ESSAYS ON INDUSTRIAL ORGANIZATION AND FIRM DYNAMICS

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ESSAYS ON INDUSTRIAL ORGANIZATION AND FIRM DYNAMICS

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This dissertation consists of three essays in the areas of Industrial Organization and Firm Dynamics and Trade, examining the interaction between firms' decision-making and government policies in determining market outcomes and the welfare consequences.

The first chapter studies how upstream market concentration and demand risk affect downstream firms' outsourcing decisions. Firms' boundary decisions are one of the most fundamental issues in economics. I focus on the volatile automobile industry and study how firms can use outsourcing to insure themselves against the demand risk. I formulate a structural model in which outsourcing allows the downstream firms to hedge the uncertain in-house production cost and upstream firms exploit downstream's insurance motive by exerting market power. I estimate the model using data on the vehicle manufacturers and upstream transmission firms in the automobile industry. In the counterfactual analysis, I evaluate the potential impact of the United States-Mexico-Canada Agreement. When the upstream market is more concentrated due to the protection of the local firms, upstream's price response to a negative shock further increases by 68%. An increase in upstream market power attenuates upstream's role of insurance and amplifies the impact of economic downturns on consumer welfare and manufacturers' profit by 65%. My paper highlights a previously overlooked welfare loss channel of market power, especially in industries heavily affected by the business cycles.

In the second chapter, I analyze the impact of trade policies on firm dynamics and the labor market. I construct a demand system with the production function to purge out the price effect in productivity measures based on sales data. It allows me to separate the firm-side physical productivity gain from the demand-side impact of trade liberalization. I use my new physical productivity measure to analyze the effect of the processing trade policies prevalent in developing countries. Required by the policy, firms import duty-free intermediate input from abroad but are forced to reexport their final products. Though firms with high productivity enter the export market, I find firms with productivity lower than non-exporters become pure processing trade firms and export as well. In addition, their productivity gains from the input tariff reduction and exporting are much smaller compared with the other exporting firms.

In the third chapter, my coauthor and I study the geographic concentration of entrants and capitalists in the US. We first document that VC investment is elastic to local vintage capital, and we propose that local vintage capital supply is an essential determinant of this spatial concentration and co-location decision. We develop a model by linking the motives of co-locating by entrants and capitalists via a core feature of vintage capital reallocation toward young firms mediated by venture capital. Since a vintage capital market with abundant supply can lower the capital cost and thus increase the profits, VC investments are attracted due to higher expected returns. This, in turn, encourages entrepreneurship and leads to a selection-induced agglomeration effect. A larger city intensifies such allocative forces and thus amplifies the agglomeration effect, which ultimately makes the city further attractive to VC investment relative to others.

BIOGRAPHICAL SKETCH

Qinshu Xue is a Ph.D. candidate in the Department of Economics at Cornell University. Her areas of specialization include empirical industrial organization, firm dynamics, and trade. A core strand of her research involves studying the interaction between firms' decision-making and government policies.

She grew up in Nanjing, China. She earned a Bachelor of Science in Economics from Shanghai University of Finance and Economics in 2014 and a Master of Science in Economics from University of Wisconsin Madison in 2015. She joined the Ph.D. program in Economics at Cornell University in the fall of 2016, and aspires to earn her Ph.D. in August 2022.

To my parents.

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CHAPTER 1

VERTICAL RELATIONS, DEMAND RISK, AND UPSTREAM CONCENTRATION: THE CASE OF THE US AUTOMOBILE INDUSTRY

1.1 Introduction

Many industries face significant demand risks for their products. The volatility in demand will further impose challenges in managing the whole supply chain. Understanding what determines the vertical relations and the choice between in-house production and outsourcing from the upstream is one of the essential questions in economics.[1] The primary goal of this paper is to understand the role of demand fluctuations and upstream market power in affecting outsourcing decisions in the automobile industry.

In this paper, I study how these two forces jointly shape the firm boundary of downstream firms and further affect the firms' profit and consumer surplus. The upstream firms create incentives for outsourcing by providing a stable price when the demand and the cost of in-house production are volatile.[2] However, they also increase prices in response to the outsourcing motives. By forcing the downstream firms' to withhold demand risk to themselves, the upstream market power elevates the cost of input, amplifying the negative impact of economic downturns on the manufacturers' profit and consumer welfare. With an endog-

[1] Lafontaine and Slade (2007) survey the theoretical and reduced-form empirical literature on vertical relations.

[2] This can be well summarized by White (2013), "A way of reducing the risks of vertical integration is through partial or tapered integration: a company can produce a portion of its needs of an item and buy the fluctuating remainder. This has the advantage of providing full utilization of its own equipment and allowing the suppliers to absorb the risk of fluctuations in demand. The company has to pay a premium to get someone else to absorb the risks, but the risk transfer is achieved..."

enized upstream's price response, my paper highlights a previously overlooked welfare loss channel of market power, especially in industries heavily affected by the business cycles.

The automobile industry lends itself to the analysis. It is highly volatile, affected by the macroeconomic environment and within-industry uncertainty about consumer taste. In the past 40 years, the auto industry represents almost 5% of the aggregate GDP in the US and accounted for almost 25% of the variance. In addition, auto production involves more than ten thousand parts, and supply chain management is at the heart of all car companies' business models. Supply contracts in the industry create a way for downstream firms to hedge the demand risk. By delegating the upstream firms to produce, the downstream firms are insured against the risk of a fluctuating in-house production cost of a particular input induced by demand volatility.

For the empirical analysis, I focus on the outsourcing decision of the transmission, a core component in the powertrain system that takes up about 7% of the cost of a car. The transmission market provides a suitable setting to study my question. First, compared with most parts that are fully outsourced nowadays, some downstream manufacturers still preserve sizable in-house production. In addition, due to technological barriers, the transmission industry in the US is highly concentrated. It is dominated by Aisin, ZF, and JATCO, which serves more than 90% of the market. However, all three transmission firms are foreign firms, and most transmissions are imported. Only Aisin has a large production site in North America.

To model the interaction between upstream transmission firms and the downstream vehicle manufacturers, I consider a static three-stage game played by the two sectors. In the first stage, upstream firms simultaneously post their prices based on the expectation of downstream manufacturers' outsourcing strategies and demand shocks. In the second stage, downstream firms choose the proportion of their product portfolio to outsource based on comparing a stable upstream price and an expected in-house production cost. When demand and cost shocks are realized in the third stage, downstream firms sell products to consumers in a simultaneous price-setting game. The model is built on two key features. First, upstream firms' prices are invariant to demand shock realization. Second, the demand shock affects in-house production cost due to curvatures in the cost function. Therefore, vehicle manufacturers can use outsourcing decisions to pass unfavorable shocks to the upstream by paying a premium. Meanwhile, the upstream firms adjust their prices, responding to manufacturers' outsourcing incentives.

I use a novel dataset that links upstream transmission firms and vehicles. Combining it with data on vehicle prices, sales, and characteristics, I first estimate the demand and marginal cost of cars together with the prices and in-house production cost of transmissions. The estimated in-house cost function exhibits a U shape, reflecting the nature of many production processes. As the demand increases, there are increasing returns to scale due to improved equipment utilization. However, when demand exceeds the capacity, it becomes costly to produce an extra unit. There is also substantial heterogeneity in in-house production cost, which is in line with the downstream firms' in-house production patterns. Firms like Daimler, making nearly all transmissions in-house, also have the lowest estimated in-house production cost. Though upstream firms differ in quality and product offerings, they all have a much lower marginal cost than most downstream firms, reflecting their efficiency in producing transmissions.

In the counterfactual analysis, I first use my estimates to quantify the industry response to a negative demand shock equivalent to the recent COVID-19 pandemic. When facing a shrinking demand, the downstream firms use outsourcing to reduce the increasing cost of in-house production. Holding upstream's price fixed, I find that outsourcing mitigates the increase in the average transmission cost by 48%. For the downstream firms actively making outsourcing decisions, their profit loss during the economic bust can be reduced by $548 million.[3] However, due to upstream's market power, the transmission prices on average increase by $137.18 in response to downstream firms' outsourcing incentives. The rise in upstream firms' prices is further passed down to downstream firms and consumers, generating a welfare loss of $470 million to the industry.

I next examine the impact of a more concentrated upstream market. This counterfactual also has important implications on the recent United States-Mexico-Canada Agreement, which aims at protecting the local transmission industry and labor market. The policy forces manufacturers to use transmissions made in North America by increasing the Regional Value Content requirement and thus increasing upstream market concentration.[4] I find switching to monopoly upstream almost doubles the transmission price and leads to a profit increase of 176% for the remaining upstream firm Aisin. Besides the widely acknowledged welfare loss due to double marginalization, a more concentrated upstream is also more responsive to the downstream firms' outsourcing incentives when facing the same pandemic demand shock. The average price charged

[3] Prices in this papers are all in 2015 dollars.

[4] Setting up a transmission production line usually costs $150M-$400M. The policy significantly lifts the entry barrier.

by the upstream firm further increases by 68%. It expands the profit loss of downstream firms by attenuating their outsourcing incentives and further decreasing the consumer surplus. As a result, an increase in upstream market concentration exacerbates the welfare loss in an economic bust by 65% to $780 million.

According to Bloom et al. (2018), microeconomic uncertainty rises sharply during the economic bust. Therefore, I also explore the propagation of idiosyncratic demand uncertainty in the production network.[5] In my model, demand uncertainty propagates in the production network through its impact on the downstream market competition and the upstream prices. Due to the convexity in the demand function, a firm benefits from increased own demand uncertainty, putting its competitor at a disadvantage.[6] When a passive competitor's demand uncertainty increases, downstream firms can use outsourcing to transmit the negative impact to the upstream firms.[7] Upstream firms' prices increase due to a direct increase in input demand from the passive downstream firms as well as an insurance motive from the other firms. However, firms actively making outsourcing decisions don't intend to outsource when their demand uncertainty increases because most of them are located on the increasing returns to scale portion when producing the transmission in-house. Therefore, a moderate increase in own demand uncertainty leads to an increasing cost advantage of producing in-house.

[5]The economic downturn is a macro-level negative shock that affects the first-moment of the demand shock. The idiosyncratic demand uncertainty is a firm-level risk due to consumer taste, affecting the variance of the demand shock.

[6]The logit error introduces the convexity in demand, commonly found in all discrete choice type demand specifications. As a result, firms are affected more by positive taste shocks than negative taste shocks. When own demand volatility increases, the expected profit will increase.

[7]Passive downstream firms always completely outsource in my data sample. Due to the technological barrier, not all downstream firms are capable of making transmissions in-house. Firms like BMW and Tata outsource all the transmissions and don't make outsourcing decisions.

Related Literature: My work relates to three broad strands of literature: (i) vertical relations under risk, (ii) propagation of shocks in the production networks, (iii) vertical integration patterns in the automobile industry.

There is extensive research about firms' ability to adapt to risk under different ownership structures. Bajari and Tadelis (2001) focus on various procurement contracts and ex-post adaptation costs. Forbes and Lederman (2009, 2010) empirically test the theory in the US airline industry. They find that airlines would use owned regional airlines instead of independent ones on city pairs with more adverse weather. These models predict that ownership should be allocated to ensure more efficient ex-post decisions. I contribute to this literature by studying the effect of risk on vertical integration decisions from an ex-ante point of view. I develop my empirical model on how vertical relations achieve assurance in facing an volatile demand by choosing which demand shocks to withhold in firm border and which shocks to pass to the upstream (Green, 1986; Carlton, 1979).

In addition, my paper is one of the first empirical papers to bridge the upstream market structure and firms' outsourcing decisions under demand risk together using the industrial organization technique. To derive sharp predictions, models in organization theory tend to focus on simple setups with the surrounding market fixed. However, they may have difficulty explaining industry-level patterns because the fixed market-level variables are often equilibrium outcomes.[8] By endogenizing the pricing response to downstream firms' outsourcing decisions, my model delivers equilibrium outsourcing patterns, as well as equilibrium upstream prices. Cost-driven vertical relationship literature also

[8] Bresnahan and Levin (2012) provide a detailed summary of different viewpoints of vertical integration from organizational economics and industrial organization.

provides some insight on how market price responds to vertical integration. Loertscher and Riordan (2019) propose a bidding model to discuss firms' incentive of producing internally to avoid the mark-up charged by upstream suppliers. A similar argument has been made by Garetto (2013) in the setup of multinational firms' input sourcing decisions. I contribute to this literature by developing a tractable structural model that embeds the demand risk in firms' cost-driven incentives, empirically quantifies the importance of this insurance motive, and analyzes the welfare effect.

My research links to the growing literature on the propagation and amplification of shocks through production networks. Previous literature builds multi-sector models to show how microeconomic shocks can translate into aggregate fluctuations through the input-output linkages (Long and Plosser, 1983; Acemoglu et al., 2012, 2017). In empirical studies, disaster-induced shocks are a natural candidate to explore as they cleanly distinguish input disruptions from demand shocks. Carvalho et al. (2020) document the impact of the Great East Japan Earthquake of 2011 along supply chains. Barrot and Sauvagnat (2016) use a broader range of natural disasters to further explore the input specificity as a micro foundation behind the input-output linkage mechanism. I contribute to this literature in two ways. First, my research provides an additional micro foundation by exploring the role of upstream market power in preventing downstream firms from effectively reallocating during times of economic downturns and increased volatility. By focusing on a specific but important sector, my model allows for variable mark-ups both for the upstream and downstream firms and yields more realistic substitution patterns than the monopolistic competition framework assumed in CES models.[9] In addition, I structurally esti-

[9] The main concern about CES for welfare analysis is that it may overestimate the degree of substitutions and lead to erroneously large responses to trade policy changes (Petrin, 2002;

mate the demand shock realization from a rich demand model in which both demand and cost side impact is carefully controlled. This method expands the types of shocks to be studied and also circumvent the common measurement issues prevalent in sale-based volatility measures.[10]

I also contribute to the theories and empirical evidence on vertical integration patterns in the automobile industry. Starting from Ford's success with the Model T, the automobile industry has long been regarded as corroborations for various vertical relation theories and empirical analysis. However, most of the research focuses on testing the different types of transaction cost (Klein et al., 1978; Klein, 1988, 2000; Monteverde and Teece, 1982; Langlois and Robertson, 1989; Masten et al., 1989). Organization theories exploit the success of the Toyota business model and closely study the difference between American and Japanese subcontracting systems (Taylor and Wiggins, 1997). While most of the previous literature focuses on within-firm efficiency gains, the drastic outsourcing trend in the automobile industry in the 1990s adds new insights into firms' outsourcing decisions by linking firms with their surrounding market. Stigler (1951) points out that markets to support disintegrated trade are themselves endogenous. My research extends the analysis of industry integration patterns by incorporating the recent rise of mega suppliers and modeling their price responses to the vertical integration decisions. My paper is also of important policy implications as it provides a quantitative framework to gauge the welfare effect of trade policies that affect the upstream market structure.

Head and Mayer, 2019).

[10]Organization literature uses the volatility in sales or self-reported perception of uncertainty as measures of the demand shock. Trade and macro literature use the variance of output growth as a measure of risk to capture the deviation from a steady-state (Walker and Weber, 1984; Acemoglu et al., 2003; di Giovanni and Levchenko, 2009). Bloom (2014) provides a summary of the uncertainty or risk proxies used in the macro and micro literature.

This paper proceeds as follows. Section 1.2 describes the industry background and the data used. Section 1.3 presents the model. Section 1.4 discusses identification and estimation procedure. Section 1.5 reports structural estimation results and Section **??** addresses the economic questions of interest via counterfactual analysis. Section **??** concludes.

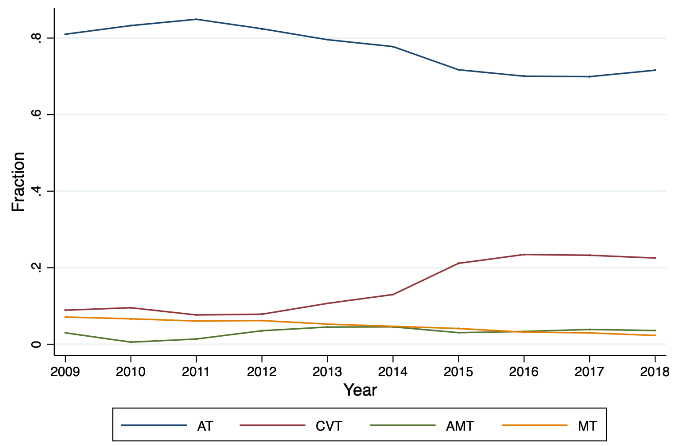
1.2 Industry Background and Data Description

1.2.1 The Transmission Industry

My research focuses on passenger motor vehicles in the US market and the upstream transmission market. Transmission is a core component, transmitting the power from engine to wheel. It greatly contributes to driving capability, fuel economy, and driver performance. Transmission products can be broadly defined as a combination of type and speed. There are four types of transmissions, each with a slightly different mechanism. (i.e. Manual transmission (MT), Auto transmission (AT), Continuous variable transmission (CVT), Automated manual transmission (AMT)). Except for CVT, each of these types has several speed options. The higher the speed, the smoother when changing gears, and the more fuel efficiency. As can be seen Figure 1.1, AT is the most popular transmission in the US due to its user friendly design. CVT has gain increasing popularity because of its fuel efficiency.

The automobile industry is regarded as a buyer market in which the upstream sectors are competitive. However, the transmission industry is one of the few exceptions. There are only a few players in the transmission industry

Figure 1.1: Market Shares of Different Transmissions 2009-2018



Notes: The shares are based on the US passenger vehicles sold in the US 2009-2018. The y axis shows the fraction of transmissions for each type.

due to the technology barrier. Table 1.1 reports the summary statistics for the industry in 2009-2018. Besides a substantial fraction of in-house production, only six firms are serving the US passenger car market. Aisin, ZF and JATCO serve the entire market in the Automatic Transmission sector, which takes up more than 70% of the total market share in the US. The second most popular transmission CVT is served by Aisin and JATCO. Most competition is concentrated in the Manual Transmission sector because it is a relatively mature technology. For the rest of the paper, I define the three minor upstream firms (GETRAG, Eaton, TREMEC) as the other-supplier group.

Moreover, the recent United States-Mexico-Canada Agreement (USMCA) regards transmission as one of the super-core components due to the "Bring Manufacturing Back to America" campaign.[11] To protect local industry and workers, the Regional Value Content (RVC) will be lifted from 66% to 75% over a four-year period. For transmissions to be considered original and qualify for pref-

[11] More information can be found https://ustr.gov/trade-agreements/free-trade-agreements/united-states-mexico-canada-agreement

Table 1.1: Summary Statistics for Transmission Firms

Transmission Types	Speed	Trans Share	in-house share	Firm	Conditional Share
AT	A4	0.066	0.91	Aisin	0.45
				JATCO	0.55
	A5	0.101	0.87	Aisin	0.66
				JATCO	0.34
	A6	0.472	0.87	Aisin	0.86
				ZF	0.14
				JATCO	0.004
	A7	0.024	0.75	JATCO	1.00
	A8	0.074	0.47	Aisin	0.24
				ZF	0.76
	A9	0.023	0.87	ZF	1.00
	A10	0.006	0.98	Aisin	1.00
CVT	CVT	0.155	0.46	Aisin	0.16
				JATCO	0.84
DCT	DCT6	0.024	0.99	GETRAG	1.00
	DCT7	0.008	0.65	ZF	0.78
				GETRAG	0.22
	DCT8	0.0005	0.61	ZF	1.00
	DCT9	0.00003	1		
MT	M5	0.016	0.91	Aisin	0.34
				GETRAG	0.55
				TREMEC	0.11
	M6	0.030	0.79	Aisin	0.09
				ZF	0.11
				Eaton	0.01
				GETRAG	0.46
				TREMEC	0.34
	M7	0.0004	0	ZF	0.46
				TREMEC	0.54

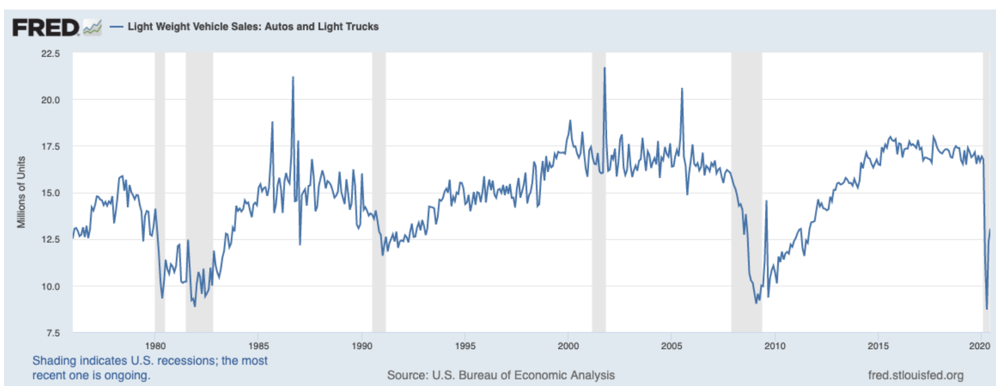
Notes: This table reports types of transmission and market concentration in the transmission market. Shared are calculated using quantity sold. Conditional share is the share of each upstream firm conditional on the outsourced transmission.

erential, duty-free treatment, they must meet the Regional Value Content and Labor Value Content. Furthermore, a car would only be considered original if the super-core components are original. However, major upstream firms like Aisin, ZF, and JATCO are foreign firms with headquarters outside North America. Under the new USMCA agreement, they are required by manufacturers to set up production plants in North America to avoid the $500 to $1200 penalties per car. The new agreement further increases the entry barrier in the transmission industry. It may force incumbent upstream firms to exit the market if they fail to establish a production site as required.

1.2.2 The Automobile Industry

Figure 1.2 shows the fluctuation of passenger vehicle sales in the past 40 years. Both macroeconomic fluctuations and industry-specific shocks like the composition of consumers, exposure to fluctuation in gasoline price and trade policies, substitution patterns with other mobility alternatives would all result in different levels of intrinsic demand risk. Typically, firms would build excess capacity to ensure final product delivery. However, after the recent financial crisis in 2008, most automobile companies significantly reduced their excess capacity to be more cost-efficient.

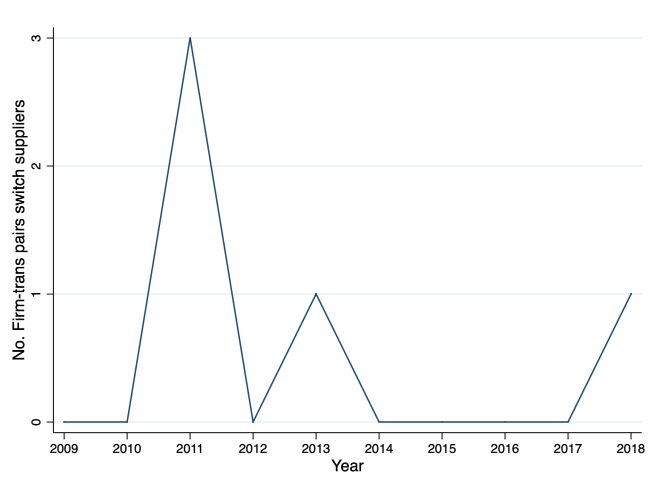
Figure 1.2: Light Weight Vehicle Sales in the US 1975-2020



Notes: The figure is downloaded from St. Louis Fed based on the statistics from US Bureau of Economic Analysis. It shows the passenger vehicle sales in the US 1975-2020.

Compared with the downstream vehicle manufacturers, the upstream transmission firms are in a better position of risk pooling. An upstream firm will design a standardized transmission product and send out an engineering team to work with downstream manufacturers to develop specific software that makes the transmission compatible with the rest of a car model. Since most customization is managed by software, the upstream firms can achieve risk pooling as the transmissions sold to different downstream firms can be made on the same machine. In addition, the supply contract in the industry also facilitates demand risk transfers. The manufacturing contracts typically last for the whole product life cycle. According to Figure 1.3, downstream firms rarely change transmission providers in my data sample. According to Mueller et al. (2008) in their extensive survey with German automobile companies, unit prices in the supply contracts are precisely specified for the initial delivery period, and prices for ensuing periods are either prespecified with stepwise price reduction schedules to account for cost reductions or are renegotiated annually. However, supply contracts almost never specify exact quantities. Even minimum quantities to be absorbed by the downstream firms are rarely specified.

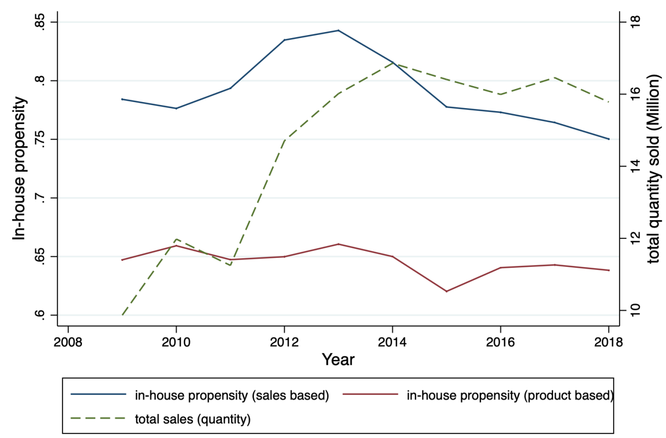
Figure 1.3: Number of Downstream Firms Switching Transmission Providers 2009-2018



Notes: The figure shows the total number of downstream firms transmission pairs that switch to a different upstream firm in each year. The maximum switching fraction is less than 4%.

Unlike many other parts which are completely outsourced, many car manufacturers still produce transmission internally in the same vein as engines and motors. Figure 1.4 documents the outsourcing trend versus the output dynamics across the years. There are some fluctuations in in-house production dynamics using either output or product measure. Even though I rarely observe upstream switches in my data, the firm is still actively making outsourcing decisions on an intensive margin. The total variation in the in-house variable is 0.478, and 30% comes from within product variation. In a rapid demand expansion period from 2009 to 2014, the in-house production share drops significantly. When the market is more stable post-2014, product-based in-house share measure begins to recover while the output-based in-house share measure still falls.

Figure 1.4: Transmission In-House Production Share 2009-2018



Notes: The dash lines is the annual output level. The blue and red solid lines are fractions of cars sold with in-house built transmission. The y axis on the left shows the level of in-house transmission fraction.

1.2.3 Data

One of the biggest obstacles in studying vertical relationships is a lack of production network data since business-to-business transactions are often kept private. The car part producers typically mark their names on the parts they produce. Therefore, such who-supplies-whom links can be tracked in a car's teardown report. However, it is still impossible to track each of the ten thousand parts for every model as it is very costly to do so. Only successful models would have tear-down reports in which all parts can be theoretically tracked. Most car parts have some standard replacement in the aftermarket. However, transmissions need to be original to allow maximum compatibility with the rest of the car. Therefore, websites like Transend collect detailed transmission product information for each car model at a trim level, including the transmission product code and the firm which produces it, for consumers to order the correct product via their platform.[12] I collect a complete transmission firm and vehicle link for all models produced in the US between 2009 and 2018 via the website.

I obtain data on light vehicle sales and prices from WardsAuto, one of the premier automotive industry publications. It provides detailed data on product characteristics, including Manufacturer Suggested Retail Price (MSRP), weight, engine displacement, horsepower, length, width, wheelbase, EPA miles per gallon rating (MPG), drive type, transmission type. I define a product at a make-model-transmission level (e.g., Honda Accord AT6). Using the characteristics at a trim level, I construct a baseline version for each product using the median product characteristics across trim variants within a model transmission pair. WardsAuto also provides detailed sales data for each model by different transmissions. Even though the MSRP may be different from the actual price consumers pay, discounts tend to be uniform across consumers and mainly differ by manufacturer brand (Nurski and Verboven, 2016). Therefore, I later use the manufacturer fixed effect to absorb the difference.

Three additional pieces of information complete the dataset. First, I collect local manufacturing wages at each assembly site as cost sifters from the Bureau of Labor Statistics.[13] Following Petrin (2002), I use consumer information from the Consumer Expenditure Survey (CEX), a rotating panel that records US

[12] https://transend.us/

[13] Local wages as cost shifters are also used in (Wollmann, 2018; Grieco et al., 2021).

household purchasing patterns. The CEX automobile supplement allows me to estimate the probability of new vehicle purchases for different income groups. Last, I sample from the Current Population Survey (CPS), which contains the demographics information in 2009-2018, to approximate the distribution of household demographics.

Table 2.1 summarizes the key variables in our data set. Since most car characteristics are correlated, I follow the literature to include only price, horsepower, size, and fuel efficiency. Each year is treated as a different market, and I observe sales for 3848 products in this ten-year period. I follow Berry et al. (1995) to use the total household in the US as a measure of the market size. Similar to their result, only 10 percent of households purchase new vehicles each year, resulting in very small shares for the new products. Apart from very few cases, a product is either produced in-house or uses a transmission from one firm. On average 65% of the products use in-house produced transmissions. Among the upstream firms, 12% of products outsource a transmission from Aisin.

1.3 A Model of Outsourcing Under Demand Risk

I build a structural model in which upstream firms' transmission prices will respond to the outsourcing decisions of the downstream firms and their demand risk. To illustrate the elements of the model, I first discuss a simple model and then describe the full model for estimation.

Table 1.2: Summary Statistics for Main Variables

Variable	Observation	Mean	Std.Dev	Min	Max
market share	3848	0.0003	0.0006	2.31E-08	0.0075
#product(/year)	3848	384.80	17.42	370	428
Product characteristics					
price (in 10^3)	3848	41.00	23.22	12.62	156.20
horsepower (in 10)	3848	24.73	9.58	7	65
Fuel efficiency (in 10)	3848	3.15	1.08	1.31	15.76
Length (in 10 cm)	3848	18.54	1.66	10.61	25.45
Foreign	3848	0.47	0.50	0	1
Pickup	3848	0.06	0.24	0	1
SUV	3848	0.31	0.46	0	1
Van	3848	0.04	0.20	0	1
Transmission Characteristics					
CVT	3848	0.10	0.30	0	1
DCT	3848	0.07	0.25	0	1
MT	3848	0.25	0.43	0	1
Transmission Low Speed	3848	0.23	0.42	0	1
Transmission High Speed	3848	0.22	0.41	0	1
Transmission Firm					
Aisin	3848	0.12	0.33	0	1
ZF	3848	0.09	0.29	0	1
JATCO	3848	0.08	0.27	0	1
Other-Supplier	3848	0.06	0.24	0	1
In-house	3848	0.65	0.48	0	1
Micro moment: Average real income					
New car purchase(in 10^4)	20,751	4.18			
No new car purchase(in 10^4)	302,788	2.85			

Notes: This table reports summary statistics for the model-transmission-modelyear observations in the sample. Each product j is defined as a combination of model-transmission-modelyear. Prices are adjusted for inflation and I use 2015 as the base year. Fuel efficiency is defined as miles per dollar following BLP (1995). I estimate the demand using modelyear 2009-2018 and there are overall 3848 products across the ten years. I further exclude cars with no transmission, which are most electric vehicles.

1.3.1 Environment

I index consumer households by i and time periods by t. In each time period (year), there are a set of downstream vehicle manufacturers F_t and a set of upstream transmission firms S_t. There are H_t types of transmissions in the upstream market offered by S_t upstream firms.

Downstream firms: Each firm f offers products J_{ft} in different time periods. Products differ in characteristics X_{jt} and their demand shock realizations ξ_{jt}. The demand shock is drawn from a distribution with a variance σ_j. Both upstream and downstream firms are assumed to know the distribution of the demand shock, but they only observe the realizations when the products are sold. In each period, firm f decides for each transmission division h what proportion of products to source from its upstream firm. The action is denoted as a_{fht} and the action space is denoted as A_{fht}, which is discrete and takes a finite number of values. If a firm produces the transmission in-house, the production cost depends on the final quantity sold and is uncertain in the stage when outsourcing decision is made. If it sources from the upstream firms, it faces a pre-committed unit price according to a supply contract.

Upstream firms: Each upstream firm s offers a set of transmissions H_{st} in each time period t. The transmission set is assumed to be exogenous. Transmissions produced by different upstream firms are considered differentiated products (e.g., differ in quality). In each period, upstream firms set the transmission prices $\boldsymbol{\tau_t}$ based on the expected demand of transmissions, internalizing downstream firms' outsourcing decisions and the demand risk.

I assume that in each year, the upstream transmission firms and downstream vehicle manufacturers play a static three-stage game. The decisions are made according to the following timing: in stage 1: upstream firms set transmission prices $\boldsymbol{\tau_t}$ simultaneously to maximize expected profit; in stage 2: after observing the transmission prices, downstream firms simultaneously decide what proportion of transmissions to produce in-house based on a comparison between the expected in-house production cost and the prices $\boldsymbol{\tau_t}$; in stage 3: the demand shock and marginal cost shock are realized, downstream firms compete in prices for their products J_t. The problem is solved in reverse order of timing. Based on the industry background and the data patterns I discussed in the previous sections, I make the following three assumptions:

Assumption 1: The who-supplies-whom relation is predetermined and downstream firms only make intensive margin outsourcing decisions.

The data pattern justifies this assumption that the choice of transmission firms rarely changes on an annual basis. According to Figure 1.3, only 4% of the firm-transmission pairs ever change their upstream. Firms in the transmission industry typically form a long-term relationship with the downstream due to an enormous upfront development cost.[14] Since the exact quantity to be delivered each year is rarely specified in the supply contracts, downstream firms adjust outsourcing decisions based on the unit prices they receive from the upstream firms. My model can accommodate choices of transmission firms at the expense of computation time by expanding the choice set. However, the choice of upstream firm is not driven by unit prices, but rather firms who are more willing to share upfront development costs are more likely to win the contract.

Assumption 2: The downstream product line is predetermined.

I do not jointly model the product entry and exit decisions. This assumption is justified by the fact that products do not enter or exit the market as frequently as the home PC market.[15] In my data sample, a product on average lives for more than four years. In addition, the decision of product entry and exit is not mainly driven by demand fluctuations and transmission unit prices. It depends more on the availability of upstream transmission products and the upfront cost

[14]According to my conversation with the industry expert, the cost of engineering design and development to integrate a transmission into a specific vehicle is about \$10M-\$50M.

[15]Unlike the home PC industry studied by Eizenberg (2014), it takes rigid safety tests to introduce a new product in the passenger vehicle market. Wollmann (2018) uses data from 1987-2012 to study the product entry and exit in the commercial vehicle market. My data panel is only ten years, and there is limited product level entry and exit.

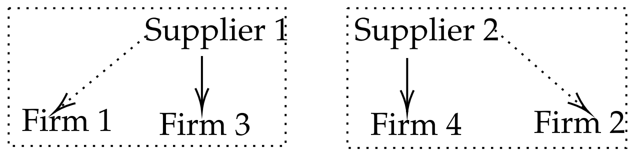
of integrating a new transmission.

Assumption 3: Transmission firms set a uniform price to the different downstream firms for the same transmission, which is invariant to demand shock realization.

The assumption is motivated by a few facts. Firstly, transmission customization is made by software which would incur an upfront fixed cost. Therefore, the marginal cost of producing transmission is almost the same across different downstream firms. Secondly, my conversation with industry experts indicates that the transmission price dispersions among downstream firms are minimal. The relatively small number of upstream and downstream firms that intensively interact over the years mitigates information asymmetry. The argument is consistent with the findings from Grennan and Swanson (2020), in which the access to information on purchasing by peers limits the room for asymmetric information and price differences.

1.3.2 A Simple Model with Linear Demand

Here I consider a simple linear demand case to illustrate the key features of my model. In this system, there are four downstream firms and two upstream firms. Each firm will produce one product. Firm 1 and 2 choose in-house produce or not. Firm 3 and 4 always outsource to make sure that upstream firms have positive input demand. Firm 1 and 3 are linked with Supplier 1 and Firm 2 and 4 are linked with Supplier 2.



I follow Spence (1976) to formulate the inverse demand function. The price depends on the quantity of other products and the effect is homogeneous.

$$p_i = \delta_i - \alpha q_i - \eta \sum_{j \neq i} q_j$$

α is the slope of demand, and η measures the substitutions among products with $(\alpha > \eta)$. δ_i is the product level characteristics and it contains two parts: $\delta_i = X_i + f(\xi_i, \sigma_i)$. ξ_j is the demand shock realization and it is a random variable with a variance of σ_i. In this linear demand, I allow some flexibility in how demand risk enters the demand by the function f. The demand function for firm i is:

$$q_i = \frac{1}{\alpha - \eta}[(\delta_i - p_i) - \frac{\eta \sum(\delta_j - p_j)}{\alpha + (n-1)\eta}]$$

The profit function for firm i is:

$$\pi_i = q_i(p_i - mc_i - (1 - I_i)\tau_{s(i)}) - I_i c(q_i)$$

I_i is an indicator of in-house production. It takes values in $\{0, 1\}$ with 1 means in-house. mc_i is the marginal cost of producing everything else. $c(q_i)$ is the cost of producing an essential part in-house ($c(q_i) = c_1 q_i + c_2 q_i^2$) and $\tau_{s(i)}$ is the price charged by the firm i's corresponding upstream firm. I denote the equilibrium profit of firm i as $\pi_i^*(\mathbf{I}, \boldsymbol{\xi}, \boldsymbol{\tau}, \theta_c, \cdot)$. Here $\theta_c = (c_1, c_2)$ is the parameters govern the shape of the in-house production cost and I omit $(\mathbf{mc}, \mathbf{X}, \alpha, \eta)$ which will be held fixed through out the exercise.

In stage 2, Firm 1 and 2 play a discrete-choice games with private information and there are four sets of action combination $\{(0,0),(1,0),(0,1),(1,1)\}$. The expected profit of firm i when it plays action k and firm j players action k' is denoted as the following when the demand shock is integrated:

$$v_i(I_i = k, I_j = k', \boldsymbol{\tau}, \boldsymbol{\sigma}, \theta_c, \cdot) = \underbrace{\int \pi_i^*(\mathbf{I}, \boldsymbol{\xi}, \boldsymbol{\tau}, \theta_c, \cdot) dF(\boldsymbol{\xi}, \boldsymbol{\sigma})}_{E\pi_i(I_i=k, I_j=k', \boldsymbol{\tau}, \boldsymbol{\sigma}, \theta_c, \cdot)} + \epsilon_i(k)$$

I further assume that both players know the distribution of the private information $\boldsymbol{\epsilon}$ and it is i.i.d across actions and firms. Therefore, Firm 2's decision will be probabilistic from Firm 1's point of view. Let $Pr(I_2 = 1)$ denotes Firm 1's belief of the probability that Firm 2 will produce in-house. The expected profit of Firm 1 choosing in-house production is:

$$V_1(I_1 = 1) = E\pi_1(I_1 = 1, I_2 = 1, \boldsymbol{\tau}, \boldsymbol{\sigma}, \theta_c, \cdot) Pr(I_2 = 1)$$
$$+ E\pi_2(I_1 = 1, I_2 = 0, \boldsymbol{\tau}, \boldsymbol{\sigma}, \theta_c, \cdot) Pr(I_2 = 0) + \epsilon_1(I_1 = 1)$$

The following condition should hold if I assume that each component in ϵ has a Type I extreme-value distribution:

$$Pr(I_1 = 1) = \frac{exp(E\Pi_1(I_1 = 1))}{exp(E\Pi_1(I_1 = 1)) + exp(E\Pi_1(I_1 = 2))} = \Psi_1^1(\mathbf{Pr}, \boldsymbol{\tau}, \boldsymbol{\sigma}, \theta_c, \cdot)$$

Here $E\Pi_1(I_1 = k)$ is the deterministic part of the expected profit of Firm 1 taking action k. A Baye-Nash equilibrium is a pair of beliefs Pr_1^*, Pr_2^* that are mutual best responses:

$$\mathbf{Pr}^* = \Psi(\mathbf{Pr}^*, \boldsymbol{\tau}, \boldsymbol{\sigma}, \theta_c, \cdot)$$

First, I derive some comparative statics of how the in-house production cost θ_c, the upstream firms' prices (τ), and the demand uncertainty σ change outsourcing decisions. They would affect the outsourcing decisions in two channels: a direct effect on the expected profit and an indirect impact on their belief Pr of the other player. I use the demand uncertainty σ as an example, but it can also be replaced by other primitives.

$$\begin{aligned}\frac{\partial \Psi_1^1(\mathbf{Pr},\sigma,\cdot)}{\partial \sigma} &= Pr(I_1=1)Pr(I_1=0)[(\frac{\partial E\pi_1(I_1=1,I_2=1,\sigma,\cdot)}{\partial \sigma}Pr(I_2=1) \\ &+\frac{E\pi_1(I_1=1,I_2=0,\sigma,\cdot)}{\partial \sigma}Pr(I_2=0))-(\frac{E\pi_1(I_1=0,I_2=1,\sigma,\cdot)}{\partial \sigma}Pr(I_2=1) \\ &+\frac{E\pi_1(I_1=0,I_2=0,\sigma,\cdot)}{\partial \sigma}Pr(I_2=0))]\end{aligned}$$

The sign would depend on how demand uncertainty σ affects the expected profit of Firm 1 under in-house or outsource conditional on the action of Firm 2. The overall effect will be an average weighted by the belief of Firm 2's strategy. Since the outsourcing strategy Pr is an equilibrium outcome, it is also affected by σ.

$$\begin{aligned}\frac{\partial \Psi_1^1(\mathbf{Pr},\sigma,\cdot)}{\partial Pr} &= Pr(I_1=1)Pr(I_1=0)[(E\pi_1(I_1=1,I_2=1,\sigma,\cdot)-E\pi_1(I_1=1,I_2=0,\sigma,\cdot)) \\ &-(E\pi_1(I_1=0,I_2=1,\sigma,\cdot)-E\pi_1(I_1=0,I_2=0,\sigma,\cdot))]\end{aligned}$$

This term captures the competition effect between the two firms. If the action of Firm 1 and Firm 2 will be independent, then $E\pi_1(I_1=1,I_2=1,\sigma,\cdot)=E\pi_1(I_1=1,I_2=0,\sigma,\cdot)$ and one would expect this second term to be zero.[16]

Theorem 1.1 (Comparative Statics of in-house production cost $c(q_i)$, upstream prices $\boldsymbol{\tau}$ and demand uncertainty σ)**.**

[16] $\frac{\partial Pr(I_1=1)}{\partial \sigma}=\frac{\partial \Psi_1^1(\mathbf{Pr},\sigma,\cdot)}{\partial \sigma}+\frac{\partial \Psi_1^1(\mathbf{Pr},\sigma,\cdot)}{\partial Pr(I_2=1)}\frac{\partial Pr(I_2=1)}{\partial \sigma}$, the rest terms are cancelled out because $Pr(I_i=1)+Pr(I_i=0)=1$ and thus $\frac{\partial Pr(I_i=1)}{\partial \sigma}=-\frac{\partial Pr(I_i=0)}{\partial \sigma}$.

1. *Given $(c(q_i), \sigma)$, when τ increases, downstream firms increase in-house production.*

2. $c_2 > 0$*, there is decreasing returns to scale of in-house production*

   - *Given (τ, σ), when $c(q_i)$ is more convex, downstream firms decrease in-house production.*

   - *Given $(\tau, c(q_i))$, when σ increases, downstream firms decrease in-house production.*

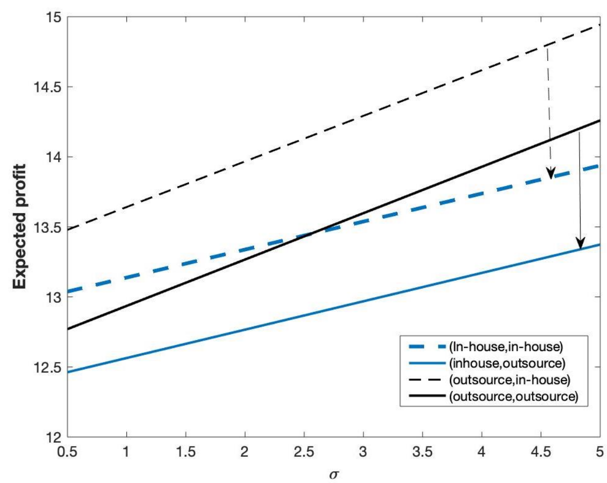
3. $c_2 < 0$*, there is increasing returns to scale of in-house production*

   - *Given (τ, σ), when $c(q_i)$ is more concave, downstream firms decrease in-house production.*

   - *Given $(\tau, c(q_i))$, when σ increases, downstream firms increase in-house production.*

The changes in in-house production cost or upstream price are straightforward. For demand uncertainty, a comparison among the four sets of actions when $c_2 > 0$ can be summarized by the following Figure 1.5. Due to a linear demand specification, the expected profit of each action is linearly increasing in the demand risk σ. Expected profit is increasing in demand risk because profit function is convex in ξ. The slope of in-house production is less steep than the outsourced ones because the convex cost function introduces a wedge between in-house and outsourcing. Compared with a constant price charged by the upstream firm, an increase in demand uncertainty also leads to an increase in in-house production cost. Such is the case regardless of the action of Firm 2. Therefore, $\frac{\partial \Psi_1^1(\mathbf{Pr}, \sigma, \cdot)}{\partial \sigma}$ is decreasing in σ. The second term $\frac{\partial \Psi_1^1(\mathbf{Pr}, \sigma, \cdot)}{\partial Pr}$ is relatively small, and the sign is largely driven by the first channel. Therefore, firms with decreasing returns to scale would increase outsourcing to transfer risks to upstream firms when demand risk increases. When $c_2 < 0$, it is the other way around.

Figure 1.5: Expected Profit of Firm 1 at Different Demand Uncertainty Level



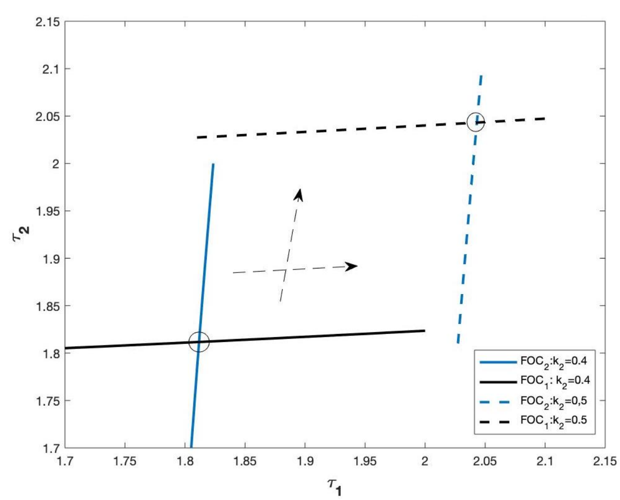
Notes: The solid lines are the expected profit of Firm 1 when Firm 2 chooses outsourcing. The dash lines are the expected profit Firm 1 when Firm 2 chooses in-house. Firm 1 compares the profit differences between outsourcing and in-house conditional on Firm 2's action.

Theorem 1.2 (Price response of upstream firms to in-house production cost $c(q_i)$ and demand uncertainty σ)**.**

1. $c_2 > 0$, *there is decreasing returns to scale of in-house production*
   - *Given σ, when $c(q_i)$ is more convex, equilibrium $\boldsymbol{\tau}$ increases.*
   - *Given $c(q_i)$, when σ increases, equilibrium $\boldsymbol{\tau}$ increases.*
2. $c_2 < 0$, *there is increasing returns to scale of in-house production*
   - *Given σ, when $c(q_i)$ is more concave, equilibrium $\boldsymbol{\tau}$ decreases.*
   - *Given $c(q_i)$, when σ increases, equilibrium $\boldsymbol{\tau}$ decreases.*

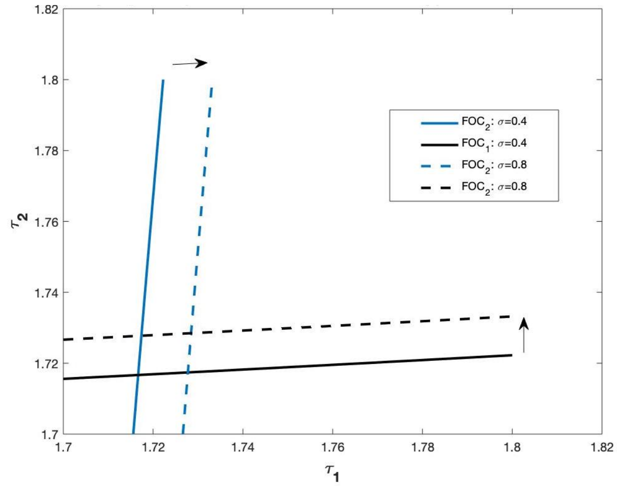
When $c_2 > 0$ and cost function $c(q_i)$ becomes more convex, the wedge in profit between in-house and outsourcing expands. Therefore, downstream firms tend to use more outsourcing due to Theorem 1, and it gives upstream firms more market power as their input demand expands. Intuitively, the increasing disadvantage of in-house production also decreases the threat downstream firms impose on the upstream firms. Therefore, upstream firms don't need to price competitively. According to Figure 1.6, the equilibrium upstream prices, which are determined by the intersection of the dashed line, is higher when the cost function of producing in-house is more convex. The equilibrium upstream prices will increase when demand uncertainty rises by Figure 1.7. When the demand is more volatile, Theorem 1 also predicts that firms would use more outsourcing due to the cost wedge between in-house and outsourcing. The increase in outsourcing propensity gives upstream the advantage to price more aggressively. Since the equilibrium upstream prices increase with demand risk, the in-house propensity will decrease. When $c_2 < 0$, it is the other way around because the downstream firms face an increasing cost advantage of producing in-house and don't have an incentive to outsource.

Figure 1.6: Equilibrium Upstream Prices at Different c(q)



Notes: The solid lines are when $c_2 = 0.4$ and dash lines are when $c_2 = 0.5$. The blue lines are the best response of Firm 2 to Firm 1's prices. The black lines are the best response of Firm 1 to Firm 2's prices.

Figure 1.7: Equilibrium Upstream Prices at Different Uncertainty Level



Notes: The solid lines are when $\sigma = 0.4$ and dash lines are when $\sigma = 0.8$. The blue lines are the best response of Firm 2 to Firm 1's prices. The black lines are the best response of Firm 1 to Firm 2's prices.

To summarize, I use the simple linear demand model to illustrate the outsourcing incentives of downstream firms when facing increasing in-house production disadvantages. The upstream firms leverage on the outsourcing incentives by increasing their prices.

1.3.3 Full Model for Estimation

Here I formally define the model and equilibrium I later bring to the data.

Stage 3: Downstream Firms Pricing Game

Consumer Demand: I model the consumer demand for passenger vehicle cars using a random coefficient logit model (Berry et al., 1995). A product is defined as a make-model-transmission combination (e.g., Honda Accord with AT6 transmission). Each buyer i decides whether to purchase a product j from J_t

choices or the outside option to maximize utility. The utility that consumer i get from purchasing j in time t is defined as the following:

$$u_{ijt} = \underbrace{X_{jt}\beta - \alpha p_{jt} + \xi_{jt}}_{\delta_{jt}\text{: linear utility}} + \underbrace{\nu_{i0}\beta_{\nu}^{0} + log(Y_i)\beta_{d}^{p} p_{jt}}_{\mu_{ijt}\text{: non-linear utility}} + \epsilon_{ijt} \tag{1.1}$$

X_{jt} includes a constant as well as car characteristics of length, horsepower, fuel efficiency, and car types. I also include transmission-specific characteristics like speed and types. In addition, the vehicle brand fixed effect and year fixed effect are added to capture consumers' average taste for a brand across years. I follow Goldberg and Verboven (2001) to consider the potential domestic brand bias by adding a dummy for foreign brands. I finally include a set of transmission firm dummies to capture quality differences among transmissions. Even though each upstream firm offers different products, I assume the quality impact is the same.[17] p_{jt} is the price of a product. ξ_{jt} is the demand shock that is unobserved by the econometrician and is only realized when the products j are sold.

Y_i and ν_{i0} are consumer specific variables. I allow an income effect on price elasticity. Similar to Grieco et al. (2021), Y_i are sampled from CPS, which contains demographic information for the sample period. I additionally consider unobserved heterogeneity for the outside option via a random coefficient on the constant term. Shocks that determine the individual's taste parameters, ν_{i0} are drawn from a multivariate normal distribution. I further assume that these unobserved errors are not correlated.

ϵ_{ijt} captures consumer i's idiosyncratic taste, which is assumed to be i.i.d and follows a Type I extreme error distribution. I normalize the mean utility of the outside option to 0 ($u_{i0t} = \epsilon_{i0t}$). The model-predicted market demand D_{jt} of

[17] e.g., ZF will offer both high-quality products in AT6 and AT8 markets.

product $j \in J_t$ is given by

$$D_{jt} = N_t \int \frac{exp(\delta_{jt} + \nu_{i0}\beta_\nu^0 + log(Y_i)\beta_d^p p_{jt})}{1 + \sum_{m \in J_t} exp(\delta_{mt} + \nu_{i0}\beta_\nu^0 + log(Y_i)\beta_d^p p_{mt})} dF_\nu(\nu_{i0}) F_d(Y_i) \tag{1.2}$$

N_t is the market size at year t. F_v and F_d are the CDF of ν_{i0} and Y_i. The demand shock ξ_{jt} can be inverted out from the linear utility δ_{jt} when the demand model is estimated.

Vehicle Prices: Downstream firms set prices simultaneously after observing the demand shock and marginal cost shock to maximize their profits. The profit function for each firm is defined as follows:

$$\pi_{ft} = \sum_{j \in J_{ft}} D_{jt}(p_{jt} - X_{jt}\gamma - \omega_{jt} - (1 - I_{jt})\tau_{sht(j)}) - I_{jt}c(D_{jt}) \tag{1.3}$$

The marginal cost of each product j at time t:

$$mc_{jt} = \underbrace{X_{jt}\gamma + \omega_{jt}}_{\tilde{mc}_{jt}} + (1 - I_{jt})\tau_{sht(j)} + I_{jt}c'(D_{jt})$$

$\tilde{mc}_{jt}$ is the marginal cost of producing final product j except for transmissions. It depends on the car characteristics and a product-specific marginal cost shock ω_{jt}. I_{jt} denotes whether a product is produced in-house, and $c(D_{jt})$ is the in-house cost function of transmission. If the transmission is produced in-house, the cost of producing the transmission depends on the quantity sold.[18] If the transmission is outsourced, it faces a price of τ_{sht} charged by the product j's corresponding upstream firm s.[19] I assume that given the transmission prices $\boldsymbol{\tau_t}$ and the outsourcing decisions $\mathbf{I_t}$, prices of J_t products are uniquely determined

[18]In the estimation, I parametrize the in-house production function by a third-order polynomial. It is more flexible as it both incorporates the increasing and decreasing returns to scale phases in the production.

[19]Due to the uniform price assumption, τ_{sht} is essentially an upstream-transmission product-time fixed-effect.

in a Nash-Bertrand price equilibrium. In matrix form, the equilibrium prices satisfy a vector of first-order conditions:

$$\mathbf{p_t} - mc_t = (T_t{}^*\Delta(\mathbf{p_t}))^{-1} D_t(\mathbf{p_t}) \tag{1.4}$$

Here T_t is a $|J_t| \times |J_t|$ vehicle product matrix. $T_{i,j} = 1$ if i and j are produced by the same firm-transmission pair and it equals to zero otherwise. $\Delta_{i,j}$ is the derivative of the market share of product j with respect to the price of product i. * is an element-by-element multiplication. The optimal price can be denoted as $p_t^*(\boldsymbol{\tau_t}, \mathbf{I_t}, \mathbf{e_t}, \cdot)$. I use a fixed point mapping to solve for the equilibrium prices.[20] They depend on the transmission prices, the outsourcing allocations and the demand and marginal cost shocks $\mathbf{e_t} = (\boldsymbol{\zeta_t}, \boldsymbol{\omega_t})$. Product characteristics $\mathbf{x_t}$ are suppressed because they are invariant in the model.

Stage 2: Downstream Firms Outsourcing Decisions

I assume that firms make outsourcing decisions simultaneously for each of their transmissions. The assumption is supported by the fact that the same transmission plant would typically produce a specific type of transmission for many car models.[21] The outsourcing decision is an action $a_{fht} \in A_{fht}$ determining the proportion of products within a firm-transmission pair that use in-house produced transmission. A_{fht} is a finite set with K options. Both the action set and the number of options can be heterogeneous.[22] To avoid the complication of

[20] For oligopolistic price competition with multiproduct firms, there may be multiple equilibria. Nocke and Schutz (2018) provide conditions for equilibrium uniqueness. However, their aggregate game approach does not allow for random coefficients in the demand model. To fix the pricing equilibrium selection mechanism, I start with the vehicle prices I observe in the data. I also try the algorithm with different starting values, and the problem always converges.

[21] For simplicity, I don't model the coordinations among transmission plants on the firm level and assume they are independent.

[22] K can be regarded as the total number of products within a firm-transmission pair. Therefore, it would be heterogeneous across firms.

modeling how each firm-transmission pair chooses the transmission for different models, I assume it uses a_{fht} to decide the allocation probabilistically.[23] A similar approach is adopted in Yang (2020) to model which smartphones of Samsung use Qualcomm SoCs. The approach permits the complementarity across different models within a firm-transmission pair while significantly reducing the computation burden. I use a sensitivity test to evaluate my simulation specifications.

The setup I use is a simplification of combinatorial discrete choice problems (CDCPs) in which agents make a discrete choice on each item, and the items are interdependent. Such CDCPs are computationally intensive since the number of potential decision sets grows exponentially in the number of available items. Jia (2008) exploits the lattice theory to reduce the computation burden effectively, but the algorithm is only applicable to oligopoly games with two players.[24] Similar algorithm is developed in international trade to study the input sourcing problems (Arkolakis and Eckert, 2017; Antràs et al., 2017). Because I incorporate a very flexible competition among downstream vehicle manufacturers, my problem is more complicated in two ways. First, unlike the CES demand commonly used in the international trade literature, the outsourcing decision in my setup also depends on the decisions of other agents.[25] Second, these reduction methods often rely on some single crossing differences or supermodularity properties of profit functions.[26] Due to the rich substitution patterns

[23]For example, if a firm-transmission pair has ten products and $a_{fht} = 1/2$, it means five products on average will be made in-house. However, which five models are to be made in-house is picked at random.

[24]In my setup, there are more than 20 firm-transmission pairs in each year. In addition, firm-transmission pairs with large market shares have more than ten models in their choice set. To consider the full set of possible combinations is computationally intractable.

[25]If there are three firm-transmission pairs, each with ten models, the total number of action pairs to consider is 2^{30}.

[26]In most cases, it would specify a parametric form of the complementarity (Seim, 2006).

and the potential business stealing effect among products in my model, there is no clear monotonic relation among choices.

I use $E\pi_{fht}(a_{fht}, a_{-fht}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot)$ to denote the expected profit for a firm f transmission type h at time t for a given action vector $\mathbf{a_t}$. I follow the literature to use a_{-fht} to denote the vector of actions for all the other players. Since firms are making decisions prior to the realization of demand and cost shocks, I draw M simulations based on the empirical distribution of $\mathbf{e_t}$. $\boldsymbol{\sigma_t}$ is the variance of demand shock.[27] In order to compute the return of action, I simulate N sets of outsourcing products and compute the average. Here $\pi^*_{jt}(\boldsymbol{\tau_t}, \mathbf{I^n_t}, \mathbf{e^m_t}, \cdot)$ is the equilibrium profit of product j when an assignment simulation draw is $\mathbf{I^n_t}$ and the shock draw is $\mathbf{e^m_t}$. The profit is aggregate to a transmission level by adding up the profit of each product j using a transmission h within a firm f.

$$E\pi_{fht}(a_{fht}, a_{-fht}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) = \sum_{j \in J_{fht}} \frac{1}{N} \sum_n \frac{1}{M} \sum_m \pi^*_{jt}(\boldsymbol{\tau_t}, \mathbf{I^n_t}, \mathbf{e^m_t}, \cdot)$$

For each firm-transmission pair, there are also K state variables which I label as $\epsilon_{fht}(a_{fht})$ which are private information to each firm-transmission pair for each action. These are the idiosyncratic sources of profitability which are not observed by the rivals. Examples include intangible assets like managerial talent or other unobserved cost differences (Seim, 2006). These state variables are distributed i.i.d across firm-transmission pairs and actions. As pointed out by Rust (1994), the Bayesian Nash Equilibrium strategies can be computed more easily than a complete information game. In addition, it is sensible to

[27] I simulate demand shock from a normal distribution $N(0, \sigma_{fht})$ where each firm-transmission pair has its own variance. For the marginal cost shocks, I draw from each product's empirical distribution.

assume private information of firms.[28] However, the i.i.d assumptions across firm-transmission pairs is a bit restrictive as it additionally implies that the profitability within a firm across different transmissions are uncorrelated. The value of firm-transmission pair fh at a given action vector $\mathbf{a_t}$ is:

$$v_{fht}(\mathbf{a_t}, \epsilon_{fht}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) = E\pi_{fht}(a_{fht}, a_{-fht}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) + \epsilon_{fht}(a_{fht})$$

Each firm-trans pair form belief Pr_t about rivals' strategy. Since the private information is independent across firm-transmission pairs, the joint distribution of belief is the product:

$$Pr_{-fht}(a_{-fht}|\boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) = \Pi_{(fh)' \neq fh} Pr_{(fh)'t}(a_{(fh)'t}|\boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot)$$

Therefore the expected value of choosing action a_{fht} is denoted as $V_{fht}(a_{fht}, \epsilon_{fht}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot)$ where the belief of the other rivals strategic are integrated:

$$V_{fht}(a_{fht}, \epsilon_{fht}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) = \sum_{a_{-fht}} E\pi_{fht}(a_{fht}, a_{-fht}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) Pr_{-fht}(a_{-fht}|\boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) + \epsilon_{fht}(a_{fht})$$

I define the deterministic part of the expected profit above as $E\Pi_{fht}(a_{fht}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot)$. The optimal action for firm-transmission pair fh:

$$\begin{aligned} Pr_{fht}(a_{fht} = 1|\boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) = Prob(\epsilon_{fht}|E\Pi_{fht}(a_{fht} = 1) + \epsilon_{fht}(a_{fht} = 1) \\ > E\Pi_{fht}(a_{fht} = k) + \epsilon_{fht}(a_{fht} = k) \text{ for } k \neq 1) \end{aligned}$$

The choice probability of action a_{fht} has a close-form expression if I assume that the private information follows a type I extreme value distribution and is i.i.d

[28] Entry games with private information usually have multiple equilibria. Espin-Sanchez et al. (2021) provide simple sufficient conditions to guarantee equilibrium uniqueness. I am currently working on extending their work to my case.

across actions.[29]

$$Pr_{fht}(a_{fht}=1)=\frac{exp(E\Pi_{fht}(a_{fht}=1,\boldsymbol{\tau_t},\boldsymbol{\sigma_t},\cdot))}{\sum_{k\in\mathbf{A}_{fht}}exp(E\Pi_{fht}(a_{fht}=k,\boldsymbol{\tau_t},\boldsymbol{\sigma_t},\cdot))}=\Psi(\mathbf{Pr_t},\boldsymbol{\tau_t},\boldsymbol{\sigma_t},\cdot) \tag{1.5}$$

The formula above is a best response function for firm-transmission part fh given its belief Pr_{-fht}. A Bayesian Nash Equilibrium is a set of $\mathbf{Pr_t}$ which are best response to one another.

$$\mathbf{Pr_t}=\Psi(\mathbf{Pr_t},\boldsymbol{\tau_t},\boldsymbol{\sigma_t},\cdot) \tag{1.6}$$

Stage 1: Upstream Firms' Expected Profit Maximization

According to Assumption 3 that upstream firms set a uniform price to the different downstream firms for the same transmission, the upstream firms' pricing setting can be regarded as a procedure in which they aggregate all demand uncertainty from downstream firms and set the unit price. I additionally assume that the price is set on an annual basis.[30] The expect profit of each upstream s for each transmission type h is as follows:

$$E\pi^{st}=\sum_{h\in H_{st}}E\pi^{sht}=\sum_{h\in H_{st}}(\tau_{sht}-mc_{sht})\underbrace{\sum_{f\in F_{sht}}\sum_{j\in J_{fht}}\sum_{\mathbf{a_t}}ED^{O*}_{jt}(\mathbf{a_t},\boldsymbol{\tau_t},\boldsymbol{\sigma_t},\cdot)Pr^*_t(\mathbf{a_t},\boldsymbol{\tau_t},\boldsymbol{\sigma_t},\cdot)}_{\text{Expected demand of transmission h from upstream firm s}}$$

Upstream firms set prices $\boldsymbol{\tau_t}$ simultaneously to maximize the expected profit. For each product j, the expected transmission demand is a weighted sum across different outsourcing action combinations. The weights here are the equilibrium outsourcing strategy. The expected transmission demand is aggregated

[29] I maintain the i.i.d assumptions for computational reasons. Lind and Ramondo (2018), for example, develop a trade model and allow extreme value productivities to be correlated across countries.

[30] In reality, downstream firms negotiate with their upstream yearly about unit price adjustment due to learning, cost efficiency gain, etc.

within each firm-transmission pair. F_{sht} denotes the set of downstream manufacturers upstream firm s has signed contract with for each transmission type h. $ED^{O*}_{jt}(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot)$ is the expected equilibrium outsourcing demand (quantity) at a given action vector $\mathbf{a_t}$.[31]

The equilibrium transmission prices τ_t satisfy a vector of first-order conditions listed below. Increasing input prices would have three separate effects. First, it directly increases the revenue for each transmission sold. Second, it affects downstream firms' propensity to use outsourcing. Third, it affects the final product demand by a cost pass-through $ED^{O*}_{jt,\tau}$. The first-order condition also indicates that upstream firms' prices respond to demand volatility $\boldsymbol{\sigma_t}$, and downstream firms' outsourcing strategies $\mathbf{Pr_t}$:

$$\begin{aligned} FOC = &\sum_{f\in F_{sht}} \sum_{j\in J_{fht}} \sum_{\mathbf{a_t}} ED^{O*}_{jt}(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) Pr^*_t(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) \\ &+(\tau_{sht} - mc_{sht}) \sum_{f\in F_{sht}} \sum_{j\in J_{fht}} \sum_{\mathbf{a_t}} ED^{O*}_{jt}(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) \frac{dPr(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot)}{d\tau_{sht}} \\ &+ (\tau_{sht} - mc_{sht}) \sum_{f\in F_{sht}} \sum_{j\in J_{fht}} \sum_{\mathbf{a_t}} ED^{O*}_{jt,\tau}(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) Pr^*_t(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) \end{aligned} \tag{1.7}$$

If several upstream firms are competing, the solution would be a fixed point that satisfies the first-order condition above. I first derive a numerical gradient and use a fixed-point algorithm to solve the equilibrium upstream firms' prices. Details can be found in Appendix A.

In my setup, the transmission prices are set by the upstream firms instead of through a bilateral bargaining.[32] The bilateral bargaining framework predicts

[31] Since the outsourcing within a firm-transmission pair is determined randomly. For a specific product, it would be assigned an outsourced transmission in some simulation draws. The expectation is computed as an average across the N simulation draws.

[32] Empirical applications of bilateral bargaining mainly focus on negotiation between content providers and cable companies (Chipty and Snyder, 1999; Crawford and Yurukoglu, 2012; Crawford et al., 2018), hospital, insurance providers and employers (Gowrisankaran et al., 2015; Ho and Lee, 2017).

that each upstream firm is paid a fraction of its marginal contribution to the downstream firm. However, downstream firms in my data almost always work with one transmission firm instead of a set of transmission firms. Therefore, upstream firms are substitutes instead of complements. In addition, the Nash-in-Nash bargaining solution assumes that negotiated price is a pair-specific Nash bargaining solution given that all other pairs reach an agreement. The Nash-in-Nash solution provides computational benefits, but it limits the risk pooling of upstream firms and propagation of demand shocks in the production network, which is my focus.[33] Last, I cannot observe any price information between the upstream and downstream firms. In addition, the marginal cost data is not available for all upstream firms in my data. I cannot use the marginal cost or price margin information to estimate the bargaining parameters as in Yang (2020). My view is that the real world is somewhere "in between" and that estimation using the base model is the best way to proceed given the available data.

In addition, I assume that the vertical contract between the upstream and downstream firms is a simple linear price that is uniform to all downstream firms for the same product.[34] First, it is consistent with the supply contact in the industry that only a unit price is specified for demand risk transfer. Second, non-linear pricing models like two-part tariffs are no longer optimal in multiple upstream firms and multiple downstream firms setup (Schmalense, 1981; Mathewson and Winter, 1984).[35] In addition, to explore changes in market prim-

[33]The framework is suitable to study price discrimination (Grennan, 2013). According to the industry background detailed in Assumption 3, price discrimination is not a key concern in the transmission industry.

[34]Nosko (2011) uses a similar model for the price setting phase of AMD and Intel for their chips later sold to the downstream PC firms.

[35]Villas-Boas (2007) uses a detailed retail price and wholesale marginal cost data to infer the vertical relation. After estimating the demand, she uses a menu approach to check which verti-

itives, it is necessary to solve counterfactuals under different circumstances. The assumption of linear contract reduce the contract space and keep the problem computationally tractable.

Equilibrium

An Equilibrium in this model is a set of upstream prices $\boldsymbol{\tau_t}$, a set of downstream firms' outsourcing strategies $\mathbf{Pr_t}$ and a set of downstream prices $\mathbf{p_t}$ that satisfy the following conditions:

1. Given $\boldsymbol{\tau_t}$, $\mathbf{Pr_t}$, and the realization of $\mathbf{e_t}$, prices of J_t products are uniquely determined in a Nash-Bertrand price equilibrium by solving the downstream firms' first-order conditions specified Equation 1.4.
2. Given $\boldsymbol{\tau_t}$, the equilibrium outsourcing strategies $\mathbf{Pr_t}$ best respond to each others based their beliefs about others strategies, and satisfy Equation 1.5. In addition, their beliefs are consistent and satisfy Equation 1.6. The set of equilibrium strategies is a Bayesian Nash Equilibrium.
3. $\boldsymbol{\tau_t}$ satisfy the upstream firms' first-order conditions implied by Equation 1.7. The transmission prices of H_{st} products are determined in a Nash-Bertrand price equilibrium based on expected demand.

1.4 Identification and Estimation

The parameters to be estimated are the demand parameters $\theta^d = (\beta, \alpha, \beta_v^0, \beta_d^p)$, the marginal cost parameters $\theta^s = (\gamma, \tau)$, the in-house cost function $c(\cdot)$ and the

cal relationships best fit the profit margin data.

marginal cost of upstream firms mc_{sht}.

1.4.1 Estimating Downstream Demand-side Parameters θ^d

From the downstream firms' demand equation,

$$D_{jt} = N_t \int \frac{exp(\delta_{jt} + \nu_{i0}\beta_\nu^0 + log(Y_i)\beta_d^p p_{jt})}{1 + \sum_{m \in J_t} exp(\delta_{mt} + \nu_{i0}\beta_\nu^0 + log(Y_i)\beta_d^p p_{mt})} dF_\nu(\nu_{i0}) F_d(Y_i)$$

Berry (1994) proves that δ_{jt} can be obtained by contraction mapping, $\delta_{jt} = f(\mathbf{D_t}, \mathbf{p_t}, \beta_\nu^0, \beta_d^p)$. Since demand of each product is determined simultaneously, δ_{jt} depend on the price and demand of products in the entire market. The mean utility formula can be rewritten as:

$$\xi_{jt} = f(D_t, p_t, \beta_\nu^0, \beta_d^p) - (X_{jt}\beta - \alpha p_{jt})$$

Since I cannot observe ξ_{jt} and ($\mathbf{D_t}$, $\mathbf{p_t}$) are correlated with ξ_{jt}, instruments for ($\mathbf{D_t}$, $\mathbf{p_t}$) are used to identify the non-linear parameters β_ν^0 and β_d^p. The number of instruments should be larger than the number of non-linear parameters. I use two types of instruments here. The first is a set of classic "BLP instruments"—exogenous characteristics of competing goods. Since car characteristics by assumption are determined prior to the realization of ξ_{jt} in my model and these characteristics affect all quantities through the demand system, they satisfy both the exclusion restriction and the relevance condition. However, these instruments often suffer from a weak IV problem as the variations across products are limited. I follow Gandhi and Houde (2019) to construct Differentiation IV, which reflects the amount of differentiation faced by each product in the market. Differentiation IV is shown to mitigate the weak IV problem significantly. I adopt the quadratic instrument as the Cragg-Donald F statistics is larger.

$$z_{jt} = \{x_{jt}, \sum_{j'}(d^k_{jt,j'})^2, \sum_{j'}(d^{\hat{p}}_{jt,j'})^2\}$$

Here $d^k_{jt,j}$ is the difference between product j and j' along the attribute k. I consider car characteristics of length, horsepower, fuel efficiency, and transmission speed. $d^{\hat{p}}_{jt,j'}$ is the difference of the predicted price between product j and j', where the projection is based on exogenous variables like characteristics and cost shifters. I additionally add the Bureau of Labor Statistics estimate of the production wage in the MSA where each assembly site locates as a cost shifter according to Wollmann (2018).[36] In the data, firms rarely reallocate products to other sites. The assembly site is unlikely to be correlated with current demand shocks. Therefore, it serves as a valid instrument for the demand equation estimation.

1.4.2 Estimating Demand Risk(σ_j)

I assume the intrinsic product-level demand will follow a normal distribution. Therefore, it is a characteristic of a product j that is invariant over time. In my demand specification, I control for systematic brand effects and time trends using fixed effects. It is reasonable to assume that the ξ_{jt} is a demand shock containing minimum characteristics variations. I use the sample variance of the demand shock realization to estimate the variance:

$$\sigma_j = sd(\xi_{jt})$$

[36]For vehicles made outside of US, I use similar wage measures. The wage data is more detailed for Canada, Mexico, and Japan. For other countries, I use the country-level wage data. All foreign data are converted into Dollars using Purchasing power parity (PPP).

A firm would typically pool the products with the same transmission together, and outsourcing decisions are made on a firm-transmission level. To aggregate the product level risk to a firm level, I use Principal Component Analysis (PCA) to construct a firm-transmission level risk measure that preserves most data variations. The PCA method is more data-driven than aggregating the product level risk by their shares as weight. In addition, this measure avoids the additional variation brought by sales weights. I first order the products within a firm-transmission pair by their sales (quantity). The first variable x_1 represents the demand risk of the product with the largest market share. Since firm-transmission pairs naturally differ in the number of products, there are many missing values in the PCA analysis. I adopt a Nonlinear Iterative Partial Least Squares algorithm to tackle the missing value problem. After construction, the first principal component, which I use as a measure of firm-transmission level risk, explains 78% of the total variation in the data.

1.4.3 Estimating Downstream Supply-side Parameters θ^s

I additionally parametrize the cost function of in-house production by a third-order polynomial to allow for curvature. The specification incorporates both increasing and decreasing returns to scale. When the vehicle demand is low, the average cost of producing a transmission in-house is high because of idle capacity and low equipment utilization. When the vehicle demand is high, the sluggish adjustment to excessive capacity drives up the average cost of production again.

$$c(D_{jt}) = c_1(D_{jt}) + c_2(D_{jt})^2 + c_3(D_{jt})^3$$

Pairing with the marginal cost function in stage 3 before:

$$mc_{jt} = X_{jt}\gamma + (1 - I_{jt})\tau_{st(j)} + I_{jt}c'(D_{jt}) + \omega_{jt}$$

τ_{st} is the price charged by upstream firm s at time t.[37] To further reduce the number of parameters needed to be estimated, I fit a second order polynomial of each upstream firm's price as $\tau_{st} = \tau_s + \tau_s^{trend} t + \tau_s^{trend_2} t^2$.[38] Therefore, instead of estimating s*t number of fixed cost, I just need to estimate 3*s number of parameters. According to the model's timing assumption, product characteristics (X_{jt}) and the decisions of outsourcing (I_{jt}) are determined before the realization of supply-side shocks.

However, the output demand which enters into the cost of producing a transmission in-house, is an equilibrium object depending on the unobserved marginal cost shock ω_{jt}. I construct a similar instrument in the spirit of Gandhi and Houde (2019). Instead of using exogenous product characteristics to predict prices, I use these product characteristics to predict the demand variable D_{jt} via Lasso. Belloni et al. (2012) show that IV estimator based on using Lasso or Post-Lasso in the first stage is root-n consistent and asymptotically normal. Therefore, the standard inference procedures can be applied. In addition, they show that the Lasso-based IV estimator with a data-driven penalty performs well compared to recently advocated many-instrument-robust procedures. The set of parameters to be estimated from the cost side is $\theta^s = (\gamma, \tau_s, \tau_s^{trend}, \tau_s^{trend_2}, c_1, c_2, c_3)$. Since a product j can either be produced in-house

[37] To reduce the number of parameters to estimate and the equilibrium upstream firms' prices to compute in the counterfactuals, I additionally assume the upstream will charge the same price τ_{st} for the different products. The price can be seen as an average price of different transmission products. Council (2015) did a direct manufacturing cost across different types of transmission. The cost increase due to an increase in transmission speed is around $50-$100. (e.g., "eight-speed transmission would have an incremental cost of $61.84 (EPA/FEV 2011) compared with a ZF six-speed."

[38] t is the number of years from the first year in my data sample. t=year-2009

or outsourced from the upstream, only identify the difference between c_1 and τ_s is identified. Therefore, I normalize the τ_O, the transmission price of the other-supplier group at year 2009 to 0. The c_1 and other τ_s are relative prices compared to τ_O.

1.4.4 Estimating Marginal Cost of Upstream Firms (mc_{st})

With the equilibrium transmission prices τ_{st} and the demand side and cost side parameters, I solve the three-stage static model for equilibrium outsourcing strategy $\Pr_t$ and the expected transmission demand for each upstream firm. I use Equation 1.7, the first-order-condition of the upstream firms to invert out marginal cost mc_{st}. A detailed solving algorithm and the computation of derivatives can be found in Appendix A. Since I only have four upstream firms and ten years, I don't additionally parametrize the marginal cost mc_{st} to allow for economies of scale based on the 40 marginal cost observations. Based on the current specification, the upstream firms face a constant marginal cost of producing transmissions. With more data, my model can additionally incorporate return-to-scale analysis of the upstream firms, but it is not a key focus of my paper.

The major challenge of estimating the model is solving the vehicle manufacturers' discrete game when they make outsourcing decisions. Since the industry is populated with many firms, each with many actions, the full solution method is very computationally intensive. In addition, the decision is made ex-ante before the realization of demand and cost shocks. I also need to integrate the shock distribution, which involves additional simulations. To keep this problem manageable, I first use data patterns to select firms actively making outsourcing decisions. In addition, I focus on the outsourcing decisions of firms with the largest market shares. I allow the firm with the largest market share for each transmission firm to make strategic outsourcing decisions actively. I then use sensitivity tests to show whether the estimates of the marginal cost of transmission firms are sensitive to the simulation specifications. A detailed simulation specification and the sensitivity test results can be found in Appendix A. For the transmission prices charged by the upstream firms and the cost function of in-house production, my identification relies on the variations in the marginal cost of vehicles.[39]

Adding the downstream firms' outsourcing choice information would increase efficiency. Since the model cannot be fully solved, it also introduces additional misspecification error when using SMLE. In addition, the relatively shorter time period covered by my data sample prevents me from using a two-stage Conditional Choice Probability (CCP) method because the conditional choice probability accurately. Weintraub et al. (2008) provide the theoretical validity of the oblivious equilibrium when the market is populated with many firms with limited heterogeneity. Appendix B provides a slightly modified oblivious equilibrium setup of my model and an implementable algorithm to solve the equilibrium. Due to the rich heterogeneity of downstream firms, the approximation by oblivious equilibrium where each firm only tracks its own state and the steady industry state behaves poorly.

[39] The marginal cost of a car is derived from the demand equation and the first-order condition of the downstream firms.

1.5 Estimation Results

I first discuss the estimated demand and marginal cost parameters of downstream firms and the cost parameters of upstream firms. I then discuss the relation between demand risk, upstream market power, and outsourcing decisions.

1.5.1 Estimation Results for θ^d and θ^s

Table 1.3 reports the estimation of the demand system. Column (1) shows the results from a logit equation, where all demand heterogeneity is ignored. Compared with the more flexible BLP demand, the price coefficient is much smaller. In addition, the sign for horsepower is not sensible. According to column (2), the demand estimation results suggest consumers favor products with a larger size, stronger horsepower, and higher fuel efficiency on average. For example, a fuel efficiency increase of 1 MPG (Miles Per Gallon) is equivalent to a price decrease of $418. Similarly, a 1-meter increase in vehicle size is equivalent to a price decrease of $380. My estimates also show a significant vehicle type effect. SUV has a premium of $5217 compared to sedans. There are also significant differences in transmissions. Transmissions made by ZF have the higher premium of $10961. Cars equipped with ZF transmissions on average have a better product quality as well. Therefore, the premium consists of the transmission premium and other potential complementarities between ZF transmission and the vehicle. The heterogeneity on the outside option is also significant. The standard deviation is about 60% of the mean. It captures the dispersion in the consumer's outside option value. Accounting for this consumer heterogeneity implies more flexible substitution patterns and more sensible markups.

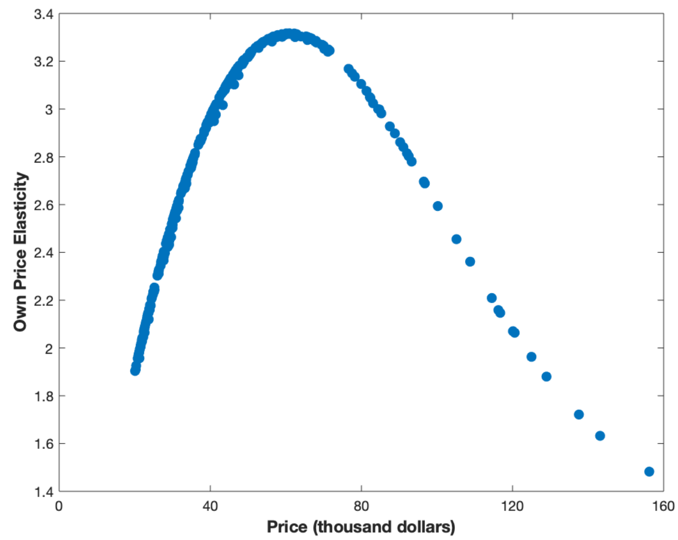
Table 1.3: Downstream Firms' Demand Estimation Results

Variable	IV	BLP	Variable	IV	BLP
	Vehicle			Transmission	
Constant	-9.118	-46.634	Low speed	-0.486	-0.421
	(1.036)	(0.411)		(0.123)	(0.119)
Constant*v		27.414	High speed	-0.116	-0.112
		(0.551)		(0.147)	(0.158)
Price	-0.049	-0.268	CVT	-0.502	-0.271
	(0.020)	(0.070)		(0.314)	(0.273)
Price*log(income)		0.081	DCT	-1.322	-1.037
		(0.018)		(0.195)	(0.199)
horsepower	-0.009	0.060	MT	-2.012	-2.012
	(0.018)	(0.025)		(0.124)	(0.138)
Fuel efficiency	0.077	0.237	Aisin	-0.486	0.149
	(0.080)	(0.096)		(0.149)	(0.155)
Size (length)	0.093	0.216	ZF	0.003	0.622
	(0.049)	(0.061)		(0.258)	(0.209)
Pick-up	-0.168	-0.634	JATCO	0.463	0.455
	(0.286)	(0.286)		(0.305)	(0.254)
SUV	0.108	0.296	Other-Supplier	-0.146	0.224
	(0.118)	(0.124)		(0.269)	(0.187)
Van	-0.256	-0.347			
	(0.213)	(0.235)			
Foreign	-0.832	-0.652			
	(0.140)	(0.155)			
Observations			3848		
Year FE			YES		
Company FE			YES		

Notes: This table reports the logit and BLP demand estimates. Here for unobserved heterogeneity and demographics, I use a product rule with a level of 12. Standard errors are clustered at the product level in parentheses. For random coefficient model I use py.blp with optimal instrument, the tolerance level for the feasibility constraints and optimality constraints are both 10^{-6} which are the same as Dubé et al. (2012).

The demand system also implies sensible elasticities. I allow the price elasticity to depend on the income level, and estimates show that consumers with a higher income level tend to be less price-sensitive. Consistent with profit maximization in oligopoly, all price elasticities are greater than 1. As shown in Figure 1.8, more expensive products have less elastic demand since they target more wealthy households. In addition, the competition among products is concentrated in the cars with mid-range prices. Table 1.4 provides detailed summary statistics of the price elasticities, marginal cost, and margins. The gross margin on average is 41.3%, broadly in line with Berry et al. (1995) ,Goldberg and

Figure 1.8: Own Price Elasticity of Products in Year 2018



Notes: The figure shows own price elasticity of the products sold in year 2018. Each data point is a model-transmission-year. Price elasticity is the percentage change in a product's sales in a year over a one percentage change in MSRP price.

Verboven (2001), Nurski and Verboven (2016). I plot the marginal cost against vehicle prices for my data sample in 2018 in Figure 1.9. In general, more expensive vehicle products also have higher marginal costs, reflecting their quality differences.

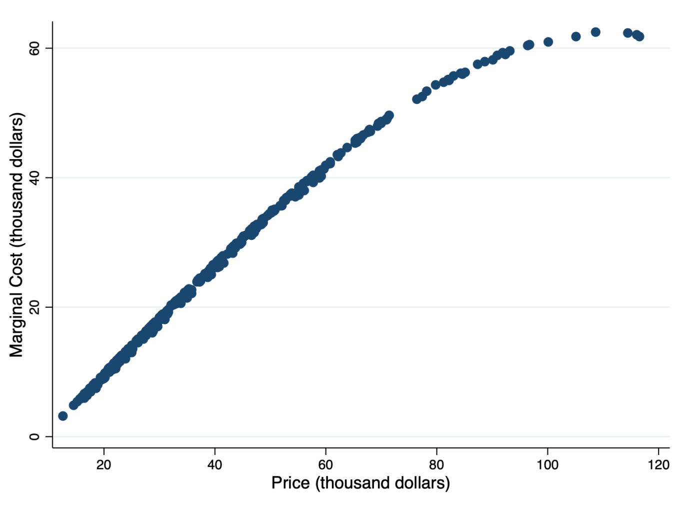
Table 1.4: Price Elasticities, Marginal Costs and Margins

Variable	Mean	Std.Dev	10%	Median	90%	Obs
Price (10^3)	41.00	23.22	20.73	34.51	68.15	3848
Own price elasticity	-2.58	0.50	-3.23	-2.61	-1.89	3848
Marginal cost (10^3)	24.85	14.42	9.75	21.28	46.92	3848
Margin	0.41	0.09	0.32	0.39	0.54	3848

Notes: The Table reports the summary statistics of own price elasticities, marginal cost and margins. Price and marginal cost are measured in 2015 dollars. Margin is 1-marginal cost/price

Table 1.5 reports the estimates of the supply system of downstream firms. Since larger horsepower, bigger size, and higher fuel efficiency all adds up to the cost of a car, the coefficient is positive and significant. Foreign vehicles are more expensive to build. Compared with sedans, SUVs are more premium and cost more. The cost of producing a transmission in-house is convex. The aver-

Figure 1.9: Marginal Cost of Products in Year 2018



Notes: The figure shows marginal cost products sold in year 2018. Each data point is a model-transmission-year. The marginal cost of each product is inverted out from the downstream firms' first order condition after demand estimation.

age cost first drops due to the economies of scale. However, the transmission production cost increases when the demand is too high, reflecting downstream's inability to go beyond the capacity. The in-house cost function is flexible enough to accommodate time trends or heterogeneity in downstream firms. Daimler, Honda, Hyundai, and Volkswagen have significantly large in-house production portions, according to the data. It also indicates some heterogeneity in their in-house production cost functions. The average cost of in-house transmission production is significantly lower for Daimler and Volkswagen. Daimler's cost further decreased from 2009 on. However, the trend is not significant for Honda, Hyundai, and Volkswagen. The labor cost estimate is negative, which is a bit counter-intuitive. However, the auto industry in the US is populated with union workers who enjoy higher wages, and the Big Three (GM, Ford, FCA) have to pay higher labor costs. On the other hand, premium brands like BMW open their assembly plants in states with low unionization rates like Texas, Mississippi, Alabama, and South Carolina. Even though vehicles made by BMW have higher marginal costs, their labor cost is lower.

For the endogenous variable D_{jt}, I use Lasso based on the exogenous car characteristics and the Differentiated IV from the demand estimation to construct a predicted value $\hat{D}_{jt}$. The Cragg-Donald F statistic is 47.05, and the critical value at 5% is 20.93. Without adding the fitted value $\hat{D}_{jt}$, the Cragg-Donald F statistic is only 6.96 and leads to unreasonable large coefficient estimates. The results also show that weak IV can lead to inconsistent estimates.

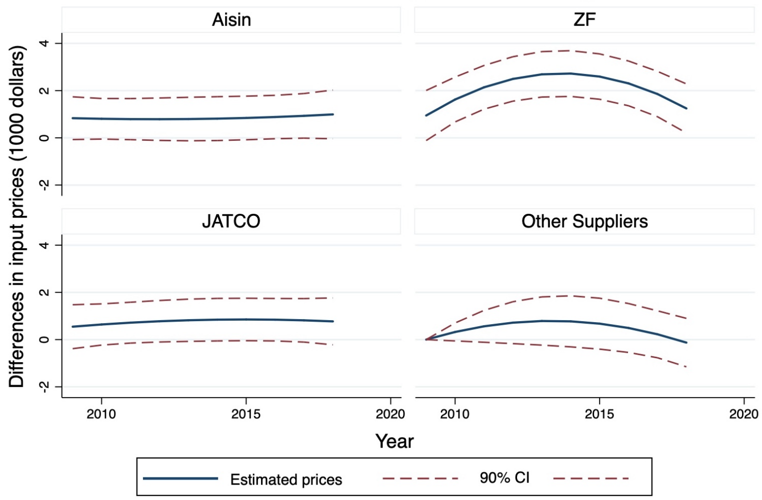
Table 1.5: Downstream Marginal Cost Estimation Results

Vehicle		Transmission	
log(hp)	12.398	c_1	0.829
	(0.294)		(0.513)
log(mpg)	4.435	c_2	-13.125
	(0.443)		(2.363)
log(size)	7.339	c_3	16.873
	(0.896)		(5.650)
foreign	1.288	$c_{1,DA}$	-3.604
	(0.104)		(0.673)
labor cost	-0.011	$c_{1,DA}^{trend}$	-0.233
	(0.004)		(0.083)
Pick-up	-2.226	$c_{1,HY}$	1.470
	(0.192)		(0.685)
SUV	0.565	$c_{1,VW}$	-1.214
	(0.099)		(0.327)
Van	-0.957	$c_{1,HO}$	2.292
	(0.186)		(0.513)
Observations		3,848	
R-squared		0.840	
Company FE Year FE		YES	

Notes: Here c_1, c_2, c_3 are the internal production cost function parameters. I fit a third order polynomial and allow for heterogeneity among different downstream firms. $c(D_{jt}) = c_{1_{jt}}(D_{jt}) + c_2(D_{jt})^2 + c_3(D_{jt})^3$. DA stands for Daimler Group, HO stands for Honda, HY stands for Hyundai and VW stands for Volkswagen.

Figure 1.10 reports the differences in the estimated transmission prices compared to a baseline group τ_O as well as the 90% CI. Compared with the other-supplier group, the three major upstream firms in the market have higher prices due to their brand premium and types of transmission products they offer. Since Aisin, ZF and JATCO mainly produce AT and CVT, they are more expensive than MT. The price differences are also significant at a 10% significance level.

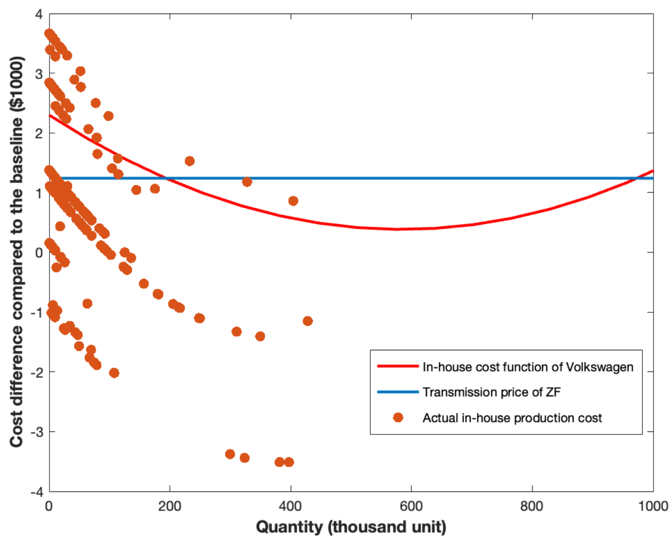
Figure 1.10: Transmission Prices Differences Across Years



Notes: The figure shows the transmission price differences compared to τ_O charged by upstream firms. Estimated transmission prices are computed as $\tau_{st} = \hat{\tau}_s + \tau_s^{\hat{trend}} t + \tau_s^{\hat{trend_2}} t^2$.

Figure 1.11 shows in-house production cost and transmission prices of ZF in the year 2018. Compared to a constant upstream price at different demand realization, the in-house production cost exhibits a convex shape. According to the estimates, the in-house production exhibits increasing returns to scale even after a moderate level of positive demand shock. It suggests that downstream firms don't need to worry about their own demand uncertainty increase under the current market condition. In economic downturns, however, shrinking demand drives up the in-house production cost. Therefore, holding the transmission prices fixed, the upstream firms provide cost insurance for the downstream firms in economic downturns.

Figure 1.11: Transmission Cost Differences: In-house Versus Outsourcing

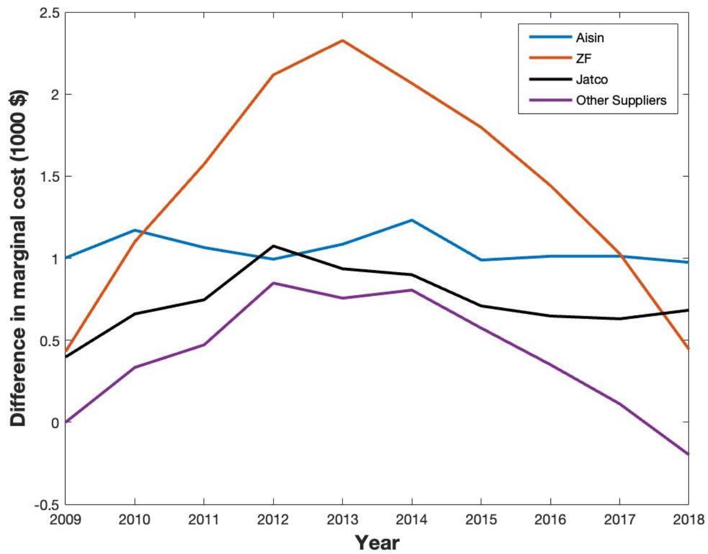


Notes: The red curve is drawn from the cost function of Volkswagen. Actual in-house production cost are computed using the estimates and realized equilibrium demand. The blue horizontal line is the equilibrium price of ZF in 2018.

1.5.2 Estimation Results for mc_{st}

In Figure 1.12, I plot the differences in the marginal cost of each upstream firm from 2009 to 2018 compared with the marginal cost of the other-supplier group in 2009. Marginal costs are all smaller than prices, suggesting my estimates are in general sensible. Consistent with the price patterns, the marginal costs of Aisin, ZF, and JATCO are also higher than the other-supplier group. Since ZF introduced the new AT9 transmission in 2013 and the later technological improvement drove down the marginal cost, the variation for the marginal cost of ZF is more significant. Because I compile all other three upstream firms in the other-supplier category, the variations in marginal cost are probably due to a change in the upstream firm and products composition. There is also a positive correlation between the profit margin and industry level HHI across time.[40]

Figure 1.12: Upstream Firms' Marginal Cost Differences



Notes: The figure plots the relative marginal cost since the transmission prices are using other-supplier group's prices in year 2009 as a base group.The marginal cost of upstream firms are inverted from Equation 1.7 and I use the estimated equilibrium upstream prices and parameter primitives of each year to back out the marginal cost.

1.5.3 Empirical Patterns between Demand risk, Upstream Market Power and Outsourcing Decision

I first explore the empirical patterns between demand risk, upstream market power, and outsourcing decisions. Since firms don't make outsourcing decisions for each product annually, the within-product variation is very small. Therefore, I only consider observations when a product is first introduced. Most firms in my model choose to produce all transmission in-house or outsource all transmission from one upstream firm for the same product, I classify the in-

[40]For the full set of stimulation specifications I use for computing the marginal cost, please refer to Appendix A Table A1.

house production as a dummy variable at the product level. A few products ($< 1\%$) choose a hybrid mode with partly in-house production. I classify the hybrid ones as in-house production as well.

Upstream market power is defined as the Herfindahl Index of upstream firms at each transmission level (HHI_{ht}). To avoid a correlation between HHI and current period demand shocks, I use the HHI in the previous period to measure the upstream market power. The demand uncertainty (σ_{fht}) is at a firm-transmission level and I use the method describe in section 4.2 to construct them. Another important aspect to consider is the scale economy of downstream firms and complementarity across products. If a firm requires a particular input for many of its products, the benefit of producing it in-house would be higher. Such scale economy is not captured by demand uncertainty and upstream market power. I use the firm-transmission level log output as a measure for the scale effect ($scale_{fht}$). The higher the scale effect, the higher the probability of in-house production. I additionally control for year and firm*transmission fixed effect to account for the time trend and firm-level heterogeneity in producting different transmission in-house. The specification is as follows:

$$\text{in-house}_{jt} = \beta_0 + \beta_1 \sigma_{fht} + \beta_2 HHI_{ht} + \beta_3 \sigma_{fht} * HHI_{ht} + \beta_4 scale_{fht} + FE + \epsilon_{jt}$$

I additionally consider the regression on a firm level to analyze the intensive margin changes. It is designed to examine how demand uncertainty and upstream market power affect in-house production decisions on the firm-transmission level. The firm typically has transmission plants producing transmissions for many different models, and the capacity plans are updated annually.

$$\text{in-house}_{fht} = \beta_0 + \beta_1 \sigma_{fht} + \beta_2 HHI_{ht} + \beta_3 \sigma_{fht} * HHI_{ht} + \beta_4 scale_{fht} + FE + \epsilon_{fht}$$

Here in-house$_{fht}$ is a weighted average of the proportion of type h transmission made in-house by firm f at time t. It is constructed from a product level, either using a simple average or shares as weights. For each product j, I use the average shares across years to measure its mean popularity. If the product is more popular, it will carry more weight in the determination of firm-level outsourcing choice.

Table 1.6 report the reduced form relationship of how demand uncertainty and upstream market power affect a firm's outsourcing decisions. The finding is consistent with the model prediction that downstream firms don't need to insure against the risk if their own demand uncertainty increases at a moderate amount. According to the regression, downstream firms increase in-house production when their demand uncertainty rises. The interaction term determines the complementarity between demand uncertainty and upstream market power. A positive and significant sign means that when upstream market power increases, the downstream firm will increase its in-house production propensity even if demand uncertainty rises. It reflects that the upstream firms may increase their prices when demand is more volatile and therefore suppress the outsourcing incentives of downstream firms.

However, one of the concerns of the reduced-form evidence is the endogeneity problem induced by the HHI measure. Since the HHI measure is based on market shares, an equilibrium outcome depending on the unobserved demand shocks, the effect of HHI on in-house propensity is not very intuitive. I will use the structural analysis in the next section to disentangle the endogeneity problem.

Table 1.6: In-house Production, Demand Uncertainty and Upstream Market Concentration

Variables	Product(new)	Firm(simple)
σ_{fht}	-0.264	0.126***
	(0.220)	(0.044)
lag HHI	-1.067**	-0.912***
	(0.515)	(0.161)
$\sigma_{fht} * lagHHI$	1.366**	0.913***
	(0.637)	(0.194)
Scale	0.027	0.020
	(0.057)	(0.014)
Observations	183	679
Adjusted/Pseudo R-Square	0.245	0.195
Year FE	YES	NO
Firm FE	YES	NO
Firm*tran FE	NO	YES

Notes: This table reports the relation between in-house production, demand uncertainty and upstream market power. Column (1) is at a product level and Column (2) is at a firm level using simple weights. Upstream market power is measured using HHI in the previous year. Interaction term is the parameter of interest and capture the interaction between upstream market power and demand uncertainty. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

1.6 Counterfactuals

In this section, I analyze how quantitatively important demand shocks and upstream market structure are in shaping the outsourcing decisions and their impacts on consumer welfare and producer surplus. With the estimated parameters and model, I first focus on a large negative demand shock equivalent to the recent pandemic and then analyze the effect of a trade policy that changes the upstream market structure. I next explore how idiosyncratic uncertainty propagates in the product network under different upstream market structures. For all the analysis in this section, I focus on the 2018 samples.

1.6.1 The Impact of an Economic Bust

The current pandemic impacts the US automobile industry drastically. Especially in the first few months of the pandemic, travels were discouraged, dealers' showrooms were closed, and the demand for new vehicles collapsed.[41] From Figure 1.2, one can see that the sales dropped by almost 50% in early 2020. Many manufacturers significantly decreased the number of shifts or even temporally shut down some plants. To mimic the economic bust, I consider shrinking the downstream market size by 1/3 and recomputing the equilibrium downstream and upstream prices.

I first quantity the insurance motive of outsourcing by comparing the transmission cost and profit of strategic downstream firms under two scenarios: no outsourcing is allowed and equilibrium outsourcing when upstream firms' prices are fixed.[42] During an economic bust, the demand for the vehicle and the input demand for transmission decreases. Due to an increasing cost disadvantage of in-house production, the weighted average cost of producing in-house increases by roughly $392 if the five strategic firm-transmission pairs cannot outsource.[43] The effects of an economic bust on the downstream firms are different because of their heterogeneity in in-house production cost and the amount of competition they face. According to Figure 1.13, outsourcing leads to a much milder increase in the transmission cost across all five firm-transmission pairs because of the stable prices provided by the upstream firms in this negative shock. As a result, the increase in average transmission cost is only $203, 48% less than the increase when there is no outsourcing option.

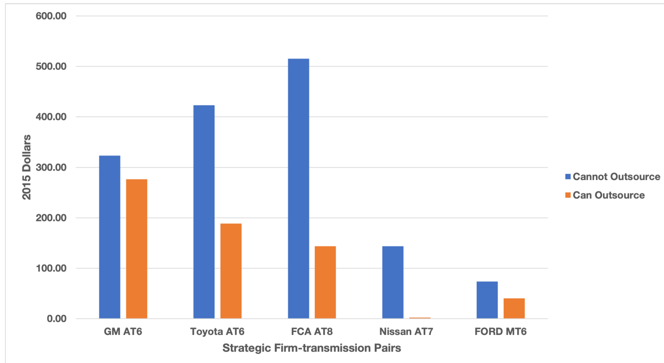
The differences in transmission cost also translate into differences in expected profit for the downstream firms. Downstream firms' profits decrease

[41] According to the report from Mckinsey, "The effects began in China, where sales plunged 71 percent in February 2020; by April, sales had dropped 47 percent in the United States and dived 80 percent in Europe."

[42] I focus on strategic firms because they actively make outsourcing decisions in my model. The upstream firms' prices are fixed at the same level before the demand shock to isolate the upstream firms' price response, which I will analyze later.

[43] I use the quantity sold for each product as weights.

Figure 1.13: Changes in Transmission Cost in Economic Bust

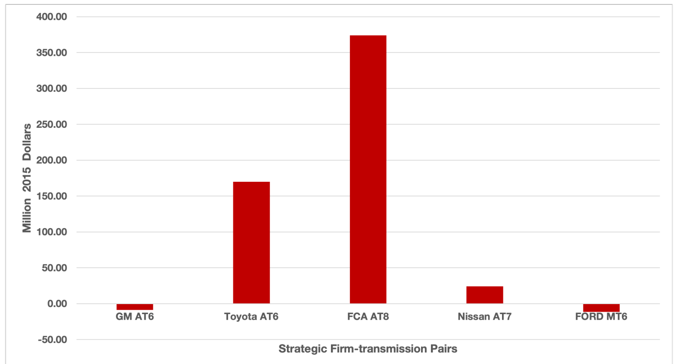


Notes: This figure shows the increase in unit transmission cost in a negative shock when the market size is decreased by 1/3. The blue bars represent changes in the first scenario when downstream firms cannot outsource. The orange bars represent changes in the second scenario when strategic downstream firms optimally outsource without upstream firms' prices fixed at the equilibrium without the negative shock.

when facing a shrinking demand. However, outsourcing enables downstream firms to transmit some in-house cost disadvantages to the upstream and attenuates the profit loss. According to Figure 1.14, the loss in expected profit is mitigated for most of the strategic firm-transmission pairs. It leads to a total reduction in the profit loss of $527 million. The attenuation is most significant for FCA AT6 and Toyota AT6 division due to a substantial cost saving of outsourcing reflected in Figure 1.13. The expected profit is also affected by the amount of competition each firm-transmission pair face. The cost-savings due to outsourcing are not as significant for GM AT6 and Ford MT6 division. They experience a moderate decrease in expected profits because competitors have a cost advantage in transmission when outsourcing is allowed. Since outsourcing brings down the cost of transmission, it also reduces the negative-shock-induced consumer welfare loss by $1.24 billion.

According to Table 1.7 column (1), most strategic firm-transmission pairs increase their outsourcing propensities to transfer the unfavorable shocks to

Figure 1.14: Differences in Profit Loss with and without Outsourcing



Notes: This figure shows the differences in strategic downstream firms' profit loss under the two scenarios in a negative shock when the market size decreases by 1/3. (profit loss=expected profit loss with outsourcing-expect profit loss without outsourcing)

the upstream firms.[44] The new equilibrium transmission prices of the four upstream firms all increase in response to the rise in their market shares, and hence the weighted average price increases by \$137.18.[45] According to Table 1.8, the price increase is most salient for Aisin and ZF, about 10% of the wholesale prices of a transmission. For smaller firm-transmission pairs like Nissan AT7 and Ford MT6, the effect of the economic bust on their in-house production cost is much smaller, and their outsourcing behaviors are barely affected. Therefore, the prices of JATCO and the other-supplier group are less affected in an economic bust. Due to the equilibrium upstream prices increase, downstream firms decrease their outsourcing propensities, but the magnitudes depend on the change in upstream firms' prices they face. Similar to the previous case, the effect on expected downstream profit is also affected by the downstream competition.

[44]For GM AT6, the quantity outsourced is roughly 93000. Therefore a 2% change in outsourcing is approximately 2000 units.

[45]The rise in market share is majorly driven by downstream firms' outsourcing incentives. In addition, downstream firms using outsourced transmission have a cost advantage over firms that uses in-house transmissions, and the increase in final good demand also leads to an increase in transmission demand.

Table 1.7: Changes in Outsourcing Propensities and Expected Downstream Profit in an Economic Bust (4 Upstream Firms)

	Before τ adjust		After τ adjust	
Firm-transmission Pairs	Δ Outsourcing (%)	Δ Profit (Billion $)	Δ Outsourcing (%)	Δ Profit (Billion $)
GM AT6 (Aisin)	2.71%	-4.32	2.22%	-4.31
Toyota AT6 (Aisin)	2.01%	-2.87	1.68%	-2.90
FCA AT8 (ZF)	1.36%	-2.775	1.28%	-2.781
Nissan AT7 (JATCO)	0.01%	-0.66	0.01%	-0.67
Ford MT6 (Other)	-0.40%	-0.17	-0.42%	-0.18

Notes: This table reports the transmission cost and downstream profit change when the market size shrinks by 1/3 with four upstream firms. I use outsourcing propensity changes instead of quantity changes because the quantity level always decreases in a negative demand shock. The prices here are in 2015 dollars.

Table 1.8: Changes in Upstream Prices and Market Shares in an Economic Bust

	Aisin	ZF	JATCO	Other Suppliers
Change in price (dollars)	214.16	128.94	4.42	37.82
Changes in price (% of wholesale prices)	10.71%	6.45%	0.22%	1.89%
Change in market share (%)	1.71%	2.19%	3.36%	3.08%

Notes: This table reports upstream firms' prices and profit changes when the market size shrinks by 1/3. The prices here are in 2015 dollars. The wholesale price of a transmission is around $2000. The optimality constraint is 10^{-6}.

Welfare Analysis: Table 1.9 shows the effect of an economic bust on consumer and producer surplus. When the industry faces an economic bust, downstream and upstream profits are significantly affected due to shrinking market demand. When upstream firms adjust their prices in the new equilibrium, the consumer surplus and downstream profits further decrease due to a rise in new equilibrium transmission prices. Even though upstream firms' profit loss is alleviated, the existence of upstream market power exacerbates an economic bust. Compared with a perfectly competitive state when upstream firms are only allowed to charge their marginal cost, the change in total welfare is very significant. Even though upstream firms don't have profit, the consumer surplus and downstream profits increase significantly because of a much lower transmission price.

Table 1.9: Changes in Welfare in an Economic Bust (Billion $)

	Upstream market power	Perfect Competition
Δ CS	-0.42	46.13
Δ Downstream Profit	-0.10	15.49
Δ Upstream Profit	0.05	-32.31
Δ Total Welfare	-0.47	29.30

Notes: This table shows the changes in consumer surplus, upstream and downstream profit in an economic bust. In the baseline group, the market size shrinks by 1/3 but the upstream firms' price is fixed at the old equilibrium when market size doesn't change. Column (1) compares welfare change due to an increase in upstream firms' prices in the new equilibrium. Column (2) compared the welfare change to a perfectly competitive market where the upstream firms' charge their market cost. All prices are measured in 2015 dollars.

1.6.2 The Impact of Increasing Upstream Market Power Induced by the United States-Mexico-Canada Agreement

From the previous analysis, upstream market power increases upstream prices whenever there is an outsourcing incentive. I next quantity how an increase in upstream concentration changes the pricing response and the downstream firms' sourcing behaviors, the expected profit, and the consumer surplus. The result also has important implications on the recent United States-Mexico-Canada Agreement that protects local suppliers by elevating the entry barrier. The agreement is in effect in July 2020 and will be phased in over four years. Because my data only cover up to 2018, I consider a case that Aisin is a monopoly in the upstream sector to quantify the potential impact. According to the previous analysis, Aisin has the largest upstream market share. This simplification is used to circumvent the assignment problem. If I allow two upstream suppliers, I need to additionally model how downstream firms originally affiliated with JATCO and the other-supplier group are assigned to different suppliers. However, the choice of an upstream firm is not merely driven by unit price differences and is not incorporated in the current version of my model. In addition, ZF currently only has one production line in North American, serving the AT9 transmission, which has limited applications.

Since there is only one upstream firm, the price charged by Aisin rises by \$2247.73, doubling the current price of a transmission. Due to the increase in price and demand, Aisin's profit increases by 176%. For policies aiming at protecting the local suppliers, it well serves the purposes. However, the increasing upstream prices lead to a decrease in consumer surplus and downstream profit. The total welfare loss is \$13.21 billion according to column (1) of Table 1.10. It is a well-acknowledged welfare loss due to the existence of double marginalization. An overlooked channel is the interaction between upstream market power and the effect of demand shocks. The rise in upstream firms' prices in an economic bust follows a similar reason as the previous case. In addition, a more concentrated upstream further increases the Aisin's price by 8% (231.10/214.16-1) and the average price charged by the upstream firm by 68% (231.10/137.18-1). As upstream market power increases, the upstream is more responsive to the economic bust.

Welfare Analysis: Columns (2) and (3) of Table 1.10 show the welfare impact of upstream market power in an economic bust. For each column, the difference is compared before and after the upstream firms' prices adjust to the shocks. Since the prices are more responsive to the outsourcing incentives when the upstream is more concentrated, the increasing upstream market power prevents downstream manufacturers from effectively reallocating in an economic bust. The increase in transmission cost is further passed down to the consumers and increases the upstream-market-power-induced consumer surplus change in the economic bust by 56.32%. Overall, a more concentrated upstream will expand the upstream-market-power-induced welfare loss by 65%.

Downstream firms intend to expand outsourcing when facing a cost disad-

Table 1.10: Upstream Market Power Induced Changes in Welfare (Billion $)

			Economic bust	
	One Upstream	One Upstream	Four Upstream	Changes (%)
Δ CS	-8.89	-0.66	-0.42	56.32%
Δ Downstream Profit	-1.92	-0.12	-0.10	24.25%
Δ Upstream Profit	-2.40	0.00	0.05	-100.95%
Δ Total Welfare	-13.21	-0.78	-0.47	65.10%

Notes: This table shows the changes in consumer surplus, upstream and downstream profit . Column 1 is a comparison before and after upstream market power change. Column 2 and 3 is welfare changes due to increasing upstream prices under different upstream market structure in an economic bust. All prices are 2015 dollars.

vantage of in-house production in the economic bust. The existence of upstream market power partially blocks the outsourcing channel because upstream firms increase their prices in response to the outsourcing incentives. As a result, the total welfare loss is larger because downstream firms cannot use outsourcing to drive down the transmissions' cost effectively, and the cost is further passed down to the consumers. When the upstream firm becomes more concentrated, the upstream firms' prices become more responsive to the economic bust and further amplify the negative demand shock. The counterfactual suggests that when protecting the local sector by increasing the entry barriers, the change in upstream market structure would also affect the upstream prices and the firm boundaries of the downstream firms. Even though the surviving firm Aisin gains substantial profit after the policy, the downstream firms become more vulnerable in times of big economic bust. In addition, compared with downstream firms' internal cost of production, upstream firms are more efficient in producing transmissions given their estimated marginal cost. With a gain in market power, the system is driven further away from an efficient allocation.

1.6.3 A Propagation of Idiosyncratic Demand Uncertainty in the Production Network

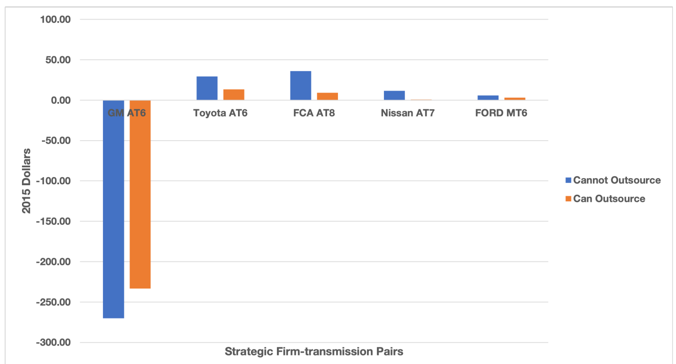
I finally examine the impact of increased idiosyncratic demand uncertainty. A downstream firm can be affected by its own demand uncertainty and the demand uncertainty of its competitor. Since upstream firms charge a uniform price based on the expected input demand, the demand uncertainty will propagate in the production network through its impact on the prices. Furthermore, the changes in transmission prices also depend on the upstream market structure. When the upstream is more concentrated, it can pool idiosyncratic shocks together, and the effect of a single shock would be mitigated. In this counterfactual exercise, I first double the variance of the demand shock of the largest GM AT6 division and then double the variance of the demand shock of downstream firms that use Aisin transmissions but are not strategic. For each of the two cases, I recompute the equilibrium upstream and downstream prices.[46]

Own Demand Uncertainty Increase: Similar to section 6.1, I compute transmission cost and profit changes of strategic downstream firms under two scenarios: no outsourcing is allowed and equilibrium outsourcing when upstream firms' prices are fixed. According to the in-house production cost estimates, firm-transmission pairs produce on the increasing returns to scale portion of the cost function. Therefore, an increase in demand uncertainty brings down the in-house production cost and provides more utilization of the equipment. In addition, the expected downstream profit also increases with demand uncertainty due to the convexity in demand function. However, an increase in

[46] I choose Aisin because all the impacts will have a larger magnitude. In addition, it allows for comparison with the later exercise. The analysis can also be done on other upstream firms or even downstream firms doing in-house.

idiosyncratic demand uncertainty poses a negative impact on its competitors and reduces their expected demand. If the products are close substitutes to the products offered by GM AT6 division, their expected profit would be affected heavily. Accordingly, the competitors experience an increase in in-house production cost and a loss in expected profit. According to Figure 1.15, Toyota and FCA are affected most significantly.

Figure 1.15: Changes in Transmission Cost with Demand Uncertainty Increase

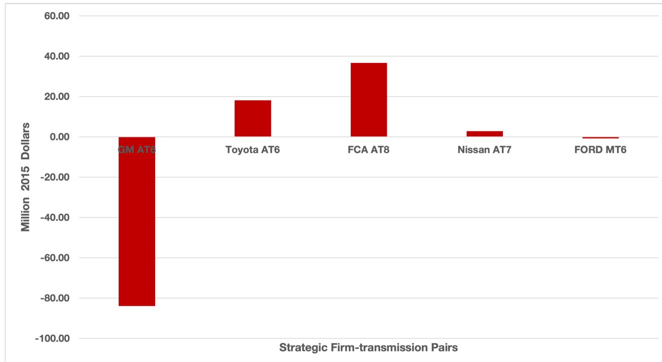


Notes: This figure shows the increase in unit transmission cost when the variance of the demand shock of GM 6AT division increases. The blue bars represent changes in the first scenario when downstream firms cannot outsource. The orange bars represent changes in the second scenario when strategic downstream firms optimally outsource without upstream firms' prices fixed at the equilibrium without the negative shock.

I next analyze the role of upstream. Unlike in the negative demand shock case, outsourcing affects the transmission cost differently. For GM AT6, it is more efficient to produce in-house since the demand uncertainty increase drives down the in-house production cost. For the other firm-transmission pairs, the upstream firms can provide a stable price. As a result, except for GM AT6, all other firm-transmission pairs reduce their in-house production quantity according to column (1) in Table 1.11. Due to the existence of upstream, the expected profit for the other firm-transmission pairs also decreases less in Figure 1.16.

Upstream firms respond to their expected demand and adjust their prices.

Figure 1.16: Differences in Profit Loss with and without Outsourcing with Demand Uncertainty Increase



Notes: This figure shows the differences in strategic downstream firms' profit loss under the two scenarios when the demand uncertainty of GM 6AT division increases. (profit loss=expected profit loss with outsourcing-expect profit loss without outsourcing)

Table 1.11: Changes in Transmission Cost and Expected Downstream Profit with Increasing Idiosyncratic Demand Uncertainty (4 Upstream)

	Before τ adjust		After τ adjust	
Firm-transmission pair	Δ Quan in-house (1000)	Δ Profit (Billion \$)	Δ Quan in-house (1000)	Δ Profit (Billion \$)
GM AT6 (Aisin)	439.34	5.58	436.94	5.50
Toyota AT6 (Aisin)	-13.06	-0.23	-14.44	-0.21
FCA AT8 (ZF)	-8.95	-0.25	-9.46	-0.21
Nissan AT7 (JATCO)	-0.29	-0.052	-0.29	-0.049
Ford MT6 (Other)	-0.60	-0.013	-0.62	-0.014

Notes: This table reports the change in transmission cost and downstream profit when the demand volatility of GM AT6 doubles and there are four upstream firms. The prices here are in 2015 dollars.

According to Table 1.12, the price drop of Aisin is most significant ($\sim 7\%$) because of the increasing in-house cost advantage of GM AT6 and its intention of in-house production. The price changes of the other three firms are a combination of downstream competition and outsourcing propensities. Overall, the effect is not very salient. Due to the increasing demand uncertainty of GM AT6, the other upstream firms all witness a profit decrease due to an impact from the downstream though the magnitude is minimal. The profit of Aisin also decreases due to the increasing in-house production of GM AT6 and its negative impact on the other competitors using Aisin transmission. According to column (3) and (4) in Table 1.11, all other strategic firms profit loss is narrowed because of a decrease in upstream prices in the new equilibrium. However, GM AT6 loses some competitive advantage in transmission cost and its profit decreases as well.

Table 1.12: Upstream Prices and Profit Changes with Increasing Idiosyncratic Demand Uncertainty

	Aisin	ZF	JATCO	Other-supplier
Change in price ($)	-137.30	-24.43	-20.00	30.63
Change in Profit (%)	-1.06%	-2.30%	-2.30%	-2.72%

Notes: This table reports the change in upstream prices and profit when the variance of the demand shock of GM AT6 doubles and there are four upstream firms. The prices here are in 2015 dollars.

I finally examine the impact of upstream firms on the producer surplus and consumer surplus with an idiosyncratic demand shock. According to Table 1.13, when the demand uncertainty of strategic firms increases. Due to an increasing cost advantage of producing in-house, the firm expands its in-house production. Upstream firms respond to the idiosyncratic shock by decreasing the transmission prices, benefiting both downstream firms and consumers. Outsourcing allows the upstream to partly absorb the downstream volatility. Even though their profit loss is larger in a new equilibrium, it is partly offset by the the total welfare gain to the industry.

Table 1.13: Welfare Changes with Increasing Demand Volatility (Billion $)

	Own demand volatility		Competitors' demand volatility	
	Before τ adjust	After τ adjust	Before τ adjust	After τ adjust
Δ Consumer Surplus	8.57	8.82	12.94	11.41
Δ Downstream variable profit	1.16	1.24	3.10	2.51
Δ Upstream variable profit	-0.85	-0.88	7.13	7.40
Δ Total welfare	8.88	9.17	23.17	21.32

Notes: This table shows the changes in consumer surplus, upstream and downstream profit when the demand uncertainty changes. In column (1) and (2), I double the demand uncertainty of GM AT6 division. In column (3) and (4), I double the demand uncertainty of Aisin's non-strategic consumers. The changes are compared to a baseline model with no demand uncertainty changes. All prices are measured in 2015 dollars.

Competitors' Demand Uncertainty Increase: Due to the inhouse-production patterns, there are firms in my dataset never produce transmissions in-house, such as Tata Group and Geely. I next double the demand uncertainty of downstream firms using Aisin transmissions which don't change outsourcing strategies, and study their impact on the strategic firms and the transmission prices. I additionally use this counterfactual to understand the role of upstream market structure in the propagation of idiosyncratic shocks.

Table 1.14 shows the changes in upstream prices when the non-strategic downstream firms of Aisin face increasing demand uncertainty. Downstream firms' volatile demand drives up Aisin's price in two ways. When the demand is more volatile, the expected downstream profit increases and thus drives up the demand of Aisin's transmission. Secondly, the strategic firm-transmission pairs like GM AT6 and Toyota AT6 divisions increase their outsourcing propensities and further drive up the prices.[47] The demand uncertainty of Aisin's downstream firms affects the other upstream firms through its effect on the downstream firms' competition. As a result, only the expected profit of Aisin increases by 51.88% when its downstream becomes more volatile. The other upstream firms are negatively affected. However, when the upstream market is only served by Aisin as a monopoly, the impact of the idiosyncratic shock on prices is smaller. Since now the Aisin serves a larger downstream base, the risk-pooling effect attenuates the price increase. Compared to a less concentrated upstream, the price response to an increase in the demand volatility is reduced by more than 50%.

Table 1.14: Upstream Prices and Profit Changes with Increasing Competitors' Demand Uncertainty

	Aisin	ZF	JATCO	Other-supplier	Only Aisin
Change in price ($)	826.91	-33.05	-35.76	24.23	385.60
Change in profit(%)	51.88%	-3.09%	-3.16%	-3.46%	17.29%

Notes: This table reports the changes in upstream prices and profit when the variances of the demand shocks of the non-strategic downstream firms using Aisin transmission double. The prices here are in 2015 dollars.

[47]The increase in in-house production cost is similar to the previous case because they now face a more fierce downstream competition.

Column (3) and (4) in Table 1.13 shows the effect of idiosyncratic shock in the industry. Consumer surplus and expected total downstream profit are driven up by the increasing demand uncertainty of non-strategic Aisin consumers. Unlike the previous case, the new equilibrium transmission price of Aisin increases. Due to the price increase of Aisin, the consumer surplus and downstream profit are both smaller. I further decompose the expected downstream profit. Strategic downstream firms like GM AT6 and Toyota AT6, which outsourced from Aisin, are negatively affected by the downstream competition and Aisin's new equilibrium price. Aisin also drives up the total upstream profit. The other upstream firms suffer from a profit loss because their downstream firms are less competitive.

1.7 Conclusion

In this paper, I build a model of vertical relation under demand risk with upstream market power. Upstream firms set prices, internalizing their effects on the downstream firms' outsourcing decisions. Downstream firms choose outsourcing strategies based on comparing a stable price provided by the upstream sectors and a fluctuating in-house production cost. I estimate the model and simulate counterfactuals to quantify the insurance motive and the role of upstream market power. When facing a negative shock similar to the recent pandemic, outsourcing significantly reduces the rise in transmission cost by 48%. However, the upstream firms leverage downstream firms' outsourcing intentions to increase their prices, creating a sizable welfare loss to the downstream firms and the consumers. I also quantify the potential impact of the United States-Mexico-Canada Agreement because it protects the local upstream sector by significantly lifting the entry barrier. In this more concentrated upstream, the prices charged by the upstream sector are more responsive to demand shocks. The increase in upstream prices further expands the upstream-market-power-induced welfare loss by 65%, amplifying an economic bust.

The automobile industry is important in its own right. It is heavily affected by macroeconomic fluctuations and the uncertain radical innovation of electric vehicles. The increasing demand risk and the countries' intention to protect local industry will make the automobile industry vulnerable to large negative shocks. By highlighting the additional welfare loss of market power in demand risk, my paper also provides crucial insight for competition policy in industries heavily affected by the business cycles.

1.A Appendix—Chapter 1

1.A.1 Algorithm used for solving the model

Timing:

- Stage 1:Each upstream supplier s compete with each other by setting the price τ_{st} to maximize expected profit.
- Stage 2: Upon observing the price τ_{st}, downstream firms simultaneously decide what proportion to produce in-house.
- Stage 3: After realizing the demand shock and marginal cost shock, downstream firms assemble the transmission either produced internally or outsourced from the upstream at a predetermined price, set prices simultaneously.

With the parameters estimated, the problem is solved backward:

Demand Equation:

$$D_{jt}(\mathbf{x_t}, \mathbf{p_t}, \theta_d) = N_t \int \frac{exp(\delta_{jt} + \nu_{i0}\beta_\nu^0 + log(Y_i)\beta_d^p p_{jt})}{1 + \sum_{m \in J_t} exp(\delta_{mt} + \nu_{i0}\beta_\nu^0 + log(Y_i)\beta_d^p p_{mt})} dF_\nu(\nu_{i0})F_d(Y_i)$$

$$\delta_{jt} = X_{jt}\beta - \alpha p_{jt} + \xi_{jt}$$

Profit equation:

$$\pi_{ft} = \sum_{j \in J_{ft}} D_{jt}(p_{jt} - X_{jt}\gamma - \omega_{jt} - (1 - I_{jt})\tau_{sht(j)}) - I_{jt}c(D_{jt})$$

The marginal cost of each product:

$$mc_{jt} = \underbrace{X_{jt}\gamma + \omega_{jt}}_{\tilde{mc}_{jt}} + (1 - I_{jt})\tau_{sht(j)} + I_{jt}c'(D_{jt})$$

The inhouse production cost function:

$$c(D_{jt}) = c_{1_{jt}}(D_{jt}) + c_2(D_{jt})^2 + c_3(D_{jt})^3$$
$$c'(D_{jt}) = c_{1_{jt}} + 2c_2(D_{jt}) + 3c_3(D_{jt})^2$$

Here I add some flexibility and heterogeneity to in-house production of c_1, reflecting the difference in producing the transmission in-house both across downstream firms and across time. Here g_j is the share of each product j. The equilibrium prices are the fixed point of the following first order condition, I omit characteristics $\mathbf{x}$, the parameters and time script.:

$$g_j(\mathbf{p}^*, \mathbf{e}, \cdot) + \sum_{j' \in J_{ft}} (p^*_{j'}(\boldsymbol{\tau}, \mathbf{I}, \mathbf{e}, \cdot) - mc_{j'}(g^*_{j'}, \boldsymbol{\tau}, \mathbf{I}, \mathbf{e}, \cdot)) \frac{\partial g_{j'}(\mathbf{p}^*, \mathbf{e}, \cdot)}{\partial p^*_j(\boldsymbol{\tau}, \mathbf{I}, \mathbf{e}, \cdot)} = 0 \qquad (1.8)$$

In matrix form:

$$FOC(\mathbf{p}^*, \boldsymbol{\tau}) = p^*(\boldsymbol{\tau}, \mathbf{I}, \mathbf{e}, \cdot) - mc(g^*, \boldsymbol{\tau}, \mathbf{I}, \mathbf{e}, \cdot) + \Delta(p^*, \boldsymbol{\tau}, \mathbf{I}, \mathbf{e}, \cdot)^{-1} g(\mathbf{p}^*, \mathbf{e}, \cdot) = \mathbf{0} \qquad (1.9)$$

Here Δ is the $\frac{\partial g_j}{\partial p_r}$ if j and r belong to the same firm-transmission pair. $\Delta = \Gamma^* g_p$ and Γ is the ownership matrix. I use a fixed point algorithm to solve for the optimal price for each set of realization of the demand and supply shock $e = (\xi, \omega)$ as well as assignment realization $\mathbf{I}$. Since the equilibrium prices $\mathbf{p_t}$ is very sensitive to extreme values, I additionally try a two-step iterative method(F is the equation (B2)) to allow for a smooth update:

$$y_k = p_k - F'(p_k)^{-1} F(p_k)$$
$$p_{k+1} = p_k - 4[3F'(\frac{2p_k + y_k}{3}) + F'(y_k)]^{-1} F(x_k)$$

In order to compute the first-stage upstream price FOC, I additionally compute the upstream price pass-through and derivative of downstream profit with respect to upstream prices $\boldsymbol{\tau}$ at the equilibrium output price $\mathbf{p}^*$:

$$p^*_{\boldsymbol{\tau}} = (\frac{\partial \mathbf{FOC}}{\partial \mathbf{p}})^{-1} \frac{\partial \mathbf{FOC}}{\partial \boldsymbol{\tau}}$$

$$\frac{\partial \mathbf{FOC}}{\partial \mathbf{p}} = \Delta - \Delta(\frac{\partial mc}{\partial g} g'_p) + G_3 + g'_p$$

Here $\frac{\partial mc}{\partial g}$ is a diagonal matrix since mc_j is only a function of g_j and element j is

$$D^I_j(2c_2N + 6c_3N^2g_j).$$

Here $G_3 = \frac{\partial \Delta}{\partial p}(p - mc)$. i refers to FOC equation i and j refers to FOC_i with respect to. p_j

$$G_3(i,j) = \sum_{k \in J_f} (p_k - mc_k) \frac{\partial^2 g_k}{\partial p_i \partial p_j}$$

$$\frac{\partial \mathbf{FOC}}{\partial \boldsymbol{\tau}} = -\Gamma^* g_p((1 - I)^* D_s)$$

$$g_\tau = g_p{}^* p_\tau$$

$$\pi_\tau = \frac{\partial \boldsymbol{\pi}}{\partial \mathbf{p}} * p_\tau + \frac{\partial \boldsymbol{\pi}}{\partial \boldsymbol{\tau}}$$

$$\frac{\partial \boldsymbol{\pi}}{\partial \mathbf{p}} = N * (diag(g) + g'_p{}^*(\mathbf{p} - mc))$$

$$\frac{\partial \boldsymbol{\pi}}{\partial \boldsymbol{\tau}} = -Ng(1 - I)^* D_s$$

The expected profit and demand are computed using simulation. Here I simulate 30 different demand and cost realization and 10 different assignment of which model will get the allocated randomly. I use M to denote the number of demand and cost shock simulation and N to denote the assignment simulations. I omit $\boldsymbol{\sigma}$. In the simulation, ξ_{jt} are drawn from the distribution $N(0, \sigma_j)$ and cost shocks are drawn from the empirical distribution of ω_{jt} of each product:

$$E_e p^*_j(\boldsymbol{\tau}, \mathbf{I}, \cdot) = \frac{1}{N} \sum_n p^*_j(\boldsymbol{\tau}, \mathbf{I}, \mathbf{e^m}, \cdot)$$

$$E p^*_j(\boldsymbol{\tau}, \mathbf{a}, \cdot) = \frac{1}{M} \sum_m E_e p^*_j(\boldsymbol{\tau}, \mathbf{I^n}, \cdot)$$

I additionally compute the expected profit of each action vector:

$$E\pi^*_j(\mathbf{p}^*, \boldsymbol{\tau}, \mathbf{a}, \cdot) = \tfrac{1}{M} \textstyle\sum_m \tfrac{1}{N} \sum_n (p^*_j(\boldsymbol{\tau}, \mathbf{I^n}, \mathbf{e^m}, \cdot) - cost(g^*_j(\mathbf{p}^*, \mathbf{e^m}, \cdot), \mathbf{I^n_j})) N g^*_j(\mathbf{p}^*, \mathbf{e^m}, \cdot)$$

$$cost_j = X_j\gamma + \omega_j + (1 - I_j^n)\tau_{s(j)} + I_j^n(c_{1_j} + c_2 N g_j^* + c_3(N g_j^*)^2)$$

The expected outsourced amount for each action combination is defined as following:

$$Eg_j^{O*}(\mathbf{p}^*, \mathbf{a}, \cdot) = \frac{1}{N}\sum_n (1 - I_j^n)\frac{1}{M}\sum_m g_j^*(\mathbf{p}^*, \mathbf{I^n}, \mathbf{e^m}, \cdot)$$
$$Eg_\tau^{O*}(\mathbf{p}^*, \mathbf{a}, \cdot) = \frac{1}{N}\sum_n (1 - I_j^n)\frac{1}{M}\sum_m g_{\tau,j}^*(\mathbf{p}^*, \mathbf{I^n}, \mathbf{e^m}, \cdot)$$

Here I only allow the 3-5 firms with leading shares to strategically respond to input prices.

$$E\pi_f^*(\mathbf{p}^*, \boldsymbol{\tau}, \mathbf{a}, \cdot) = \sum_{j \in J_f} E\pi_j^*(\mathbf{p}^*, \boldsymbol{\tau}, \mathbf{a}, \cdot)$$

Here the action is a and there are 5 actions to choose from. For a given guess of strategy profile, I additionally compute

$$E\Pi_{fh}(a_{fh}, \boldsymbol{\tau}, \cdot) = \sum_{a_{-fht}} E\pi_{fht}(a_{fh}, a_{-fh}, \boldsymbol{\tau}, \cdot) Pr_{-fh}(a_{-fh}|\boldsymbol{\tau}, \cdot)$$

$$Pr_{fh}(a_{fh} = 1) = \frac{exp(E\Pi_{fh}(a_{fh} = 1, \boldsymbol{\tau}, \cdot))}{\sum_{k \in \mathbf{A}_{fh}} exp(E\Pi_{fh}(a_{fh} = k, \boldsymbol{\tau}, \cdot))} = \Psi(\mathbf{Pr}, \boldsymbol{\tau}, \cdot) \tag{1.10}$$

I denote the equilibrium strategy as $Pr^*(p^*, \boldsymbol{\tau}, \mathbf{a}, \cdot)$

In the stage 1, I compute the expected input demanded of each supplier and the FOC breaks down of each supplier is:

$$E\pi^s = (\tau_s - mc_s) \underbrace{\sum_{f \in F_s}\sum_{j \in J_f}\sum_{\mathbf{a}} ED_j^{O*}(\mathbf{a}, \boldsymbol{\tau}, \cdot) Pr^*(\boldsymbol{\tau}, \mathbf{a}, \cdot)}_{\text{Expected demand of transmission from upstream firm s}}$$

$$FOC = \sum_{f \in F_s}\sum_{j \in J_f}\sum_{\mathbf{a}} ED_j^{O*}(\mathbf{a}, \boldsymbol{\tau}, \cdot) Pr^*(\boldsymbol{\tau}, \mathbf{a}, \cdot)$$
$$+(\tau_s - mc_s)\sum_{f \in F_s}\sum_{j \in J_f}\sum_{\mathbf{a}} ED_j^{O*}(\mathbf{a}, \boldsymbol{\tau}, \cdot)\frac{dPr^*(\boldsymbol{\tau}, \mathbf{a}, \cdot)}{d\tau_s}$$
$$+(\tau_s - mc_s)\sum_{f \in F_s}\sum_{j \in J_f}\sum_{\mathbf{a}} ED_{j,\tau}^{O*}(\mathbf{a}, \boldsymbol{\tau}, \cdot) Pr^*(\boldsymbol{\tau}, \mathbf{a}, \cdot)$$

Eg_{τ}^{O*} is defined before. As for:

$$\frac{dPr_f^k(p^*, \boldsymbol{\tau}, a, \cdot)}{d\tau_s} = Pr_f^k \frac{dE\Pi_f^k}{d\tau_s} - Pr_f^k \sum_K Pr^{k\prime}{}_f \frac{dE\Pi^{k\prime}{}_f}{d\tau_s}$$

Here k is an action and f is a firm-transmission pair. Vector-wise:

$$\frac{d\mathbf{Pr}}{d\tau_s} = \mathbf{Pr}(I - A)\frac{dE\Pi}{d\tau_s}$$

Where $A = \mathrm{Pr}_f^1 \ldots \mathrm{Pr}_f^K$ for rows equal to f.

$$\frac{dE\Pi_f^k}{d\tau_s} = \sum_{-a_f} E\pi_{f,\tau}^k Pr(-a_f) + \sum_j \sum_{-a_{f_{1,2}}} E\pi_f^k(a_{f_2} = j, -a_{f_{1,2}})Pr(-a_{f_{1,2}})\frac{dPr_{f_2}^j}{d\tau_s}$$

$E\pi_\tau$ is defined above. f_2 is another firm whose strategy profile Pr_{f_2} will also be affected by τ_s.

1.A.2 Sensitivity Test for Second Stage

Active firm transmission pairs are those that changed the in-house proportions in my data sample. The active firm-transmission pair, which has the largest market share of each upstream firm, is defined as the strategic firm. I use the sensitivity test to see if I need to include the second largest firms. The set of strategic firm transmission pairs for each year are listed below.

I additionally provide the sensitivity test for simulation specifications. The baseline simulation specification is five firm-transmission pairs. The action space is divided into six discrete choices. Then the discrete in-house proportions are $\{0, 0.2, 0.4, 0.6, 0.8, 1\}$. Each firm-transmission pair would have a different choice set due to the data patterns. In my data, if a firm-transmission pair's in-house production range is $[0.3 - 0.7]$, then its choice set is $\{0.2, 0.4, 0.6, 0.8\}$.

From the sensitivity test table, one can see the importance of including the largest consumer(firm-transmission pair) for each upstream firm. The marginal cost of upstream firms cannot be accurately estimated with 2-4 suppliers. However, the marginal gain is very small when moving to 6 upstream firms. In addition, adding more simulation draws for shocks and random assignment is also quantitatively less important. There is gain from using a more refined grid because the difference in marginal cost is 2.69% when I allow seven discrete choices upstream. This suggests that more computational effort should be devoted to refining the choice grid.

Table 1.15: Strategic Firm-Transmission Pairs for Each Year

Year	Downstream Firm	Upstream Firm	Transmission Type
2009	GM Group	Aisin	A4
2009	Ford Group	Aisin	A6
2009	Hyundai Kia Automotive Group	JATCO	A5
2009	Ford Group	TREMEC (Other)	M5
2010	Ford Group	Aisin	A6
2010	GM Group	Aisin	A4
2010	Hyundai Kia Automotive Group	JATCO	A5
2010	VW Group	GETRAG (Other)	M6
2011	GM Group	Aisin	A6
2011	Ford Group	Aisin	A6
2011	FCA	JATCO	CVT
2011	VW Group	GETRAG (Other)	M6
2012	GM Group	Aisin	A6
2012	Ford Group	Aisin	A6
2012	FCA	JATCO	CVT
2012	VW Group	GETRAG (Other)	M6
2012	FCA	ZF	A8
2013	GM Group	Aisin	A6
2013	Hyundai Kia Automotive Group	Aisin	A6
2013	VW Group	GETRAG (Other)	M6
2013	FCA	ZF	A8
2013	FCA	JATCO	CVT
2014	GM Group	Aisin	A6
2014	Toyota Group	Aisin	A6
2014	FCA	ZF	A8
2014	VW Group	GETRAG (Other)	M6
2014	Renault-Nissan Alliance	JATCO	A7
2015	GM Group	Aisin	A6
2015	Toyota Group	Aisin	A6
2015	FCA	ZF	A8
2015	Renault-Nissan Alliance	JATCO	A7
2015	VW Group	GETRAG (Other)	M6
2016	GM Group	Aisin	A6
2016	Toyota Group	Aisin	A6
2016	FCA	ZF	A8
2016	Renault-Nissan Alliance	JATCO	A7
2016	FCA	TREMEC (Other)	M6
2017	GM Group	Aisin	A6
2017	Toyota Group	Aisin	A6
2017	FCA	ZF	A8
2017	Renault-Nissan Alliance	JATCO	A7
2017	Ford Group	GETRAG (Other)	M6
2018	GM Group	Aisin	A6
2018	Toyota Group	Aisin	A6
2018	FCA	ZF	A8
2018	Renault-Nissan Alliance	JATCO	A7
2018	Ford Group	GETRAG (Other)	M6

Notes: This table reports for each year each upstream firm's largest consumer (the firm-transmission pair). I focus on firm-transmission pairs which adjust their in-house production proportions in the sample period. Firm-transmission pairs which always outsource or in-house are assumed as non-strategic players.

Table 1.16: Sensitivity Test for Simulation Specifications

Players	Action	Assignment (N)	Shock (M)	mc_{Aisin}	mc_{ZF}	mc_{JATCO}	mc_{Other}	Total differences
2	6	10	30	5.14%	0.72%	0.02%	2.26%	5.67%
4	6	10	30	5.35%	0.52%	0.02%	0.02%	5.38%
5	6	10	30					
6	6	10	30	-0.20%	0.15%	0.01%	-0.06%	0.26%
5	5	10	30	-4.37%	-1.71%	-0.50%	0.02%	4.72%
5	6	20	100	-0.82%	0.34%	-0.08%	-0.10%	0.90%
5	7	10	30	2.36%	1.29%	0.04%	0.18%	2.69%

Notes: This table reports the sensitivity test for the simulation specifications. The analysis is based on year 2018 and the reference group is the row in red. Column (5)-(9) shows the changes in marginal cost estimated compared to the reference group. Column (9) is the L_2 norm of the 4 columns before.

1.A.3 Another Equilibrium Solving algorithm

Due to the rich heterogeneity in demand and a large number of players simultaneously making decisions in stage 2, the problem is very computationally intensive to solve completely. Therefore, I also try an oblivious equilibrium in stage 2 so that the conditional choice specific expected profit would not depend on the specific action of other players but some equilibrium statistics. I discretize firm-transmission pairs to a finite number of types based on linear utility and demand risk. Therefore I only need to consider a finite number of strategy profiles. There are Q types of firm-transmission pair, and $\mathbf{n_t} = (n_t^1, ...n_t^Q)$ denotes the number of firm-trans pairs at each type.

Instead of fulling compute equilibrium at different action:

$$V_{fht}(a_{fht}, \epsilon_{fht}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) = \sum_{a_{-fht}} E\pi_{fht}(a_{fht}, a_{-fht}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) Pr_{-fht}(a_{-fht}|\boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) + \epsilon_{fht}(a_{fht})$$

Downstream firm-transmission pairs' profits are based on the stead state equilibrium $\hat{n}_t(a_{-fht})$

$$U_q(a_{fht}, \epsilon_{fht}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) = E\Pi_q(a_{fht}, \hat{n}_t(a_{-fht}), \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) + \epsilon_{fht}(a_{fht})$$

$\hat{n}_t(a)$ is a proxy of competitor's action distribution at a specific strategy profile. This indicates the number of type l firm-transmission pair at each action.

$$\hat{n}_t^q(a) = n_t^q Pr_q(a|\boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot)$$

If $\epsilon_{fht}(a_{fht})$ follows an extreme type I distribution,

$$p_q(a|\boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) = \frac{exp(E\Pi_q(a_{fht}, \hat{n}_t(a_{-fht}), \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot))}{1 + \sum_{a' \in A} exp(\Pi_q(a'_{fht}, \hat{n}_t(a_{-fht}), \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot))} \tag{1.11}$$

An oblivious equilibrium is a set of Pr^* that are best responding to each other. Upstream firms simultaneously post prices, profit function for each supplier:

$$\pi_{st} = (\tau_{st} - mc_{st}) \underbrace{\sum_{q_s \in s} \sum_{q_s} \sum_{a} \hat{n}^*_{qt}(a) ED^{O*}_{qt}(\hat{n}^*_t, \boldsymbol{\tau_t}, bm\sigma_t, \cdot)}_{\text{Transmission demand of supplier s}} \tag{1.12}$$

Here $\hat{n}^*_{qt}(a)$ is the number of firm-trans pairs at action a for type q in an oblivious equilibrium.
$ED^{O*}_{qt}(\hat{n}^*_t, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot)$ is the expected outsourced equilibrium output of each type q given the equilibrium firm distribution $\hat{n}^*_t$.

There is a potential problem with this setup. Often the case $\hat{n}^q_t(a)$ is not an integer. In the original Weintraub et al. (2008) and the implementation Weintraub et al. (2010), they randomize between the two nearest integers. This method works well if we have a large number of firms. If I just focus on the integer number of firms in my setup, the algorithm cannot converge to a bayesian equilibrium because the grid is not fine enough. Therefore, I first use an approximation to discover the relationship between the number of firms at each action and the expected profit of each action combination. The algorithm is as follows:

The complete algorithm for solving stage 2 and computing equilibrium input prices is as follows:

1. For a given upstream price vector τ_t, simulate P draws of different $n_t(a)$ vector. For a specific $n_t(a)$ vector, simulate N draws of demand risk realization to compute the expected profit and demand.

2. Use the following equation and compute a reduced form relation for a given τ.

$$E\pi_q(a_{fht}, n_t(a_{-fht}), \tau_t, \cdot) \approx \hat{\beta}_0 + \hat{\beta}_1 a_{fht} + \hat{\beta}_2 n_t(a_{-fht})$$

3. Similarly project expected demand for each type-action.
4. From an initial guess of Pr, iterate using projected profit and Equation B4 until an equilibrium strategy profile is reached.
5. Compute numerical gradient by perturbing τ_t and redo 1-4.
6. Update upstream prices using FOC of upstream firms and redo 1-5 until converges.

It is more suitable for questions with a large number of firms but small heterogeneities among firms. In my setup, the number of firm-transmission pairs is not large enough for the law of large numbers to hold. To circumvent the non-integer number of firms at each action, I still need to generate enough number of $n_t(a)$ draws to get a good approximation and I need to redo the exercise for each τ_t. The downstream firms' price competition still makes it computationally intensive to solve. Therefore, it introduce approximation errors with little gains in computation.

CHAPTER 2

EXPORTING AND PRODUCTIVITY DYNAMICS IN THE CHINESE FOOTWEAR INDUSTRY

2.1 Introduction

A seemingly robust result that characterizes exporters is that exporters are of higher measured productivity than non-exporters.[1] In addition, opening up to trade, often measured by tariff reduction, would increase measured productivity. These are often cited as an argument for active export promotion in many developing countries. My paper seeks to empirically test the two empirical regularities of exporters in China.

Though the literature has documented the superior performance of exporters, the empirical findings characterizing China's exporting firms are a bit puzzling. Lu (2010) documents that China's exporters are significantly less productive and sell less in the domestic market than non-exporters, especially in labor-intensive industries. Unlike the US firms, the exporting firms in the labor-intensive industry in China have a U-shape exporting intensity. In addition, most paper use revenue-based productivity measures that contains price effect. Foster et al. (2008) raised a major problem of using revenue in firm-level survey data to calculate productivity that it is impossible to distinguish the quantity-productivity from the output price effect. A valid estimate of productivity would benefit my paper in analyzing the relationship between trade liberal-

[1]Melitz (2003) builds a theoretical model that firms who self-select into the export market should have higher productivity. Such findings have been supported by Bernard and Bradford Jensen (1999) for the US, Van Biesebroeck (2005) for sub-Saharan Africa. Studies by Aw et al. (2000) for Korean and De Loecker (2007) for Slovenia find that exporters also generate higher productivity upon entering the export market.

ization and firm-level productivity because the productivity estimates would be biased if exporters and non-exporters face systematically different demand shocks.

Production function and productivity estimation are tools used extensively to study the relationship between trade openness and firm or industry performance. Due to the revenue data's non-separable quantity and price information, I construct a CES demand model alongside a control function approach to control price effect and the simultaneity bias from physical productivity measure following De Loecker (2011). Even though I can not observe the price of each product, I use observable demand shifters from variations in trade protections as valid instruments and identify the productivity effects.

For the empirical analysis, I focus on the footwear industry in China between 2000 and 2006. The footwear industry of China is a labor-intensive industry and is the world's largest exporter. Understanding its productivity evolution is meaningful. In addition, China entered the WTO in 2001. The sample period is ideal for studying the effect of trade liberalization on firms' performance. Third, the footwear industry is highly exposed to export and different demand shocks. Therefore, it helps to construct a set of plausibly exogenous demand shifters.

The empirical fact discovered by **?** can be partly explained by the export-promoting policy and the prevalence of processing trade in China. Processing trade firms typically import all or part of the intermediate input and re-exports finished products after processing or assembling. In an effort to stimulate export, the final product using imported input would be exempted from input tariff as long as it is not sold in the domestic market. Therefore, if a firm chooses to re-export all its products, it becomes a pure processing trade company. I find that when controlling for the price effect, firms with high physical productivity enter into the exporting market. However, due to processing trade policies, low productivity firms enter the market to become processing trade companies and export as well. However, when using revenue-based productivity measures, the processing trade firms are falsely measured high productivity due to the price effect in their exporting countries.

From the estimated physical productivity measures, I next examine the productivity dynamics due to trade liberalization. Pure exporters witness a significant increase in productivity because output tariff reductions and the pro-competition effect enhance the firm selection. The input tariff reduction allows firms to employ cheaper and better intermediate inputs and boost firm-level productivity. In addition, there are sizable gains from exporting for pure exporters. However, the processing trade firms benefit less from trade liberalization and exporting. By selecting the less productive firms into exporting, my findings suggest that the processing trade policy is less efficient in promoting the footwear industry's overall productivity.

Literature Review: My paper can be seen as broadly contributing to the following strand of literature.

The well-known simultaneity and selection bias caused by unobserved productivity in estimating production function can be addressed using a control function approach following the insights of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015). Typically, the annual firm survey data will report the total revenue and expenditure in labor, capital, and intermediate goods. Many papers are using such data to estimate productivity in various countries. However, when a country is opening up to trade, the impact of liberalization on demand and price will be confounded with its impact on productivity, which might generate invalid welfare implications. To solve the problem raised by Foster et al. (2008), I follow De Loecker (2011) to construct a demand system in the standard production function approach to back out the relation between price and quantity when only revenue is observed on a firm level.

Studies by Klette and Griliches (1996), Katayama et al. (2009) point out problems using revenue data to obtain true efficiency measures. However, its importance in practice has only been checked when quantity data is available. De Loecker (2011) proposes a novel method to recover the relationship between price and quantity when quantity data is missing, but its applicability in different contexts has not been explored. Apart from the theoretical attractiveness of adding a demand model, the estimation procedure relies on demand shifters highly correlated with price. In addition, to identify the different price effect across export destinations, the variations in demand shifters across nations is also demanding. My paper applies the gist of De Loecker (2011) and intends to understand the empirical importance of separating the price effect when studying trade liberalization in China.

Third, processing trade is an important type of trade in developing countries and often receives special tariff treatment. Understanding the productivity dynamics of such firms is of policy relevance. My finding is consistent with existing literature that evaluates the processing trade in China. Yu (2015) uses the revenue-based productivity measure, and a selection model shows that low productivity firms self-select into processing trade in order to enjoy this special tariff treatment. With the existence of a large number of processing trade firms, he further documents that the effect of input tariff cut is weaker for processing trade companies since they had already been exempted from input tariff. Dai et al. (2016) use matched microdata of Chinese manufacturing firms in 2000-2006 to show that after teasing out the processing trade firms, the productivity of exporters is higher than non-exporters.

The remainder of this paper is organized as follows. Section 2.2 will describe the background information of Chinese exporters and the footwear industry, the three primary datasets I use, and perform some preliminary analysis. Section 2.3 will discuss the production function and the demand system I use to estimate productivity. Section 2.4 introduces the empirical strategies. The main results are presented in Section 2.5. Section 2.6 concludes.

2.2 Background on footwear market and data

In this section, I will first provide some background information about the footwear industry in China and the trade regime which is also common in developing countries and the tariff treatment of exporting firms in China. Furthermore, I will describe my three main dataset and use them to present the distinct exporting patterns of Chinese exporters.

2.2.1 Footwear market, processing trade and special tariff treatment

Processing trade is defined as "business activities in which the operating enterprise imports all or part of the raw or ancillary materials, spare parts, components, and packaging materials, and re-exports finished products after processing or assembling these materials/parts". The footwear industry, like many processing trade industry in China is subjected to special tariff treatment. Began in the early 1980s, government encourages Chinese firms to import all or part of the intermediate inputs and re-export final valued-added goods after local processing. For processing trade firm, the imported material is duty-free but due to this cost advantage, the firm cannot sell the final product in domestic market. I take Figure 2.1 from Yu (2015) as an illustration.

Owing to this special tariff treatment, there are mainly three kinds of firms. First, firms don't use any duty free imported input in any of its product at all. This first type can either be an non-exporter or an exporter. If it is an exporter, it is engaged in ordinary trade since it uses domestic inputs or imported inputs with tariff. Second, firms enjoy special tariff treatment in all its products and only export. This type is also called pure processing trade firms. Third, a hybrid firm which participate in both ordinary and processing trade.

As a part of its negotiated WTO entry, the average output tariff gradually reduced from 43.2% in 1992 to 15.3% in 2001 when China entered the WTO. (Brandt et al., 2017) The same is happening in the footwear industry as well. As one can see in Figure 2.2, the output tariff kept decreasing during the sample period. The reduction had a downward pressure on output prices in the do-

Figure 2.1: Trade Regime Illustration from Yu (2015)

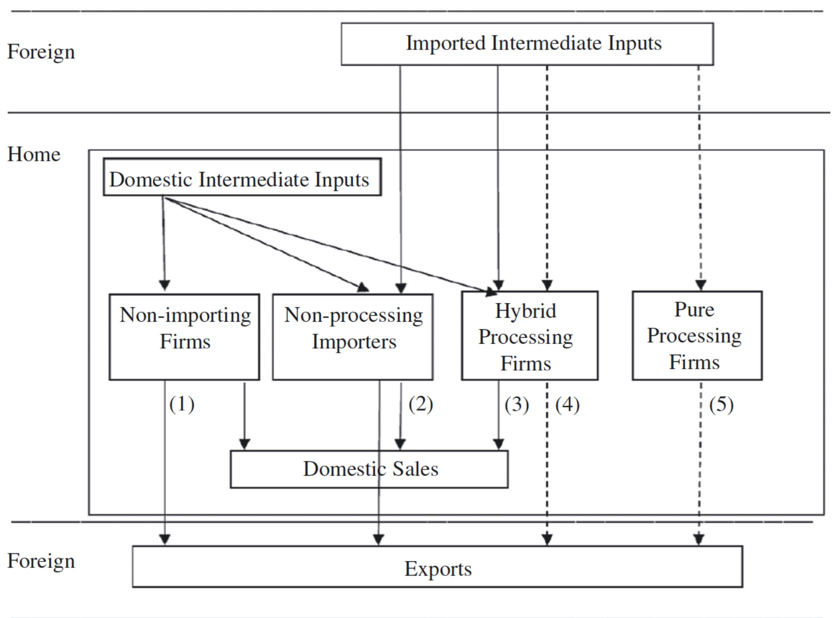
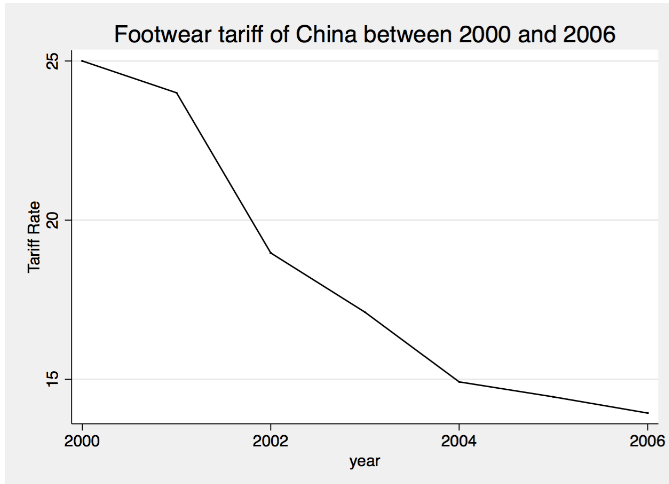


Fig. 3. *Four Types of Chinese Firms*
Note. Dotted lines denote firms' processing imports/exports; solid lines represent firms' non-processing imports/exports.

mestic market. Research on the impact of tariff reduction on firm performance show that firms benefit not only from pro-competitive environment but also a reduction on input tariff, which gives them access to better intermediate inputs. However, the effect of tariff reduction on imported input would be different from those suggested in existing literature because firms engaging in processing trade are not fully affected by the reduction in import tariff.

To investigate the effect of trade liberalization on firms productivity, I rely on the following three panel data set: the production data, the custom data and the tariff data.

Figure 2.2: Output Tariff of Footwear Industry of China



Note: The output tariff is calculated using the effectively applied tariff for the footwear industry. (HS-2 digit level with code 64)

2.2.2 Production data

The Annual Survey of Manufacturing is an extensive survey of Chinese Manufacturing firms collected every year by the Chinese National Bureau of Statistics. This survey contains all state-owned industrial firms and non-state-owned firms with sales above 5 million RMB (roughly 0.9 million dollars). Aggregates for employment, sales, capital and exports for these firms match almost perfectly the totals reported annually in China's Statistical Yearbook (Brandt et al., 2012).

The data contains standard information on firm-level production and is comparable to the Longitudinal Research Database (LRD) maintained by the U.S. Bureau of the Census or to the widely used census data for Colombia and Chile (Brandt et al., 2012). My sample covers firms active in the Chinese footwear industry during the period 2000-2006. [2] I adopt the method of constructing real capital, output and input deflator from Brandt et al. (2012) and mainly use the Stata code provided on their website.[3]

There are several well documented concerns using the AMS. First, the sample is subjected to the above-scale sample selection. Though the data contains all state-owned firms, the footwear industry is mainly private-owned. Therefore, the data cannot be used to study exit behavior. There might also be potential selection bias as small firms appearing in the sample will be particularly productive. Second, the Chinese AMS is not an establishment-level dataset and the basic unit is legal unit. Subsidiaries that are not legal units, so-called “industrial activity units (plants) are not included in the survey. However, for footwear industries, nearly 97% of the firms contain only one "industrial activity unit". Therefore, it is a quasi-plant level dataset.

Follow the literature by Brandt et al. (2017), I exclude firms with employees less than 8 people. As I am focusing on the footwear industry, I select firms with CIC code 18 (texile industry), 19 (Leather industry), 29 (Rubber industry) and 30 (Plastic industry). I exclude from my sample firms which are not footwear firms based on their main products provided in the dataset. I also exclude from my sample firms with negative or missing capital, sales and intermediate input information. In addition, I exclude firms with abnormal intermediate input to sales ratio. I delete samples whenever the ratio is smaller than 0.2 or larger than 2 and further delete 334 observations. Table 2.1 presents the summary statistics of the key variables I use for production function estimation.

[2] It is due to data availability issue. Details about reasons I choose the time period can be found in supplementary materials.

[3] https://feb.kuleuven.be/public/u0044468//CHINA/appendix/

Table 2.1: Summary Statistics of Production Data

Year	Revenue	Capital	Employment	Intermediate inputs	Rev p/w	Price index	No. of Firms
2000	9.955	8.025	5.627	9.752	4.312	0.984	1467
2001	9.842	8.195	5.509	9.651	4.310	0.977	1877
2002	9.870	8.227	5.465	9.683	4.389	0.985	2221
2003	9.992	8.277	5.529	9.761	4.445	0.983	1965
2004	9.893	7.967	5.430	9.605	4.463	1.000	3111
2005	10.019	8.121	5.423	9.696	4.622	1.027	3499
2006	10.217	8.273	5.484	9.897	4.775	1.044	3302

Notes: This table reports summary statistics for production data for years 2000 to 2006. Numbers are in log-term. Revenue, Capital and Intermediate inputs are originally measured in 1000 RMB

From Table 2.1, the average revenue is overall increasing during the sample period while the employment level declines. In addition, the average revenue per worker also increases, which can be regarded as a crude measure for productivity, also increased overtime. However, revenue also contains the information of price variation. In the last column, I list the output price index of China. Since it also increases during the sample period, it is hard to tell the dynamics of physical productivity.

2.2.3 Custom Data

I use the Chinese Monthly Customs Transactions from 2000-2006. This is a dataset at the HS 6-digit product level. The dataset contains the price and quantity information of each product for every firm-product-destination combination. The dataset also contains mainly three types of trade regimes for each transaction as I briefly discuss in Section 2.2.1. I collect data with HS-id beginning with 64, indicating the product is traded is in footwear industry. In addition, I exclude all trading company transactions as I cannot match them with ASM dataset.[4] In order to fully investigate the exporting behavior of firms, I

[4]Trading companies(intermediaries) are potentially useful as they provide information about the countries Chinese trading companies are in contact with. But due to the huge data volume,

match the custom data with the ASM production data to obtain information of exporting destination, trade regime and revenue in each destination.

The major problem of linking trade data with firm level data is that there is no common identifier of the two dataset. Therefore, I use firm name and geographic information to construct a mapping between the two datasets and later use identification ID to link different years together within each dataset.[5] However, such could only provide a lower bound of firms' exporting revenue. Prior to 2004, many private firms could only export through third parties (trade intermediaries). Even after 2004, private firms can act as "indirect" exporters and authorize intermediaries to sell for them abroad. Because of this, I cannot identify then in the Custom dataset even though they should be defined as exporters. Therefore, I consider two measures of exporting status. $Exp1 = 1$ is exporters I successfully matched in the Chinese Monthly Customs Transactions dataset. These firms can be regarded as developing export networks on their own. Alternatively, I use export delivery value in the Annual Survey of Manufacturing to construct a second measure of exporting status. $Exp2 = 1$ are firms with a positive export delivery value in addition to firms which I have already defined as exporters in *Exp1*. If a firm has a positive export delivery value but cannot be matched in the Customs Transactions dataset, it is defined as using trading companies to export.

Table 2.2 summarizes the number of firms in my sample and number of exporters based on different measures. In 2004, the Annual Survey of Manufacturing didn't collect export delivery value, so I am using the average export delivery value of that firm in neighboring years as a proxy for the value of that

I ignore them in this version of my paper.

[5] detailed information can be found in the appendix of Yu (2015).

year. As one can see in Table 2.2, nearly half of the exporting firms were using intermediaries to export in that time. Not including them in the exporting group will lead to an overestimation of firm's domestic sales. So for the rest of the paper analysis, I will define exporters as $Exp2 = 1$ and use *Exp1* to distinguish firms using intermediaries to trade.

Table 2.2: Number of Firms in the Sample and Export Rate

Year	No. of firms	No. of EXP1	Export Rate 1	No. of EXP2	Export Rate 2
2000	1467	533	36.33%	930	63.39%
2001	1877	605	32.23%	1139	60.68%
2002	2221	711	32.01%	1374	61.86%
2003	1965	668	33.99%	1215	61.83%
2004	3111	982	31.57%	1866	59.98%
2005	3499	1092	31.21%	2117	60.50%
2006	3302	1115	33.77%	2001	60.60%

Notes: This table reports the number of firms in the sample and export rate. The export rate is defined as the percentage number of firms exporting in a given period using different measures.

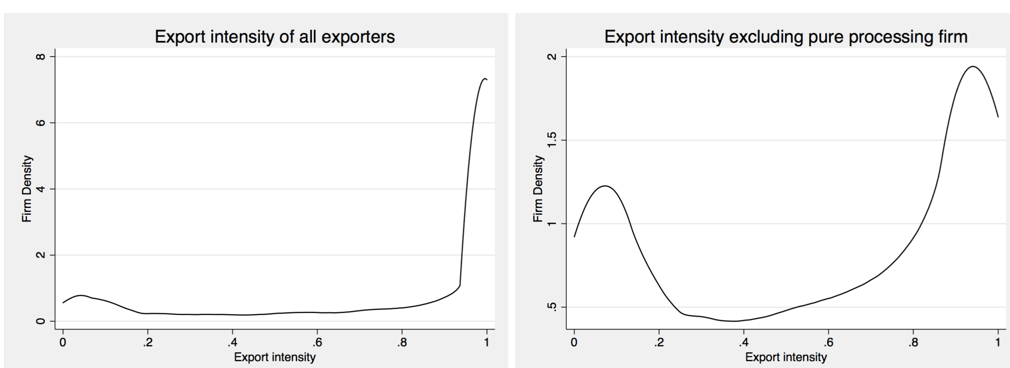
2.2.4 Trade Data

Trade and tariff data are available on WITS in TRAINS and UN COMTRADE database from 2000-2006 for all footwear at a HS 6-digit disaggregated level. I use the volume adjusted effectively applied tariff as my measurement of the tariff that exporters are facing. In addition, I consider a HS-2 level tariff as a measure of the competitive environment of the footwear industry in a country. The net import value of total footwear product can be found in UN COMTRADE dataset and is used to construct aggregate demand.

2.2.5 Exporting patterns of Chinese exporters in the footwear industry

Guided by Melitz (2003), exporters are firms initially perform well in the domestic market and due to the opening up, they self selection into exporting market. A direct prediction of the model is that a large proportion of exporters should have a small exporting intensity. Such theory is supported by empirical facts using US and OECD data shown in the Table 2.2 of Lu (2010). Lu (2010) documented an exporting pattern among Chinese exporters, the exporter intensity is U-shaped, with a large proportion of firms exporting more than 90% of their total production. As one can see in Figure 2.3 , the U-shaped exporting intensity pattern also applied to the footwear industry in my paper. This observation can partly be explained by the fact that pure processing trade companies are not allowed to sell in domestic market. After excluding the pure processing trade companies, the export intensity of exporters are still U-shaped.

Figure 2.3: Export Intensity in the Footwear Industry



Note: Export intensity is defined as the proportion of foreign sales of exporters. Left one is the export intensity of all exporters, the right one exclude pure processing trade firms.

According to Yu (2015), low-productivity firms self-select into processing trade possibly to enjoy the special tariff treatment. Therefore, it would potentially lead to a different relationship between productivity and export due to this selection. Before I analysis the performance of pure processing trade firms in detail, I first present in Table 2.3 the share of numbers and export values of pure processing trade firms in the footwear industry. As one can see, nearly half of the exporting firms are pure processing firms and the share in term of export values is more than half except for 2003. Even though the proportion of pure processing firms is getting smaller over time, the export value of incumbent pure processing firms is getting bigger.

Table 2.3: Share of Number of Firms and Export Value, by Processing Status

Year	# Exp firms	# Pure processing firms	# other Exp firms	# firm share	Exp share
2000	930	481	449	51.72%	56.65%
2001	1139	575	564	50.48%	57.92%
2002	1374	685	689	49.85%	56.40%
2003	1215	670	545	55.14%	35.63%
2004	1866	748	1118	40.09%	60.84%
2005	2117	890	1227	42.04%	61.39%
2006	2001	850	1151	42.48%	60.94%

Notes: This table reports the share of number of firms and export value, by processing status. The export share is calculated using the export value of pure processing trade firms in a year divided by the total value.

2.2.6 How exceptional are exporters?

In order to examine the true productivity exporters and non-exporters, I first perform a preliminary analysis to show whether there are systemic difference between the exporters and non-exporters in the footwear industry of China between 2000-2006. Compared with previous analysis done in the developed economies, the industry is more labor intensive and China was a transition economy. Therefore, the patterns may be different. Following Bernard and

Bradford Jensen (1999) and De Loecker (2007), I run the following OLS regression:

$$x_{it} = \alpha + \beta exp_{it} + \gamma l_{it} + \sum_s \delta_s D_s + \sum_p \delta_p D_p + \sum_t \delta_t D_t + \epsilon_{it}$$

x_{it} refers to the characteristics and performance of firm i at time t. I also include in the firm characteristics, the sales performance of domestic market due to the unique exporting patterns. exp_{it} is a dummy variable indicating whether a firm exports at time t. l_{it} is the log labor of a firm aims to control for the firm size. In addition, I control for category (S) and state(p) fixed effects.

According to Table 2.4, exporting firms are significantly larger and have higher wages. In addition, the result is robust among different subgroups or using different export status measures. Such finding is consistent with Bernard and Bradford Jensen (1999) for the USA, Bernard and Wagner (1997) and De Loecker (2007) and the magnitude is also comparable. When using a more conservative export status measure, exporters uses significant more capital especially for small firms. If I switch to $Exp2$, the difference is no longer significant. The interesting finding comes from domestic performance. Even if I use the conservative measure $Exp1$, exporters' sale in the domestic market are only 8.5% higher than non-exporters. While, their sales as total is 18.7% higher. When I deduct the sales of intermediaries from domestic sales, exporting firms were doing significantly worse in the domestic market.

The last column compares pure processing trade firms with other exporters. Since they don't sell in domestic market, their domestic performance is left as blank. Compared to other exporters, there is no significant difference in employees and wages. However, pure processing firms earn less revenue and use less

Table 2.4: Characteristics Differentials for Exporters and Non-exporters

	Exp1		Exp2		Pure processing trade
x_{it}	All Firms	Small Firms	All Firms	Small Firms	All Firms
Employee	0.911***	0.421***	0.741***	0.385***	-0.045
Domestic sales	0.081***	0.067	-1.559***	-1.481***	-
Total sales	0.180***	0.160***	-0.011	0.056*	-0.207***
Capital per worker	0.263***	0.329***	-0.079	-0.021	-0.353***
Average wage	0.174***	0.171***	0.100***	0.124***	0.004
Number of firms	17,442	13,132	17,442	13,132	10,642

Notes: This table reports the characteristics differentials for exporters and non-exporters. x_{it} are log values with appropriate price deflators. The table is presenting β estimates. Small firms are firms with less than 520 employees. *** means significant at 1%. ** means significant at 5%. * means significant at 10%.

capital, implying their performance is worse than other exporters. The result[6] confirms that there is a substantial difference between the exporters and non-exporters in terms of firm size and performance. In addition, the systematic performance difference between the exporters and non-exporters in the domestic market called into question of using a common domestic output price deflator to deflate total revenue. Therefore, the question of whether the exporters are truly exceptional in terms of physical productivity is still not clear.

2.3 A Model of Production and Demand

Since firm level quantity data are not observed, to single out the productivity response to trade policies, I introduce a demand system at each destination market into the production framework to purge out the price effect. I additionally model the exporting decisions for firms selling to different destination market.

Environment: I index firms by i and time periods by t. All firms are single product firms. They locate in the home market and produce products belong to one of the four segments (denoted by s): textile, leather, rubber and plas-

[6]Details of differentials in performances between exporters and non-exporters across time can be found in Section 2.A.4

tic. There are a set of destinations D_t. In each period, each firm makes export decision of how much to export to each of the destination including the home country. [7]

2.3.1 Firms Serving only One Market

I start out with a simple model where each firm just serves one destination market.

Demand side: Following the traditional trade literature, I consider a standard horizontal product differentiation demand system.

$$max\ U(\{Q^d_{jt}\}^{J^d}_{i=1}) = [\sum_{j=1}^{J^d} V^{d\,1/\eta}_{jt} Q^{d\ (\eta-1)/\eta)}_{jt}]^{(\eta)/\eta-1)}$$
$$\text{s.t. } \sum_j \tilde{P^d_{jt}} Q^d_{jt} = R^d_t$$

Q^d_{jt} the the quantity demanded of good j at time t in destination d. The elasticity of substitution among products is denoted by (η). V^d_{jt} is a product specific demand shifter. $\tilde{P^d_{jt}}$ is the price of product j at market d at time t and R^d_t is the total expenditure a representative consumer (the wholesaler) spends on importing foreign footwear products. Firms are assumed to participate in monopolistic competition in each destination market, which can be rationalized by a wholesaler or retailer at each destination market deciding among different products to import as suggested by Roberts et al. (2017).[8] Since each firm i is a single

[7]This assumption departs from previous exporting models where domestic market is typically assumed as a default choice when firms are self selected into export market (Aw et al., 2011; Roberts et al., 2017). Because in my model, there are also processing trade firms which don't sell in the home market.

[8]This assumption allows me to find the empirical measure of market and related aggregate demand and price index.

product firm, I will use Q_{it}^d to present the quantity demanded from a firm i at time t in destination d for the rest of the paper. The demand function is:

$$Q_{it}^d = \frac{R_t^d V_{it}^d}{\tilde{P_{it}^d}^{\eta} \sum_{J_t^d} (\tilde{P_{jt}^d})^{(1-\eta)} V_{jt}^d} = Q_t^d (\frac{\tilde{P_{it}^d}}{P_t^d})^{-\eta} V_{it}^d \tag{2.1}$$

Q_t^d is the destination specific aggregate level demand shifter which is equal to R_t^d / P_t^d. The destination specific price index which is:

$$P_t^d = \sum_{J_t^d} (\tilde{P_{jt}^d})^{(1-\eta)} V_{jt}^d)^{(1/(1-\eta))}$$

I further derive the log-level demand equation for q_{it}^d:

$$q_{it}^d = q_t^d - \eta(\tilde{p_{it}^d} - p_t^d) + \xi_{it}^d$$

$\xi_{it}^d = ln(V_{it}^d)$ and represents the unobserved demand shocks. All lower case variables are logarithm of upper case variables defined before. To convert the price ($\tilde{p_{it}^d}$) firm charges in the destination market to the price (p_{it}^d) firm actually receive in its revenue, I use an ad valorem trade cost as in Roberts et al. (2017) between the home country and each destination, where τ_t^d takes into account shipping cost, possible tariff and exchange rate effects. Therefore, the demand equation which reveal the relationship between price and quantity firm i at time t becomes:

$$q_{it}^d = q_t^d - \eta(p_{it}^d - \tau_t^{d,s}) + \eta p_t^d + \xi_{it}^d$$

Firm side: Standard Cobb-Douglas production function where a firm i produces a unit of output Q_{it} at time t using labor (L_{it}),intermediate input (M_{it}) and capital (K_{it}). In addition, firm level production also depends on unobserved productivity shock ω_{it} and iid idiosyncratic shock u_{it}:

$$Q_{it} = L_{it}^{\alpha_l} M_{it}^{\alpha_m} K_{it}^{\alpha_k} exp(\omega_{it} + u_{it}) \tag{2.2}$$

Since physical quantity Q_{it} is typically not observed in most datasets, researchers rely on the measured revenue R_{it} and a detailed producer price index P_t to eliminate price effect.

$$ln(R_{it}) - p_t = q_{it} = \alpha_l l_{it} + \alpha_m m_{it} + \alpha_k k_{it} + \omega_{it} + u_{it}$$

With the help of a demand structure defined above, one can replace the price index by a firm specific demand equation Equation 2.1. Therefore, the revenue of a firm in each destination can be written as:

$$ln(R_{it}^d) = r_{it}^d = \frac{\eta - 1}{\eta} q_{it}^d + \frac{1}{\eta}(q_t^d + \xi_{it}^d) + p_t^d + \tau_t^{d,s}$$

Here I deflate the log revenue by the price index of destination d at time $\tilde{r}_{it}^d = r_{it}^d - p_t^d$

$$\tilde{r}_{it}^d = \frac{\eta - 1}{\eta} q_{it}^d + \frac{1}{\eta}(q_t^d + \xi_{it}^d) + \tau_t^{d,s} \tag{2.3}$$

Comparing Equation 2.3 with the commonly used revenue based productivity measure, there are two effects. First, the production function parameters are corrected. In addition, the revenue based productivity measure would pick up variations in the demand. The worry is particularly salient on my setup because trade liberalization would also impact prices. Therefore, the productivity estimates using a deflated revenue approach would also contain firm level price and demand variations.

2.3.2 Firms Serving Multiple Markets

Since most footwear companies in the data typically sell to multiple destination market, I need to additional aggregate the data from destination market level to a firm level. Instead of proposing a fixed portion C_{it}^d to export to destination markets, I model this intensive margin decision of each firm.

Firm side:

$$max \sum_{D_{it}} Q_{it}^{d} P_{it}^{d}$$

$$s.t. \sum_{D_{it}} Q_{it}^{d} = Q_{it}$$

Given a quantity level Q_{it} a firm produces, a firm i chooses Q_{it}^{d} optimally to maximize the total revenue responding to the demand at different destination. Here I additionally assume that the destination set D_{it} is predetermined. [9]Implied by the constant elasticity η across the destination market and the same marginal cost c_{it} across the market. P_{it}^{d} is the same across different destination market. Destination market price $\tilde{P}_{it}^{d}$ are different due to the differences in transportation cost $\tau_t^{d,s}$. Therefore. in equilibrium:

$$q_{it}^{d} - q_{it}^{k} = \underbrace{(q_t^d - q_t^k) + (\xi_{it}^{d} - \xi_{it}^{k}) + \eta(p_t^d - p_t^k) + \eta(\tau_t^{d,s} - \tau_t^{k,s})}_{c_{it}^{d,k}}$$

Here $c_{it}^{d,k}$ is the difference between destination d and k by setting q_{it}^{k} as the baseline group and $c_{it}^{k,k} = 0$. Since $\sum_{D_{it}} Q_{it}^{d} = Q_{it}$, the equilibrium q_{it}^{k} is:

$$q_{it}^{k} = q_{it} - ln(\sum_{D_{it}} exp(c_{it}^{d,k})) + c_{it}^{k,k}$$

The equilibrium p_{it}^{k} is:

$$p_{it}^{k} = p_{it} = -\frac{1}{\eta}(q_{it}^{k} - q_t^k - \xi_{it}^{k}) + p_t^k + \tau_t^{k,s}$$

Here I deflate the log revenue by the price index of destination d at time $\tilde{r}_{it}^{k} = r_{it}^{k} - p_t^k$ and rewrite the relationship among revenue at each destination, which I can observed in data, quantity and demand shifters which are typically not available to researchers. Because information used for production function and

[9]Given Q_{it}, the production cost $c_{it} * Q_{it}$ is fixed. I assume that products sold to different destination markets from the same country has the same marginal cost c_{it}. I don't additionally model how Q_{it} is determined.

productivity estimation are only available at firm level. I have to aggregate information in each destination market into my production function framework by summing up the deflated log revenue across all destination a firm sells to in period t:

$$\sum_{D_{it}} \tilde{r}_{it}^d = \underbrace{\frac{\eta-1}{\eta}\sum_{D_{it}} c_{it}^{d,k} - ln(\sum_{D_{it}} exp(c_{it}^{d,k}))\sum_{D_{it}}\frac{\eta-1}{\eta}}_{C_{it}} + q_{it}\sum_{D_{it}}\frac{\eta-1}{\eta} + \sum_{D_{it}}\frac{1}{\eta}(q_t^d + \xi_{it}^d) + \sum_{D_{it}}\tau_t^d$$

Plug in Equation 2.2 the regression equation of interest is:

$$\tilde{r}_{it} = C_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \sum_{D_{it}} \frac{1}{\eta} q_t^d + \omega_{it}^* + \xi_{it}^* + u_{it}^* \tag{2.4}$$

Here $\tilde{r}_{it} = \sum_{D_{it}} \tilde{r}_{it}^d$. n_{it} is the number of markets firm i sells to in time t. $\beta_h = \alpha_h n_{it} \frac{\eta-1}{\eta}$ where $h = \{l, m, k\}$, $\omega_{it}^* = \omega_{it} n_{it} \frac{\eta-1}{\eta}$ and $\xi_{it}^* = \frac{1}{\eta}\sum_{D_{it}} \xi_{it}^d + \sum_{D_{it}} \tau_t^d$, $u_{it}^* = u_{it} n_{it} \frac{\eta-1}{\eta}$.The coefficients of labor, material and capital are reduced form parameters which also include demand elasticity in each destination. Therefore, the parameters and productivity would typically be scaled up even if we assume no demand heterogeneity. In fact, as firms are exporting to different destination, the revenue could also be affected by the destination demand elasticity η and the aggregate demand shifter q_t^d.

2.4 Estimation and identification

In this section I will discuss the estimation procedure of Equation 2.4. The ultimate goal is to recover the unobserved productivity ω_{it} from the unobserved demand shock ξ_{it}. The firm level unobserved demand should be affected by variation in inputs, the aggregate level demand in each destination market and also trade protection in different market. Since firms in my data export to different countries, the protection rates varies across firms and acts as a firm-specific residual demand shock. Owning to this, I can decompose the unobserved demand shock into four parts following De Loecker (2011).

$$\xi_{it} = \xi_{dest} + \xi_s + \xi_t + \tau q r_{it} + \tilde{\xi}_{it} \tag{2.5}$$

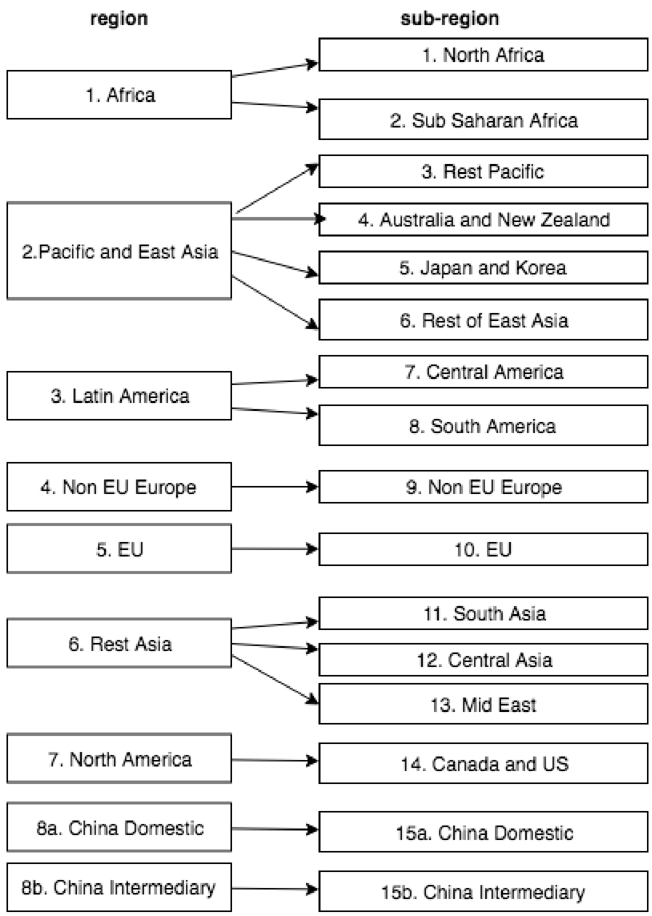
The first three parts take into account the destination, segment and time fixed affect which I use to control for unobserved demand shocks. A potential worry is the systematic difference in technology across destinations. This worry will be eliminated as I will focus on the productivity change across time for an given firm therefore the time invariant productivity difference across destination will be canceled out. In addition, the estimates can be regarded as a conservative measure containing both productivity change and firm's reaction to destinations while I am still able to purge out the price effect.

Apart from the domestic market, other market is defined as the import footwear market in each region.[10] Figure 2.4 is a illustrative graph about the three layer of destinations that I define. A region is regarded as a market and the subregion level is where I have different fixed-effect to control for subregional demand differences. Because I can also observe firm's exporting countries, I additionally control for country level fixed effect. The demand elasticity is assumed to be homogeneous across regions and time invariant, which is a strong assumption. Therefore, I hope to capture the rest difference with the set of time fixed effects. As I mentioned in section 2, nearly half of the exporters are using trading intermediaries to export. I construct a intermediary market to separate its revenue from domestic sales. First, firms using trading companies are different from non-exporters. Second, they face different demand shocks.

Under the assumption of constant η across region, $c_{it}^{d,k} = r_{it}^{d} - r_{it}^{k}$. Therefore,

[10] For a more detailed discussion about market definition, please refer to Section 2.A.1.

Figure 2.4: Illustrative Graph about Relation among Region, Subregion and Country



I can use the revenue information to construct C_{it}. De Loecker (2011) uses $1/n_{it}$ as a proxy for the unobserved c_{it}^d where n_{it} is the total number of regions a firm sells to, arguing that the tariff protection measure will pick up changes in c_{it}^d due to demand change. However, the sales to each region is in fact not homogeneous and should respond to the demand shock in the region. Table 2.5 presents the number of destinations including domestic market a firm sell to and the popularity of the destination. Here the destination is defined on a region level.

Table 2.5: Proportion of Firms by Regions

Destination	2000	2001	2002	2003	2004	2005	2006
Region1-Africa	0.100	0.093	0.093	0.115	0.129	0.135	0.157
Region2-East Asia and Pacific	0.296	0.250	0.251	0.265	0.241	0.228	0.270
Region3-Latin America	0.124	0.118	0.124	0.125	0.112	0.109	0.127
Region4-Non EU Europe	0.136	0.120	0.123	0.142	0.121	0.125	0.152
Region5-EU	0.177	0.170	0.167	0.185	0.186	0.191	0.219
Region6-Rest of Asia	0.121	0.108	0.110	0.138	0.135	0.130	0.144
Region7-North America	0.252	0.228	0.216	0.234	0.198	0.192	0.214
Region8a-China Domestic	0.672	0.694	0.692	0.659	0.760	0.649	0.651
Region8b-China Intermediary	0.593	0.570	0.581	0.580	0.542	0.566	0.566

Notes: This table reports the proportion of firms by regions. Proportions are computed using firm numbers.

Except for domestic market and intermediary market, the North America, East Asia and Pacific and EU are top choices for exporters. Distant region like Africa, Latin America account for a smaller proportion. The pattern is similar to Roberts et al. (2017) but different in magnitude as they look at exporters engaged in ordinary trade. One thing to notice is that the proportion is sensitive to region definition. Since I rely on the regional aggregate demand to identify demand elasticities, combining the East Asian and Pacific market together can give me meaningful estimates. That is the reason I am combining these two regions together.

2.4.1 Constructing firm specific tariff protection

The fourth part in Equation 2.5 is a composite variable measuring the trade environment a firm is exposed to. The trade protection is measured by tariff level and consists of two parts:

$$qr_t^d = \sum_f a_{ft}^d tarrif_{ft}^d$$

$$qr_{it} = \sum_d \frac{W_{it}^d}{W_{it}} qr_t^d$$

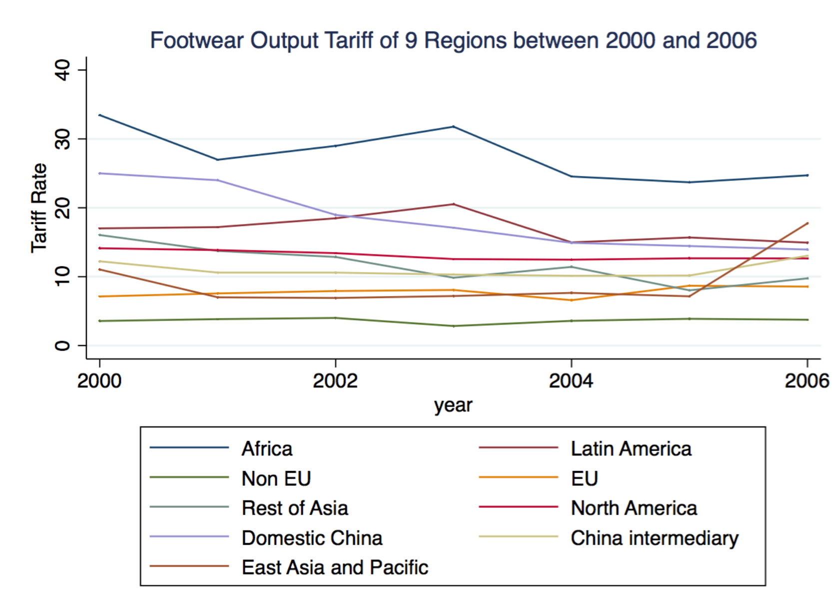
$tarrif^d_{ft}$ is a market's d tariff to a partner country f at time t in the footwear industry. a^d_{ft} is the weight of country f in market d's total footwear import at time t. Therefore I consider qr^d_t as a measure of market level openness to trade. A higher qr^d_t means higher tariff barrier and thus a less opened market. I will use the volume adjusted effectively applied tariff which is available in TRAINS at the region level for the total footwear to measure qr^d_t. The protection level faced by exporters using intermediaries is a weighted sum of all markets except the domestic market and I use Chinese export share to a specific market in the footwear industry as a weight. The second term measures a firm's specific exposure to export environment where $\frac{W^d_t}{W_{it}}$ takes into account a weighted sum of export.(For the weights I consider both a simple average and a revenue weights.) Finally I use revenue in each region as the weight because it yields a most reasonable estimates and in addition control for firm's intensive margin decision in allocating final goods when facing different demand shocks.

As we can see from the Figure 2.5 and Figure 2.6, firms face highest protection level in African market and lowest protection in Non-EU European market. On average firms face less protection until 2005 and the protection level slightly increases because of the sharp increase in tariff in East Asia and Pacific market.

2.4.2 Aggregate demand and price index in each destination market

From my definition of market, the empirical measure of price index is the import price index (IPI) at each destination market I collect from CEIC dataset. I use a weighted average of representative countries in each region and make sure the

Figure 2.5: Tariff Protection in Nine Regions across Time



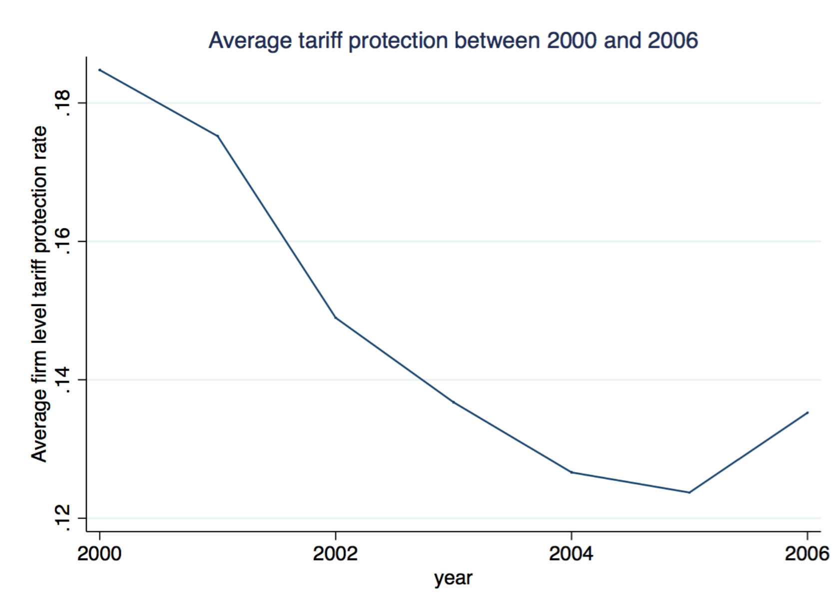
Note: Nine regions are defined in Figure 2.4. The output tariff is also measure at a HS-2 digit level with code 64.

price index follows similar trends. For the Chinese domestic market, I use the output deflator calculated in Brandt et al. (2012).[11] Similar to the trade protection level of intermediary market, the price index of the intermediary market is a weighted average of price index in all foreign regions where the weight is Chinese footwear export share in that region. As one can see from the Figure 2.7, price levels across market are hard to compare because the price index is relative to a base year of the same region. Therefore, it provides across time difference within a region. I would use the regional fixed effect to control for the price difference across regions.

The empirical measure of aggregate demand shifter is the total import of footwear category at each region in each period. The aggregate demand for do-

[11] Details of how I construct a price index at each region can be found in 2.A.1

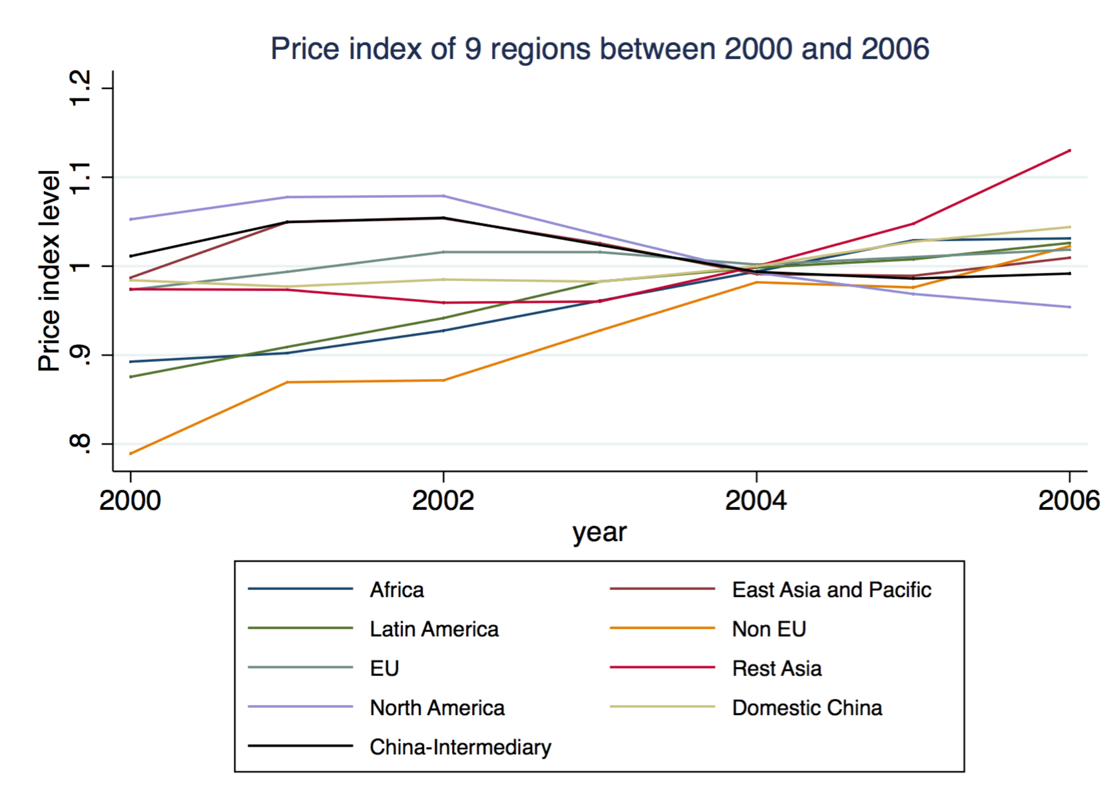
Figure 2.6: Firm Exposure to Tariff Protection qr_{it} across Time



Note: The firm level tariff protection is a weighted average of regional tariff protection where the weight is sales in each region at a particular year.

mestic market is constructed using the total production plus net import in the footwear industry. I use the measure from WITS UN COMTRADE dataset and the group is predefined as in Figure 2.4. Essentially I am relying on this aggregate demand shifter to identify the demand elasticity parameters. If there is no substantial difference among them, then it is hard to identify those parameters. The aggregate demand for Chinese intermediary market is defined as a weighted average of all its trading partners' aggregate demand with the same weights as before. In Figure 2.8 I present the aggregate demand shifters across time. As we can see, China's domestic market has the highest demand, followed by the North America market. Africa market has the lowest aggregate demand. There are substantial differences in aggregate demand and thus would benefit identification of region level price elasticities estimates. In addition, the aggre-

Figure 2.7: Price Index p_t^d across Time



Note: Price index is an average of Import Price Index in the footwear industry of representative countries in each region. The base year in each country is 2004 and therefore the figure reflects price level compared with price level in 2004.

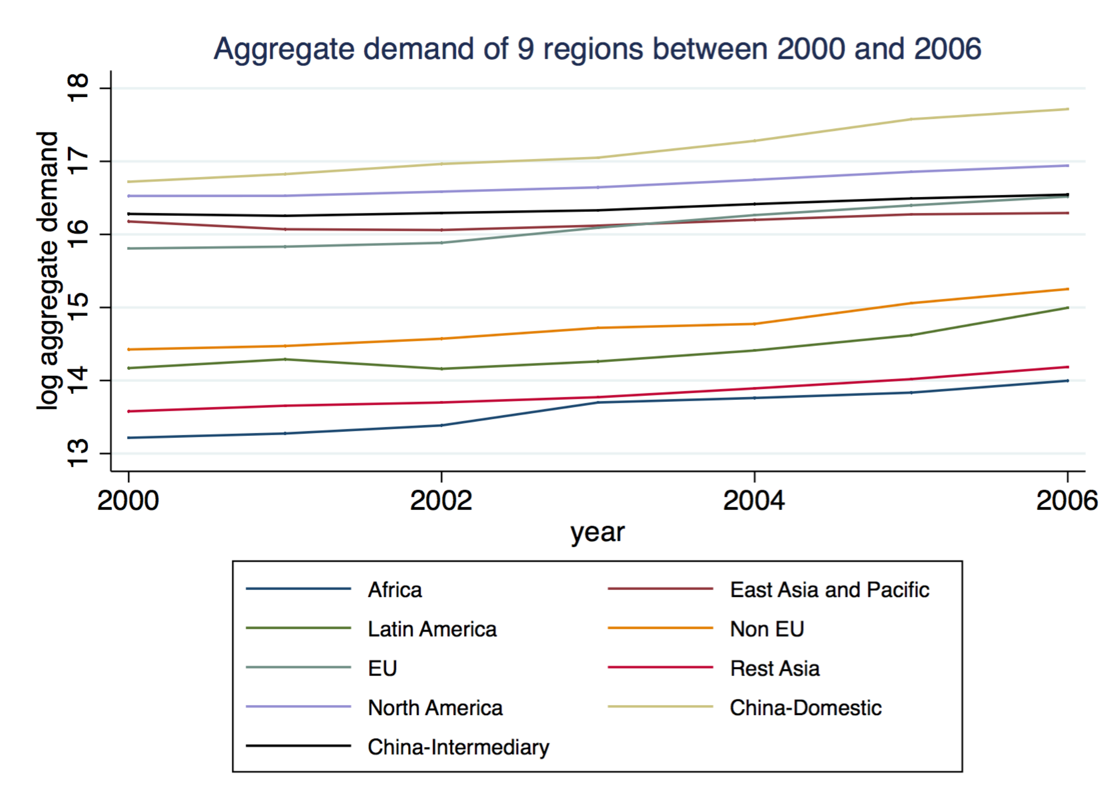
gate demand can be regarded as exogenous as each firm's share is negligible in each region.

Therefore, the main estimation equation of interest is:

$$\tilde{r_{it}} = \beta_{nd}c_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_q \sum_{D_{it}} q_t^d + \omega_{it}^* + \delta_d + \delta_g + \delta_t + \tau q r_{it} + \epsilon_{it} \tag{2.6}$$

$\beta_q = 1/\eta$ represents the set of subregions and countries. δ_g represent the set of segments.(Leather, textile, rubber and plastic) and δ_t represents the set of time, which are all dummy variables. q_t^d is set to zero when a firm is not observed

Figure 2.8: Aggregate Demand Shifter q_t^d across Time



Note: The aggregate demand shifter is the deflated total import value of footwear industry in each region in each year. The unit is 1000 usd.

selling to region d at time t. ϵ_{it} captures all the production and demand side idiosyncratic shocks.

The protection variation (qr_{it}) will affect a firm in two ways. First it will affect the residual demand in the same period. Second it will affect a firm's future productivity through firms' reaction to increased competition by eliminating inefficiencies. Similar to De Loecker and Goldberg (2014), I also add a dummy variable to indicate a firm's exporting experience, allowing the model to detect learning from exporting. Therefore, the law of motion of productivity becomes as follows:

$$\omega_{it} = g_t(\omega_{it-1}, qr_{it-1}, dexp2_{it-1}) + \nu_{it} \tag{2.7}$$

In practice, I fit a second order polynomial similar to the existing literature.

Given the assumption that a region's tariff change cannot be influenced by an individual firm. I rely on the following moment conditions to identify τ, which measures firm's instantaneous response to tariff change:

$$E(\nu_{it}|qr_{it}) = 0 \tag{2.8}$$

In addition, the following moment condition holds by construction.

$$E(\nu_{it}|qr_{it-1}) = 0 \tag{2.9}$$

2.4.3 Using a static input

To overcome the problem of zero investment in the dataset, I follow the method of Levinsohn and Petrin (2003) by using a static input demand condition to control for unobserved productivity. Following the concern of Ackerberg et al. (2015) as there is not enough variation to affect labor and material input separately, I don't identify any coefficient in the first stage. Empirically, I use a third order polynomial to get an estimates of $\hat{\phi}_t$ which separates the observed demand shock and unobserved productivity from the unobserved idiosyncratic demand and production shock.[12] In the second stage, I use the law of motion defined in Equation 2.7 and the moment condition in Equation 2.8 to identify parameter of interest.

[12]For more detailed assumption, the input demand equation and the monotonicity condition, one can refer to Section 2.A.3

I follow De Loecker (2011) to include subregion and country fixed effect in the nonparametric regression of ω_{it+1} on ω_{it}, qr_{it} and $dexp2_{it}$ due to a practical reason. Because I would be solving a non-linear GMM, the estimates would suffer from a curse of dimensionality and would yield very inaccurate estimates. Therefore, in the empirical analysis, I will mainly focus on the changes in productivity for an individual firm due to export and tariff reduction.

$$\omega_{it+1} = \hat{\phi_{t+1}} - \beta_{nd}c_{it+1} - \beta_l l_{it+1} - \beta_m m_{it+1} - \beta_k k_{it+1} - \beta_q \sum q^d_{t+1} - \tau qr_{it+1} - \delta_g - \delta_t \tag{2.10}$$

$$\nu_{it+1} = \omega_{it+1} - g_{t+1}(\omega_{it}, qr_{it}, dexp2_{it}) \tag{2.11}$$

Finally, the GMM conditions I am using to identify the parameters are:

$$E = \left\{ \nu_{it+1}(\beta_k, \beta_l, \beta_m, \beta^d, \tau, \delta) \begin{pmatrix} k_{it+1} \\ m_{it} \\ l_{it} \\ q^d_t \\ qr_{it+1} \\ D \end{pmatrix} \right\} = 0 \tag{2.12}$$

I will follow this two-step approach and use the bootstrap to get right inference. The parameter τ is identified as the tariff is assumed to be exogenous. The parameters β_q are identified under the assumption that the shocks to productivity is not correlated with lagged total output in each destination market.

2.5 Main Results

In this section I first present my TFP estimates which controls for price effect and compare it with the revenue deflated estimates. Second, I will show effect of tariff reduction on productivity dynamics through my estimates.

2.5.1 TFP measures and TFP dynamics

As stressed by Bernard et al. (2003), if the markup is positively correlated with physical productivity, then the revenue-based productivity would work well. From my estimates, the markups are measured by the inverse of elasticities in each region (η^d). The markups are not clearly ranked among the regions, therefore it is hard to tell the relationship between markup and true efficiency. For the main result part, I would use the following equation to estimate the productivity residual and plug in the estimates of production function and demand coefficient.[13]

$$\hat{\omega_{it}} = (\hat{\phi_t} - \hat{\beta_l} l_{it} - \hat{\beta_m} m_{it} - \hat{\beta_k} k_{it} - \sum_d \hat{\beta^d} q_t^d - \hat{\tau} qr_{it} - \hat{\delta_g} D_{ig} - \hat{\delta_t} D_{it}) / (\sum_{d_i} \frac{\hat{\eta^d} - 1}{\hat{\eta^d}})$$

While the usual deflated revenue-based productivity is calculated using the Stata package prodest with the following equation

$$\hat{\omega_{it}^{st}} = \hat{\phi_t^{st}} - \hat{\beta_l^{st}} l_{it} - \hat{\beta_m^{st}} m_{it} - \hat{\beta_k^{st}} k_{it}$$

To get the estimated productivity, I plug in the estimates I get from Table 2.11 and Table 2.12. I set the parameter to zero if its 90% confidence interval contains zero. Therefore, in the estimates, the coefficient on capital, price elasticity in East Asia and Pacific region, the tariff protection, time fixed effect and the fixed effect of Textile and rubber segments are set to zero.

As one can see, due to a dimensionality problem I discussed in Section 2.4, my productivity estimates which controls for price effect contains country and

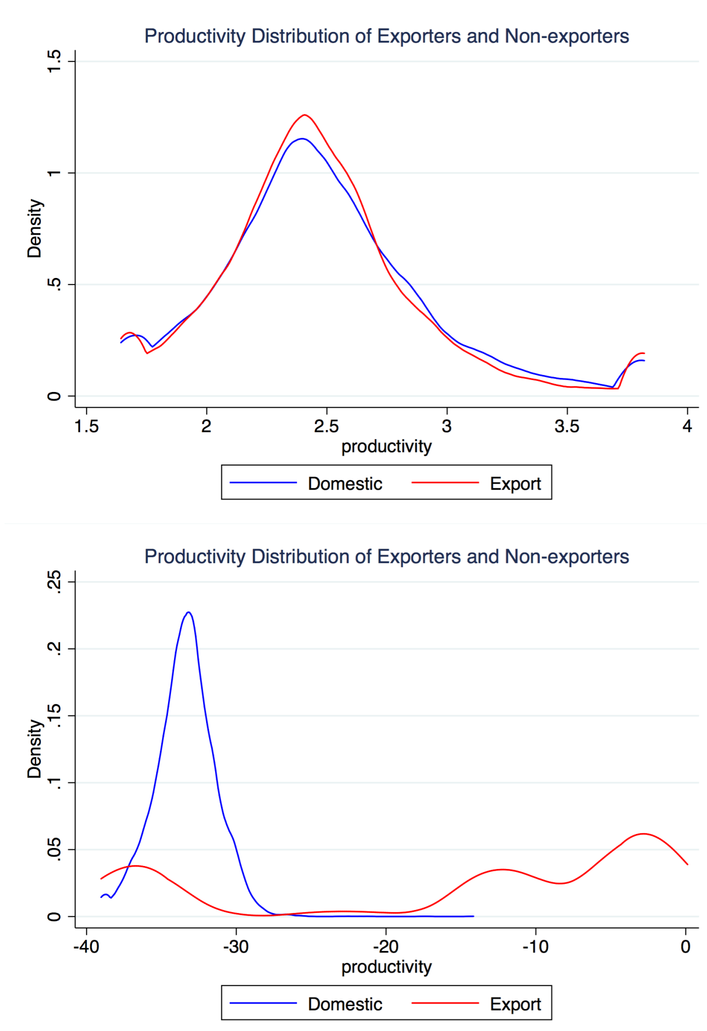
[13]Details of estimates of production function and elasticities can be found in Section 2.A.4

subregion fixed effect. Therefore, there is no direct comparison between my productivity estimates and the revenue-based productivity estimates. However, looking at the productivity distribution within each measure across different groups can still be informative.

Figure 2.9 shows the productivity distribution using two measures. Since the productivity is very spread, I present a winsorized productivity distribution to better present the difference across groups. On the top is the revenue-based TPF measure using a common price deflator in my paper is the output price deflator of domestic footwear market. At the bottom is the TFP distribution I in addition control for price effects. I plot three types of groups, exports are those I can find directly in the custom dataset, indicating they establish relationship with foreign buyers to trade. The red line represents firms which use trading companies to trade. Therefore, they don't have to pay additional effort and cost to establish a relationship with foreign buyers or go through registration procedures to export. The black line represents firms which only serves the domestic market.

As one can see, if I use a common deflator, it is impossible to tell the productivity difference between exporters and non-exporters. However, if I in addition control for price effect, productivity of exporters are more dispersed. There are two direct implications from the productivity estimates when additionally control for price effect. First, compared with non-exporters, the productivity of exporters are in general higher. The empirical finding is partly in line with theoretical model predictions (Melitz, 2003) as exporters who need to pay extra fixed cost to enter a foreign market should have the higher productivity. Second, there is an overlap in productivity between the exporters and non-exporters in

Figure 2.9: TFP Distribution for Exporters and Non-exporters Using Two Measures

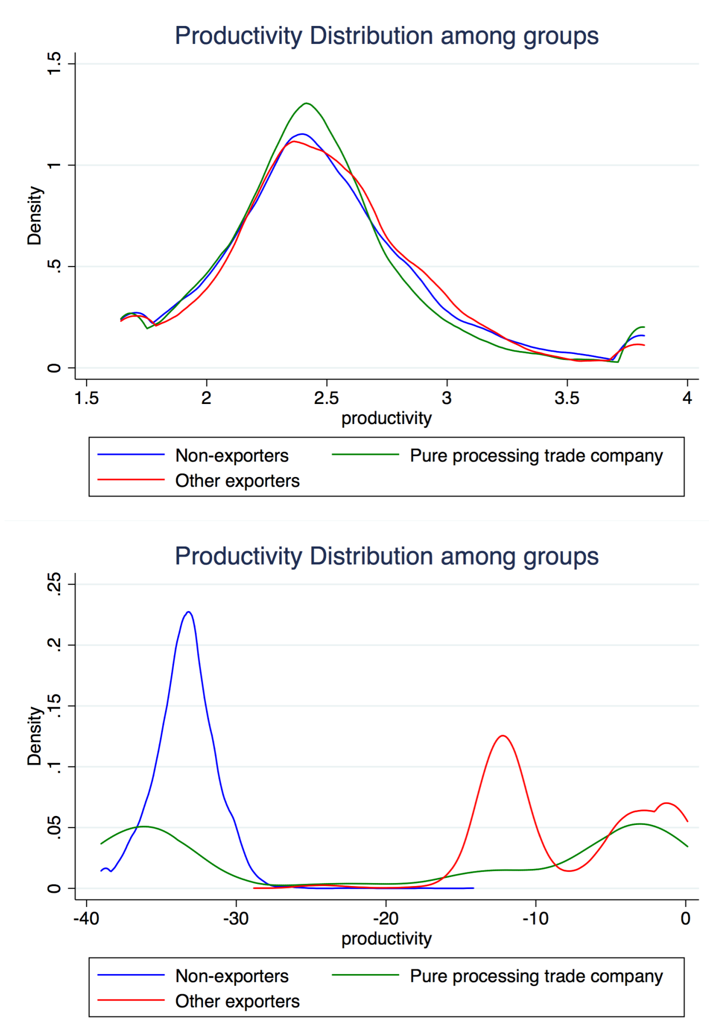


Note: On the top is the revenue-based TPF measure using a common price deflator (output price deflator of domestic footwear market). At the bottom is the TFP distribution I in addition control for price effects. The distribution is winsored to modify the top 2.5% and bottom 2.5% extreme value the footwear industry. As I briefly mentioned in Section 2.2, the exporting behavior of Chinese footwear manufacturers would in addition be affected by the special tariff treatment. According to Yu (2015), he built up a model of firms self select into processing trade and verify empirically in China low productivity firms self-select into processing trade. Thus the overlap could be potentially be explained by the existence of processing trade firms.

Therefore, I also compare the productivity of those pure processing firms with other firms based on whether they have sales in domestic market, given that a pure processing trade company cannot sell in domestic market. In Figure 2.10 I further split the exporters to pure processing trade firms and other exporters. The graph using my new measure shows that the productivity of pure processing firms are very dispersed. Compared with other exporters, the average productivity of the processing trade firms is lower which is consistent with finding by Yu (2015). Except for the fact the pure processing trade firms don't serve the domestic market while 85% of other firms serve the domestic market, the destination of both types are similar.

To test whether the estimates controlling for price effect is robust, I also plot the production distribution between exporters and non-exporters across years. The distribution pattern is very similar to Figure 2.9. In addition, I also split the exporters by whether it uses intermediary to export. Firms using trading companies don't need to physically enter a foreign market and thus avoid some of the fixed cost, therefore they are different from firms directly export. Among exporters using intermediary, other exporters and non-exporters group, exporters using intermediary have a substantially lower productivity than other exporters while they are still in general more productive than non-exporters. The distri-

Figure 2.10: TFP Distributions among Groups Using Two Measures



Note: On the top is the revenue-based TPF measure using a common price deflator. At the bottom is the TFP distribution I in addition control for price effects. The distribution is winsored to modify the top 2.5% and bottom 2.5% extreme value bution pattern is very similar across years.[14].

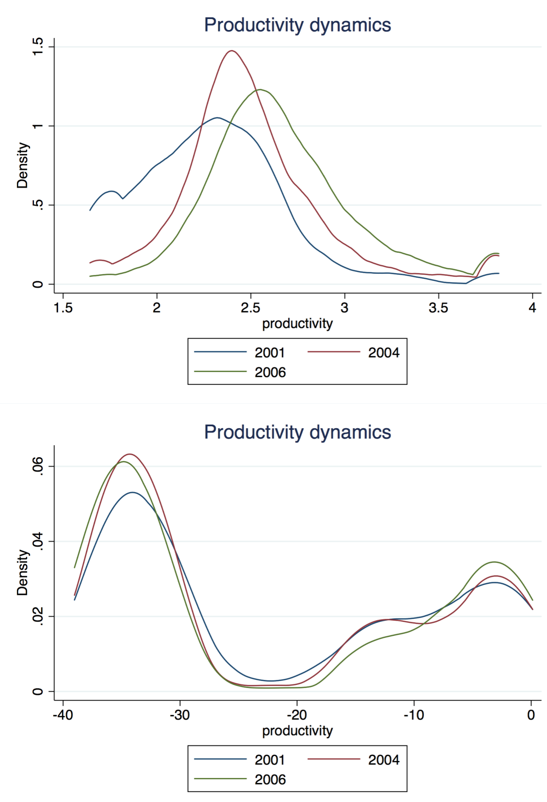
Next, I will illustrate the industry level and firm level TFP dynamics. Both Figure 2.5 and Figure 2.6 indicate firms faces a less protected environment in the global market until 2006. Even in 2006, except for East Asia and Pacific region, most regions still saw a decrease in output tariff. How is the environment affecting the aggregate level physical productivity of the footwear industry as a whole? I pick three preventative years on Figure 2.11. There is a noticeable shift of the industry TFP distribution to the right if using a revenue-based TFP. However, one may fear the increase would potentially due to the demand effect since in Figure 2.8, the aggregate demand shifter for all regions rises. When I control for such demand effect, the industry level TFP are very close. Since it is very hard to tell the difference across time, I in addition follow Olley and Pakes (1996) to calculate a weighted industry level productivity by using the following equation, where I use the firm's employment share to calculate s_{it}:

$$\omega_t = \sum s_{it}\omega_{it}$$

As can be seen in Table 2.6, the growth rate of aggregate TFP using the two measures seems to fluctuate and most of the time works in opposite directions. With the footwear industry opening up gradually, the selection effect would allocate resources to more profitable firms and thus increase the aggregate productivity. It seems the empirics are at odds with the theory. I further conduct a static decomposition following Olley and Pakes (1996) to check whether such tariff reduction would allocate resources to more productive firms by checking the covariance between employment share and productivity. It moves in the same direction with the weighted productivity. Therefore, it suggests that tar-

[14]Details can be found in 2.A.4

Figure 2.11: Productivity Dynamics across Time Using Different Measures



Note: On the left is the revenue-based TPF measure using a common price deflator. On the right is the TFP distribution I in addition control for price effects. The distribution is winsored to modify the top 2.5% and bottom 2.5% extreme value

iff reduction is not pushing resources to allocate to more productive firms from my estimates. This pattern is also very consistent among the three groups: non-exporters, pure processing trade firms and firms who export by themselves.

2.5.2 The effect of trade liberalization on firms' productivity

Brandt et al. (2017) document that during China's accession to WTO, the productivity of incumbents are more responsive to output tariff cut while new en-

Table 2.6: Aggregate TFP Dynamics

Year	weighted TFP2	Growth	unweighted TFP2	weighted TFP1	Growth	unweighted TFP1
2000	-13.193		-19.955	4.161		5.885
2001	-14.659	-0.111	-21.649	3.206	-0.229	2.954
2002	-14.109	0.037	-21.511	2.538	-0.208	2.355
2003	-13.533	0.041	-21.799	2.525	-0.005	2.445
2004	-14.798	-0.093	-22.282	2.960	0.172	2.751
2005	-15.309	-0.035	-23.025	3.042	0.028	3.084
2006	-14.971	0.022	-22.318	2.773	-0.088	2.803

Notes: This table reports the aggregated TFP dynamics across years. TFP2 is the physical TFP and TFP1 is a revenue based TFP measure. Weighted averages across years use shares as weights.

trants are more responsive to input tariff cut. Yu (2015) studying the same period with a focus on processing trade, further documents that the effect of input tariff cut on productivity is weaker for processing trade companies. The consensus is that tariff protection would promote firm level productivity. While China is experiences a decrease in output tariff, for exporters in the footwear industry in China, the reduction of tariff is prevalent across the world and this less protected environment further promote export. Therefore, firms would not only benefit from the input tariff reduction or a pro-competitive environment in home country, but also learning from exporting when opening up to trade. Therefore, I plan to explore the role of different mechanism in a non-parametric estimation.

A standard method to study this problem is a two-stage approach in which productivity is first estimated and then the impact of trade liberalization on productivity is estimated by running the following equation:

$$\hat{\omega}^{st} = c + \lambda q r_{it} + \epsilon_{it} \tag{2.13}$$

Therefore, in order to get a consistent estimator of λ, protection should be exogenous to the error term. If I use a revenue-deflated productivity estimates, the estimates itself contains price effect. Therefore, the strong assumption is protection is only affecting price through productivity, which is at odd with the pro-competitive mechanism. In addition, as pointed out by De Loecker (2011), such equation just allow for instantaneous respond of tariff reduction to productivity but ignore the productivity evolution of a firm, which would underestimate the impact.

Therefore, I am going to estimate the impact of tariff reduction on the productivity change by estimating a polynomial specification of firm's productivity evolution function.

$$\Delta\omega_{it} = \alpha_0 + \alpha_1\omega_{it-1} + \alpha_2\omega_{it-1}^2 + \alpha_3 qr_{it-1} + \alpha_4 dexp2_{it-1} + \alpha_5\omega_{it-1} * qr_{it-1} + \nu_{it}$$

As one can see, the τ I estimated in Table 2.7 column (2)-(4) by adding a demand system is supposed to capture the price change to protection variation and α_3 in the equation above is supposed to capture the productivity response to tariff reduction. I use the difference instead of a level effect because my productivity estimates contains destination fixed effect. If the destination stay fixed during the sample period, it would be canceled out. α_4 is designed to capture the learning by exporting effect.

Table 2.7: Impact of Tariff Reduction

TFP measure	TFP1	TFP2	TFP2	TFP2
α_1	-1.011	0.318	0.066	0.475
	(0.006)	(0.036)	(0.010)	(0.072)
α_2	0.000	0.008	0.001	0.010
	(0.000)	(0.001)	(0.000)	(0.001)
α_3	-3.752	-36.844	-7.992	-28.788
	(2.275)	(4.862)	(2.167)	(6.135)
α_4	-0.120	1.704	0.384	3.287
	(0.316)	(0.270)	(0.050)	(0.841)

Notes: This table reports the impact of tariff reduction. TFP2 is the physical TFP and TFP1 is a revenue based TFP measure. *** means significant at 1%. ** means significant at 5%. * means significant at 10%. All standard errors are clustered at firm level

Column 1 of Table 2.7 uses the revenue-based TFP measure. α_1 is the persistence parameter. α_3 which indicates a firm's productivity react to tariff reduction is negative but not significant and there is no learning from exporting. The second column is where I correct for the price effect. If last period's TFP increases, then the difference between the two period would increase. In addition, this method also presents significant productivity increase due to tariff reduction. If the tariff increase by 1%, then the tariff difference will be decreasing by 0.368. Compared with De Loecker (2011), it seems to be a very large number. However, the difference is a level difference instead of a percentage difference as my productivity estimates are negative and I cannot take log. Therefore, the sign rather than the magnitude is more meaningful. In addition, my estimates show there is significant learning by exporting. If a firm export in the previous period, his productivity difference will increase by 1.704.

My productivity estimates contains destination fixed effect. Once a firm switch to a new region, the productivity estimates should also include the change in fixed effects between the two destinations. Even though I control for some of the destination fixed effect through aggregate demand and protection exposure, firms may still match on unobserved demand heterogeneity. Therefore, in column 3 I run a subsample of firms which didn't switch during my sample period and therefore the fixed effects are canceled out across time. As one can see, the magnitude of the impact of tariff reduction is smaller, but it is still negative and significant. In addition, the subsample is still able to detect significant learning from exporting. In column 4, I present the effect on pure processing trade companies. Compared with the full sample, the impact of tariff reduction is smaller which is consistent with findings of Yu (2015) and there is also learning by exporting.

The tariff reduction is in fact exhibits time patterns which could be reflected from the protection exposure. Therefore, I additionally run the protection impact across time to see whether it would match the protection exposure trend. As one can see in Table **??**, α_3 changes with time and is initially smaller than year 2004, 2005 and 2006 when the tariff sharply decreases. Even though the protection seems to pick up in 2006, I assume the tariff reduction would impact productivity with a lag and thus will not affect the productivity evolution. Such pattern cannot be detect using a revenue-deflated productivity estimates.

Table 2.8: Impact of Tariff Reduction across Year

Year	2001	2002	2003	2004	2005	2006
α_1	0.338**	0.200	0.179	-0.182	0.801***	0.106
	(0.171)	(0.134)	(0.188)	(0.183)	(0.186)	(0.220)
α_2	0.0103***	0.0102***	0.0121***	0.00128	0.00175	0.00973***
	(0.00249)	(0.00230)	(0.00248)	(0.00193)	(0.00153)	(0.00188)
α_3	-31.24***	-11.22	-21.36	-42.67***	-54.26***	-46.47***
	(11.71)	(9.109)	(15.26)	(14.77)	(16.70)	(17.70)
α_4	2.397	-1.293	-5.460*	0.0488	7.660***	-2.028
	(3.047)	(2.823)	(3.277)	(3.153)	(1.972)	(2.464)
No. of observation	1,332	1,703	1,502	1,583	2,917	3,241

Notes: This table reports the impact of tariff reduction across years. *** means significant at 1%. ** means significant at 5%. * means significant at 10%. All standard errors are clustered at firm level

2.6 Conclusion

In this paper, I test the method proposed by De Loecker (2011) to overcome the problem of not observing physical quantity in estimating physical productivity for the China footwear industry during the period of 2000-2006. By adding a demand system at each of the nine regions I previously defined, I am able to derive a relation between quantity and price and thus purge out the price effect from revenue-based productivity estimator. With my new estimates, I am able to identify that exporters on average have higher productivity than non-exporters in the footwear industry. In addition, during the period of opening up and worldwide tariff reduction in the footwear industry, there is significant productivity increase from tariff reduction within firm and exporters witness increase in their productivity once entering the export market.

Due to the existence of processing trade, some Chinese exporters don't serve domestic market in my sample at all. This observation is different from most export models as they typically assume the domestic market as the default option when firms self-select into exporting market. The different selection mechanism would yield different implications on productivity. Therefore, I also evaluate the performance of pure processing trade firms. Compared with other exporters, they are less affected by tariff reduction. In addition, there also exist significant productivity increase when these firms enter the export market. Compared with revenue-based TFP measures, my estimates purge out price effect which is essential in the context of export and I show that these two TFP measures yield very different results both in the productivity distribution and evolution.

2.A Appendix—Chapter 2

2.A.1 Data and Code

Production Data: The Annual Survey of Manufacturing is an extensive survey of Chinese Manufacturing firms collected every year by the Chinese National Bureau of Statistics. This survey contains all state-owned industrial firms and non-state-owned firms with sales above 5 million RMB (roughly 0.9 million dollars). Aggregates for employment, sales, capital and exports for these firms match almost perfectly the totals reported annually in China's Statistical Yearbook (Brandt et al., 2017).

The data contains standard information on firm-level production and is comparable to the Longitudinal Research Database (LRD) maintained by the U.S. Bureau of the Census or to the widely used census data for Colombia and Chile (Brandt et al., 2012). For this paper, I use data from 2000-2006 for three reasons.

1. The data file for 2009 misses important variables, such as revenue, wages, material input, and fixed assets. The data files for 2010 and 2011 that we obtained had incorrect information for employment.
2. The data file from 2008 doesn't contain intermediate input.
3. The data file for the Chinese Monthly Customs Transaction only starts at 2000.

Because my ultimate goal is to carry out a productivity estimation exercise, it is impossible to estimate without intermediate inputs. In addition, I need the demand side variation to separate unobserved demand shocks from physical productivity. Therefore, I need to compile the Annual Survey of Manufacturing data with the Chinese Monthly Customs Transaction which contains detailed information of destination.

The estimation of the production function requires information on plant-level revenues, value added(thinking about it), input use: labor as measured by full time equivalent production workers, raw materials and a measure of the capital stock. I follow (Brandt et al., 2012) to construct the latter and mainly use the stata code provided on their website.[15] Fixed assets are reported in three ways in AMS:

1. Original fixed asset(fa^o): sum of past investments at historical price.
2. Net fixed asset: Original fixed asset-fixed depreciation
3. Total fixed asset(fa): Net fixed asset+construction materials and ongoing construction

Therefore, the basic idea is to construct a category by province annual growth rate of capital accumulation and use the price index of each year to back out the real capital stock from the birth year to the first year each firm appeared in my database. And later on, use the nominal capital accumulation in my database and price index of the year to calculate the real capital stock. The basic step is as follows:

1. Construct an average growth rate(g_s) of nominal capital stock between 1993 and 1998 at category level for each province. (Use information from 1993 annual enterprise survey)

[15] https://feb.kuleuven.be/public/u0044468//CHINA/appendix/

2. Denote the birth year of a firm as b. For firms open before 1978, assume their initial capital stock is the same as 1978.(Before 1978, China underwent a huge revolution and the damage to manufacturing industry was detrimental.)

3. initial nominal capital stock:$nk_b = fa_a/(1+g_s)^{a-b}$

4. Initial real capital stock:$rk_b = nk_b * 100/p_b$, p_b is an investment price index at firm's birth year.

5. Nominal capital law of motion before year a:$nk_{t+1} = nk_t * (1+g_s)$

6. Real capital law of motion:$rk_{t+1} = rk_t * (1-\delta) + nk_t * g_s * 100/p_{t+1}$

7. Get rk_a by the law of motion above.

8. For years after year a: $rk_{t+1} = rk_t * (1-\delta) + (fa^o_{t+1} - fa^o_t) * 100/p_{t+1}$

I adopted the investment price index from (Brandt et al., 2012) as we are studying the similar period and using the same dataset. In addition, I follow their calibration of $\delta = 0.09$.(Later would examine through sensitivity analysis) In the Stata Code of Brandt et al(2014), there are a few points to mention:

1. They use firms enter before 1993 to calculate g_s in order for the dataset to be more comparable.

2. When using the AMS, they assume there is no capital accumulation(nominal investment) if the dataset reports a decrease in fa^o in two consecutive years.

3. Since it is an unbalanced data set, if a firm appears only in 2000 and 2006,then the capital growth rate in the time gap is calculated using a local interpolation.

There are several concerns using the AMS.

1. The problem with above-scale sample selection: Though the data contains all state-owned firms. The footwear industry is mainly private-owned. Therefore, the data cannot be used to study exit behavior and there might be potential selection bias. As for small firms, they will be particularly productive in order to be contained in the sample.
2. the Chinese AMS is not an establishment-level dataset and the basic unit is legal unit. Subsidiaries that are not legal units, so-called "industrial activity units (plants) are not included in the survey. However, for footwear industries, nearly 97% of the firms contain only one "industrial activity unit". Therefore, it is a quasi-plant level dataset.

Custom Data: I use the Chinese Monthly Customs Transactions from 2000-2006 at the 6-digit product level. The dataset allows me to construct a unit value price of exports for every firm-product-destination combination. The dataset also contains mainly three types of trade regimes. Processing trade firms can import duty-free raw materials, components and capital equipment but cannot sell to domestic market.

According Figure 2.1

1. Ordinary trade: include export which doesn't use any imported materials
2. Processing with imported materials: a Chinese corporation purchases raw materials and components (either from the ultimate foreign purchaser or a third party). Therefore it has to make foreign currency payments. The ownership of those imported commodities remains that of the Chinese

enterprise. The Chinese enterprise exports the finished products to any foreign customer after processing and assembling.

3. Processing with supplied materials (Assembly):raw materials and components are supplied by a foreign company and processed by a Chinese enterprise on a consignment basis. Ownership of raw materials and components remains that of the foreign customer. The Chinese company does not have to make foreign exchange payments, and is paid through charging a processing fee. Finished products are owned and distributed by the foreign customer.

In that context it does not matter if the materials and components were imported or supplied. The amount of imported materials and components used in the manufacture of the finished products is free from tariffs and import-related taxes. However, if the finished products are intended to be sold on the Chinese market, Chinese customs will levy duties and interest on deferred payments subject to valid approval documents for sale on the Chinese market issued by the relevant authorities.

The major problem of linking trade data with firm level data is the fact that:

- There is no identifier to link the two dataset.
    1. Use firm name and geographic information to construct a mapping between the two datasets.
    2. Use identification ID to link different years together within each dataset.
- Inconsistency in industry classification.(Having think of a good way to categorize the sports shoes.)

- Firms report large exports cannot be found in custom dataset:

    1. Prior to 2004, many private firms could only export through third parties (trade intermediaries). Even after 2004, private firms can act as "indirect" exporters and authorize intermediaries to sell for them abroad.

    2. Parent companies with many subsidiaries will choose some of the subsidiaries to register with the Chinese Customs.

Trade protection Data: A large proportion of the sales in the footwear industry is exported to the world. In addition, the footwear industry is highly tariffed by countries like Italy and Brazil. Therefore, there is potentially a lot of variation in the demand side.
I will first use the tariff data as a measurement of trade protection in each country. I export all tariff data available on WITS TRAINs database from 2000-2006 for all footwear HS-6 level products. The following are four types of tariff data collected by Trains and I am using the volume adjusted effectively applied tariff as my measurement of the tariff that exporters are facing.

1. Most-Favored Nation Tariffs:MFN tariffs are what countries promise to impose on imports from other members of the WTO, unless the country is part of a preferential trade agreement.

2. Preferential Tariffs: Preferential trade agreement, under which they promise to give another country's products lower tariffs than their MFN rate.

3. Bound Tariffs: specific commitments made by individual WTO member governments. The bound tariff is the maximum MFN tariff level for a

given commodity line. When countries join the WTO or when WTO members negotiate tariff levels with each other during trade rounds, they make agreements about bound tariff rates, rather than actually applied rates.

4. effectively applied tariff: WITS uses the concept of effectively applied tariff which is defined as the lowest available tariff.

Next, I will consider adding in non-tariff measures in the TRAINS database if the variation is not enough.

Price Deflators: To make nominal variables comparable over time, I need a price deflator to express values in constant year prices. Here I choose year 2004 as the reference year. I use the output deflator benchmark calculated in Brandt et al. (2012). This benchmark deflator uses the additional information reported in the survey from 2000-2003. In surveys from 2000-2003, the firms were asked to report the output both in nominal and real price and such could be used as a firm level price index. Later, they calculate a weighted average of such price-index using the current price output as weights to get the segment average price.For 2004-2006, they use the 2-digit ex-factory price index from China Statistical Yearbook to extend the more detailed deflator.

This I also follow Brandt et al. (2012) to construct using the output deflators and input shares calculated from the 2002 National Input–Output (IO) table. Most of the sectors defined in the IO table are less detailed than the industry definition used in the firm-level data and they constructed a concordance table linking the IO sectors to the four-digit industries. We first calculate an aggregate output price index for each IO sector as an un-weighted average of underlying industry prices. They then obtain the input deflator for each IO sector by calculating a input-share weighted average of these output deflators.

Market definition and aggregate demand shifter: Here I will follow the definition of market and aggregate demand shifter from Roberts et al. (2017). Therefore, the general environment can be think of as at each region, the wholesaler is purchasing footwear products from all over the world. The aggregate demand shifter is defined using the total import of footwear category at that destination in each period. Here I use the measure from WITS UN COMTRADE dataset and the group is predefined as above. Essentially I am relying on this aggregate demand shifter to identify the demand elasticity parameters. If there is no substantial difference among them, then it is hard to identify the parameters. I will compare my estimates using these two method. I will follow De Loecker (2011) to compute the aggregate demand shifter in domestic market as industry weighted deflated revenue. And $q_t^{domestic} = \sum_i ms_{it} R_{it}^d / P_t^d$

Since I am applying the same PPI or Wholesale Price Index in each destination market, it is important to check whether the various measures moves in similar patterns. However, one thing to notice is the across market PPI comparison. I hope the destination fixed effect is going to absorb this difference.

The estimation code is as follows:

1. Run first stage to get ϕ_{it} by either doing a polynomial or a local kernel estimation on (x_1=k_{it}, l_{it}, m_{it}) and (x_2=$n_{it}, qr_{it}, \sum_d q_{st}^d, D$) and thus we can have an estimation of ϕ_{it}
2. Start with an initial guess of β_1 and β_2, corresponding to x_1 and x_2 and back out productivity ω_{it} and ω_{it-1}.
3. Use another polynomial to non-parametric estimation by regressing ω_{it} and ω_{it-1} and qr_{it-1} to back out the innovation term ν_{it}.

4. This is the residual that enters the moment equation and we can use it to construct sample analogues.
5. I want to separately estimate the elasticity of demand because if I jointly estimate both, the problem will suffer from curse of dimensionality.

First, I didn't correct for the unobserved demand side variations and use a control function approach followed by Ackerberg et al. (2015). There is a Stata code called prodest and the standard error is bootstrapped. Second, I follow De Loecker (2011) and the original LP code is adjusted by including the additional demand variables capturing quota protection (qr_{it}). Third, due to the problem of dimensionality, I didn't estimate the destination fixed effect. I use Julia to run the GMM estimation and generate 500 boostrap samples to do inference of my estimates.

2.A.2 Discussion about Gross Output Production Function and Value-added Production Function

Definitions: The data consists of firms $i = 1, ..., I$ over period $t = 1, ..., T$. Firm i's output, capital, labor and intermediate inputs are given by $(Q_{it}, K_{it}, L_{it}, M_{it})$ and they log values will be denoted in lowercase by $(q_{it}, k_{it}, l_{it}, m_{it})$. We assume that firms operate in a monopolistic competition in each destination market but are price takers in the intermediate input market. We let P_{it}^{d} denote the output price of firm i in destination d at time t and p_{mt} be the price if intermediate inputs faced by the firm.

Let $\mathcal{I}_{it}$ denote the "information set" of the firm in period t, it consists of all information the firm can use to solve its period t decision problem. If the choice of a generic input is a function of $\mathcal{I}_{it-1}$, then we say it is a predetermined input in period t, as it was effectively chosen at (or before) t 1. If an input's optimal period t choices are affected by lagged values of that same input, then we say the input is **dynamic**. If an input is predetermined, dynamic, or both, we say it is **non-flexible**. If an input is chosen in this period and its choice does not depend on lagged values, so it is neither predetermined nor dynamic, then we say it is **flexible**.

Assumption 1. The relationship between output and the inputs takes the form

$$Q_{it} = F(K_{it}, L_{it}, M_{it})e^{\omega_{it}+\epsilon_{it}}$$

The production function F is differentiable at all (k, l, m) R^3_{++} and strictly concave in m. ω_{it} is the part of productivity that is known to the firm before making its period t decisions, whereas ϵ_{it} is an ex-post productivity shock realized only after the period decisions are made.

Assumption 2. $\omega_{it} \in \mathcal{I}_{it}$ is known to the firm at the time of making its period t decisions, whereas ϵ_{it} is not. I assume $P_\epsilon(\epsilon_{it}|\mathcal{I}_{it}) = P_\epsilon(\epsilon_{it})$. Furthermore ω_{it} is Markovian so that its distribution can be written as $P_\omega(\omega_{it}|I_{it1}) = P_\omega(\omega_{it}|\omega_{it-1}, qr_{it-1})$. The function $g(\omega_{it-1}, qr_{it-1}) = \mathbb{E}[\omega_{it}|\omega_{it-1}, qr_{it-1}]$ is continuous.

If we express $\omega_{it} = g(\omega_{it-1}, qr_{it-1}) + \nu_{it}$, by construction ν_{it} satisfies $\mathbb{E}[\nu_{it}|\mathcal{I}_{it-1}] = 0$. ν_{it} can be interpreted as the unanticipated at period t-1, "innovation" to the firm's persistent productivity ω_{it} in period t. We normalize $\mathbb{E}[\epsilon_{it}|\mathcal{I}_{it}] = 0$, without loss of generality. Given this normalization, it follows that $\mathbb{E}[\epsilon_{it}|k_{it}, l_{it}, m_{it}] = 0$. This assumption by itself corrects for potential selection bias when firms choose export destination. Because this is a non-parametric specification and such nest decision making models where the destination choice depend on firm's previous productivity and export status.

Assumption 3. Intermediate inputs m_{it} and l_{it} are flexible inputs, i.e., it is chosen at time t independently of the amount of m and l the firm employed in the previous period. We treat capital k_{it} predetermined, i.e., as chosen in the previous period (hence $k_{it} \in \mathcal{I}_{it}$).

The following assumption formalizes the environment in which firms operate.

Assumption 4. Firms are price takers in the labor and intermediate input market, with p_{mt} and p_{lt} denoting the common intermediate input price and labor input price. And they are engaged in monopolistic competition in which prices are P^d_{it}.

Firm's problem:

$$max_{M_{it},L_{it}} P(Q_t)\mathbb{E}[F(k_{it},l_{it},m_{it})e^{\omega_{it}+\epsilon_{it}}|\mathcal{I}_{it}] - p_{mt}M_{it} - p_{lt}L_{it}$$

Q_t is the aggregate output in the segment and the FOC for M_{it} becomes:

$$\begin{aligned}(\frac{\partial P_{it}}{\partial Q_t}\frac{\partial Q_t}{\partial Q_{it}} + \frac{\partial P_{it}}{\partial Q_{it}})\frac{\partial}{\partial M_{it}}F(k_{it},l_{it},m_{it}))e^{\omega_{it}}F(k_{it},l_{it},m_{it}))e^{\omega_{it}}+ \\ P_{it}(Q_t)\frac{\partial}{\partial M_{it}}F(k_{it},l_{it},m_{it}))e^{\omega_{it}} = p_{mt}\end{aligned}$$

Because here we assume monopolistic competition, $\frac{\partial Q_t}{\partial Q_{it}} = 0$ and from assumption 2, $\mathbb{E}[\epsilon_{it}|\mathcal{I}_{it}] = 0$. The equation above can be simplifies as follows:

$$(\eta_{it}+1)\frac{\partial}{\partial M_{it}}F(k_{it},l_{it},m_{it})e^{\omega_{it}} = p_{mt}$$

Where η_{it} is the elasticity faced by firm i. Therefore it implies the input demand function is

$$m_{it} = \mathbb{M}_t(k_{it}, l_{it}, \omega_{it}, X_{demand})$$

Here I use X_{demand} to denote the observable demand shifters which will affect η_{it}.

Using a static input, the material demand function can be defined as follows.

$$m_{it} = m_t(k_{it}, l_{it}, \omega_{it}, qr_{it}, \sum_d q_t^d, D, n_{it}) \tag{2.14}$$

Here I assume firms are engaged in monopolistic competition in each region. Firms are price takers in the input market. Therefore, input demand is affected by the firms productivity, capital stock, labor usage and the demand(aggregate demand shifter in each region and the country and region specific fixed effect, the segment and time effect). Since the markup is constant and is correlated with productivity, there is a monotone relationship between productivity and material input conditional on other factors.Therefore I can rely on a function to proxy for productivity:

$$\omega_{it} = h_t(k_{it}, m_{it}, l_{it}, qr_{it}, \sum_d q_t^d, D, n_{it}) \tag{2.15}$$

I follow the concern of Ackerberg et al. (2015) as there is not enough variation to affect labor and material input separately. Therefore, I don't identify any coefficient in the first stage. The first stage is designed to separate the observed demand shock and unobserved productivity from the unobserved idiosyncratic demand and production shock.

$$\tilde{r_{it}} = \phi_t(k_{it}, l_{it}, m_{it}, qr_{it}, \sum_d q_t^d, D, n_{it}) + \epsilon_{it} \tag{2.16}$$

Comparison with Value added production function, the value added is defined as follows:

$$P_{it}Q_{it} - p_{mt}M_{it}$$

and is a common alternative empirical approach which requires less parameters to estimate and is immune to the identification problem of gross output production which I will discuss in the following subsection.

However, one thing to notice is the fact that value added production function holds capital and labor fixed while the gross output production function controls for capital, labor and intermediate inputs. Therefore, the value added production function will possibly ignore any potential substitutions between intermediate inputs and capital and labor and yield very different results of productivity estimation. For a more complete discussion, one can refer to Gandhi et al. (2020) for both theoretical and empirical evidence.

2.A.3 Invertibility conditions

To proof the invertiblity condition of LP method in an imperfect competition setup, it is key to prove that higher productivity firms are not able to charge higher markups. If we have CES demand and monopolistic competition, the mark up is constant across all the firms regardless of its productivity, thus the monotonicity assumption is satisfied. However, one has to worry about whether more productive firms can choose to export to countries with higher mark up and thus breaks the monotonicity condition.

$$f_{L\omega}f_{mL} > f_{LL}f_{m\omega}$$

This second equation is sufficient to guarantee the invertibility.

$$f_{L\omega}f_{mL} - f_{LL}f_{m\omega} > \frac{1}{\eta}((f_{LL}f_m f_\omega + f_L^2 f_{m\omega}) - (f_{L\omega}f_L f_m + f_L f_\omega f_{mL}))$$

2.A.4 Additional Empirical Results and Findings

Differentials for exporters and non-exporters by year: The following two tables present the difference between exporters and non-exporters in different years by using an OLS regression and $Exp2$ as a measure of export status for each year. Across all years, exporting firms hire more workers, pay more wages and their performance are sometimes better in total sales.

$$x_{it} = \alpha + \beta exp_{it} + \gamma l_{it} + \sum_s \delta_s D_s + \sum_p \delta_p D_p + \epsilon_{it} \tag{2.17}$$

Table 2.9: Differentials for Exporters and Non-exporters by Year (All Firms)

Year	Employee	Domestic sales	Total sales	Capital p/w	Average wage	No. of firms
2000	0.880***	-1.465***	0.150**	-0.050	0.184***	1467
2001	0.812***	-1.510***	0.084	0.074	0.146***	1877
2002	0.745***	-1.476***	-0.011	-0.062	0.137***	2221
2003	0.862***	-1.631***	-0.058	-0.136**	0.148***	1965
2004	0.690***	-2.105***	-0.052	-0.113	0.056***	3111
2005	0.733***	-1.367***	-0.032	-0.115	0.051*	3499
2006	0.673***	-1.326***	-0.07	-0.113	0.057**	3302

Notes: This table reports the differentials for exporters and non-exporters by years. *** means significant at 1%. ** means significant at 5%. * means significant at 10%. All standard errors are clustered at firm level

Table 2.10: Differentials for Exporters and Non-exporters by Year (Small Firms)

Year	Employee	Domestic sales	Total sales	Capital p/w	Average wage	No. of firms
2000	0.464***	-1.430***	0.243***	0.023	0.225***	1035
2001	0.467***	-1.447***	0.167**	0.138*	0.194***	1388
2002	0.406***	-1.444***	0.024	0.002	0.142***	1677
2003	0.421***	-1.476***	0.021	-0.086	0.202***	1430
2004	0.335***	-2.001***	-0.001	-0.091	0.077***	2428
2005	0.384***	-1.306***	0.046**	-0.043	0.065**	2692
2006	0.354***	-1.238***	0.012	-0.056	0.075***	2482

Notes: This table reports the differentials for exporters and non-exporters by years. *** means significant at 1%. ** means significant at 5%. * means significant at 10%. All standard errors are clustered at firm level

Production function coefficients and demand parameters: The importance of controlling for simultaneity and selection bias in estimating productivity has been extensively discussed in Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2015) and others. Productivity and input usage are often correlated, simply running an OLS regression would potentially lead to overestimates of coefficients of labor and intermediary inputs as long as the cost advantage would be partly passed through to output prices. While firms will higher capital level are less likely to exit, the selection bias suggests the coefficient of capital would be underestimated (Olley and Pakes, 1996).

$$\hat{r_{it}} = \beta^k_{ols} k_{it} + \beta^l_{ols} l_{it} + \beta^m_{ols} m_{it} + \epsilon_{it}$$

As one can see in Table 2.11, the OLS estimates use a deflated revenue by a price deflator in Chinese domestic market. Without controlling for simultaneity bias, I simply estimate the above equation. The proxy is estimated using the prodest package in Stata which taken into account the concerns of Ackerberg et al. (2015) and jointly estimate the labor coefficient with capital and material in the second stage. I use a third order polynomial in the first stage and a bootstrapped sample of 500. For the proxy method, I still use a common price deflator common across firms. The result after controlling for the simultaneity bias is consistent with theory. Both the coefficient for labor and material are getting smaller due to the positive relationship between input demand and productivity. The coefficient on capital gets smaller too. Since I am using a above-scale sample, firms who disappear from my sample may not necessarily exit the market. This could potentially breaking down the negative relation between capital and productivity.

The third column is which I add the demand system to control for unob-

Table 2.11: Production Function Estimates

	OLS	Proxy	With Demand	Single Market
Capital	0.026	0.020	0.030	0.027
	(0.003)	(0.000)	(0.270)	
Labor	0.120	0.114	0.795	0.148
	(0.009)	(0.000)	(0.200)	
Material	0.845	0.839	1.020	0.833
	(0.012)	(0.000)	(0.390)	
No. of obs	17,442	17,442	17,442	9,630

Notes: This table reports the production function estimates. For both proxy and with demand, the standard errors are bootstrapped. The bootstrapped sample is 500. *** means significant at 1%. ** means significant at 5%. * means significant at 10%. All standard errors are clustered at firm level

served prices. Keeping the results comparable with column 2, I use a third order polynomial in the first stage and also bootstrap for 500 times. As one can see, the labor and material coefficient significantly increases. Since both prices and input demand would respond to a demand shock, the effect of omitted price effect on production function estimates becomes vague. As expected, the change in capital coefficient is not large as capital is assume predetermined.

When a firm exports to different markets, I use the inverse of total region as a proxy for the actually quantity proportion sold in each region. Fearing such proxy may introduce bias, I run the estimation with demand on a subsample where each firm serves one region. As one can expect, the subsample are only firms either sell in domestic market or in the intermediary market. Thus the estimation should be similar to the proxy one as the price deflator for the domestic market is the same as in proxy. However, with the additional intermediary market, the estimates moves in direction similar to column 3. Indicating that, adding the demand system would correct for an underestimation of labor coefficient due to unobserved price effect.

In Table 2.12 I show the full set of demand parameters I estimate using a GMM method. As I mentioned in Section 2.4, adding the full set of country and subregion fixed effect would lead to a very inaccurate result as I would otherwise estimate 130 parameters. I follow De Loecker (2011) to include them as part of the productivity estimate in ω_{it} and focus on the change in productivity in which the time invariant fixed effect would cancel out. Therefore, my productivity are not directly comparable to usual estimates as it includes destination fixed effect. However, the within firm productivity dynamics and the difference between exporters and non-exporters are still informative as fixed effects are assumed to be time invariant when I additionally control for time fixed effect.

Moreover, I still control for qr_{it} which would pick up firm's response towards demand shocks. As one can see, between 2000-2006, there are three distinct time period. From 2000 to 2001 is the pre-WTO period. Between 2002-2005, the tariff in almost all region decrease, leading to a decrease in average protection exposure measured by qr_{it}. At 2006, due to the tariff increase in East Asia and Pacific region, the protection exposure goes up. Therefore, I add three time dummies to control for the time trend. The time trend is in practice very sensitive to initial value and the estimates can be very volatile. Since the time trend would also determine the productivity dynamics across years, I would like to minimize its bias on the actual productivity dynamics. Therefore, I am setting the initial guess to 0 for the three time dummies. In addition, I control for the segment but their actual differences are very small.

In Table 2.12, the first column is my estimates of the demand parameters. Compared with column 6, which is the estimates of demand in Roberts et al. (2017), most of their estimates fall into the confidence interval of my estimates but my elasticities are smaller in magnitude. Their estimates are very informative benchmark because I study the same industry as theirs in a similar time

Table 2.12: Region Specific Demand Estimators

Parameters	β Include	β Not Include	90% Confidence Interval Include	Elasticity Include	Elasticity Range Include	Elasticity Reference	Elasticity Reference2 Demand only
No. of Destination (N_{it})	10.232		[1.060, 20.870]				
Region1-Africa	0.624	0.252	[0.450, 0.870]	-1.601	[-1.149,-2.222]	-3.186(0.334)	-3.286(0.687)
Region2-East Asia and Pacific	0.129	-2.232	[-0.120, 1.070]	-7.751	[-0.935,-∞]	-2.850(0.326)	-2.140 (1.474)
Region3-Latin America	0.809	-0.816	[0.440, 1.220]	-1.236	[-0.820,-2.273]	-2.889(0.335)	-2.941(0.654)
Region4-Non EU Europe	0.427	0.945	[0.000, 0.590]	-2.343	[-1.695,-∞]	-2.297(0.325)	-1.157(0.699)
Region5-EU	0.626	-0.251	[0.380, 0.960]	- 1.599	[-1.042, -2.632]		
Region6-Rest of Asia	0.510	0.991	[0.330, 0.940]	-1.960	[-1.064,-3.030]	-2.943(0.326)	-2.949(0.644)
Region7-North America	0.791	-3.336	[0.020, 1.210]	-1.264	[-0.826,-50.000]	-2.720 (0.319)	-1.735(0.845)
Region8a-China Domestic	0.582	-1.639	[0.320, 1.160]	-1.718	[-0.862,-3.125]		
Region8b-China Intermediary	0.615	0.011	[0.400, 1.430]	- 1.627	[-0.699,-2.500]		
qr (tariff protection)	-1.784		[-41.58, 93.96]				
dgyear1(2000-2001)	-1.137		[-2.750, 0.060]				
dgyear2(2002-2005)	0.440		[-0.530, 2.590]				
dgyear3(2006)	0.546		[-1.660, 1.110]				
Texile	-0.069		[-0.820, 0.510]				
Rubber	0.083		[-1.020, 0.600]				
Plastic	-0.995		[-1.800, -0.110]				

The confidence interval for demand parameters are bootstrapped. The bootstrap sample is 500. I report the confidence interval instead of the standard error is because the test statistics may not follow a standard normal or student's t-distribution.
The standard error for elasticity estimates are in parentheses for column 6 and 7

period and follows similar market definitions. However, their paper use a subsample of the firms I studied (firms engaged in ordinary trade only), therefore the elasticity estimated would be different if the products sold by ordinary and processing trade are systematically different. Mine therefore can be regarded as an average elasticity across all the products.

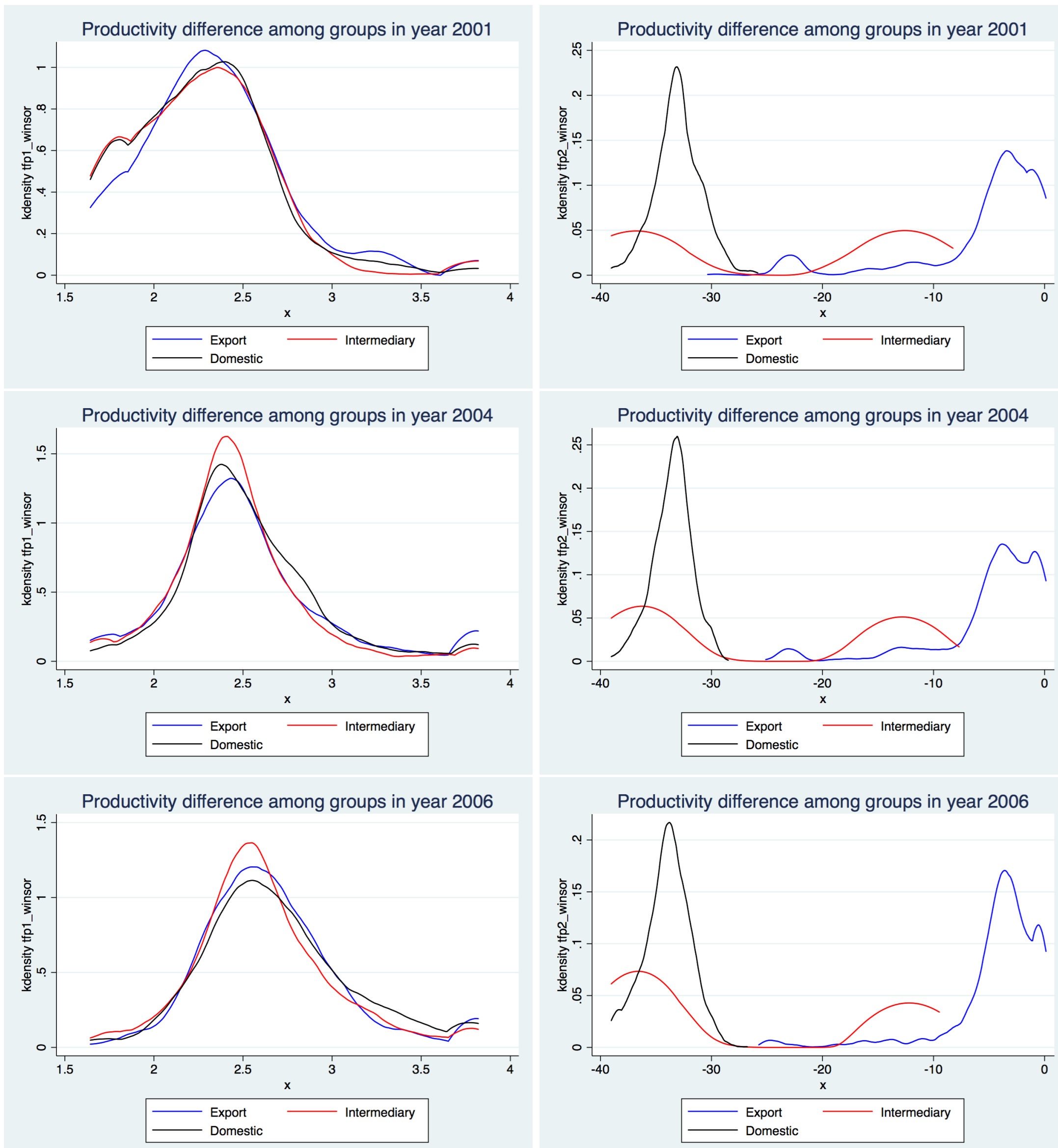
We do discover similar trends that low income regions like Africa and Rest of Asia have higher price elasticity than high income regions like North America and EU. I need to point out that my estimates could suffer from endogenous selection bias as firms self select into different regions to serve. As one can see in column 7, Roberts et al. (2017) also lists the estimates only using the demand equation. For most of the elasticity estimates, it becomes smaller in magnitude and noisier, which is similar to my estimates. They also get a insignificant estimates for the elasticity in East Asia and Pacific market. Therefore, correcting for the possible selection bias is what I would do in a follow up revise when I fully model the exporting behavior of firms.

Since I follow De Loecker (2011) to not seek to estimate the country and subregion fixed effect but simply control them in the first stage. In column 2, I report the demand estimates in which I only control for time and segment fixed effect but not the subregion and country ones. As one can see, some of the coefficients become negative, indicating a positive price quantity relation. For Latin America and Non-EU Europe, the estimates get much bigger, which is typically observed in the literature. Therefore, even through I don't estimate them directly, to control for such demand shocks would lead to a more accurate demand elasticity estimates.

Firms with an additional destination would have a significantly higher revenue which is consistent with empirical result. A 1 % increase in number of destination would lead to a 10.23% percent increase in the total revenue. The time effect is not significant according to my bootstrap result. This is partly because when constructing the price deflator, part of the time trend has been taken into account. In addition, the aggregate demand also picks up time trend which are common across same region. Therefore, in my estimates of TFP, the time effect would be set as zero. The segment effect is also very small and most of them are insignificant. Since the default is firms producing leather shoes, the results indicates that firms producing plastic shoes would earn 99.5% less revenue than firms producing leather shoes, which is in fact very large.

TFP distribution across time: I further plot the distribution across years. As one can see the pattern is persistent across year. Since my estimates also contains country and subregion fixed effect, the results may potentially be contaminated. I hope my region level aggregate demand shifter would pick up some region level difference.

Figure 2.12: TFP Distribution Using Different Measure across Year



CHAPTER 3

VINTAGE CAPITAL AND VENTURE CAPITAL INVESTMENT CONCENTRATION

3.1 Introduction

Recent works on business dynamism and productivity have highlighted the roles of entrants and financial intermediaries separately. Entrants play a significant role in job creation in the US economy, as documented in Haltiwanger et al. (2013), and are the main body of the most high-growth and innovative firms (Lerner and Nanda, 2020). Meanwhile, financial intermediaries, especially venture capital, provide essential financing support to mitigate finance frictions for young firms, encourage firm creation, and reduce resource misallocation. Nevertheless, these two important drivers of firm dynamics and productivity growth are highly concentrated in specific areas (Bay-Boston-NY), leaving the economic activity across the space strikingly uneven (Gaubert, 2018) and also leaving an open question for place-based policies to attract new entrepreneurship and capital to counter-balance the spatial inequality.

So, why are the geographic choice of new entry and inflow of capitalists highly clustered? In this paper, to understand the tremendous spatial disparities, We link the motives of co-locating by entrants and capitalists via a core feature of vintage capital reallocation toward young firms mediated by venture capital. The hypothesis is motivated by two empirical patterns. First, venture capital investment is increasing in the availability of local vintage supply, even when the overall asset specificity or asset immobility demanded by the VC-backed firms is high. This supports the localness of vintage capital transactions, which can drive the spatial concentration. Second, venture capital investment in an early stage of firms illustrates a higher positive response to local vintage capital supply than that in a later stage. This coincides with the well-documented empirical pattern that young firms are more financially constrained and dependent on used capital seasoned by those older, established firms from the same region (Ma et al., 2021). Therefore, the local vintage capital supply attracts entrants, further attracting VC investment because of more deal-flows and lower financing costs (more profits).

To formalize the mechanism, this paper then integrates vintage capital induced co-location of entrants and VC investment into a theoretical framework where entrepreneurship and VC capital flow are endogenously determined. Beginning with a simple static partial equilibrium model with exogenous city size and availability of vintage capital that features used capital reallocation and firm-to-VC matching, we highlight a straightforward mechanism where the supply of local vintage capital leads to more entrepreneur-VC matches, which thus encourages ex-post entry. Following this, more business opportunity powered by greater financial accessibility, in turn, yields tougher selection and thus higher productivity, leveling up the surplus of the operating business. This, in turn, invites more VC investment, amounting to a virtuous circle.

Guided by the baseline mechanism with exogenous vintage capital supply, we assess the important spatial implications of local vintage capital supply by extending to a simple infinite-horizon steady-state equilibrium model with endogenous cities and vintage capital supply. Beyond the insight derived from the partial equilibrium approach, a simple model with endogenous vintage capital supply sheds additional light on understanding how the firm-VC matching, selection, agglomeration, and sorting interact and emerge at equilibrium: More talented individuals sorting into larger cities invites more VC investment to incubate profitable business. Increasing commercial opportunities induces tough competition, thus leading to greater selection and lower misallocation. Less misallocation implies higher capital demanded due to increased output, which yields larger stock of vintage capital along the horizon. As a result, lower capital cost further pushes up the profitability and wages, thus attracting more talents and thus VC investment.

Finally, to close the theory, we examine the endogenous location choices made by individuals with heterogeneous talents. More talented individuals sort into larger cities which invite more VC investment due to more promising return of investment in those more productive start-ups. More financial accessibility amplifies the local economic performance through a selection-induced agglomeration channel, ultimately leaving the most talented individual and mass of VC investment concentrated in largest cities, such as Bay-Boston-NY areas.

Literature Review: This paper connects and contributes to three threads of literature. First, we expand an additional dimension on the literature on agglomeration. This body of works explores the role of resource allocation in contributing to agglomeration through the labor market. Behrens et al. (2014) and Gaubert (2018) study the agglomeration effect when internalizing the endogenously spatial sorting of entrepreneurs and workers. Moretti (2021) provides empirical support on a large scale of agglomeration as a source of knowledge spillover by which the talents are further attracted. Bilal (2021) micro-found the agglomeration in alternative respect by introducing the heterogeneous job separation rate across cities, which affects entrepreneurs' location choices and the local ex-post agglomeration effect exhibited in job-finding rate, implying more efficient labor allocation in a larger city.

A key implication of this literature is that the populated city is more productive as the individual allocation is more efficient when a city is large. This paper extends the resource allocation channel by introducing a capital market that highlights interactions between the productivity of a city, entrepreneurship, and capital market efficiencies powered through venture capitalist engagement. A more efficient allocation of used capital market mediated by venture capitalists reduces labor misallocation through two margins: (1) it reduces misallocation by offering individuals more financial accessibility, which amounts to more entrepreneurship opportunities. (2) More entrepreneurship opportunities amount to the more arduous selection, and more productive firms emerge. A larger city intensifies the allocative forces, making the city larger relative to others.

Second, this paper connects to the literature on the role of financial constraints in firm dynamics. This paper leverages the seminal contribution by Midrigan and Xu (2014), who argue that the aggregate impact of finance frictions primarily affects the economy through distorting the firms' entry decisions, and further elaborates on the competition effect and agglomeration effect induced by the distorted entry decisions due to VC-firm matching frictions. Another closed related body of literature studies the implication of used capital reallocation. Eisfeldt and Rampini (2006) study how the aggregate capital reallocation is intertwined with the business cycle. Lanteri (2018) studies how costly capital reallocation affects efficiency. Ma et al. (2021) provide empirical evidence to argue that used capital reallocation is a vital capital acquisition channel for young firms. The major take-away of this literature focuses on the critical roles of (used/vintage) capital reallocation in supporting entrants. We adopt the idea and further examine the linkage from local capital reallocation efficiency to VC-firm matching, which further generates stark spatial disparities in young firms' activities and industry dynamism.

The rest of the paper is organized as follows: Section 3.2 presents empirical evidence on VC-entrants' co-location and the relationship between VC investment and local vintage capital supply; Section 3.3 describes a partial equilibrium model that demonstrates how the local vintage capital market attracts VC investment which amounts to local agglomeration effect; Section 3.4 generalizes the framework by extending it into a steady-state general equilibrium model along infinite time horizon with endogenous vintage capital supply and location choices by individuals; Section 3.5 concludes.

3.2 Empirical Patterns

Our primary data source is the VentureXpert database provided by Thomson Financial. It contains detailed information about the dates of venture financing rounds, the VC firms and VC-backed companies involved, the estimated amounts invested by VC firm, and the ultimate outcome of each VC-backed company. The primary sample includes all VC investments made between 1980 and 2016 and focuses on the venture stage (seed, early, expansion, or later stage). We focus on investments made by US-based VC in private companies headquartered in the US and exclude those by angels and buyout funds.

The second data source is Compustat North American Fundamentals, which covers public firms in the United States since 1976. It reports a broad set of in-

Table 3.1: VC-firm Matching Data: Summary Statistics

Variable	obs	Mean	Std. Dev.	Min	Max
VC's Annual investment	36063	6474.23	78537.71	2.48e-06	1.16e+07
Annual (non-zero) # VC firms in MSA	1,789	106.29	94.07	1	271
Annual (non-zero) # VC-backed start-ups in MSA	4,090	151.98	141.77	1	418
Annual # VC firms	37	1254.24	670.98	236	2251
Annual # VC-backed startups	37	3173.84	1833.45	341	7077
Age of startups when receiving VC investment	36,063	9.36	11.78	1	79

Notes: This table reports the summary statistics of the venture capital data. Observation is at company-firm-round level. The units of investment terms are all 1000 dollars.

cumbent firm-level information such as firm's industrial classification (SIC), zip code, revenues from resale of capital and capital stock, reflecting the dynamic capital redeployment across firms and abundance of regional vintage capital stock.

Table 3.2: Compustat Data: Summary Statistics

Variable	obs	Mean	Std. Dev.	Min	Max
Resale of vintage capital	144,430	6.22	138.96	0	16563
Investment in property, plant, and equipment	144,430	1092.11	5816.51	0	300478
Sales/Revenue	144,430	1222.18	6581.92	0	327223

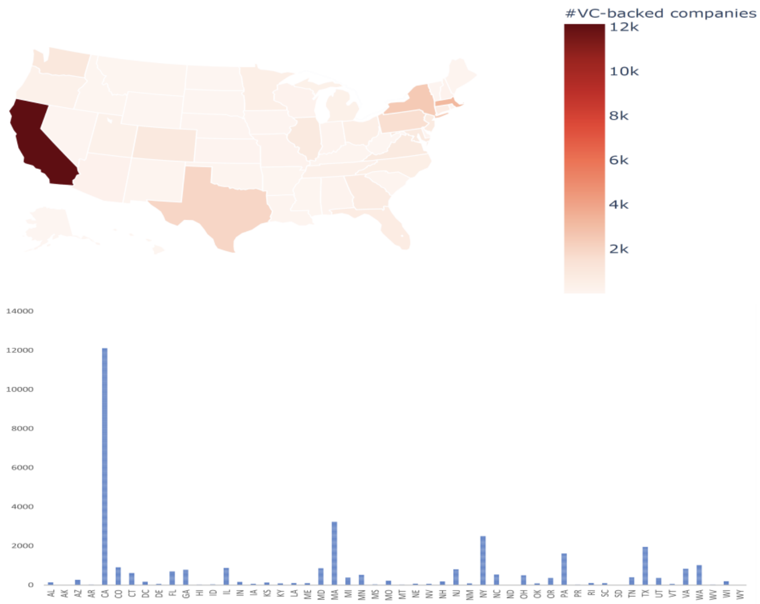
Notes: This table reports the summary statistics from Compustat. Observation is at firm level. The units of investment terms are all 1000 dollars.

The key empirical pattern derived from the data is the concentration of VC investment. We examine two different measures of concentration: (1) measured by the number of VCs' headquarters by regions; (2) measured by the number of start-ups invested by VCs by regions.

From Figure 3.1, it is easy to see that US venture capital is heavily clustered in four MSA: San Jose, San Francisco, Boston, and NY. (We later refer these four cities the venture capital centers.) More than half of all venture capital offices in the US are located in those metropolitan areas.

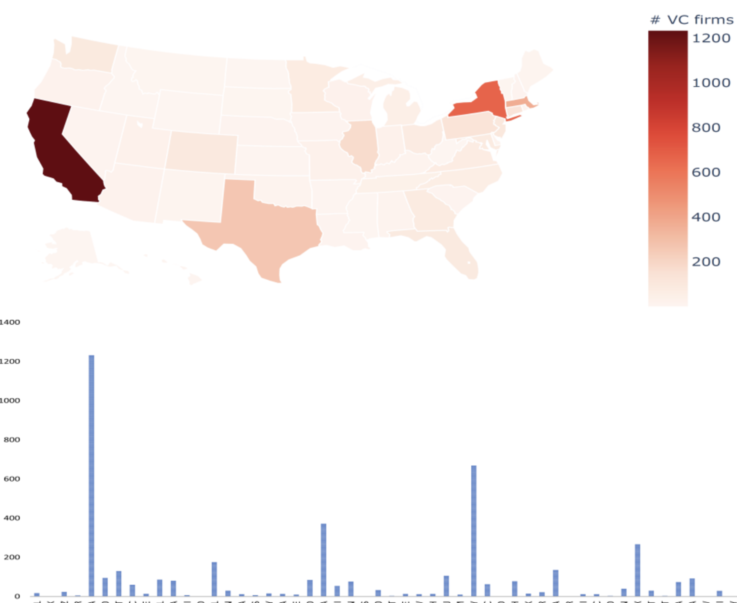
Figure 3.2 illustrates similar implication of VC investment concentration: more than half of all companies financed by venture capital are located in those

Figure 3.1: VC Concentration



venture capital centers areas. The distribution of VC-backed companies are slightly more concentrated than VC firms.

Figure 3.2: VC-backed Companies Concentration



3.2.1 VC investment and Vintage Capital Reallocation

To understand to what extent the local vintage capital market plays a role in driving the secular pattern, we begin with documenting the evidence that reveals the relationship between aggregate VC investment in a given area at a given year and the local measure of aggregate used capital reallocation. [1] We firstly follow Eisfeldt and Rampini (2006) by adopting sales of property, plant, and equipment from Compustat as a measure of the amount of capital reallocation. Specifically, we run the following linear regression:

$$\log(\mathrm{I}^{VC}+1)_{m,s,t} = \beta \cdot \log(K^{\text{Resale}}+1)_{m,s,t} + \delta_{FE} + \epsilon_{m,s,t}$$

We aggregate VC firm × VC-backed company × round investment flow up to yearly Metropolitan Statistical Area-Industry (SIC) level denoted by $\mathrm{I}^{VC}_{m,s,t}$. We sum up the sales of property, plant, and equipment reported by companies whose headquarter is located in the given region by MSAs across years to measure the amount of used capital reallocation at a given industry level. The simple regression includes fixed effect for year, and industry fixed effect.

As one can see in Table 3.3, the result illustrates a positive correlation between the investment of venture capital and the local capital reallocation activity. Specifically, a 10 percent increase in the value of the capital sale is associated with a one percent increase in VC investment inflow into the area. However, the observed capital reallocation is an equilibrium outcome, and it thus is subject to endogeneity problems. For instance, an increase in VC investment may increase the value of old capital held by the incumbent companies in the area and result

[1] Since we are not able to observe the inter-companies capital transaction records mediated by venture capitalists nor the detailed vintage of capital reallocated, we, therefore, focus on the response of aggregate VC investment by region to the local vintage capital supply.

in more sales of assets, amounting to reverse causality. Therefore, to study the factors that drive the VC investment, instead of using the capital sales data, we examine the relationship between VC investment and local old capital supply in the spirit of Ma et al. (2021). we proxy the availability of old local capital by aggregating incumbent companies' local total capital value in the previous year.

Table 3.3: VC & Capital Resale

$\log(K^{\text{Resale}})_{m,s,t}$	0.106***
	(0.009)
Fixed Effect	Yes
N	59015
adj. R^2	0.011

Notes: Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Formally, we hypothesize that the local old capital supply will attract VC investments (concentration of VC investment) and thus benefit new start-ups (concentration of VC-backed companies). We construct the local old capital availability based on *type* by leveraging the BEA inter-sector input-output table following Kermani and Ma (2020).

$$K^e_{\varphi,m,t} = \sum_s \omega_{s\varphi} \sum_{j \in \mathcal{J}_{m,s,t}} K^e_{j,t-1}$$

For any given company in a given industry s, it requires capital goods with different *types*. The BEA input-output table provides information on how many fractions of capital goods employed by companies in a given sector s are type φ denoted by $\omega_{s\varphi}$. Notice that we use the capital held by the company in $t-1$ as a proxy for the old capital available at time t.

In the same manner, we construct the VC investment for capital goods type

φ:

$$I^{VC}_{\varphi,m,t} = \sum_s \omega_{s\varphi} \sum_{i \in \mathcal{I}_{m,s,t}} I^{VC}_{m,s,t}$$

Armed with the constructed measures, we run the analog linear regression as before.

$$\log(\mathrm{I}^{VC} + 1)_{\varphi,m,t} = \beta \cdot \log(K^e + 1)_{\varphi,m,t} + \delta_{FE} + \epsilon_{\varphi,m,t}$$

The fixed effect absorbs the year-specific and capital type-specific effects. The estimated result yields a positive correlation between the old capital availability. However, it is still insufficient to conclude causality as potential confounding factors exist. For example, VC investments may be driven by the technology spillover while the companies working with frontier technologies are capital-intensive. Furthermore, in general, large firms have more capital and more talents. More talents tend to generate more spin-offs and thus run more start-ups, which can attract VC investments.

Table 3.4: VC & Capital Supply

$\log(K^e + 1)_{\varphi,s,t}$	0.096***
	(0.004)
Fixed Effect	Yes
N	59142
adj. R^2	0.019

Notes: Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.2.2 Heterogeneous Demand of VC investment for Vintage Capital

To alleviate the endogeneity concern, we further examine the VC-firm match level data by exploiting the potential factors that amount to heterogeneous VC investment demand for local vintage capital. In particular, we leverage the corporate finance literature on the differential demand for vintage capital across firms' ages and the specificity degree of asset demanded.

The firm's financing stages along its life cycle have important implications on its demand for used capital. Young firms are riskier and financially constrained and thus have a stronger preference over vintage capital (Ma et al., 2021). This motivates to exploit the variation in the VC investment across seniority of firms since VC investment in immature firms is very likely to prefer vintage capital as the early round of capital inflow is very likely insufficient. If the intangible spillover from capital-intensive firms solely drives the VC investment, we should see the negligible effect of local vintage capital supply in VC investment across different stages of VC-backed firms in the same industry.

With this identification strategy in mind, we show that a more abundant supply of vintage capital influences VC investment differently across different stages of VC-backed firms' financing/life cycle. Specifically, we estimate a VC investment decision model for firms in the early and later stages based on the latent supply of local capital across sectors. As an alternative indicator of the financing stage of start-ups, we also adopt the age of VC-backed firms since its registration to supplement the estimated results.

$$\begin{aligned}\log(I^{VC}_{i,a,s,m,t}) = \beta_1 \cdot \log(K^e_{\varphi(s),m,t} + 1) \times \textit{Financing Stage}_{s,m,t} + \beta_2 \cdot \log(K^e_{\varphi(s),m,t} + 1) \\ + \beta_3 \cdot \textit{Financing Stage}_{s,m,t} + \delta_{FE} + \epsilon_{\varphi,m,t}\end{aligned}$$

where i indexes individual venture capitalists and a indexes the staging in which a given VC engages. The unit of observation is a potential VC investment by VC i in location m for sector s at staging a in year t. Since the financing stage indicator cannot be reconstructed to capital type level, we assign input weight to the latent capital supply faced by a firm in a given sector s before aggregating:

$$K^e_{\varphi(s),m,t} = \sum_{\varphi} \omega^D_{\varphi,s} K^e_{\varphi,m,t}$$

where $\omega^D_{\varphi,s}$ is the fraction of type φ capital used by sectors s on average given by the BEA input-output table. The layer of heterogeneous demand for a specific type of capital across sectors captures additional variations in the latent supply of vintage capital.

The differential effects of latent vintage capital supply across financing staging are summarized by the coefficient β_1. The second coefficient β_2 demonstrates, again, how local supply shapes venture capital investment choice. The third term controls for the staging fixed effect, which is supposed to be increasing in the staging as higher staging implies expansion of business. Regressions include fixed effects that control for location (MSA level) $\times$ year and sector (2-digit SIC level), netting out the industrial differentials or local economic trends correlated with both supply and new entrants.

Table 3.5 presents the results. In column (1), we report the baseline sensitivity of all VC investments to the local vintage capital measure. The estimates yield a similar result to our previous specification. In column (2), we use the staging information reported by the VentureXpert database to measure the financing stage of VC-backed firms. This confirms the stylized fact about the firm's life cycle that it enters rapid expansion during later financing stages. The interaction with the financing stage is significant and negative. As start-ups are mature and less financially constrained, the VC investment in such firms becomes less sensitive to local vintage capital supply. In column (3), we adopt the firm's age as an alternative proxy of the financing stage and yield very similar estimates.

Table 3.5: VC Investment Response to Vintage Capital Supply

	(1)	(2) *(staging)*	(3) *(age)*
$\log(K^e_{\varphi(s),m,t}+1)$	0.082***	0.142***	0.102***
	(0.004)	(0.005)	(0.003)
Financing Stage		1.978***	0.825***
		(0.019)	(0.013)
$\log(K^e_{\varphi(s),m,t}+1) \times$ *Financing Stage*$_{s,m,t}$		-0.064***	-0.052***
		(0.003)	(0.002)
Fixed Effect	Yes	Yes	Yes
N	81973	81973	81973
adj. R^2	0.683	0.801	0.753

Standard errors in parentheses

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

To supplement the argument for the causal effects of vintage capital supply on VC investment choice, we then exploit the demand variation due to asset specificity. As argued by Kermani and Ma (2020) and Lanteri (2018), asset specificity is an important component in determining the demand for such assets. Investment in sectors that demand more specific assets should prefer less local vintage capital as the seasoned capital has been at least partially specifically designed or manufactured for the original owner.

To this end, we construct two measures of asset specificity at the capital type level. First, we follow Rauch (1999) and classify the asset type based on whether they are traded on organized exchanges, which has been used as a proxy for specificity (Nunn, 2007; Barrot and Sauvagnat, 2016). For robustness, we adopt an alternative proxy for specificity using the mobility index of assets proposed by Kermani and Ma (2020). A highly specific piece of asset is more likely to involve expensive re-installation costs and transportation costs. We extract the transportation cost share from the BEA input-output table at the commodity level.

With these additional variations in demand for local vintage capital, we run the analog investment choice model estimation:

$$\log(I^{VC}_{i,s,m,t}) = \beta_1 \cdot \sum_{\varphi \in \Psi(s)} \log(K^e_{\varphi,m,t} + 1) \times \mathit{Asset\ Specificity}_{\varphi,m,t}$$

$$+\beta_2 \cdot \log(K^e_{\varphi(s),m,t} + 1) + \beta_3 \cdot \sum_{\varphi \in \Psi(s)} \mathit{Asset\ Specificity}_{\varphi,m,t} + \delta_{FE} + \epsilon_{\varphi,m,t}$$

where $\Psi(s)$ is the set of assets that are demanded in sector s. The regression includes the direct effect of asset specificity on VC investment. It is not surprising to see a positive correlation between asset specificity and VC investment as such capital can still be expensive conditional on the firm-asset match is good. The interaction term captures the differential effects of local capital supply across sectors that are dependent on asset specificity differently.

Table 3.6 presents similar results even though the sensitivity of local capital is diluted after controlling for asset specificity. The estimates of interacted terms are negative and significant, reflecting lower sensitivity to local capital supply when the asset specificity demanded is high.

3.3 A Model of Vintage Capital induced VC investment

Building on the empirical evidence presented above, we build a model that connects the empirical finding on VC investment choice as a function of local vintage capital supply to entrepreneurship and resources allocation. In this section, we firstly begin with a simple static partial equilibrium model that features used

Table 3.6: VC Investment Response to Asset Immobility and Specificity

	(1)	(2)
$\log(K^e_{\varphi(s),m,t}+1)$	0.022***	0.021***
	(0.005)	(0.004)
Transportation cost share	1.043***	
	(0.256)	
$\sum_{\varphi\in\Psi(s)} \log(K^e_{\varphi,m,t}+1) \times \textit{Transportation cost share}_{\varphi,m,t}$	-0.082**	
	(0.036)	
Asset Specificity		0.570***
		(0.163)
$\sum_{\varphi\in\Psi(s)} \log(K^e_{\varphi,m,t}+1) \times \textit{Asset Specificity}_{\varphi,m,t}$		-0.034***
		(0.010)
Fixed Effect	Yes	Yes
N	30275	30275
adj. R^2	0.241	0.155

Standard errors in parentheses

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

capital reallocation and firm-to-VC matching. We impose market clearing in the market for used capital and derive analytical results on the equilibrium VC investment and entrepreneurship (entry). To better highlight the role of local vintage capital in interacting with firms and venture capitalists, we abstract from endogenous location choices by both individuals and venture capitalists, and we further take the local vintage capital as exogenously given at the beginning of the economy.

3.3.1 Environment

We start by focusing on a single location with an exogenous mass of individuals residing in the region denoted by N. Conditional on location, each individual is ex-ante homogeneous in talents z at birth. Once the economy begins to operate, each individual subsequently draws type $x \sim G(\cdot)$. This heterogeneity can be interpreted as serendipity shock or a pairwise location-individual level shock that subsumes many uncertain local interactions and affect productivity, such as being acquainted with the right people at the right time. The ex-post productivity of an individual is captured by a simple multiplicity of her talent and serendipity: $\mathcal{Z} \equiv z \cdot x$. For simplicity, let the ex-post productivity distribution denote by $F(\cdot)$ with a lower bound at 0. Upon the realization of ex-post shock, an individual may face an occupational choice between becoming an entrepreneur by converting the productivity to managerial ability in a one-to-one fashion and working as local labor at $\mathcal{Z}^{\gamma}$ effective working hours. The occupational choice shock depends on whether the individual successfully obtains financing from a venture capitalist, which is extensively discussed later. The power parameter γ captures the elasticity of effective labor supply with respect to underlying individual ex-post productivity.

Preference: For the simple exposition, we assume the preference takes simple logarithm form on final good consumption without leisure utility:

$$U = \log(C) \tag{3.1}$$

This implies that each individual simply maximizes their net surplus/income and supplies their labor inelastically whenever possible. Furthermore, there is no additional residing cost in the simple single-location model for individuals.

Technological Assumptions and Production: A competitive final good manufacturer is assumed to produce a final good bundle using locally produced differentiated intermediate inputs via a standard constant elasticity of substitution technology with parameter $\sigma > \gamma + 1$.

$$Y = \left[\int_{\mathcal{J}} y(j)^{\frac{\sigma-1}{\sigma}} dj \right]^{\frac{\sigma}{\sigma-1}} \tag{3.2}$$

where $y(j)$ is the quantity of input j demanded for the final good bundle, and $\mathcal{J}$ is the endogenously determined set of intermediate inputs produced by the entrepreneurs in the resided location.

Production - Intermediate input: Recall that entrepreneurs bear ex-post heterogeneous productivity $\mathcal{Z}$ which amounts to hicks-neutral managerial ability in a standard Cobb-Douglas production function:

$$y(j) = \overline{\alpha}\mathcal{Z}(j) \cdot k(j)^{1-\alpha} l(j)^{\alpha} \tag{3.3}$$

where $l(j)$ is labor demand in efficiency units for the production of variety j and $k(j)$ is capital demand for the production of variety j and $\overline{\alpha} \equiv \alpha^{-\alpha}(1-\alpha)^{\alpha-1}$ is a demand shifter for normalization.

Financial Frictions for Capital Acquisition: To operate, an entrepreneur needs to acquire capital to materialize the production. Yet each entrepreneur is assumed to possess no wealth or credibility to obtain finance in the credit market before operation.[2] Thus, each potential entrepreneur must first search for a venture capitalist to receive financing ability. We further assume there is no extra cost in searching for venture capitalists, which immediately follows that all individuals first participate in the venture capital market for a match before making an occupational choice. Once a match is successful, the two parties split the surplus through simple Nash bargaining with bargaining power β assigned to the entrepreneur given the nature of equity holding relationship between venture capitalist and entrepreneur.

Matching with Venture Capitalist: Let the endogenously determined mass of VCs chosen to invest in the location denoted by V. The market tightness for

[2] Each entrepreneur can pay wage after realizing revenue, which is a common timing assumption that fits empirical facts.

venture capital investment is given by the ratio of the mass of venture capitalists over the mass of individuals in the location:

$$\theta = \frac{V}{N} \tag{3.4}$$

The matching function is given by $\mathcal{M}(\theta)$ which follows the probability at which an individual successfully match with a venture capitalist is $\lambda(\theta) = \frac{\mathcal{M}(\theta)}{N}$ and the probability at which a venture capitalist meet with an individual is $q(\theta) = \frac{\mathcal{M}(\theta)}{V} = \frac{\lambda(\theta)}{\theta}$. We impose concavity on the meeting technology such that $\lambda(\theta) \to 1$ and $\lambda'(\theta) \to 0_+$ when $\theta \to \infty$ and $\lambda(\theta) \to 0$ and $\lambda'(\theta) \to \infty$ when $\theta \to 0$.

Conditional on a match, an individual decides whether to start a business or not. If deciding to become an entrepreneur, such an individual is then granted the financing capability for capital acquisition by her paired VC. In particular, each entrepreneur paired with VC can then source capital through two channels in the static framework. First, a firm can invest newly produced capital, supplied perfectly elastically from some capital goods producer outside of this economy or self-produced using simple linear technology at one unit of the final good bundle. Alternatively, a firm can invest in used capital available in the local region. Furthermore, following Lanteri (2018), the substitutability between new and vintage capital is imperfect, which means a firm needs to bundle the vintage capital with some newly produced capital to make the capital workable.

Formally, the investment technology takes the sum of the capital amount sourced from two capital sourcing channels:

$$k(j) = \tilde{I}_n(j) + \Delta(I_n(j), I_v(j)) \tag{3.5}$$

where $\tilde{I}^n_j$ is the investment in newly-produced capital and $\Delta(\cdot)$ is the investment in capital bundle which takes both new capital $I_n(j)$ and vintage capital $I_v(j)$.

We take a special case of capital bundle function for a simple exposition of the mechanism:

$$\Delta(I_n(j), I_v(j)) = \overline{\eta} I_n^{\eta}(j) I_v^{1-\eta}(j), \quad \overline{\eta} = \eta^{-\eta}(1-\eta)^{\eta-1} \tag{3.6}$$

The cost of a unit of capital bundle in the unit of final good in the location is

$$r_\Delta = \frac{1}{\chi} r_v^{1-\eta} \tag{3.7}$$

where r_v is the unit cost of vintage capital. This immediately follows that the capital rent at equilibrium must take the lower cost of capital choice given the investment technology:

$$r = \min\{r_\Delta, 1\} \tag{3.8}$$

Throughout this paper, we focus on the scenario where there is no pure new investment channel.[3]

3.3.2 Selection and Matching

Solving the cost minimization problem of the final good bundle by taking the set of entrepreneurs as given yields the demand for intermediate input:

$$y(j) = (\frac{P}{p(j)})^{\sigma} Y \tag{3.9}$$

where P summarizes the final good price index $P = \left(\int_{\mathcal{J}} p(j)^{1-\sigma} dj \right)^{\frac{1}{1-\sigma}}$ and Y captures the economic size of the location in the unit of final good bundle.

[3]Or alternative assumptions on parameters is required to ensure $r_\Delta < 1$, e.g. sufficiently large χ.

Similarly, solving the cost minimization problem of entrepreneur obtains the marginal cost of input:

$$mc(\mathcal{Z}) = \frac{1}{\mathcal{Z}} r^{\alpha} w^{1-\alpha} \equiv \frac{c}{\mathcal{Z}} \tag{3.10}$$

where both cost of capital r and wage rate w are in the unit of final good. Given the demand function derived as in (9) and monopolistic competition structure, the profit-maximizing price for each intermediate input displays a constant markup over marginal cost:

$$p(\mathcal{Z}) = \frac{\sigma}{\sigma - 1} mc(\mathcal{Z}) \equiv \overline{\sigma} \cdot mc(\mathcal{Z}) \tag{3.11}$$

Substituting out $p(j)$ in the price index with (11) allows us to express the aggregate productivity of the economy as a function of wage and capital cost:

$$\mathbb{Z} \equiv \left[\lambda(\theta)N\right]^{\frac{1}{\sigma-1}} \left(\int_{\underline{\mathcal{Z}}} \mathcal{Z}^{\sigma-1} dF(\mathcal{Z}) \right)^{\frac{1}{\sigma-1}} = \overline{\sigma} c \tag{3.12}$$

where $c = r^{\alpha} w^{1-\alpha}$ and $\underline{\mathcal{Z}}$ is the cutoff above which the individual paired with a VC chooses to become an entrepreneur. The aggregate productivity of the economy depends on the population size of the location N and the probability at which an individual match with a venture capitalist. The multiplicity of the two gives the mass of individuals who meet a venture capitalist while $\lambda(\theta)N(1 - F(\underline{\mathcal{Z}}))$ captures the mass of entrepreneurs. The expression in (12) also suggests that both real wage and real capital rent are increasing in aggregate productivity, indicating the selection forces stemming from stronger labor demand from more productive entrepreneurs/firms.

Leveraging the connection between marginal cost and aggregate productivity allows us to further rewrite the demand function:

$$y(\mathcal{Z}) = (\frac{\mathcal{Z}}{\mathbb{Z}})^{\sigma} Y \tag{3.13}$$

the relative productivity $\frac{\mathcal{Z}}{\mathbb{Z}}$ plays a key role in determining its revenue share. Combine with equations (10) and (11), the operating profit becomes:

$$\pi(\mathcal{Z}) = \frac{1}{\sigma}(\frac{\mathcal{Z}}{\mathbb{Z}})^{\sigma-1}Y \tag{3.14}$$

Occupational choice and selection: Individuals choose their occupation by comparing their prospective entrepreneurial profit given by (14) with their labor income $w \cdot \mathcal{Z}^{\gamma}$ conditional on meeting with a venture capitalist successfully in the first place. The indifference condition characterizes the selection cutoff $\underline{\mathcal{Z}}$:

$$\beta\pi(\underline{\mathcal{Z}}) = w \cdot \underline{\mathcal{Z}}^{\gamma} \quad \Rightarrow \quad \underline{\mathcal{Z}}^{\sigma-1-\gamma} = \frac{\sigma}{\beta}\mathbb{Z}^{\sigma-1}\frac{w}{Y} \tag{3.15}$$

Given that $\sigma > \gamma + 1$, the selection is tougher when the average productivity is higher since it is more difficult to compete against more productive and numerous firms for labor if holding wage and total income constant. Finally, holding other constant, higher wage also levels up the selection cutoff because higher wage means a more favorable outside option. Nevertheless, note that the equilibrium effect induced by a higher selection cutoff is endogenously average productivity and real wage, which means a better understanding of the relationship across selection cutoff, average aggregate productivity, and real wage requires solving the equilibrium via labor market cleaning.

The selection cutoff not only demonstrates individual occupational choice when taking wage, demand and aggregate productivity as given but also links to the effective labor demand and supply. Firms with ex-post productivity above $\underline{\mathcal{Z}}$ demand labor at

$$l(\mathcal{Z}) = \frac{1-\alpha}{\overline{\sigma}w}(\frac{\mathcal{Z}}{\mathbb{Z}})^{\sigma-1}Y$$

Thus the aggregate labor demand given selection cutoff $\underline{\mathcal{Z}}$ is

$$L^D = \lambda(\theta)N\int_{\underline{\mathcal{Z}}} l(\mathcal{Z})dF(\mathcal{Z}) = \frac{1-\alpha}{\overline{\sigma}w}Y \tag{3.16}$$

It is noticeable that the aggregate labor demand is simply derived from the fact that the labor income share in the local economy is $\frac{1-\alpha}{\sigma}$ of the aggregate demand/income.

On the other hand, the aggregate labor supply given the selection cutoff is given by

$$L^S = \underbrace{(1-\lambda(\theta)) \cdot N \int \mathcal{Z}^\gamma dF(\mathcal{Z})}_{\text{individuals fail to match with VC}} + \underbrace{\lambda(\theta) \cdot N \int_0^{\underline{\mathcal{Z}}} \mathcal{Z}^\gamma dF(\mathcal{Z})}_{\text{matched but below selection cutoff}} \tag{3.17}$$

Imposing the labor market clearing condition with $L^S = L^D$ together with the indifference condition (15) characterize the selection cutoff equilibrium as a function of VC finance market tightness θ.

Proposition 1 (Selection and Matching): Given the population size of the location, N, the productivity distribution $F(\cdot)$ and VC-to-population ratio θ, the selection cutoff exists and is unique. Furthermore, the selection is tougher when more VCs decide to invest in the location.

Proof: Using equation (15), (16), (17) to eliminate $w, Y, \mathbb{Z}$ yileds an implicit solution for $\underline{\mathcal{Z}}$:

$$\beta \underline{\mathcal{Z}}^{\sigma-\gamma-1}\left[\int \mathcal{Z}^\gamma dF(\mathcal{Z}) - \lambda(\theta)\int_{\underline{\mathcal{Z}}} \mathcal{Z}^\gamma dF(\mathcal{Z})\right] = \lambda(\theta)(1-\alpha)(\sigma-1)\int_{\underline{\mathcal{Z}}} \mathcal{Z}^{\sigma-1} dF(\mathcal{Z}) \tag{3.18}$$

Since $\sigma > \gamma + 1$, this implies the left-hand side of the equation is strictly increasing in $\underline{\mathcal{Z}}$ from 0 to infinity while the right-hand side is strictly decreasing in $\underline{\mathcal{Z}}$ and goes to zero when taking the selection cutoff to infinity. Furthermore, both sides are differentiable (thus continuous) in $\underline{\mathcal{Z}}$, ensuring the unique solution of $\underline{\mathcal{Z}}$. Moreover, note that the population size is taken exogenously given. It is easy to show that the left-hand side of an equation (18) is strictly decreasing in

θ while the right-hand side is strictly increasing in θ. Therefore, a higher market tightness due to a greater mass of VC investing in the location leads to a higher selection cutoff. $\square$

The basic intuition is that greater finance accessibility means more entrants, leading to tougher competition and thereby lifting the selection cutoff. The following Corollary highlights the implications of more VC investment.

Corollary 1: Given population size N, the aggregate productivity is strictly increasing in VC investment. *Proof*: See Appendix.

The greater finance accessibility contributes to higher aggregate productivity in two channels: (1) it increases entrepreneurship at an extensive margin; (2) more entrepreneurship opportunities induce tougher selections, increasing the productivity at the intensive margin. Nevertheless, the higher selection cutoff can offset excessively offset the entrepreneurship from the extensive margin as the VC choose over relatively more productive start-ups trading off a large number of less profitable business opportunities when the distribution of ex-post productivity is a heavy tail, e.g., Pareto distribution.

The above two results summarize how the VC-firm matching market affects the selection cutoff and aggregate productivity. We move forward to examine the role of vintage capital supply in shaping the interplay across VC investment decisions, VC-firm matching induced selection, and the local agglomeration effect.

3.3.3 Vintage Capital Supply and Agglomeration

In the static framework, we fix the mass of vintage capital at K_v^S, which is not in the usage of any firms in the economy but owned by a latent local government. The capital demand for a firm with $\mathcal{Z}$ is given by:

$$k(\mathcal{Z}) = \frac{\alpha}{\overline{\sigma}r}(\frac{\mathcal{Z}}{\mathbb{Z}})^{\sigma-1}Y \tag{3.19}$$

Given the investment technology, this implies that the demand of vintage capital at firm level is characterized as

$$I_v(\mathcal{Z}) = (1-\eta)\frac{r}{r_v}k(\mathcal{Z}) = (1-\eta)\frac{\alpha}{\overline{\sigma}r_v}(\frac{\mathcal{Z}}{\mathbb{Z}})^{\sigma-1}Y$$

Integrating over the mass of entrepreneurs, the aggregate demand of vintage capital is

$$K_v^D = \lambda(\theta)N\int_{\underline{\mathcal{Z}}} I_v(\mathcal{Z})dF(\mathcal{Z}) = (1-\eta)\frac{\alpha}{\overline{\sigma}r_v}Y \tag{3.20}$$

We do not focus on the unemployed state of capital due to the match frictions in the vintage capital market and assume there is an equilibrium price r_v that clears the market. This amounts to the capital market clearing condition:

$$K_v^D = K_v^S$$

Given the fixed supply in the static framework, one can express the aggregate equilibrium demand/income as a function of K_v^S and its associated cost:

$$Y = \frac{\overline{\sigma}r_v}{(1-\eta)\alpha}K_v^S \tag{3.21}$$

Not surprisingly, holding other constant, a more abundant supply of vintage capital implies higher aggregate income for the local economy. This expression, together with the labor market clearing condition, allows us to connect the expenditure share of local vintage capital to the that of labor at equilibrium:

$$\alpha w L^S = \frac{(1-\alpha)}{(1-\eta)}r_v K_v^S \tag{3.22}$$

Since that equilibrium labor supply is a function of selection cutoff, this implies the relative cost of vintage capital in the unit of labor is a function of selection cutoff. A higher selection cutoff means tougher competition and higher aggregate productivity, which means the competition for vintage capital is also tougher, thus pushing up the relative cost of vintage capital in the unit of labor cost. On the other hand, recall that unit cost of input is a function of selection cutoff: $\overline{\sigma} r^{\alpha} w^{1-\alpha} = \mathbb{Z}$. Higher aggregate productivity pushes up the cost of labor and capital simultaneously. Therefore, the two conditions amount to the identification of real wage and vintage capital cost.

Lemma 1: Let $H(\underline{\mathcal{Z}};\theta) \equiv (1-\lambda(\theta)) \cdot \int \mathcal{Z}^{\gamma} dF(\mathcal{Z}) + \lambda(\theta) \cdot \int_0^{\underline{\mathcal{Z}}} \mathcal{Z}^{\gamma} dF(\mathcal{Z})$. Given the productivity distribution $F(\cdot)$, VC finance market tightness θ, the real wage is increasing in vintage capital stock and real rent of vintage capital is decreasing in the stock. Formally,

$$w = \overline{\chi}_w \cdot (K_v^S)^{\frac{\alpha(1-\eta)}{1-\alpha\eta}} H(\underline{\mathcal{Z}};\theta)^{-\frac{\alpha(1-\eta)}{1-\alpha\eta}} N^{\frac{1}{1-\alpha\eta}[\frac{1}{\sigma-1}-\alpha(1-\eta)]} \left[\lambda(\theta) \int_{\underline{\mathcal{Z}}} \mathcal{Z}^{\sigma-1} dF(\mathcal{Z})\right]^{\frac{1}{(1-\alpha\eta)(\sigma-1)}} \tag{3.23}$$

$$r_v = \frac{\alpha(1-\eta)}{1-\alpha} \overline{\chi}_w \cdot (K_v^S)^{-\frac{1-\alpha}{1-\alpha\eta}} H(\underline{\mathcal{Z}};\theta)^{\frac{1-\alpha}{1-\alpha\eta}} N^{\frac{1}{1-\alpha\eta}[\frac{1}{\sigma-1}+1-\alpha]} \left[\lambda(\theta) \int_{\underline{\mathcal{Z}}} \mathcal{Z}^{\sigma-1} dF(\mathcal{Z})\right]^{\frac{1}{(1-\alpha\eta)(\sigma-1)}} \tag{3.24}$$

Notice that the real wage is only strictly increasing in the population size N when the input market competition is not that tough (low σ), or labor share is low (high α). Since the population elasticity of aggregate productivity is $\frac{1}{\sigma-1}$, this implies the population elasticity of wage has to be adjusted to ensure the population elasticity of marginal cost is also $\frac{1}{\sigma-1}$ given equation (12). A high capital share implies a weak rent response to population size, leaving lower downward pressures on wages. Furthermore, a high capital share means a lower labor share, indicating an already high sensitivity of wages to the population.

In other words, a higher capital share makes capital rent increase in population size with a 'milder' sense, which does not depress the wages when population-scale up. On the other hand, high elasticity of substitution ensures higher profits for firms which prevents making the wages decrease in population due to higher labor supply. Throughout the paper, we assume that $(1-\alpha)(\sigma-1) \leq 1$ corresponds to the set of well-documented empirical facts on lower labor share and higher markup (less competition) in the US industry.

Proposition 2 (Agglomeration): (1) When both the population size and vintage capital stock are exogenously given, the economy demonstrates the agglomeration effect with respect to population size if $\frac{1}{\sigma-1} > (1-\alpha)$; (2) the agglomeration effect is complemented by vintage capital stock holding θ constant.

$$\frac{\partial w}{\partial N} > 0 \quad and \quad \frac{\partial \frac{Y}{N}}{\partial N} > 0$$
$$\frac{\partial^2 w}{\partial N \partial K_v^S} > 0 \quad and \quad \frac{\partial^2 \frac{Y}{N}}{\partial N \partial K_v^S} > 0$$

where

$$Y = \frac{\overline{\sigma}}{1-\alpha}\overline{\chi}_w \cdot (K_v^S)^{\frac{\alpha(1-\eta)}{1-\alpha\eta}} H(\underline{\mathcal{Z}};\theta)^{\frac{1-\alpha}{1-\alpha\eta}} N^{\frac{1}{1-\alpha\eta}\left[\frac{1}{\sigma-1}+1-\alpha\right]} \left[\lambda(\theta)\int_{\underline{\mathcal{Z}}} \mathcal{Z}^{\sigma-1} dF(\mathcal{Z})\right]^{\frac{1}{(1-\alpha\eta)(\sigma-1)}} \tag{3.25}$$

By fixing the market tightness θ, the above result demonstrates the direct channel of availability of vintage capital goods in increasing per-capita income and real wage rate through cost reduction on the capital bundle.

Moreover, on the top of this conventional channel, this result features the causal relationship between vintage capital stock and venture capital participation/investment. Treating θ as a parameter, a higher matching rate with venture capitalists immediately implies a higher wage rate due to tougher competition and greater aggregate productivity. The higher aggregate productivity further pushes up the per-capita income.

Corollary 2: If $\frac{1}{\sigma-1} \geq (1-\alpha)$, wage rate and income per capita are strictly increasing in the VC investments given location population N:

$$\frac{\partial w}{\partial \theta} > 0, \quad \frac{\partial \frac{Y}{N}}{\partial \theta} > 0$$

and furthermore, the agglomeration effect is increasing in VC investments:

$$\frac{\partial^2 w}{\partial N \partial \theta} > 0, \quad \frac{\partial^2 \frac{Y}{N}}{\partial N \partial \theta} > 0$$

Proof: See Appendix.

3.3.4 Entry of Venture Capital and Equilibrium

Each venture capital is assumed to be ex-ante homogeneous. Upon residing in a location, each requires to pay a fixed cost in the unit of the local final good bundle at f_{VC} as a prerequisite for start-up searching. The expected value of the entry is then given by

$$J_{VC} = (1-\beta)q(\theta) \int_{\underline{\mathcal{Z}}} \pi(\mathcal{Z}) dF(\mathcal{Z}) \tag{3.26}$$

The free entry condition implies

$$J_{VC} = f_{VC}$$

Recall that the selection cutoff is increasing in θ from equation (18). This implies a higher θ can reduce the value of venture capital in two channels: (1) lower probability of meeting a potential entrepreneur and (2) conditional on a meeting, the ex-post productivity of the young entrepreneur is more likely to be not competent enough due to higher selection cutoff. This amounts to a relationship between θ and per-capita income.

$$J_{VC} = \frac{1-\beta}{\sigma} q(\theta) \frac{1}{\lambda(\theta) N} Y = \frac{1-\beta}{\sigma\theta} \frac{Y}{N} \tag{3.27}$$

From this point, holding θ as a constant, together with the result derived in Proposition 2, the agglomeration effect not only leads to greater per-capita welfare but also the value of venture capital. This implies the negative impact of higher θ on VC's value is partially offset by the general equilibrium effect given that $\frac{\partial \frac{Y}{N}}{\partial \theta} > 0$ shown in Corollary 2.

Furthermore, recall that $\theta = \frac{V}{N}$, this leads to an explicit expression that links the participation of venture capitalists and residing/searching cost:

$$\frac{Y}{N} = \frac{\sigma f_{VC}}{1-\beta} \cdot \theta \quad \Rightarrow \quad V = \frac{1-\beta}{\sigma} \frac{Y}{f_{VC}} \tag{3.28}$$

Note that the demand curve for VC investment in equation (25) is non-decreasing in θ, and the supply curve captured by (28) is strictly increasing in θ. This follows that, for some f_{VC}, there exists a unique solution θ^* solving the equilibrium. Furthermore, since both demand and supply are (weakly) upward sloping, it immediately indicates an amplification channel facilitated by venture capitalists when the vintage capital stock increases.

Proposition 3 (Amplification): Higher vintage capital stock induces greater aggregate per-capita income, attracting more venture capitalists. More venture capital participation reduces misallocation and induces tougher competition and greater aggregate productivity, further pushing up per-capita income.

Definition 1: An equilibrium of the static model with exogenously given vintage capital stock K_v^S and population size N is: (1) an occupational choice with threshold $\underline{\mathcal{Z}}$; (2) a profit maximization problem; (3) a real cost vector $(w, \{r, r_v\})$ that clears both labor, capital bundle and vintage capital market; (4) aggregate output and aggregate productivity $(Y, \mathbb{Z})$; (5) the ratio of mass of VC investment over population size N, θ that solves the free entry problem of VC investment such that:

1. the occupational choice and threshold $\underline{\mathcal{Z}}$ is summarized by equation (18).
2. a profit maximization problem is characterized by equations (9) - (14).
3. wage and rent of vintage capital and capital bundle satisfies equations (7), (12),(21) and (22).
4. Aggregate output is captured by equation (25), and aggregate productivity satisfies equation (12).
5. the entry problem is captured by equation (28).

3.4 A Model of Endogenous Vintage Capital Stock and Location Choice

This section focuses on a simple infinite horizon environment along a steady-state, inheriting the critical components from the static framework. On top of a dynamic setting, we further endogenize the vintage capital stock by linking the capital stock previously owned by the exiting incumbents to the locally available vintage capital supply.[4] Finally, this framework features a location choice decision by both venture capitalists and individuals.

Preference: Time is discrete, and its horizon is infinite. The discount factor is ρ. Each individual maximizes their income per period and is hand-to-mouth.

A Simple Dynasty: Newbie and Retirement: Each individual faces a retirement shock arriving at Poisson rate δ regardless of her occupation. Upon anyone's retirement, a new individual is born in the economy and draws her talent

[4] We abstract from the case where the incumbent firms optimally sell the old capital to invest in new equipment or relax the financial distress due to idiosyncratic shocks and leave them for future study.

z from a distribution $\Phi(\cdot)$ and sorts into locations indexed by $o \in \mathcal{O}$. Upon residing, each individual draws location-specific shock x from an independent distribution $G(\cdot)$ which amounts to ex-post productivity $\mathcal{Z} = z \cdot x$. After realizing their ex-post productivity, each newbie of a given location has a chance to be paired with a venture capitalist, which amounts to a commercial opportunity as an entrepreneur of a start-up. We assume each individual can only enter the VC market once for the simple exposition. That is, if an individual fails to match with a VC, she has to be a worker since then.[5] Furthermore, relocation or immigrants are not allowed.

Location and Residing cost: There is a set of ex-ante homogeneous locations indexed $\mathcal{O}$. We assume no latent characteristics of the location, and the sorting and ex-post heterogeneity stems from assignment problems from the individual's talent z to the location's population $N(z)$ in the spirit of Behrens et al. (2014). That is, each city is assigned a specific talent at equilibrium. There is an upfront fixed cost for residing in a location o with population N at ψN^{ζ}.[6] Intuitive interpretation for the increasing residing cost in population size includes higher commuting costs and housing prices in population-dense areas.

3.4.1 Production and Capital Stocking

The production function and investment technology are summarized by the same settings from equations (2) - (8) in the static framework. For an entrepreneur with ex-post productivity $\mathcal{Z}$, she employs a measure of capital k_{-1}

[5] Allowing individuals always to possess an opportunity to start a business generates no conflicting implications of our simple model.

[6] An implicit assumption is that the economy admits a bank system can only provide housing loans to individuals but not to business.

during the previous period and starts the current period with $(1-d)k_{-1}$ due to depreciation. She then chooses the amount of capital bundle $\Delta(I_n, I_v)$ to maximize its expected discounted profits/surplus taking the wages and capital cost as given. As in the static model, there is no additional fraction in sourcing for vintage capital.[7] After the investment in the current period, she starts to produce with capital stock k.

The period profit/surplus is therefore characterized by $\pi(\mathcal{Z}, k) = p(\mathcal{Z})y(\mathcal{Z}, k) - wl(\mathcal{Z}) - r\Delta(I_n, I_v)$, and an entrepreneur's problem (before surplus split with VC) conditional on $(\mathcal{Z}, k_{-1})$ and location o follows:

$$J_o^E(\mathcal{Z}, k_{-1}) = \max_{\{p,y,l,\Delta(\cdot)\}} p \cdot y(Z, k) - wl - r\Delta + \rho\left[\delta R_v(\mathcal{Z}, k) + (1-\delta)J_o^E(\mathcal{Z}, k)\right] \tag{3.29}$$

where δ is the rate of retirement, $R_v(\mathcal{Z}, k)$ is the resale revenue of vintage capital conditional on receiving the retirement shock

$$R_v(\mathcal{Z}, k) = r_v \cdot (1-d)k$$

and Δ is the investment in capital bundle subject to law of motion of capital stock:

$$k = (1-d)k_{-1} + \Delta$$

We are focusing on the steady-state equilibrium where each firm is continually operating at optimal capital stock as it can always purchase the capital bundle and recover to the optimal level immediately. It turns out that the recursive problem can be simplified into a simple static problem where each firm chooses the optimal capital level at a discounted presented cost of capital by internalizing the longevity of assets and the value of resale.

[7]For example, allocation of vintage capital can be subject to search/match frictions. See Ottonello (2017), Ramey and Shapiro (2001), Gavazza (2016).

Lemma 2: In a steady-state Equilibrium, the dynamic problem faced by a firm with ex-post productivity $\mathcal{Z}$ is equivalent to

$$\max_{p,y,l,k} p \cdot y - wl - \big[1 - \rho(1-d)[\delta \frac{r_v}{r} + (1-\delta)]\big] rk \tag{3.30}$$

Proof: Rewrite the recursive problem in equation (**??**) by substituting Δ out:

$$\begin{aligned} J_o^E(\mathcal{Z}, k_{-1}) &= \max_{\{p,y,l,\Delta(\cdot)\}} p \cdot y(Z,k) - wl - r[k - (1-d)k_{-1}] + \rho\big[\delta R_v(\mathcal{Z},k) + (1-\delta) J_o^E(\mathcal{Z},k)\big] \\ &= r(1-d)k_{-1} + \underbrace{\max_{\{p,y,l,\Delta(\cdot)\}} \{p \cdot y(Z,k) - wl - rk + \rho\big[\delta R_v(\mathcal{Z},k) + (1-\delta) J_o^E(\mathcal{Z},k)\big]\}}_{\textit{constant denoted by B}} \end{aligned}$$

Given the steady state, the maximized sub-problem is a constant. It follows $J_o^E(\mathcal{Z}, k) = r(1-d)k + B$ and

$$\begin{aligned} J_o^E(\mathcal{Z}, k_{-1}) = r(1-d)k_{-1} + \max_{\{p,y,l,\Delta(\cdot)\}} &\{p \cdot y(Z,k) - wl - rk \\ &+ \rho\big[\delta R_v(\mathcal{Z},k) + (1-\delta)[r(1-d)k + B]\big]\} \end{aligned}$$

Substituting out $R_v(\mathcal{Z}, k)$ we have reduced firm's problem to

$$\max_{\{p,y,l,\Delta(\cdot)\}} p \cdot y(Z,k) - wl - rk + \rho\big[\delta(1-d)\frac{r_v}{r} + (1-\delta)(1-d)\big] rk$$

$\square$

Firm recognizes the longevity of assets reflected by $(1-d)(1-\delta)rk$ as the capital purchase today also saves the investment next period. Furthermore, the resale value of asset as vintage capital summarized by $\delta(1-d)r_v k$. Define $\tilde{r}(r) \equiv \big[1 - \rho(1-d)[\delta \frac{r_v}{r} + (1-\delta)]\big] \cdot r$ as the adjusted cost of capital. The firm's marginal cost, revenue, labor and capital demand are

$$mc(\mathcal{Z}) = \frac{1}{\mathcal{Z}} \tilde{r}^{\alpha} w^{1-\alpha}$$

$$p \cdot y(\mathcal{Z}) = (\frac{\mathcal{Z}}{\mathbb{Z}})^{\sigma} Y$$

$$l(\mathcal{Z}) = \frac{1-\alpha}{\overline{\sigma} w} (\frac{\mathcal{Z}}{\mathbb{Z}})^{\sigma-1} Y$$

$$k(\mathcal{Z}) = \frac{\alpha}{\overline{\sigma}\tilde{r}}(\frac{\mathcal{Z}}{\mathbb{Z}})^{\sigma-1}Y$$

where $\mathbb{Z} = [\lambda(\theta)N]^{\frac{1}{\sigma-1}}(\int_{\underline{\mathcal{Z}}} \mathcal{Z}^{\sigma-1}dF(\mathcal{Z}))^{\frac{1}{\sigma-1}}$ summarizing the aggregate productivity. [8]

By solving the privately optimal allocations, one can obtain the explicit expression of the value of a firm at state $(\mathcal{Z}, N)$ at a steady-state:

$$J_o^E(\mathcal{Z},k) = \frac{1}{\overline{\sigma}[1-\rho(1-\delta)]}\left[\overline{\sigma} - (1-\alpha) - \alpha\frac{r}{\tilde{r}}[d-(1-d)\rho\delta\chi r_v^{\eta}]\right](\frac{\mathcal{Z}}{\mathbb{Z}})^{\sigma-1}Y$$

Notice that when the firm has optimal capital stock in the previous period, it invests dk^* amount of capital bundle to hire back to the optimal level after the depreciation for the next period. On the other hand, the new entrant with zero capital stock immediately stocks up to the optimal capital level. The recursive problem of a new entrant is given by

$$J_o^E(\mathcal{Z},0) = p^*y^*(\mathcal{Z}) - wl^* - rk^* + \rho[(1-\delta)J_o^E(\mathcal{Z},k) + \delta R_v(\mathcal{Z},k^*)] \tag{3.31}$$

where the revenue, labor demand and capital demand are the solutions to equation (30). Using the solution to $J_o^E(\mathcal{Z},k)$, the solution to the entrant problem ends up with a straightforward form:

$$J_o^E(\mathcal{Z},0) = \frac{1}{1-\rho(1-\delta)}\frac{1}{\sigma}(\frac{\mathcal{Z}}{\mathbb{Z}})^{\sigma-1}Y \tag{3.32}$$

The solution is intuitive since the value of an entrant is simply earning discounted present profit stream with the adjusted capital cost upon its birth.

[8] To see why the mass of firms in the local economy is $\lambda(\theta)N[1-F(\mathcal{Z})]$ along the path steady-state equilibrium, let the mass of firms denote by h and consider the outflow and inflow of firms:

$$\underbrace{\delta \cdot h}_{\text{outflow}} = \underbrace{\delta N\lambda[1-F(\mathcal{Z})]}_{\text{inflow}} \quad \Rightarrow \quad h = \lambda N[1-F(\mathcal{Z})]$$

3.4.2 Worker's Problem

If an individual with ex-post productivity $\mathcal{Z}$ chooses to work as labor, it provides $\mathcal{Z}^{\gamma}$ efficiency unit of labor at equilibrium local wage w. There is no unemployment state for a worker, but each individual is subject to retirement shock regardless of her occupation. Formally, the recursive problem of a worker is

$$J^W(\mathcal{Z}) = \mathcal{Z}^r \cdot w + \rho(1-\delta)J^W(\mathcal{Z})$$

Along the steady-state equilibrium, the solution is

$$J^W(\mathcal{Z}) = \frac{1}{1-\rho(1-\delta)}\mathcal{Z}^r \cdot w \tag{3.33}$$

3.4.3 Occupational Choice and Selection

The characterization of steady-state recursive problems yields precisely the same solution we derived in the state model.

$$\max\{\beta J^E(\mathcal{Z},0), J^W(\mathcal{Z})\} \Rightarrow \underline{\mathcal{Z}}^{\sigma-1-\gamma} = \frac{\sigma}{\beta}\mathbb{Z}^{\sigma-1}\frac{w}{Y}$$

Not surprisingly, together with the labor market clearing at each period, the steady-state selection cutoff in the dynamic setting confronts the same condition:

$$\beta\underline{\mathcal{Z}}^{\sigma-\gamma-1}\left[\int \mathcal{Z}^{\gamma}dF(\mathcal{Z}) - \lambda(\theta)\int_{\underline{\mathcal{Z}}}\mathcal{Z}^{\gamma}dF(\mathcal{Z})\right] = \lambda(\theta)(1-\alpha)(\sigma-1)\int_{\underline{\mathcal{Z}}}\mathcal{Z}^{\sigma-1}dF(\mathcal{Z})$$

Recall that the ex-post productivity is a multiplicity of an individual's talent z and location-specific matching shock $x \sim G(\cdot)$, and the model features a sorting equilibrium at which individuals reside a given location is talent-homogeneous.

The following property ensures common selection cutoff conditional on financing probability $\lambda(\theta)$.

Lemma 3: Let $F(\mathcal{Z}) = zG(x)$, then $\underline{\mathcal{Z}} = z \cdot \underline{x}$, where $\underline{x}$ is implicit solution to

$$\beta \underline{x}^{\sigma-\gamma-1}\left[\int x^{\gamma} dF(\mathcal{Z}) - \lambda(\theta)\int_{\underline{x}} x^{\gamma} dG(x)\right] = \lambda(\theta)(1-\alpha)(\sigma-1)\int_{\underline{x}} x^{\sigma-1} dG(x) \tag{3.34}$$

In other words, the selection cutoff is identified by location-specific shock conditional on talent z residing in the location. Note that the selection effect within a location is controlled by financing accessibility θ, which is endogenously connected to the efficiency of vintage capital reallocation.

3.4.4 Vintage Capital Market and Cost of Capital

Departure from the static model, the vintage capital supply at each period depends on the capital stock of incumbents which experience the retirement shock:

$$K_v^S = \delta\lambda(\theta)N\int_{\underline{\mathcal{Z}}} k_{-1}(\mathcal{Z})dF(\mathcal{Z}) = (1-d)\delta\lambda(\theta)N\int_{\underline{\mathcal{Z}}} k(\mathcal{Z})dF(\mathcal{Z}) \tag{3.35}$$

Before spelling the demand for vintage capital, it is convenient to start by examining the demand for the capital bundle at any given period conditional on location with population N:

$$K^D = (1-\delta)\lambda(\theta)N\int_{\underline{\mathcal{Z}}}\Delta(\mathcal{Z})dF(\mathcal{Z}) + \delta\lambda(\theta)N\int_{\underline{\mathcal{Z}}} k(\mathcal{Z})dF(\mathcal{Z}) = [(1-\delta)d+\delta]\frac{\alpha Y}{\overline{\sigma}\tilde{r}}$$

The capital demand is composed of two channels: the capital bundle demanded by the incumbent firms that invest $\Delta(\cdot)$ to maintain its optimal capital level and the entrants that purchase capital from 0 stock. Given the aggregate demand function for the capital bundle, the corresponding demand function for vintage capital is

$$k_v^D = (1-\eta)\frac{r}{r_v}K^D = (1-\eta)\frac{r}{r_v}[(1-\delta)d+\delta]\frac{\alpha Y}{\overline{\sigma}\tilde{r}} \tag{3.36}$$

The Cobb-Douglas form in investment technology results in the demand for vintage capital that is proportional to that for the capital bundle, which further pins down the cost of vintage capital immediately:

$$r_v = \Big[\frac{(1-\eta)[(1-\delta)d+\delta]}{\delta(1-d)\chi}\Big]^{\frac{1}{\eta}} \tag{3.37}$$

The cost of vintage capital decreases in the inverse of specificity friction χ and longevity of vintage asset $(1-d)$. The adjusted capital cost is then a constant as well, which allows us to examine the real wage as a function of aggregate productivity directly:

$$w = \Big(\frac{1}{\overline{\overline{\sigma}}}\Big)^{-\frac{1}{1-\alpha}} \chi^{\frac{\alpha}{(1-\alpha)\eta}} \Big[(1-\eta)\Big[\frac{(1-\delta)d+\delta}{\delta(1-d)}\Big]\Big]^{-\frac{\alpha}{1-\alpha}\frac{1-\eta}{\eta}} \cdot \mathbb{Z}^{\frac{1}{1-\alpha}} \tag{3.38}$$

This implies the wage rate is increasing in the location's population. Furthermore, the agglomeration effect for the local wage is decreasing in specificity frictions if holding financial accessibility θ constant:

$$\frac{\partial^2 w(\theta)}{\partial N \partial \chi} > 0, \quad \frac{\partial^2 w(\theta)}{\partial N \partial d} < 0$$

Using the real wage, indifference condition for occupational choice, and labor market clearing condition, one can back out the per-capita income by taking population N and talent in the location z as given:

$$\begin{aligned} \frac{Y}{N} = & \frac{\overline{\sigma}^{\frac{\alpha}{1-\alpha}}}{1-\alpha} \chi^{\frac{\alpha}{(1-\alpha)\eta}} \Big[(1-\eta)\Big[\frac{(1-\delta)d+\delta}{\delta(1-d)}\Big]\Big]^{-\frac{\alpha}{1-\alpha}\frac{1-\eta}{\eta}} \cdot \\ & H(\underline{x},\theta) \cdot \Big[\lambda(\theta) N \int_{\underline{x}} x^{\sigma-1} dG(x)\Big]^{\frac{1}{\sigma-1}\frac{1}{1-\alpha}} \cdot z^{r+\frac{1}{1-\alpha}} \end{aligned}$$

where the selection cutoff $\underline{x}$ solves equation (34). The per capita income is proportional to real wage and thus exhibits an agglomeration effect when holding θ fixed. We close the local equilibrium by obtaining θ by solving the venture capitalist's free entry problem.

3.4.5 Venture Capitalist's Problem

The venture capital in the model provides necessary financing services to the business by enabling them to access finance for operation. We abstract from the scenario where a venture capital simultaneously manages multiple deal flows. We follow the setting in the static model where the matches between VC and potential entrepreneur is governed by a random match technology $\mathcal{M}(\theta)$. The financing accessibility is summarized by the ratio of VC searching efforts over the mass of potential entrepreneurs (newbies residing in the location) $\theta = \frac{V}{\delta \cdot N}$. A venture capitalist posts an ad and incurs a location-dependent search cost $f_{VC}(\cdot)$. Explicitly, the real cost of participating in searching for a start-up in a location with talent z is

$$f_{VC}(z) = \tilde{f} \cdot z^{\gamma} w \tag{3.39}$$

That is, the search cost is proportional to the (lowest) wage earned by the local individual. It follows that the expected value of VC investment is

$$J^{VC}(z) = (1-\beta)q(\theta)\int_{\mathcal{Z}} J^{E}(\mathcal{Z},0)dF(\mathcal{Z}) = \frac{1}{1-\rho(1-\delta)}\frac{1-\beta}{\sigma\theta}\frac{Y}{N} \tag{3.40}$$

where $\underline{x}$ solves (34). The free entry condition implies

$$J^{VC}(z) = f_{VC}(z) \tag{3.41}$$

This amounts to the supply curve of VC investment with respect to income per capita:

$$\frac{Y}{N} = \frac{\sigma[1-\rho(1-\delta)]}{1-\beta} \cdot f_{VC}(z) \cdot \theta \tag{3.42}$$

The higher per-capita income summarizes the expected value of VC investment, which therefore attracts more VC investment. The demand curve of VC investment is summarized by equation (39) together with the constant wage expenditure share of total income:

$$\frac{Y}{N} = \frac{\overline{\sigma}}{1-\alpha} \cdot H(\underline{x}, \theta) \cdot z^r \cdot w$$

Higher per-capita income is increasing in the aggregate productivity and therefore demands greater VC investment to induce tougher selection. To derive a sharp solution, we impose $G(\cdot)$ following Pareto distribution with tail parameter μ with lower support at 1. This allows us to characterize the VC market tightness in explicit form.

Lemma 4: If $G(x) = 1 - x^{-\mu}$ with $\mu > \sigma - 1$, for sufficient low β, there exists unique solution to the local economy equilibrium given the location population N with the talent normalized selection cutoff satisfying

$$\underline{x}^{\mu-\gamma} = \lambda(\theta)\left[1 + \frac{(1-\alpha)(\sigma-1)(\mu-\gamma)}{\beta(\mu-\sigma+1)}\right]$$

and mass of venture capital is linear in location's population:

$$V = \frac{1}{1-\rho(1-\delta)} \frac{1-\beta}{(1-\alpha)(\sigma-1)} \cdot H^* \cdot N$$

where $H^* = \frac{\mu(1-\alpha)(\sigma-1)}{\beta(\mu-\sigma+1)+(1-\alpha)(\sigma-1)(\mu-\gamma)}$.

Proof: One can obtain $\underline{x}$ by solving equation (34) with imposing the Pareto distribution form of $G(\cdot)$. Then solve the demand and supply curve in equation (39) and (43) for VC investment V. A low β ensures the selecting cutoff to be greater than 1. □

The implication of the closed-form solution to selection cutoff is straightforward: greater financial accessibility generates tougher competition and selection. With the Pareto distribution assumption, the total labor supply at equilibrium is constant because the increase in the labor supply due to tougher selection cutoff is exactly offset by the decrease in the labor supply due to more financial accessibility. This implies the per-capita income is affected by financial accessibility only through the aggregate productivity channel. Since the fixed cost of VC entry is proportional to local wage, it means the cost is also proportional to the local aggregate productivity. This ensures that the overall VC investment in the location is linear in the population size as the demand and supply elasticity with respect to aggregate productivity is the same.

The above section has solved the local equilibrium conditional on the population N. We proceed to solve the endogenous size of location as a function of talent and evaluate how parameters that affect local vintage supply shape the location size and the sorting outcome.

3.4.6 Individual's Location Choice and Vintage Capital Market

Each individual draws talent z upon birth and then chooses the location with population N to reside. Before characterizing the location choice problem faced by each individual, it is helpful first to examine the expected value of an individual with talent z residing in a talent-homogeneous location with population N:

$$\mathbb{E}[J^0(z)] = \int \left[\lambda(\theta) \cdot \max\{J^E(z \cdot x, 0), J^W(z \cdot x)\} + [(1 - \lambda(\theta)]J^W(z \cdot x)\right] dG(x) - \psi N^\zeta \tag{3.43}$$

From previously established results, both values of being an entrepreneur and being a worker exhibit an increasing return to population size. More population means more business, which implies greater average productivity and thus a higher real wage. On the other hand, more population is associated with more business, generating more vintage capital and thus more profits for firms.

The following result further demonstrates how talent complements such local agglomeration channel, setting the stage for the positive assortative matching between talent and size of a location.

Lemma 5: Individuals with greater talents benefit more from residing in a location with a more significant population.

$$\frac{\partial^2 \mathbb{E}[J^0(z)]}{\partial z \partial N} > 0$$

Proof: Recall that $J^E(zx, 0) = \frac{\beta}{1-\rho(1-\delta)} \frac{1}{\sigma} (\frac{zx}{\tilde{\sigma} c})^{\sigma-1} Y = \frac{1}{1-\rho(1-\delta)} z^\gamma (\frac{x}{\underline{x}})^{\sigma-1} \cdot w$. Rewrite the conditional expected value:

$$\begin{aligned}\mathbb{E}[J^0(z)] = \frac{1}{1-\rho(1-\delta)} z^\gamma \cdot w \cdot \Big[\lambda(\theta)[\underline{x}^\gamma \int_{\underline{x}} (\frac{x}{\underline{x}})^{\sigma-1} dG(x) \\ + \int_0^{\underline{x}} x^\gamma dG(x)] + (1-\lambda(\theta)) \int x^\gamma dG(x)\Big] - \psi N^\zeta\end{aligned}$$

Note that $\underline{x}$ is a constant, and $\frac{\partial^2 w}{\partial z \partial N} > 0$ from equation (38). The result then immediately follows. □

The complementarity between an individual's talent and location size is fully summarized by the minimum local revenue of an individual at $z^\gamma w$. A natural question arises as to how an individual with some talent z' values a location populated by individuals with talent z. Formally, a location choice problem for an individual with talent z' is

$$\begin{aligned}\mathbb{E}[J^0(z', z)] = \max_z \frac{1}{1-\rho(1-\delta)} z'^\gamma w \Big[\lambda(\theta)[(\frac{z'}{z \cdot \underline{x}})^{\sigma-1-\gamma} \int_{\frac{z \cdot \underline{x}}{z'}} x^{\sigma-1} dG(x) \\ + \int_0^{\frac{z \cdot \underline{x}}{z'}} x^\gamma dG(x)] + (1-\lambda(\theta)) \int x^\gamma dG(x)\Big] \\ - \psi N^\zeta(z)\end{aligned} \tag{3.44}$$

For an individual with talent z' resided in a location with talent z, her occupational choice is then disciplined by $\frac{z \cdot \underline{x}}{z'}$. Consider a case where $z' > z$, then an individual with z' can benefit from being more likely to become an entrepreneur, yet she is paid at a lower equilibrium wage given that others' talent at z and thus faces lower conditional expected value of both being worker and entrepreneur. The following result shows that the value of an individual is maximized when she chooses to reside in a location with others sharing a common talent.

Proposition 4 (Sorting and Agglomeration): For sufficiently large ζ, The endogenous optimal location population is increasing in talent z. Specifically,

$$N(z) = (A_N + \frac{A_z(\zeta - \tilde{\sigma})}{\tilde{\gamma}})^{\frac{1}{\zeta-\tilde{\sigma}}} \cdot z^{\frac{\tilde{\gamma}}{\zeta-\tilde{\sigma}}} \tag{3.45}$$

where $\tilde{\sigma} \equiv \frac{1}{(\sigma-1)(1-\alpha)}$ and $\tilde{\gamma} \equiv \gamma + \frac{1}{1-\alpha}$.
Proof: See Appendix.

The proposition, together with *Lemma 4*, identifies the equilibrium VC investment as a function of talent in the location. Moreover, the VC investment concentration in high-talent locations is intensified when vintage capital is more durable or bears lower specificity.

Corollary 3: The VC investment is strictly increasing in the talent residing in the location.

$$V(z) = \frac{1}{1-\rho(1-\delta)} \frac{1-\beta}{(1-\alpha)(\sigma-1)} \cdot H^* \cdot (A_N + \frac{A_z(\zeta-\tilde{\sigma})}{\tilde{\gamma}})^{\frac{1}{\zeta-\tilde{\sigma}}} \cdot z^{\frac{\gamma+\frac{1}{1-\alpha}}{\zeta-\tilde{\sigma}}} \tag{3.46}$$

Moreover, the complementarity between VC investment and talent is further increasing in vintage capital durability and decreasing in specificity:

$$\frac{\partial^2 V(z)}{\partial z \partial \chi} > 0, \quad \frac{\partial^2 V(z)}{\partial z \partial d} < 0$$

It is noticeable that the VC investment elasticity of talent depends on the capital share of the production function. In particular, a higher capital share implies greater dispersion in VC investment and population size across locations. Furthermore, since we do not allow for additional synergy between VC investors and start-ups, VC investment elasticity is independent of VC market tightness though the VC investment level will increase if the VC-entrepreneur matching friction is mitigated. Future work on incorporating a richer notion of VC-Entrepreneurship pairing with direct productivity enhancement is an essential next step.

3.5 Conclusion

The geographic concentration of new entry and inflow of capitalists is not just a curiosity—it has important implications for urban design and infrastructure investment policy. A dynamic and energetic business environment welcomes young firms and capital, in turn, plants seeds for long-term local economic prosperity. This paper attempts to join the motives of co-location of capitalists and entrants through a vintage capital market and stresses that the efficiency of local vintage capital reallocation plays an essential role in explaining the empirically observed spatial disparities in terms of economic activities. Firstly, we empirically document the concentration of VC investment in the US and then explore the positive response of VC investment to the local vintage capital supply. Given the empirical support, we then build a partial equilibrium model with exogenous local vintage supply to evaluate its roles in attracting VC investment which further generates a selection-induced agglomeration effect through financing more productive entrepreneurs. Finally, we extend the theoretical framework to allow endogenous local vintage capital supply and co-location choices by potential entrepreneurs and VC investment. The sorting mechanism generates striking even spatial heterogeneity in terms of capital investment, entrants, and population coupled with the heterogeneous local agglomeration effects. Such spatial inequality intensifies when the local vintage capital market is more efficient.

There are a number of interesting extensions and related topics to be explored in future work. Firstly, in this model, we do not allow for other financial institutions, such as banks function as alternative financing service providers. It would be an important question to ask about the roles of local vintage capital in distinguishing the two financing services. Secondly, the model does not allow for either idiosyncratic or aggregate shocks to firms that can generate more capital reallocation patterns between operating firms along the business cycle. A third potentially crucial point to be examined is how the exiting strategies of VC are affected by the vintage capital market, which will shape additional interactions between dynamism in the VC market and firms' dynamism. Lastly, constructing a more quantitatively tractable framework based on this theory can help derive crucial counterfactual policy implications given the detailed data. We hope that this work can shed light on those directions.

3.A Appendix—Chapter 2

Proof of Corollary 1: It is equivalent to show that the value of both two hand sides are increasing in θ at solution.

$$\beta\underline{\mathcal{Z}}^{\sigma-\gamma-1}\left[\int \mathcal{Z}^{\gamma}dF(\mathcal{Z}) - \lambda(\theta)\int_{\underline{\mathcal{Z}}}\mathcal{Z}^{\gamma}dF(\mathcal{Z})\right] = \lambda(\theta)(1-\alpha)(\sigma-1)\int_{\underline{\mathcal{Z}}}\mathcal{Z}^{\sigma-1}dF(\mathcal{Z})$$

Given that $\sigma - 1 > \gamma$, it is sufficient to show that the value of two hand sides are increasing in θ at solution in the following equation:

$$\beta\underline{\mathcal{Z}}^{\sigma-\gamma-1}\left[\int \mathcal{Z}^{\gamma}dF(\mathcal{Z}) - \lambda(\theta)\int_{\underline{\mathcal{Z}}}\mathcal{Z}^{\sigma-1}dF(\mathcal{Z})\right] = \lambda(\theta)(1-\alpha)(\sigma-1)\int_{\underline{\mathcal{Z}}}\mathcal{Z}^{\sigma-1}dF(\mathcal{Z})$$

Rearrange the above solution, one can obtain:

$$\lambda(\theta)\int_{\underline{\mathcal{Z}}}\mathcal{Z}^{\sigma-1}dF(\mathcal{Z}) = \frac{\beta\underline{\mathcal{Z}}^{\sigma-\gamma-1}\cdot\int \mathcal{Z}^{\gamma}dF(\mathcal{Z})}{(1-\alpha)(\sigma-1)+\beta\underline{\mathcal{Z}}^{\sigma-\gamma-1}}$$

After taking derivative w.r.t θ on two sides, it is easy to see the right hand side is strictly increasing in θ since proposition 1 has established that $\mathcal{Z}'(\theta) > 0$. Thus at solution the value of right-hand side increases at equilibrium. Therefore, for the original equation,

$$\frac{\partial[\lambda(\theta)\int_{\underline{\mathcal{Z}}}\mathcal{Z}^{\sigma-1}dF(\mathcal{Z})]}{\partial\theta} > 0 \quad \Rightarrow \frac{\partial\mathbb{Z}}{\partial\theta} > 0$$

Now consider the case where $F(\mathcal{Z}) = 1 - \mathcal{Z}^{-\mu}$ with $\mu > \sigma - 1$ and lower support at 1. Using equation (18), one can obtain

$$\underline{\mathcal{Z}}^{\mu-\gamma} = \max\frac{(1-\alpha)(\sigma-1)(\mu-\gamma)}{\beta(\mu-\sigma+1)}\lambda(\theta), 1 \equiv \max B\cdot\lambda(\theta), 1$$

The mass of operating firms is then $(B\cdot\underline{\mathcal{Z}}^{\gamma})^{-1}$ if $\underline{\mathcal{Z}} > 1$ otherwise B^{-1}. □

Proof of Corollary 2: To save notations, let $B \equiv \int z^{\gamma}dF(z)$, $Q_{\gamma}(\underline{\mathcal{Z}},\theta) \equiv \lambda(\theta)\int_{\underline{\mathcal{Z}}}\mathcal{Z}^{\gamma}dF(\mathcal{Z})$ and $Q_{\sigma-1}(\underline{\mathcal{Z}},\theta) \equiv \lambda(\theta)\int_{\underline{\mathcal{Z}}}\mathcal{Z}^{\sigma-1}dF(\mathcal{Z})$. Note that $Q_{\sigma}(\underline{\mathcal{Z}},\theta) >$

$Q_\gamma(\underline{\mathcal{Z}},\theta)$ for all $(\underline{\mathcal{Z}},\theta)$ and $\frac{Q'_\gamma(\theta)}{Q'_\sigma(\theta)} < \frac{\int_{\underline{\mathcal{Z}}} \mathcal{Z}^\gamma dF(\mathcal{Z})}{\int_{\underline{\mathcal{Z}}} \mathcal{Z}^{\sigma-1} dF(\mathcal{Z})} < \underline{\mathcal{Z}}^{\gamma-\sigma+1}$. Since $\frac{Y}{N} \propto w \propto H(\underline{\mathcal{Z}},\theta) \cdot Q_\sigma^{\frac{1}{(1-\alpha)(\sigma-1)}}$, it is sufficient to show that

$$\frac{\partial\left[H(\underline{\mathcal{Z}},\theta) \cdot Q_\sigma^{\frac{1}{(1-\alpha)(\sigma-1)}}\right]}{\partial\theta} = \frac{\partial\left[(R - Q_\gamma(\theta)) \cdot Q_\sigma^{\frac{1}{(1-\alpha)(\sigma-1)}}(\theta)\right]}{\partial\theta} > 0$$

Expand the expression, one can have

$$\begin{aligned}
\frac{\partial\left[(R - Q_\gamma(\theta)) \cdot Q_\sigma^{\frac{1}{(1-\alpha)(\sigma-1)}}(\theta)\right]}{\partial\theta} &\propto R - \left[Q_\gamma + (\sigma-1)(1-\alpha)Q_\sigma \frac{Q'_\gamma(\theta)}{Q'_\sigma(\theta)}\right] \\
&> R - [Q_\gamma + (\sigma-1)(1-\alpha)\underline{\mathcal{Z}}^{\gamma-\sigma+1}Q_\sigma] \\
&> 0
\end{aligned}$$

where the last inequality comes from $\beta \in (0,1)$. and equation (18):

$$R - Q_\gamma = \frac{(1-\alpha)(\sigma-1)}{\beta}\underline{\mathcal{Z}}^{\gamma-\sigma+1}Q_\sigma > (1-\alpha)(\sigma-1)\underline{\mathcal{Z}}^{\gamma-\sigma+1}Q_\sigma$$

□

Proof of Proposition 4: Firstly, note that real wage is a function of talent z:

$$w = (\overline{\sigma}r^\alpha)^{-\frac{1}{1-\alpha}} \cdot z^{\frac{1}{1-\alpha}} \cdot [\lambda(\theta)N(z)]^{\frac{1}{(\sigma-1)(1-\alpha)}}[\int_{\underline{x}} x^{\sigma-1}dG(x)]^{\frac{1}{(\sigma-1)(1-\alpha)}}$$

This implies $\frac{\partial w}{\partial z} = \frac{1}{1-\alpha}\frac{w}{z} + \frac{1}{(\sigma-1)(1-\alpha)}\frac{w}{N(z)}N'(z)$. A equilibrium at which all individuals resided in a given location share common talent must satisfy the first-order condition with respect to z equal to zero when evaluating at $z' = z$:

$$\frac{\partial \mathbb{E}[J^0(z',z)]}{\partial z}|_{z'=z} + \frac{\partial \mathbb{E}[J^0(z',z)]}{\partial N}N'(z)|_{z'=z} = 0$$

Expand two terms, we obtain:

$$\frac{\partial \mathbb{E}[J^0(z',z)]}{\partial z}|_{z'=z} = \tilde{A}_z z^{\gamma+\frac{\alpha}{1-\alpha}} N^{\frac{1}{(\sigma-1)(1-\alpha)}}$$

where

$$\tilde{A}_z = \frac{\lambda(\theta)^{\frac{1}{(\sigma-1)(1-\alpha)}+1}}{1-\rho(1-\delta)}[(\frac{1}{1-\alpha}+\gamma)+(\sigma-1)\frac{1-\beta}{\beta}]$$
$$\times (\frac{1}{\bar{\bar{\sigma}}}r^{\alpha})^{\frac{1}{1-\alpha}}\underline{x}^{\frac{1}{1-\alpha}+\gamma}[\int_{\underline{x}}(\frac{x}{\underline{x}})^{\sigma-1}dG(x)]^{1+\frac{1}{(\sigma-1)(1-\alpha)}}$$

and

$$\frac{\partial \mathbb{E}[J^0(z',z)]}{\partial N}|_{z'=z} = \tilde{A}_N z^{\gamma+\frac{1}{1-\alpha}} N^{\frac{1}{(\sigma-1)(1-\alpha)}-1} - \psi\zeta N^{\zeta-1}$$

where

$$\tilde{A}_N = \frac{\beta+(\sigma-1)(1-\alpha)}{(\sigma-1)\beta+\gamma(\sigma-1)(1-\alpha)\beta+(\sigma-1)^2(1-\alpha)(1-\beta)}\tilde{A}_z$$

Notice that both $\tilde{A}_N$ and $\tilde{A}_z$ are constant as θ and $\underline{x}$ are solved at local economy in the previous sections. Let $A_i \equiv \frac{\tilde{A}_i}{\psi\zeta}, \quad i \in \{z, N\}$, and let $\tilde{\sigma} \equiv \frac{1}{(\sigma-1)(1-\alpha)}$ and $\tilde{\gamma} \equiv \gamma + \frac{1}{1-\alpha}$. We can express the FOC in the form of ordinary differential equation:

$$[A_n z^{\tilde{\gamma}} - N(z)^{\zeta-\tilde{\sigma}}]\frac{N'(z)}{N(z)} + A_z z^{\tilde{\gamma}-1} = 0$$

Guess $N(z) = Az^{\nu}$, one can obtain the desired solution. □

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