{\eta_D+1}{\eta_D}}\exp(u^D_{jt}) \\ &= \Phi^D_t(Q^D_{jt})^{-\frac{1}{\eta_D}}\exp(\frac{\eta_D+1}{\eta_D}a^S_{jt})[\alpha_L L^\gamma_{jt} + \alpha_M M^\gamma_{jt} + \alpha_K K^\gamma_{jt}]^{\frac{1}{\gamma}\frac{\eta_D+1}{\eta_D}}\exp(u^D_{jt}). \end{aligned} \tag{B.9}$$

Plug (B.8) into (B.9), I arrive at

$$R^D_{jt} = (\frac{\eta_D}{\eta_D+1})[\alpha_L(L_{jt})^\gamma + \alpha_M M^\gamma_{jt} + \alpha_K K^\gamma_{jt}](L_{jt})^{\rho-\gamma}E^S_{jt}(L^S_{jt})^{-\rho}\exp(u^D_{jt}) \tag{B.10}$$

Replace L_{jt} and M_{jt} with (B.6) and (B.7), I obtain the following estimating equation.

$$\ln R^D_{jt} = \ln\frac{\eta_D}{\eta_D+1} + \ln[E^M_{jt} + E^L_{jt}(1 + \frac{\alpha_K}{\alpha_L}(\frac{K_{jt}}{L^S_{jt}})^\gamma(\frac{E^S_{jt}}{E^L_{jt}})^{\frac{\gamma}{\rho}})] + u^D_{jt}, \tag{B.11}$$

where $E^M_{jt} = P^M_{jt}M_{jt}$.

Use (B.7) and the normalization restriction that the geometric mean of all inputs is one, I obtain the identifying restriction for α_M.

$$\frac{\alpha_M}{\alpha_L} = \frac{\bar{E}^M}{\bar{E}^L}(\frac{\bar{E}^L}{\bar{E}^S})^{\frac{\gamma}{\rho}},$$

where $\bar{E}$ refers to the geometric mean of all expenditures. To identify α_K, I restrict that the sum of distribution parameters is one.

$$\alpha_L + \alpha_M + \alpha_K = 1$$

I estimate the production function parameters including the demand market elasticity through constrained nonlinear least squared (NLLS).

$$
\begin{aligned}
(\hat{\eta}_D, \hat{\gamma}, \hat{\rho}, \hat{\alpha}_L, \hat{\alpha}_M, \hat{\alpha}_K) &= \arg\min \hat{Q}(\Theta) \\
\text{subject to } \frac{\alpha_M}{\alpha_L} &= \frac{\bar{E}^M}{\bar{E}^L}(\frac{\bar{E}^L}{\bar{E}^S})^{\frac{\gamma}{\rho}}, \\
\text{and } \alpha_L + \alpha_M + \alpha_K &= 1,
\end{aligned}
$$

where $\Theta = (\eta_D, \theta, \sigma, \alpha_L, \alpha_M, \alpha_K)$, and $\hat{Q}$ is the sample objective function corresponding to (2.11).

For the derivation of (2.12), I use equations (B.4) and (B.5). Take the ratio with respect to these equations, I represent Q^X_{jt} as a function of Q^D_{jt}.

$$
Q^X_{jt} = (\frac{1}{\kappa}\frac{\eta_X}{\eta_X+1}\frac{\eta_D+1}{\eta_D}\frac{\Phi^D_t}{\Phi^X_t})^{\eta_X}(Q^D_{jt})^{\frac{\eta_X}{\eta_D}}. \tag{B.12}
$$

Use (3.9) and (2.7), I translate (B.12) to

$$
\ln R^X_{jt} = -\eta_X \ln \kappa + (\eta_X + 1)\ln(\frac{\eta_X}{\eta_D}\frac{\eta_D+1}{\eta_X+1}) + \frac{\eta_X+1}{\eta_D+1}\ln R^D_{jt} + \delta_t + u_{jt}, \tag{B.13}
$$

where $u_{jt} = u^X_{jt} - \frac{\eta_X+1}{\eta_D+1}u^D_{jt}$.

B.2 Recovering Unobservables

Use equation (B.7) to obtain the amount of material M_{jt}. Then, by dividing E^M_{jt} by the recovered M_{jt}, I recover the material prices P^M_{jt}.

I use (B.1), (B.4), and (B.12) to recover skilled labor-augmenting efficiencies. I first use (B.12) and obtain

$$
Q_{jt} = Q^D_{jt} + e_{jt}(\frac{1}{\kappa}\frac{\eta_X}{\eta_X+1}\frac{\eta_D+1}{\eta_D}\frac{\Phi^D_t}{\Phi^X_t})^{\eta_X}(Q^D_{jt})^{\frac{\eta_X}{\eta_D}}, \tag{B.14}
$$

where e_{jt} is an indicator of exporting. Then, by the construction of production function, I have

$$
Q^D_{jt} + e_{jt}(\frac{1}{\kappa}\frac{\eta_X}{\eta_X+1}\frac{\eta_D+1}{\eta_D}\frac{\Phi^D_t}{\Phi^X_t})^{\eta_X}(Q^D_{jt})^{\frac{\eta_X}{\eta_D}} = \exp(a^S_{jt})[\alpha_L L^\gamma_{jt} + \alpha_M M^\gamma_{jt} + \alpha_K K^\gamma_{jt}]^{\frac{1}{\gamma}} \tag{B.15}
$$

Use (B.1) and (B.4), I further obtain

$$\exp(a_{jt}^S) = \frac{\eta_D + 1}{\eta_D}\frac{1}{\alpha_L} L_{jt}^{\rho-\gamma}(L_{jt}^S)^{-\rho} E_{jt}^S (\Phi_t^D)^{-1} (Q_{jt}^D)^{-1} [\alpha_L L_{jt}^\gamma + \alpha_M M_{jt}^\gamma + \alpha_K K_{jt}^\gamma]^{1-\frac{1}{\gamma}} \tag{B.16}$$

Thus, the equations (B.15) and (B.16) constitute a nonlinear simultaneous equations with two unknowns (a_{jt}^S, Q_{jt}^D). I can solve for these two unknowns numerically.

Finally, I obtain a_{jt}^U using recovered a_{jt}^S and recovered $\tilde{a}_{jt}^U$.

$$\begin{aligned} a_{jt}^U &\equiv a_{jt}^S + \tilde{a}_{jt}^U \\ &= a_{jt}^S + \frac{1}{\rho}\ln\frac{E_{jt}^U}{E_{jt}^S} + \ln\frac{L_{jt}^S}{L_{jt}^U}. \end{aligned} \tag{B.17}$$

Appendix C

Appendix of Chapter 3

C.1 Example of Das et al. (2007)'s Method

This appendix describes how the method allows observed z_{it} and simulated z_{is} to be correlated with a simple example.

Consider a case in which $T = 3$, and $(e_{j1}, e_{j2}, e_{j3}) = (1, 0, 1)$. Then, by the definition of z_j^+ and Σ_+, I obtain

$$z_j^+ = \begin{bmatrix} z_{j1} \\ z_{j3} \end{bmatrix},$$

and

$$z_j^+ \sim N(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} v_z & \rho_z^2 v_z \\ \rho_z^2 v_z & v_z \end{bmatrix}),$$

where $v_z = \frac{\sigma_z^2}{1-\rho_z^2}$. Furthermore, by the definition of Σ_{z+} and Σ_{zz}, I can construct A and B which are essential to simulate the $\mathbf{z}_j$:

$$\Sigma_{z+} = E(\begin{bmatrix} z_{j1} \\ z_{j2} \\ z_{j3} \end{bmatrix} \begin{bmatrix} z_{j1} & z_{j3} \end{bmatrix}) = \begin{bmatrix} v_z & \rho_z^2 v_z \\ \rho_z v_z & \rho_z v_z \\ \rho_z^2 v_z & v_z \end{bmatrix}$$

and

$$\Sigma_{zz} = \begin{bmatrix} v_z & \rho_z v_z & \rho_z^2 v_z \\ \rho_z v_z & v_z & \rho_z v_z \\ \rho_z^2 v_z & \rho_z v_z & v_z \end{bmatrix}.$$

Hence,

$$A = \Sigma_{z+}\Sigma_{+}^{-1} = \begin{bmatrix} 1 & 0 \\ \frac{\rho_z}{1+\rho_z^2} & \frac{\rho_z}{1+\rho_z^2} \\ 0 & 1 \end{bmatrix},$$

$$BB' = \Sigma_{zz} - \Sigma_{z+}\Sigma_{+}^{-1}\Sigma_{z+}' = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \frac{\sigma_z^2}{1+\rho_z^2} & 0 \\ 0 & 0 & 0 \end{bmatrix},$$

and

$$B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \frac{\sigma_z}{\sqrt{1+\rho_z^2}} & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$

Thus, in generic simulation k, the constructed $\mathbf{z}_j^k$ is defined as the following:

$$\mathbf{z}_j^k = \begin{bmatrix} z_{j1} \\ \frac{\rho_z}{1+\rho_z^2} z_{j1} + \frac{\rho_z}{1+\rho_z^2} z_{j3} + \frac{\sigma_z}{\sqrt{1+\rho_z^2}} \epsilon_{j2}^k \\ z_{j3} \end{bmatrix}.$$

Notice that along with simulations, z_{j1}^k and z_{j3}^k do not vary and fixed at the observed values (z_{j1}, z_{j3}).

The important feature is that in simulations, z_{j2}^k is a linear combination of observed values z_{j1} and z_{j3}. This feature allows for simulated z_{j2}^k to be serially correlated with observed values z_{j1} and z_{j3}.

Also, it is necessary to check whether z_{j2}^k is drawn from AR(1) specification. To do so, I first show that autocorrelations between z_{j1} and simulated z_{j2}^k, and between z_{j3} and simulated z_{j2}^k remain fixed at ρ_z in simulations. Note that

$$\begin{aligned} \mathrm{Cov}(z_{j1}, z_{j2}^k) &= \frac{\rho_z}{1+\rho_z^2}\mathrm{Cov}(z_{j1}, z_{j1}) + \frac{\rho_z}{1+\rho_z^2}\mathrm{Cov}(z_{j1}, z_{j3}) \\ &= \frac{\rho_z}{1+\rho_z^2} v_z + \frac{\rho_z}{1+\rho_z^2}\rho_z^2 v_z \\ &= \rho_z v_z. \end{aligned}$$

Since $z_{j2}^k = \frac{\rho_z}{1+\rho_z^2} z_{j1} + \frac{\rho_z}{1+\rho_z^2} z_{j3} + \frac{\sigma_z}{\sqrt{1+\rho_z^2}} \epsilon_{j2}^k$,

$$\mathrm{Cov}(z_{j2}^k, z_{j2}^k) = 2(\frac{\rho_z}{1+\rho_z^2})^2 v_z + 2(\frac{\rho_z}{1+\rho_z^2})^2 \rho_z^2 v_z + \frac{1-\rho_z^2}{1+\rho_z^2} v_z$$

$$= v_z.$$

Hence, in simulations, the autocorrelation between z_{j1} and z_{j2}^k is fixed at ρ_z. Analogously, the autocorrelation between z_{j2}^k and z_{j3} is also fixed at ρ_z. Second, by showing that the conditional variance of z_{j2}^k conditioning on z_{j1} is σ_z^2, I can confirm that the simulated value z_{j2}^k is also following the same AR(1) specification that the observed values follow. Notice that

$$\begin{aligned} E((z_{j2}^k - \rho_z z_{j1})^2) &= E((z_{j2}^k)^2 - 2\rho_z z_{j2}^k z_{j1} + \rho_z^2 z_{j1}^2) \\ &= v_z - \rho_z^2 v_z \\ &= \sigma_z^2. \end{aligned}$$

Therefore, the simulated values drawn from the proposed method follow the same AR(1) process.

C.2 Detail of the random-walk Metropolis-Hastings Algorithm

This appendix describes how I design the random-walk Metropolis-Hastings algorithm in practice.

Since I should estimate 19 dynamic parameters, implementing the algorithm without breaking Θ_D into multiple blocks is highly inefficient (low acceptance rates). To obtain reasonable acceptance rates, I break parameter vectors into seven blocks.

$$
\begin{aligned}
\Theta_D^1 &= (\rho_z, \log \sigma_z), \\
\Theta_D^2 &= (\Phi_0^X, \alpha_e^{'}), \\
\Theta_D^3 &= \alpha_m^{'}, \\
\Theta_D^4 &= (\gamma^{SM}, \gamma^{SX}), \\
\Theta_D^5 &= (\nu^{SM}, \nu^{SX}), \\
\Theta_D^6 &= (\gamma^{FM}, \gamma^{FX}), \\
\Theta_D^7 &= (\nu^{FM}, \nu^{FX}).
\end{aligned}
$$

The random-walk Metropolis-Hasting algorithm used in this chapter involves the following steps.

1. Start with $b = 0$ and $j = 1$.

2. Draw a candidate parameter vector $\Theta_{D,b}^{j*} = \Theta_{D,b}^{j} + \varphi_b^j$, where $\varphi_b^j \sim N(0, \Sigma^j)$

3. Define

$$
\alpha_b^j = \min\{0, \log \frac{\pi(\Theta_{D,b+1}^1, \cdots, \Theta_{D,b}^{j*}, \Theta_{D,b}^{j+1}, \cdots, \Theta_{D,b}^7 | D)}{\pi(\Theta_{D,b+1}^1, \cdots, \Theta_{D,b}^{j}, \Theta_{D,b}^{j+1}, \cdots, \Theta_{D,b}^7 | D)}\}
$$

4. Draw $u \sim Unif(0,1)$ and update the parameters

$$
(\Theta_{D,b+1}^1, \cdots, \Theta_{D,b+1}^{j}, \Theta_{D,b}^{j+1}, \cdots, \Theta_{D,b}^7) = \begin{cases} (\Theta_{D,b+1}^1, \cdots, \Theta_{D,b}^{j*}, \Theta_{D,b}^{j+1}, \cdots, \Theta_{D,b}^7), & \text{if } \log u \leq \alpha_b^j \\ (\Theta_{D,b+1}^1, \cdots, \Theta_{D,b}^{j}, \Theta_{D,b}^{j+1}, \cdots, \Theta_{D,b}^7). & \text{otherwise} \end{cases}
$$

5. If $j < 7$, $j = j + 1$, and go to step 2. If $j = 7$, and $b < B$, let $b = b + 1$, and go to step 2. If $j = 7$ and $b = B$, the chain is over.

The most important parameters in MCMC are the covariance matrices $(\Sigma^1, \cdots, \Sigma^7)$ which are governing acceptance rates of the chain. In practice, I can consider that the chain steps over the support of the posterior distribution quickly if acceptance rates are ranging in the reasonable interval $(0.15, 0.7)$. Given this discussion, I specify Σ^j as a diagonal matrix and choose variances ensuring that acceptance rates are in the reasonable range.

C.3 MCMC Diagnostics

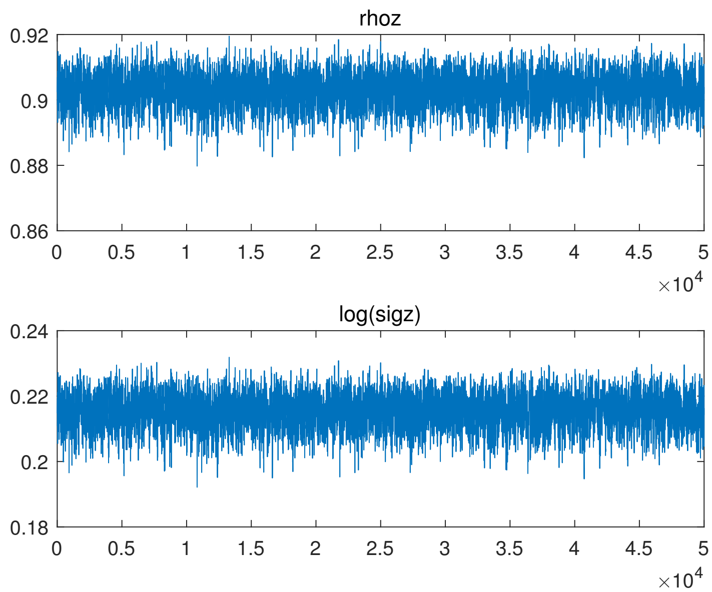

Figure C.1. MCMC Trace Plot: Export Demand Parameters

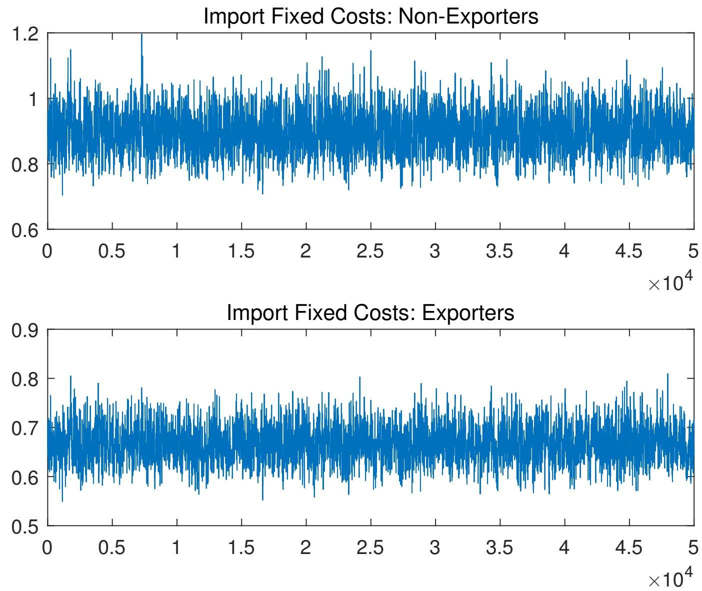

Figure C.2. MCMC Trace Plot: Fixed Costs of Importing

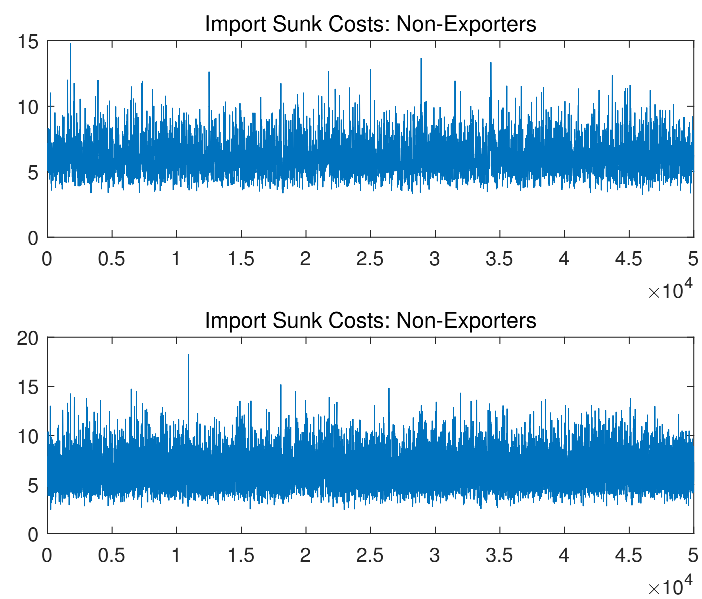

Figure C.3. MCMC Trace Plot: Sunk Costs of Importing

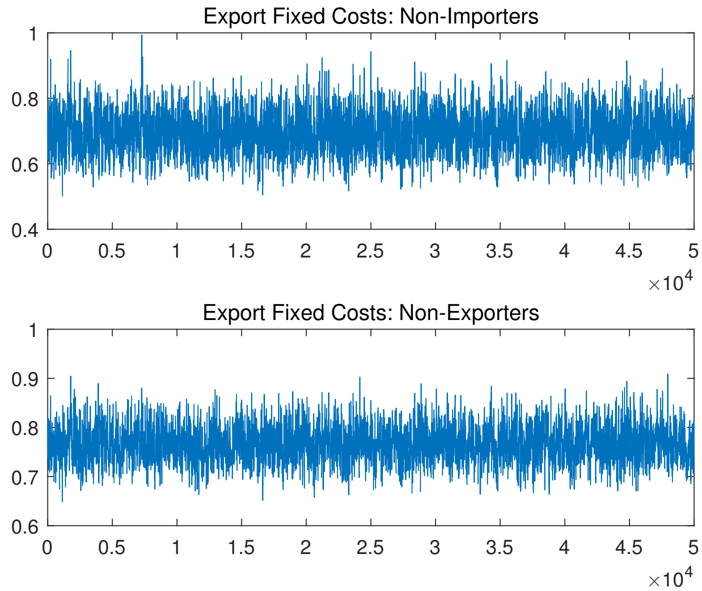

Figure C.4. MCMC Trace Plot: Fixed Costs of Exporting

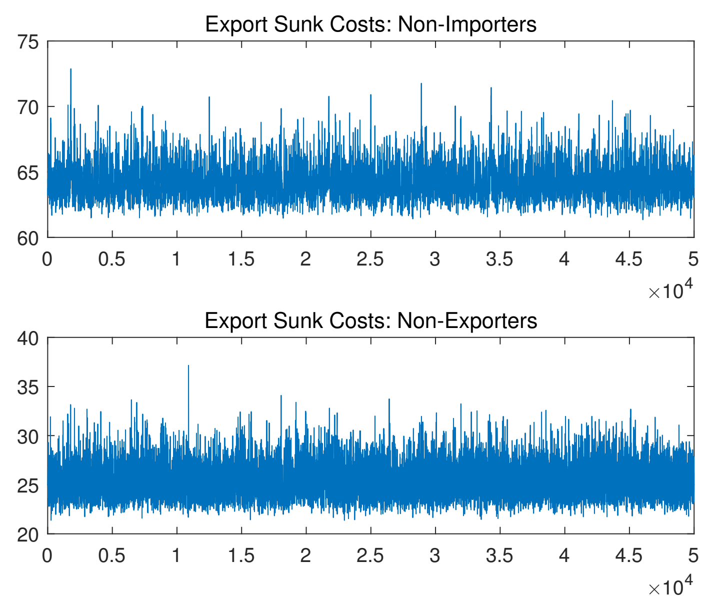

Figure C.5. MCMC Trace Plot: Sunk Costs of Exporting

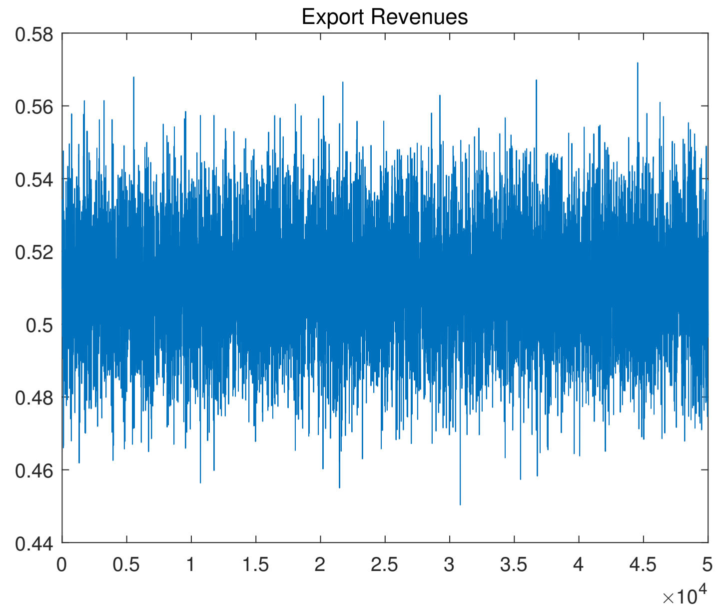

Figure C.6. MCMC Trace Plot: Baseline Export Revenue

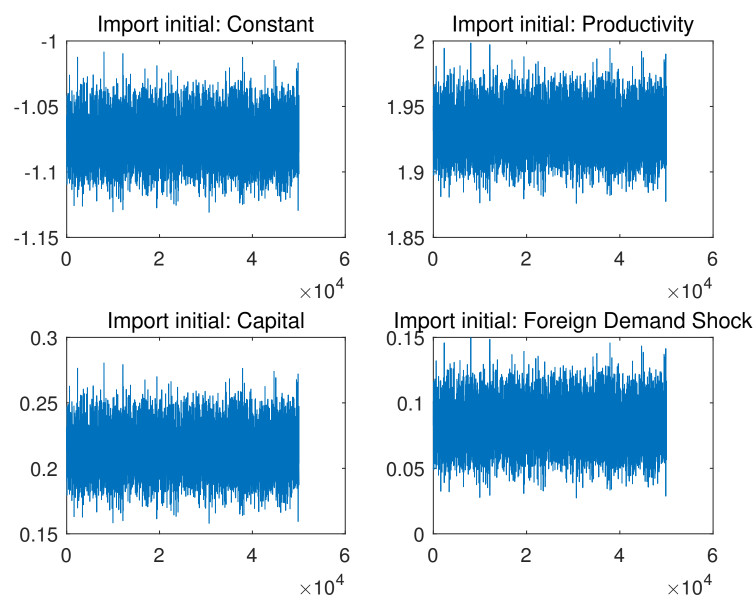

Figure C.7. MCMC Trace Plot: Initial Condition Parameters for Import

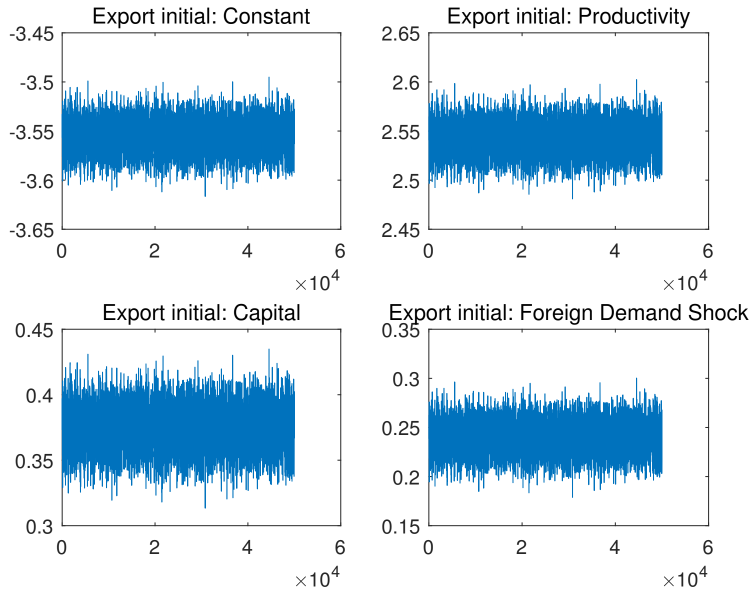

Figure C.8. MCMC Trace Plot: Initial Condition Parameters for Export

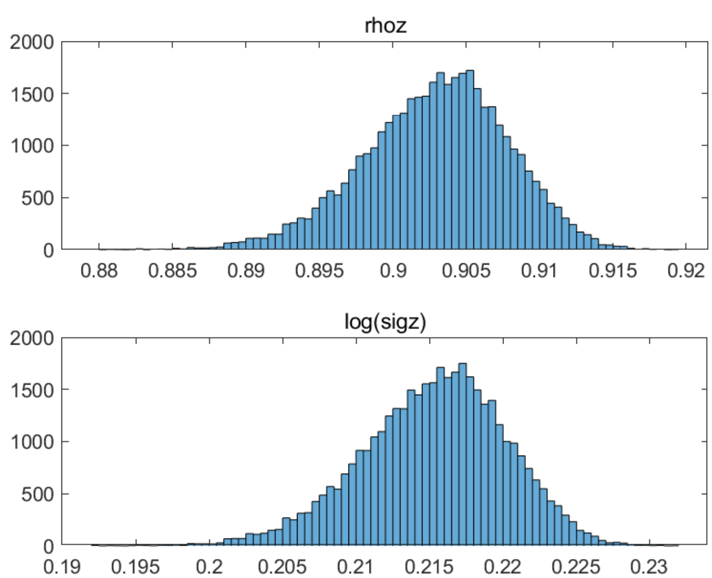

Figure C.9. MCMC Histogram: Export Demand Parameters

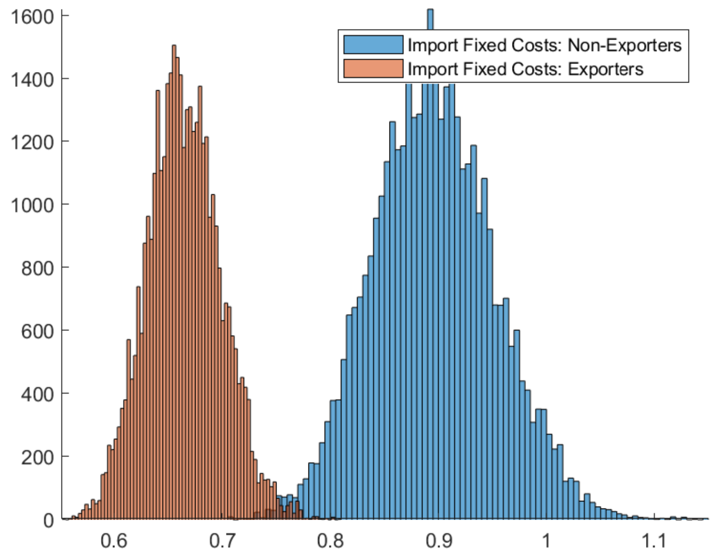

Figure C.10. MCMC Histogram: Fixed Costs of Importing

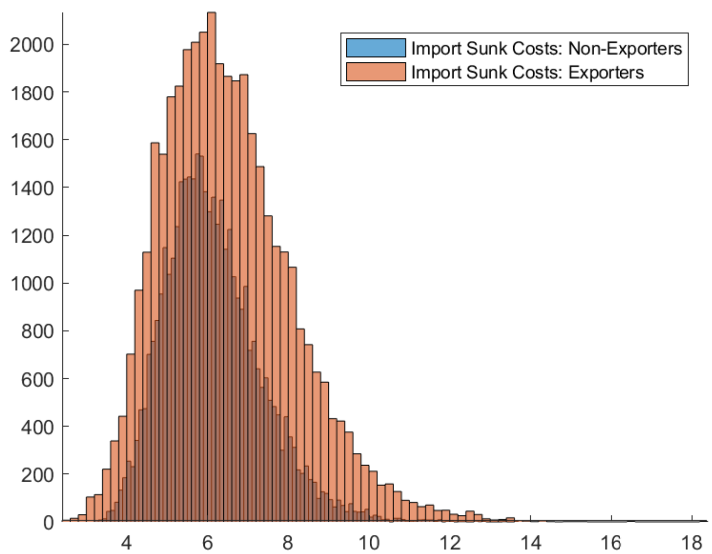

Figure C.11. MCMC Histogram: Sunk Costs of Importing

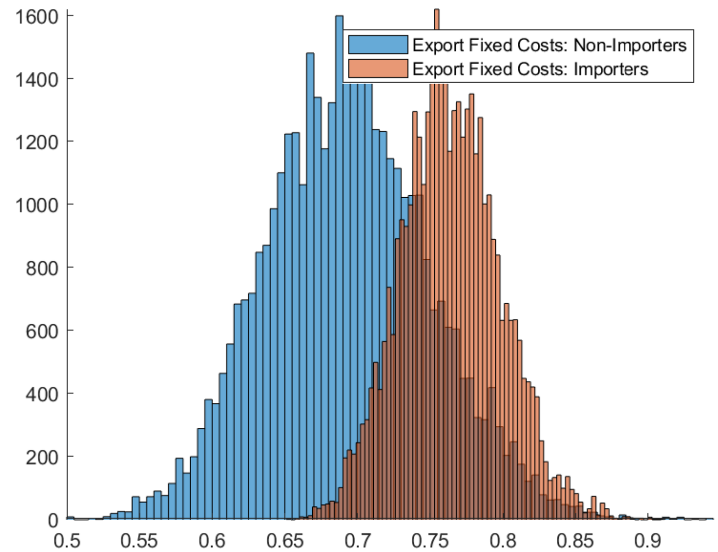

Figure C.12. MCMC Histogram: Fixed Costs of Exporting

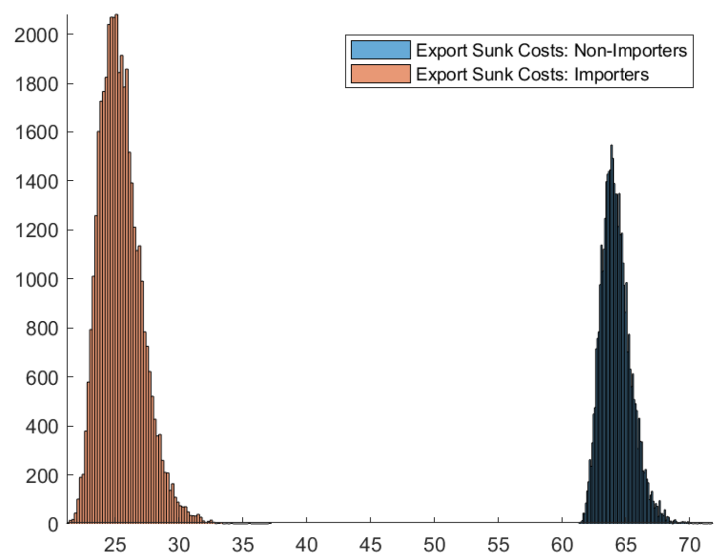

Figure C.13. MCMC Histogram: Sunk Costs of Exporting

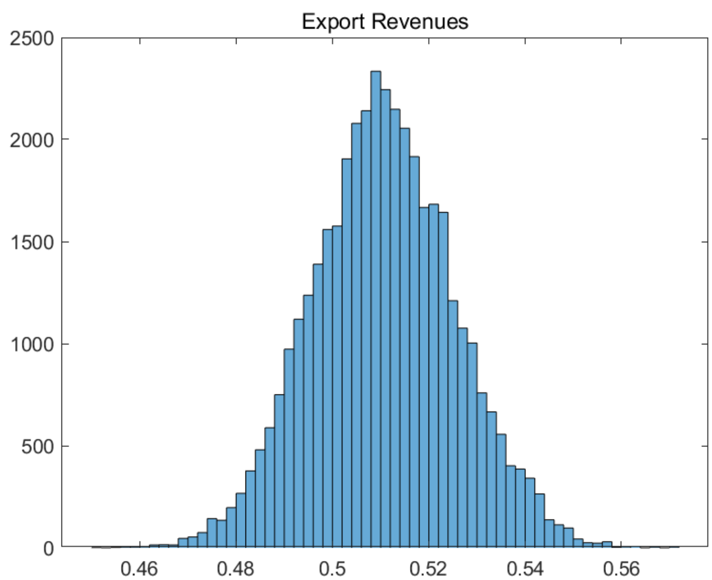

Figure C.14. MCMC Histogram: Baseline Export Revenue

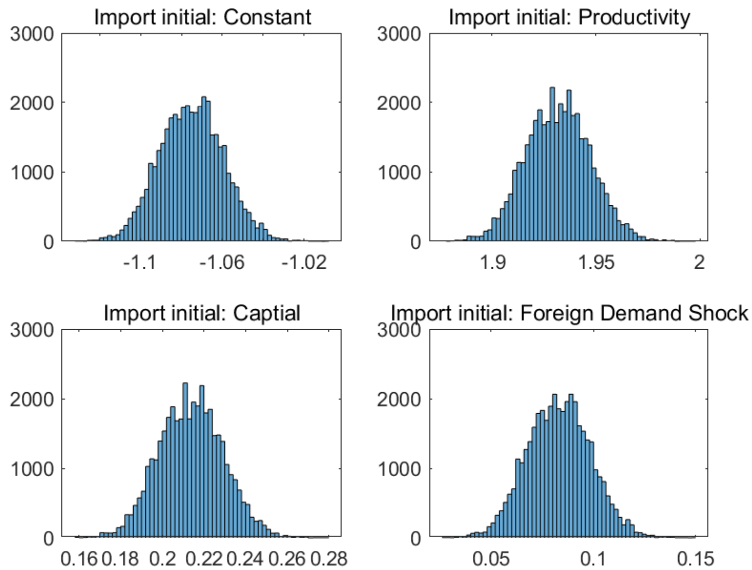

Figure C.15. MCMC Histogram: Initial Condition Parameters for Import

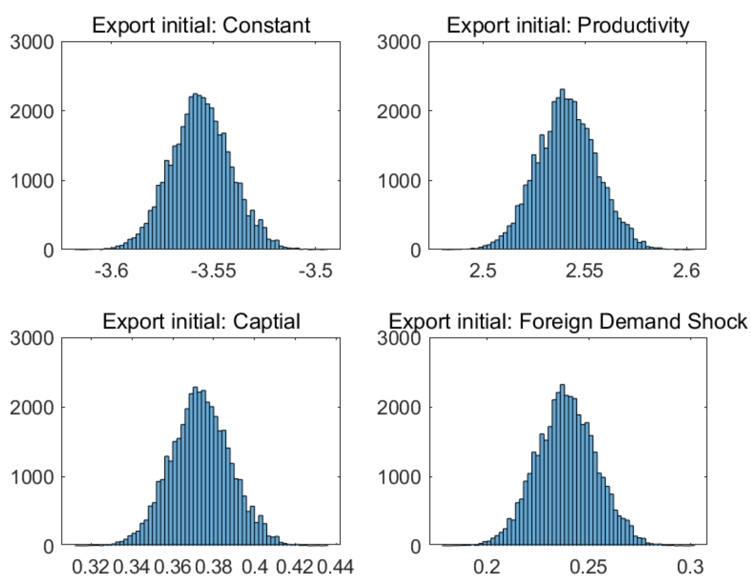

Figure C.16. MCMC Histogram: Initial Condition Parameters for Export

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