Vertical Relations, Demand Risk, and Upstream Concentration: the Case of the US Automobile Industry *

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This paper studies how upstream market concentration and demand risk affect downstream firms' outsourcing decisions. 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. The model delivers equilibrium outsourcing patterns, as well as equilibrium upstream prices. I estimate the model using data on the vehicle manufacturers and upstream transmission firms in the automobile industry. Facing a negative demand shock equivalent to the recent pandemic, outsourcing from upstream firms mitigates the rise in transmissions' production cost by 48%. However, endogenizing upstream's price response to downstream's outsourcing incentives offsets the mitigation by 12%. Next, I evaluate the potential impact of the United States-Mexico-Canada Agreement. When the upstream market is more concentrated under the protectionist trade policy, the upstream's price response to the same pandemic demand shock is more significant. It further amplifies the negative impact on consumer welfare and manufacturers' profit.

Keywords: demand risk, outsourcing, trade protection, imperfection of upstream

JEL codes: D43, D81, L13, L22, L62

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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 endogenized 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

[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..."

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 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

[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.

[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.

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.

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 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

[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.

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

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 estimate 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

[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; 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.

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.

This paper proceeds as follows. Section 2 describes the industry background and the data used. Section 3 presents the model. Section 4 discusses identification and estimation procedure. Section 5 reports structural estimation results and Section 6 addresses the economic questions of interest via counterfactual analysis. Section 7 concludes.

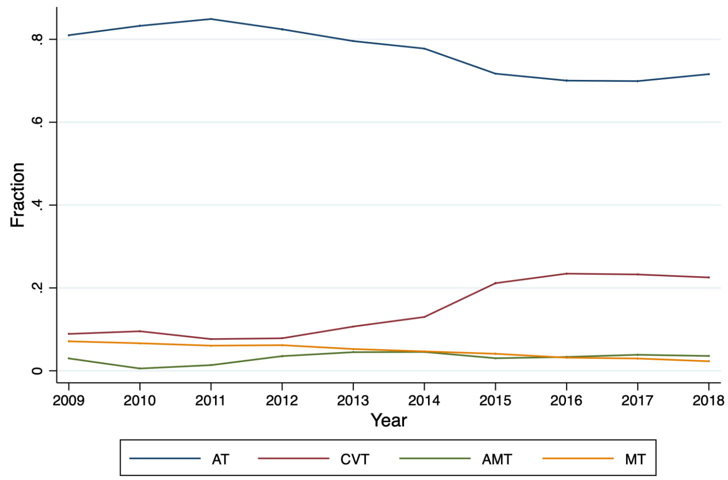
2 Industry Background and Data Description

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, 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 due to the technology barrier. Table 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

Figure 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.

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 preferential, 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.

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

Table 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

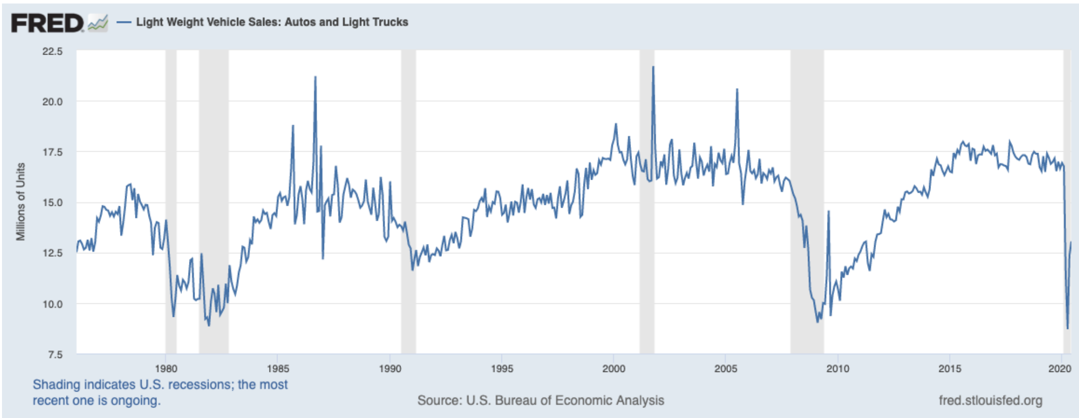
Notes: This table reports types of transmission and market concentration in the transmission market. Shared are calculated using quantity sold. Conditional share is the share of each upstream firm conditional on the outsourced transmission.

2.2 The Automobile Industry

Figure 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.

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

Figure 2: Light Weight Vehicle Sales in the US 1975-2020

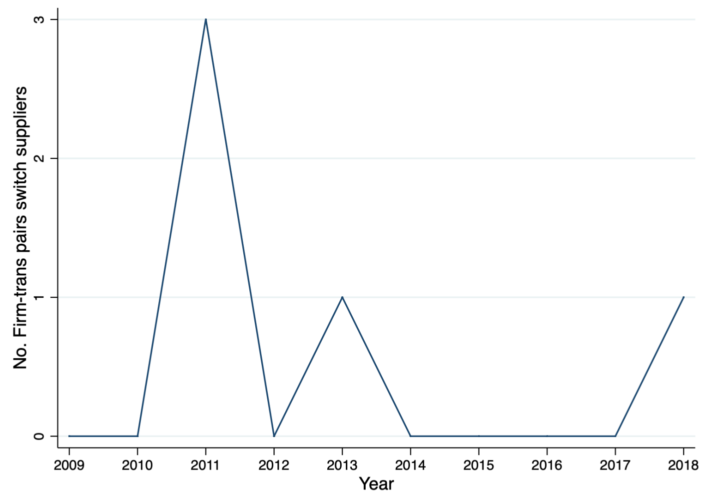


Notes: The figure is downloaded from St. Louis Fed based on the statistics from US Bureau of Economic Analysis. It shows the passenger vehicle sales in the US 1975-2020.

manufacturing contracts typically last for the whole product life cycle. According to Figure 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.

Unlike many other parts which are completely outsourced, many car manufacturers still produce transmission internally in the same vein as engines and motors. Figure 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 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%.

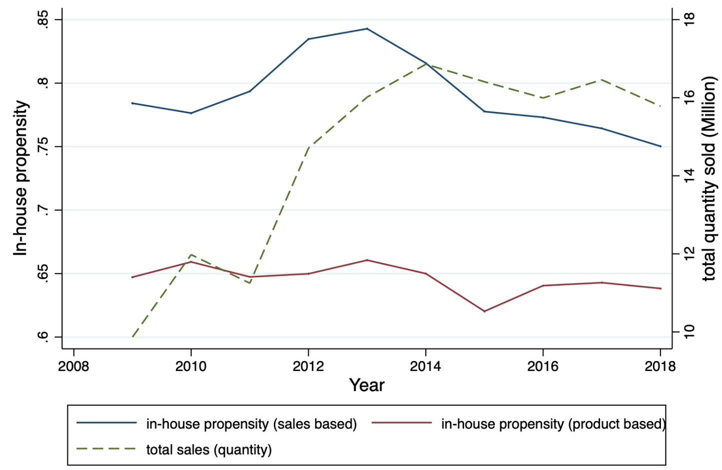
2.3 Data

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 tear-down 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.

[12] https://transend.us/

Figure 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.

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 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 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

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

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.

Table 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.

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.

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 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 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.

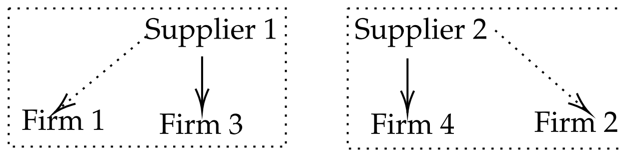
3.2 A Simple Model with Linear Demand

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

[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.

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:

$$V_1(I_1 = 1) = \underbrace{E\pi_1(I_1 = 1, I_2 = 1, \boldsymbol{\tau}, \sigma, \theta_c, \cdot) Pr(I_2 = 1) + E\pi_2(I_1 = 1, I_2 = 0, \boldsymbol{\tau}, \sigma, \theta_c, \cdot) Pr(I_2 = 0)}_{E\Pi_1(I_1=1)} + \epsilon_1(I_1 = 1)$$

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.

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

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]

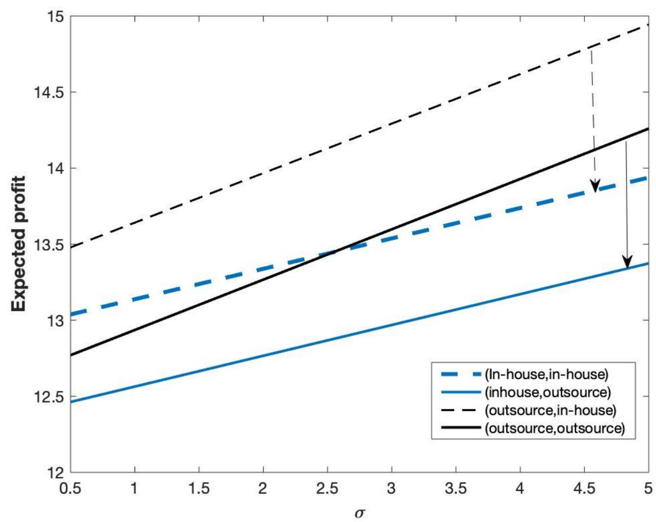
Theorem 1 (Comparative Statics of in-house production cost $c(q_i)$, upstream prices τ and demand uncertainty σ)

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 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.

[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 $\frac{\partial Pr(I_i=1)}{\partial \sigma} = -\frac{\partial Pr(I_i=0)}{\partial \sigma}$.

Figure 5: Expected Profit of Firm 1 at Different Demand Uncertainty Level



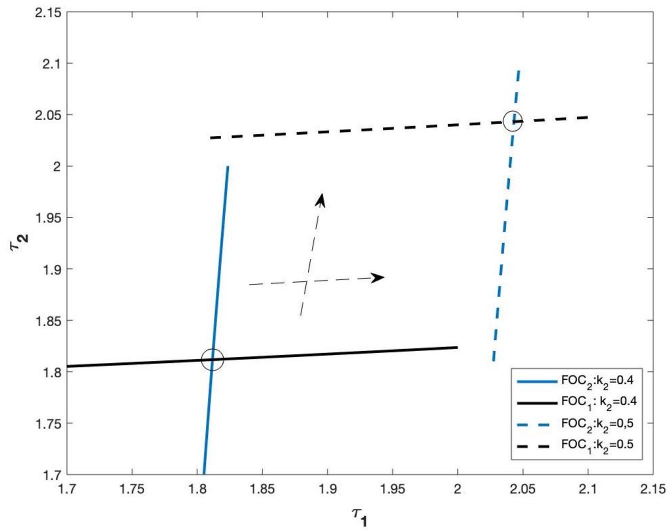
Notes: The solid lines are the expected profit of Firm 1 when Firm 2 chooses outsourcing. The dash lines are the expected profit Firm 1 when Firm 2 chooses in-house. Firm 1 compares the profit differences between outsourcing and in-house conditional on Firm 2's action.

Theorem 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 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 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 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.

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.

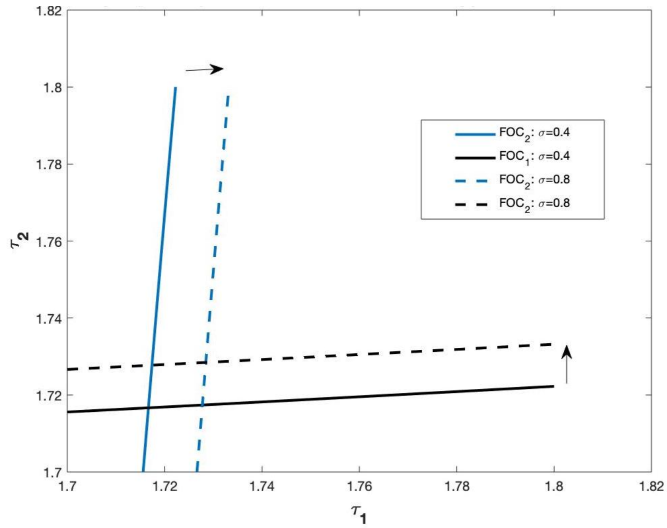
3.3 Full Model for Estimation

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

3.3.1 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

Figure 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.

utility that consumer i get from purchasing j in time t is defined as the following:

$$u_{ijt} = \underbrace{X_{jt}\beta - \alpha p_{jt} + \xi_{jt}}_{\delta_{jt}\text{: linear utility}} + \underbrace{\nu_{i0}\beta_{\nu}^{0} + log(Y_i)\beta_{d}^{p} p_{jt}}_{\mu_{ijt}\text{: non-linear utility}} + \epsilon_{ijt} \tag{1}$$

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

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

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 product $j \in J_t$ is given by

$$D_{jt} = N_t \int \frac{exp(\delta_{jt} + \nu_{i0}\beta_\nu^0 + log(Y_i)\beta_d^p p_{jt})}{1 + \sum_{m \in J_t} exp(\delta_{mt} + \nu_{i0}\beta_\nu^0 + log(Y_i)\beta_d^p p_{mt})} dF_v(\nu_{i0}) F_d(Y_i) \tag{2}$$

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:

$$\pi_{ft} = \sum_{j \in J_{ft}} D_{jt}(p_{jt} - X_{jt}\gamma - \omega_{jt} - (1 - I_{jt})\tau_{sht(j)}) - I_{jt}c(D_{jt}) \tag{3}$$

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

$$\mathbf{p_t} - mc_t = (T_t{}^*\Delta(\mathbf{p_t}))^{-1} D_t(\mathbf{p_t}) \tag{4}$$

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

[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.

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 $\mathbf{e_t} = (\boldsymbol{\xi}_t, \boldsymbol{\omega}_t)$. Product characteristics $\mathbf{x_t}$ are suppressed because they are invariant in the model.

3.3.2 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 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

[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.

[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

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 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 assume private information of firms.[28]

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).

[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.

[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

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 across actions.[29]

$$Pr_{fht}(a_{fht} = 1) = \frac{exp(E\Pi_{fht}(a_{fht} = 1, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot))}{\sum_{k \in \mathbf{A}_{fht}} exp(E\Pi_{fht}(a_{fht} = k, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot))} = \Psi(\mathbf{Pr_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) \tag{5}$$

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.

$$\mathbf{Pr_t} = \Psi(\mathbf{Pr_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) \tag{6}$$

3.3.3 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

to my case.

[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.

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 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 $\mathbf{Pr_t}$:

$$\begin{aligned} FOC = & \sum_{f \in F_{sht}} \sum_{j \in J_{fht}} \sum_{\mathbf{a_t}} ED^{O*}_{jt}(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) Pr^*_t(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) \\ & + (\tau_{sht} - mc_{sht}) \sum_{f \in F_{sht}} \sum_{j \in J_{fht}} \sum_{\mathbf{a_t}} ED^{O*}_{jt}(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) \frac{dPr(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot)}{d\tau_{sht}} \\ & + (\tau_{sht} - mc_{sht}) \sum_{f \in F_{sht}} \sum_{j \in J_{fht}} \sum_{\mathbf{a_t}} ED^{O*}_{jt,\tau}(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) Pr^*_t(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) \end{aligned} \tag{7}$$

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

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

[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.

bilateral bargaining.[32] The bilateral bargaining framework predicts 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 primitives, it is necessary to solve counterfactuals under different circumstances. The assumption of linear contract reduce the contract space and keep the problem computationally tractable.

3.3.4 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

[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).

[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 vertical relationships best fit the profit margin data.

Nash-Bertrand price equilibrium by solving the downstream firms' first-order conditions specified Equation 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 5. In addition, their beliefs are consistent and satisfy Equation 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 7. The transmission prices of H_{st} products are determined in a Nash-Bertrand price equilibrium based on expected demand.

4 Identification and Estimation

The parameters to be estimated are the demand parameters $\theta^d = (\beta, \alpha, \beta^0_\nu, \beta^p_d)$, the marginal cost parameters $\theta^s = (\gamma, \tau)$, the in-house cost function $c(\cdot)$ and the marginal cost of upstream firms mc_{sht}.

4.1 Estimating Downstream Demand-side Parameters θ^d

From the downstream firms' demand equation,

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

Berry (1994) proves that δ_{jt} can be obtained by contraction mapping, $\delta_{jt} = f(\mathbf{D_t}, \mathbf{p_t}, \beta^0_\nu, \beta^p_d)$. 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:

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

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^0_ν and β^p_d. 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.

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:

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

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

[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).

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.

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

[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

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 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.

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 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.

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.

5.1 Estimation Results for θ^d and θ^s

Table 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

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

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.

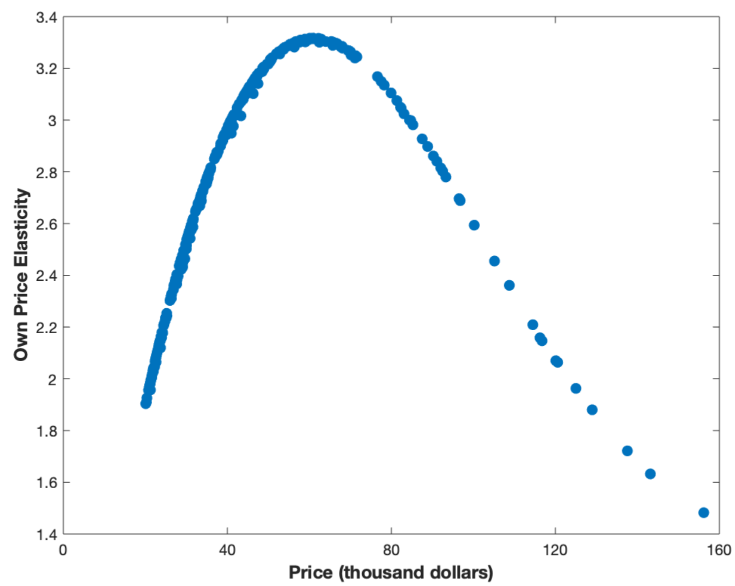
Table 3: Downstream Firms' Demand Estimation Results

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).

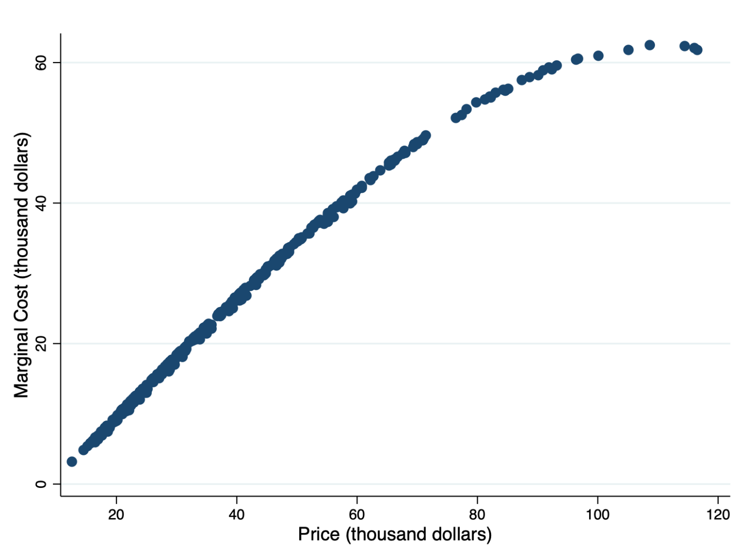
The demand system also implies sensible elasticities. I allow the price elasticity to depend on the income level, and estimates show that consumers with a higher income level tend to be less price-sensitive. Consistent with profit maximization in oligopoly, all price elasticities are greater than 1. As shown in Figure 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 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 Verboven (2001), Nurski and Verboven (2016). I plot the marginal cost against vehicle prices for my data sample in 2018 in Figure 9. In general, more expensive vehicle products also have higher marginal costs, reflecting their quality differences.

Figure 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.

Figure 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.

Table 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 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 average 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.

Figure 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,

Table 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.

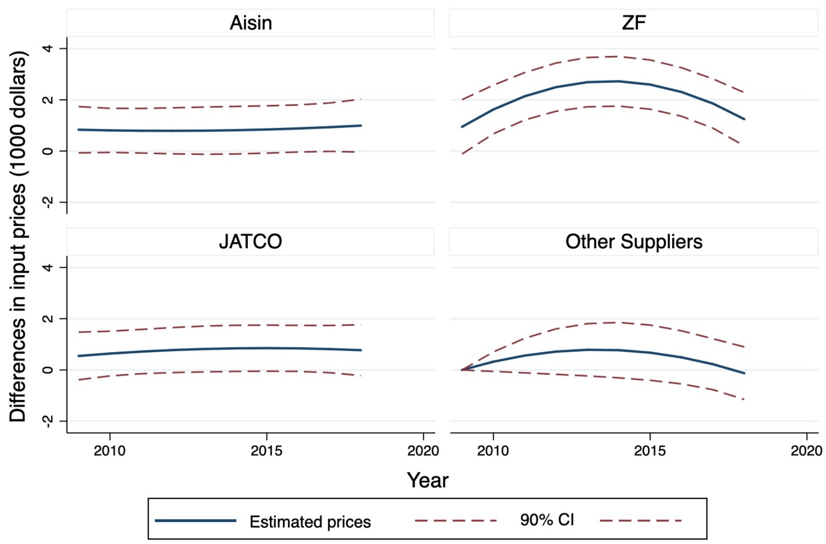
they are more expensive than MT. The price differences are also significant at a 10% significance level.

Figure 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.

5.2 Estimation Results for mc_{st}

In Figure 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

Figure 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 $\tau_{st} = \hat{\tau}_s + \tau_s^{\hat{trend}} t + \tau_s^{\hat{trend_2}} t^2$.

and products composition. There is also a positive correlation between the profit margin and industry level HHI across time.[40]

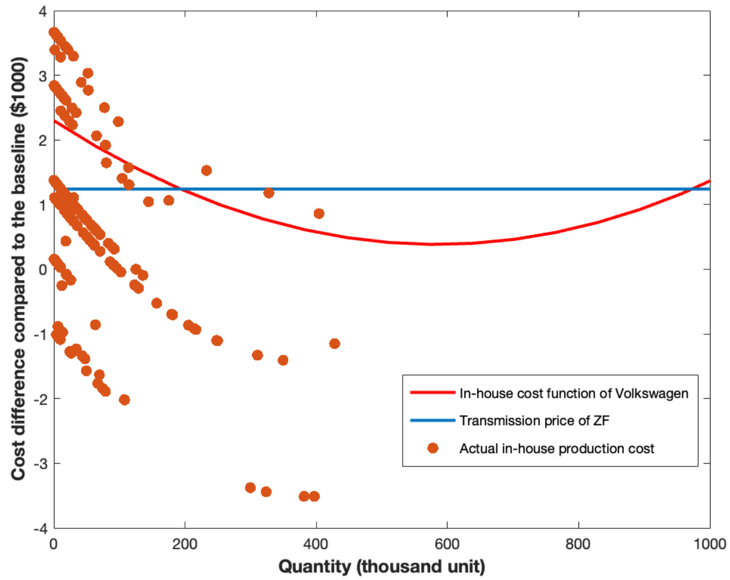
5.3 Empirical Patterns between Demand risk, Upstream Market Power and Outsourcing Decision

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-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

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

Figure 11: Transmission Cost Differences: In-house Versus Outsourcing



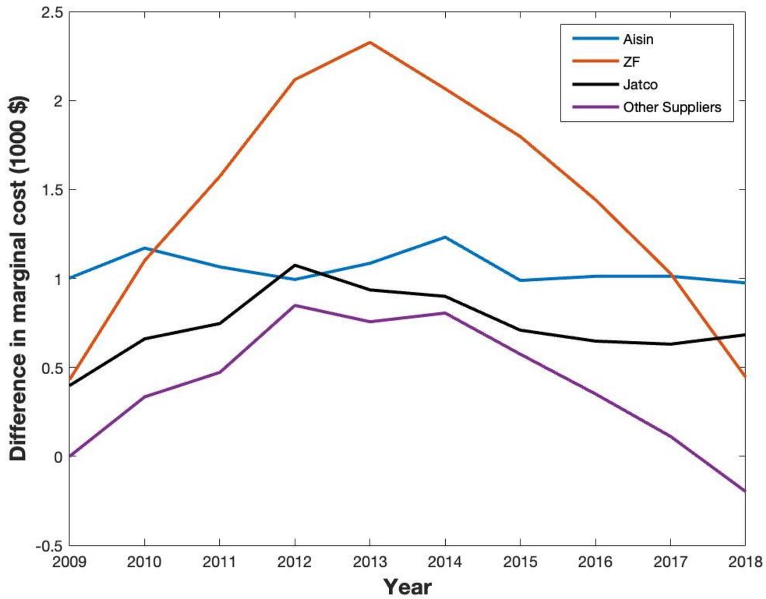
Notes: The red curve is drawn from the cost function of Volkswagen. Actual in-house production cost are computed using the estimates and realized equilibrium demand. The blue horizontal line is the equilibrium price of ZF in 2018.

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 annu-

Figure 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 7 and I use the estimated equilibrium upstream prices and parameter primitives of each year to back out the marginal cost.

ally.

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

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 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.

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

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.

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.

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 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 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.

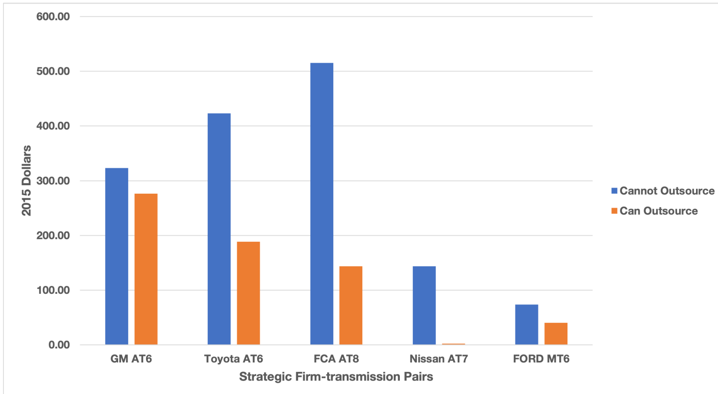
The differences in transmission cost also translate into differences in expected profit for the downstream firms. Downstream firms' profits decrease when facing a shrinking demand. However, outsourcing enables downstream firms to transmit some in-house cost disadvantages to the upstream and attenuates the profit loss. According to Figure 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 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

[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.

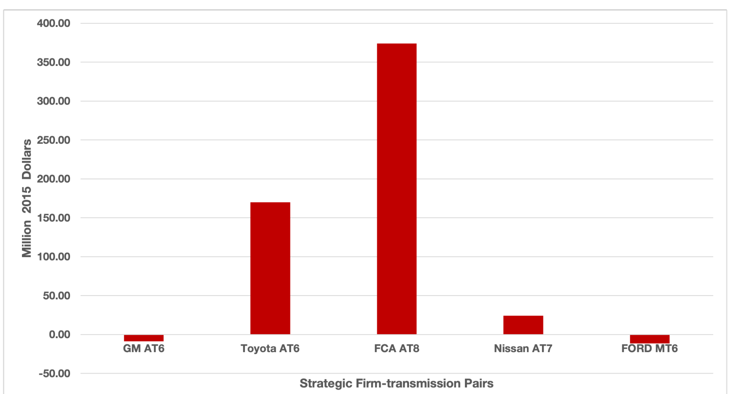
Figure 13: Changes in Transmission Cost in Economic Bust



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.

the cost of transmission, it also reduces the negative-shock-induced consumer welfare loss by $1.24 billion.

Figure 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)

According to Table 7 column (1), most strategic firm-transmission pairs increase their outsourcing propensities to transfer the unfavorable shocks to the upstream firms.[44] The new equilibrium transmission prices of the four upstream firms all increase in response to the rise

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

in their market shares, and hence the weighted average price increases by $137.18.[45] According to Table 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.

Table 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 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 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

[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.

lower transmission price.

Table 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.

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 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 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%.

Table 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.

Downstream firms intend to expand outsourcing when facing a cost disadvantage 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.

6.3 A Propagation of Idiosyncratic Demand Uncertainty in the Production Network

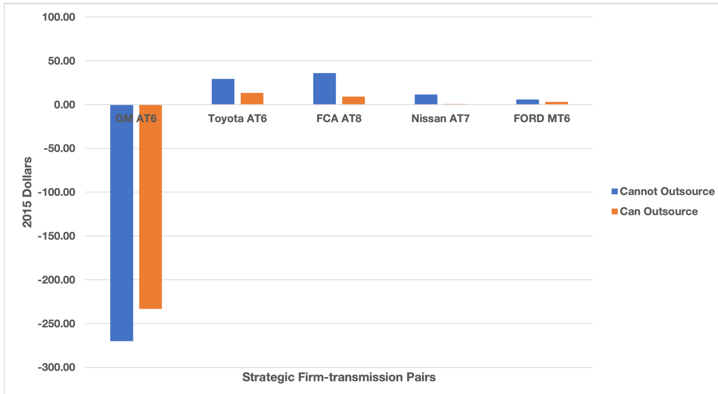
I finally examine the impact of increased idiosyncratic demand uncertainty. A downstream firm can be affected by its own demand uncertainty and the demand uncertainty of its competitor. Since upstream firms charge a uniform price based on the expected input demand, the demand uncertainty will propagate 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 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 15, Toyota and FCA are affected most significantly.

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

[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.

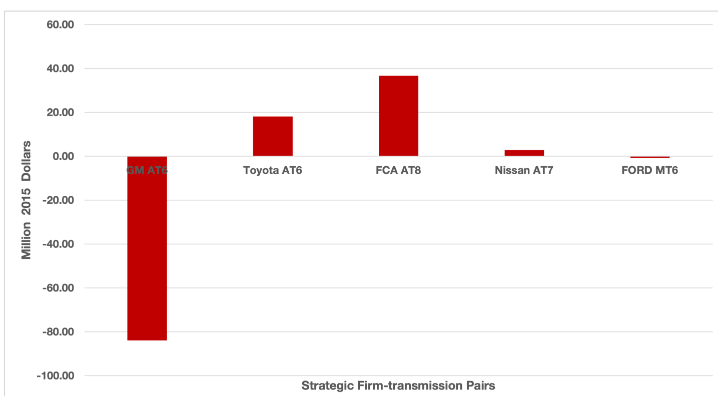
Figure 15: Changes in Transmission Cost with Demand Uncertainty Increase



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.

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 11. Due to the existence of upstream, the expected profit for the other firm-transmission pairs also decreases less in Figure 16.

Figure 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)

Upstream firms respond to their expected demand and adjust their prices. According to Table 12, the price drop of Aisin is most significant ($\sim 7\%$) because of the increasing in-house

Table 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.

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 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 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 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.

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

Table 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.

the transmission prices. I additionally use this counterfactual to understand the role of upstream market structure in the propagation of idiosyncratic shocks.

Table 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 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.

Column (3) and (4) in Table 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

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

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.

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.

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Appendix A: 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 **x**, the parameters and time script.:

$$g_j(\mathbf{p}^*, \mathbf{e}, \cdot) + \sum_{j' \in J_{ft}} (p_{j'}^*(\boldsymbol{\tau}, \mathbf{I}, \mathbf{e}, \cdot) - mc_{j'}(g_{j'}^*, \boldsymbol{\tau}, \mathbf{I}, \mathbf{e}, \cdot)) \frac{\partial g_{j'}(\mathbf{p}^*, \mathbf{e}, \cdot)}{\partial p_j^*(\boldsymbol{\tau}, \mathbf{I}, \mathbf{e}, \cdot)} = 0 \quad \text{(B1)}$$

In matrix form:

$$FOC(\mathbf{p}^*, \boldsymbol{\tau}) = p^*(\boldsymbol{\tau}, \mathbf{I}, \mathbf{e}, \cdot) - mc(g^*, \boldsymbol{\tau}, \mathbf{I}, \mathbf{e}, \cdot) + \Delta(p^*, \boldsymbol{\tau}, \mathbf{I}, \mathbf{e}, \cdot)^{-1} g(\mathbf{p}^*, \mathbf{e}, \cdot) = \mathbf{0} \quad \text{(B2)}$$

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 **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:

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

$$cost_j = X_j\gamma + \omega_j + (1 - I^n_j)\tau_{s(j)} + I^n_j(c_{1_j} + c_2 N g^*_j + c_3(Ng^*_j)^2)$$

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

$$E g^{O*}_j(\mathbf{p}^*, \mathbf{a}, \cdot) = \frac{1}{N}\sum_n (1 - I^n_j)\frac{1}{M}\sum_m g^*_j(\mathbf{p}^*, \mathbf{I^n}, \mathbf{e^m}, \cdot)$$

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

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

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

$$Pr_{fh}(a_{fh}=1) = \frac{exp(E\Pi_{fh}(a_{fh}=1,\boldsymbol{\tau},\cdot))}{\sum_{k\in\mathbf{A}_{fh}} exp(E\Pi_{fh}(a_{fh}=k,\boldsymbol{\tau},\cdot))} = \Psi(\mathbf{Pr},\boldsymbol{\tau},\cdot) \tag{B3}$$

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:

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

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

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.

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.

Table A1: 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.

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 A2: 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.

Appendix B: 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,

$$p_q(a|\boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) = \frac{exp(E\Pi_q(a_{fht}, \hat{n}_t(a_{-fht}), \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot))}{1 + \sum_{a' \in A} exp(\Pi_q(a'_{fht}, \hat{n}_t(a_{-fht}), \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot))} \tag{B4}$$

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:

$$\pi_{st} = (\tau_{st} - mc_{st}) \underbrace{\sum_{q_s \in s} \sum_{q_s} \sum_{a} \hat{n}_{qt}^*(a) ED_{qt}^{O*}(\hat{n}_t^*, \boldsymbol{\tau_t}, bm\sigma_t, \cdot)}_{\text{Transmission demand of supplier s}} \tag{B5}$$

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