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

Qinshu Xue

This paper studies how upstream market concentration and demand risk affect the outsourcing decisions of downstream firms. When facing demand shocks, outsourcing allows the downstream firms to hedge the uncertain in-house production cost, while upstream firms exploit the downstream's insurance motive by exerting market power. I specify and estimate the model using data on 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 the production cost of transmission 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. The policy 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

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, these upstream firms also increase prices in response to the outsourcing motives. By forcing the downstream firms to retain 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 on consumer welfare. By endogenizing the 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 and is affected by the macroeconomic environment, the ongoing technological disruption, and the within-industry uncertainty about consumer taste.[3] 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. With production relegated to upstream firms, the downstream firms are insured against the risk of a fluctuating in-house production cost of a particular input induced by demand volatility.

In addition, the auto industry is seeing a shift in power from the vehicle manufacturers to the suppliers. For the empirical analysis, I focus on the outsourcing decision of the transmission, a core component in the powertrain system that accounts for about 7% of the cost of a car. The transmission market provides a suitable setting to study my question. First, compared with most parts that are fully outsourced nowadays, some downstream manufacturers still preserve sizable in-house production. In addition,

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

[2]This is 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..."

[3]According to Ramey and Vine (2006), the auto industry represents almost 5% of the aggregate GDP in the US and accounted for almost 25% of the variance in the past 40 years. Their paper shows that the volatility declined in the early 2000s. Following their exact computation method, I find that the auto industry still accounts for more than 20% of the variation in the aggregate GDP growth from 2004 through 2019.

due to technological barriers, the transmission industry in the US is highly concentrated. It is dominated by Aisin, ZF, and JATCO, which serve more than 90% of the market. Despite some technical differences, the core economic mechanism can also be applied to other industry setups which witnessed massive merger and acquisition in the past few years.

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.

I derive equilibrium outsourcing patterns, as well as the upstream transmission prices which are often held as exogenous in the previous literature. The model is built on two key features. Vehicle manufacturers use outsourcing decisions to hedge the risk of a fluctuating in-house production cost due to the demand shock. Meanwhile, the upstream firms provide a stable price regardless of demand shock realization, responding to manufacturers' outsourcing incentives. The insight goes beyond the automobile industry because many important sectors share a similar market structure.

I use a novel dataset that links upstream transmission firms and vehicles. Combining this dataset 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 that make nearly all transmissions in-house, also have the lowest estimated in-house production cost. I then use the equilibrium assumptions in my model to recover the upstream firms' marginal 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 insurance motive of outsourcing and the effect of upstream market power. When facing a shrinking demand comparable to that caused by the recent to the recent COVID-19 pandemic, the downstream firms use outsourcing to reduce the increasing cost of in-house production. Holding upstream's price fixed, outsourcing mitigates the increase in the average transmission cost by 48%. For the downstream firms that actively make outsourcing decisions, their profit loss during the economic bust could have been reduced by $548

million.[4] 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 for 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.[5] 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.

Related Literature: My work relates to three broad strands of literature: (i) vertical relations under risk, (ii) propagation of shocks in the production networks, and (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 the regional airlines they own instead of independent ones on city pairs with more adverse weather. These models predict that ownership should be allocated to ensure more efficient expost 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 a volatile demand by choosing which demand shocks are retained within the 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 together with firms' outsourcing decisions under demand risk 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, these models may have difficulty explaining industry-level patterns because the fixed market-level variables are often equilibrium outcomes.[6] By endogenizing the pricing response to downstream firms' outsourcing decisions, my model delivers equi-

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

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

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

librium 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 for producing internally to avoid the markup charged by upstream suppliers. A similar argument has been made by Garetto (2013) in the setup of multinational firms' input sourcing decisions. I contribute to this literature by developing a tractable structural model that embeds the demand risk in firms' cost-driven incentives, empirically quantifies the importance of this insurance motive, and analyzes the welfare effect.

My research links to the growing literature on the propagation and amplification of shocks through production networks. Previous literature builds multi-sector models to show how microeconomic shocks can translate into aggregate fluctuations through the input-output linkages (Long and Plosser, 1983; Acemoglu et al., 2012, 2017). In empirical studies, disaster-induced shocks are a natural candidate to explore as they cleanly distinguish input disruptions from demand shocks. Carvalho et al. (2020) document the impact of the Great East Japan Earthquake of 2011 along supply chains. Barrot and Sauvagnat (2016) use a broader range of natural disasters to further explore the input specificity as a micro foundation behind the input-output linkage mechanism. I contribute to this literature in two ways. First, my research provides an additional micro foundation by exploring the role of upstream market power in preventing downstream firms from effectively reallocating during economic downturns and increased volatility. By focusing on a specific but important sector, my model allows for variable markups both for the upstream and downstream firms and yields more realistic substitution patterns than the monopolistic competition framework assumed in CES models.[7] In addition, I structurally estimate the demand shock realization from a rich demand model in which both demand and cost-side impacts are carefully controlled. This method expands the types of shocks to be studied and also circumvents the common measurement issues prevalent in sale-based volatility measures.[8]

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 for corroborating various vertical relation theories and empirical analysis. However, most of the research focuses on testing the different types of transaction cost (Klein et al., 1978; Klein, 1988, 2000; Monteverde and Teece, 1982; Langlois and Robertson, 1989; Masten et al., 1989). Organization theories exploit the success of the Toyota business model and closely study the difference between American and Japanese subcontracting systems (Taylor and Wiggins, 1997).

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[7]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).

[8]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.

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 also contributes 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 that transmits 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. At higher speeds, gears change more smoothly and fuel efficiency is improved. As can be seen Figure 1, AT is the most popular transmission in the US due to its user-friendly design. CVT has gained 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 from 2009 to 2018. Aside from a substantial fraction of in-house production, only six firms are serving the US passenger car market. Aisin, ZF, and JATCO serve the entire market in the AT sector, which takes up more than 70% of the total market share in the US. The second most popular transmission, CVT, is manufactured 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, under the recent United States-Mexico-Canada Agreement (USMCA) and the "Bring Manufacturing Back to America" campaign, transmissions are regarded

Figure 1: Market Shares of Different Transmissions 2009-2018
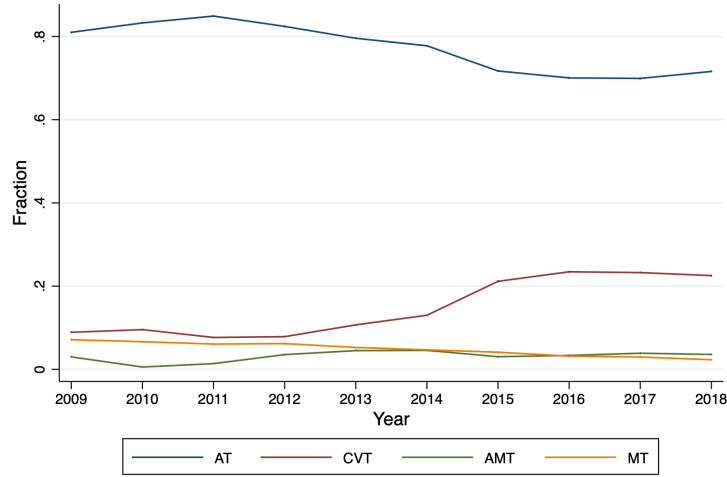
Notes: This figure shows the market shares of different transmissions sold in the US. The shares are based on the US passenger vehicles sold in the US 2009-2018. The y axis shows the fraction of transmissions for each type.

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.

as a super-core component.[9] To protect local industry and workers, the Regional Value

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

Content (RVC) of a car will be lifted from 66% to 75% over a four-year period. For transmissions to be considered original and qualified for preferential, duty-free treatment, they must meet the requirements for 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 penalty 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.

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.

Figure 2: Light Weight Vehicle Sales in the US 1975-2020
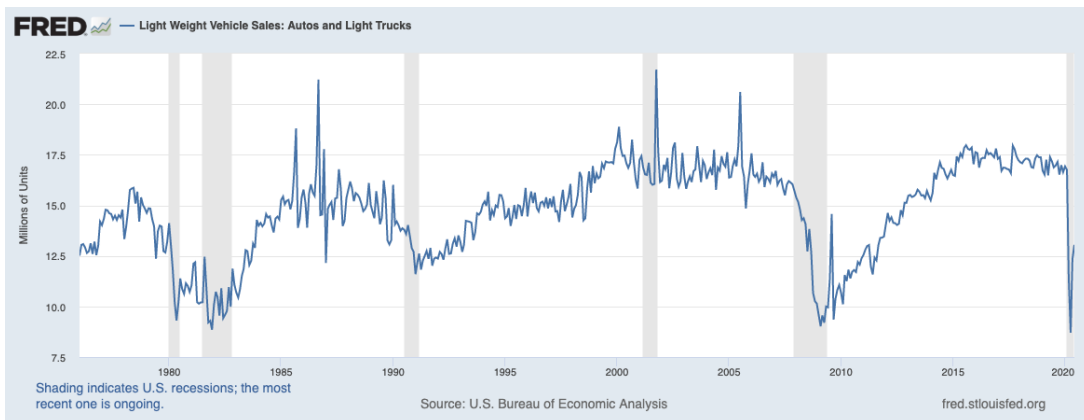
Notes: This figure is downloaded from St. Louis Fed and is based on the statistics from US Bureau of Economic Analysis. It shows the passenger vehicle sales in the US 1975-2020.

Compared with downstream vehicle manufacturers, upstream transmission firms are in a better position for 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 down-

stream firms are physically really similar.[10] In addition, the supply contract in the industry also facilitates demand risk transfers. The manufacturing contracts typically last for the whole product life cycle. As Figure 3 indicates, according to my data sample, downstream firms rarely change transmission providers. According to Mueller et al. (2008) in their extensive survey of German automobile companies, supply contracts almost never specify exact quantities. Even minimum quantities to be absorbed by the downstream firms are rarely specified. However, the unit prices in supply contracts are precisely specified for the initial delivery period, and prices for ensuing periods are either pre-specified with stepwise price reduction schedules to account for cost reductions or are renegotiated annually.

Figure 3: Number of Downstream Firms Switching Transmission Providers 2009-2018
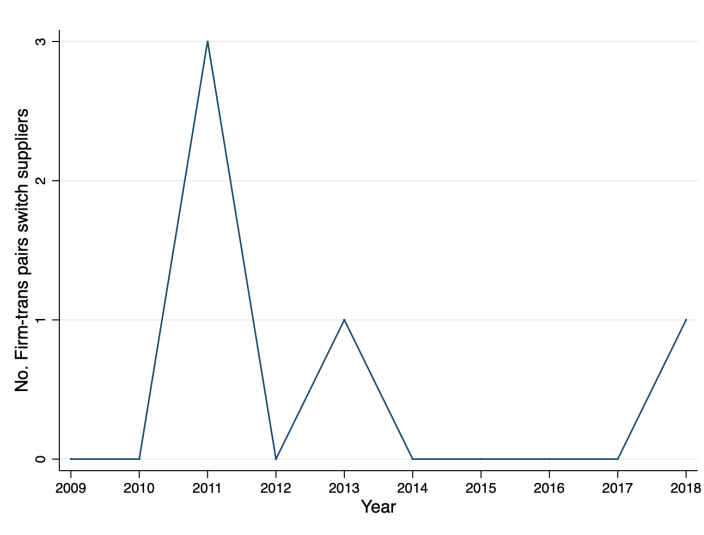

Notes: This figure shows the total number of downstream firms-transmission pairs that switch to a different upstream firm in each year. The maximum switching fraction is less than 4%.

Unlike many other parts which are completely outsourced, transmissions are still produced 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 measures. Even though my data rarely indicates upstream switches, the firms are 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, the product-based in-house share measure begins to recover while the output-based in-house share measure still falls.

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[10]Udo Rügheimer, automotive spokesman at Bosch said "We are in the ideal position for scale effects. We sell similar components, not identical, but similar components to...the Tata Nano and also the Mercedes S-Class. In principle, the parts can be produced on the same machine."

Figure 4: Transmission In-House Production Share 2009-2018
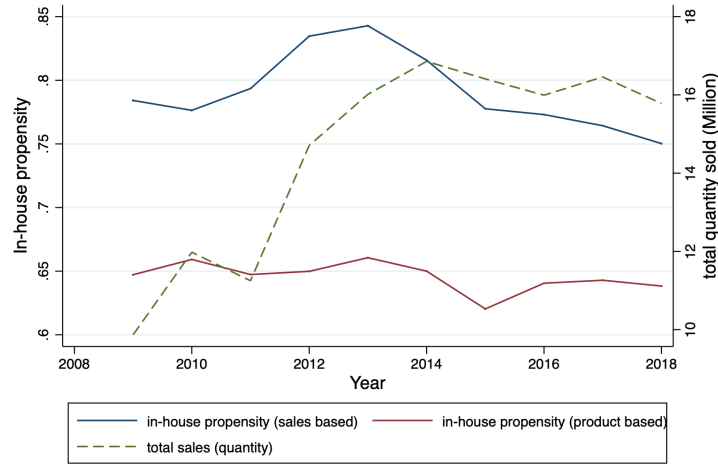
Notes: The dashed line is the annual output level. The blue and red solid lines represent fractions of cars sold with in-house built transmission. The y axis on the left shows the level of in-house transmission fraction.

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. Producers of car parts 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. In reality, it is still impossible to track each of the ten thousand parts for every model as it is very costly to do so. 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 that produces it, for consumers to order the correct product via their platform.[11] I collect a complete transmission firm and vehicle link for all models produced in the US for the years 2009 through 2018 via the website.

I obtain data on light vehicle sales and prices from WardsAuto, one of the premier automotive industry publications. WardsAuto 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, and transmission type. I define a product at a make-model-transmission level (e.g., Honda Accord AT6). Using the characteristics at a trim level, I construct a baseline version for each product using the median product characteristics across trim variants within a model transmission pair. WardsAuto also provides detailed sales data for each model by different transmissions. Even though the MSRP may be different from the actual price consumers pay, discounts tend to be uniform across consumers and mainly differ by manufacturer brand (Nurski and Verboven, 2016).

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[11]https://transend.us/

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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.[12] 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 2009-2018 demographics information, 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 3,848 products in this ten-year period. I follow Berry et al. (1995) to use the total households 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 use outsourced transmissions 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 2015 is used 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 3,848 products across the ten years. I further exclude cars with no transmission, which are most electric vehicles.

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

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 in 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 the outsourcing decision is made. If the firm sources from the upstream firms, it faces a precommitted 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., to differ in quality). In each period, upstream firms set the transmission prices τ_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 τ_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 τ_t; in stage 3, the demand shock and marginal cost shock are realized and 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 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 of how much to outsource.

The data pattern justifies this assumption in that the choice of transmission firms rarely changes on an annual basis. As Figure 3 indicates, 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 firms due to an enormous upfront development cost.[13] 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; 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 they do in the home PC market.[14] In my data sample, a product on average lives for more than four years. In addition, the decision on product entry and exit is neither driven mainly by demand fluctuations nor 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 that 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 of Grennan and Swanson (2020) that the access to information on purchasing by peers limits the room for asymmetric information and price differences.

3.2   Full Model for Estimation

Here I formally define the model and equilibrium I later bring to the data.[15]

3.2.1   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).

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[13]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.

[14]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.

[15]I also provide a simple linear model for illustrative purpose in Appendix A.

Each buyer i decides whether to purchase a product j from J_t choices or the outside option to maximize utility. The utility that consumer i get from purchasing j in time t is defined as the following:

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

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, transmission types, and transmission firm dummies.[16] 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. 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 v_{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, v_{i0} are drawn from a multivariate normal distribution. I further assume that these unobserved errors are not correlated.

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

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

N_t is the market size at year t. F_v and F_d are the CDF of v_{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:

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

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[16]Transmission firm dummies capture quality differences among transmissions firms. Even though each upstream firm offers different products, I assume the quality impact is the same. For example, ZF will offer both high-quality products in AT6 and AT8 markets.

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.[17] If the transmission is outsourced, it faces a price of τ_{sht} charged by the product j's corresponding upstream firm s.[18] I assume that given the transmission prices τ_t and the outsourcing decisions 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 zero otherwise. $\Delta_{i,j}$ is the derivative of the market share of product j with respect to the price of product i. $*$ is an element-by-element multiplication. The optimal price can be denoted as $p_t^*(\tau_t, \mathbf{I_t}, \mathbf{e_t}, \cdot)$. I use a fixed point mapping to solve for the equilibrium prices, which depend on the transmission prices, the outsourcing allocations and the demand and marginal cost shocks $\mathbf{e_t} = (\xi_t, \omega_t)$. Product characteristics $\mathbf{x_t}$ are suppressed because they are invariant in the model.[19]

3.2.2   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.[20] 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 het-

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

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

[19]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.

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

erogeneous.[21] 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.[22] 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 (CD-CPs) 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.[23] Similar algorithms are developed in the international trade literature to study the input sourcing problems (Arkolakis and Eckert, 2017; Antràs et al., 2017). Because I incorporate a very flexible competition among downstream vehicle manufacturers, my problem is more complicated in two ways. First, unlike the CES demand commonly used in the international trade literature, the outsourcing decision in my setup also depends on the decisions of other agents.[24] Second, these reduction methods often rely on some single crossing differences or supermodularity properties of profit functions.[25] 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 $E\pi_{fht}(a_{fht}, a_{-fht}, \tau_t, \sigma_t, \cdot)$ 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 $\mathbf{e_t}$. σ_t is the variance of demand shock.[26] To compute the return of action, I simulate N sets of outsourcing products and compute the average. Here $\pi_{jt}^*(\tau_t, \mathbf{I_t^n}, \mathbf{e_t^m}, \cdot)$ is the equilibrium profit of product j when an assignment simulation draw is $\mathbf{I_t^n}$ and the shock draw is $\mathbf{e_t^m}$. The profit is aggregated to a transmission level by adding up the profit of each product j using a transmission h within a firm f.

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

[22]For example, for a firm-transmission pair that has ten products and $a_{fht} = 1/2$, on average five products will be made in house. However, the five models to be made in house are picked at random.

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

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

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

[26]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.

$$E\pi_{fht}(a_{fht}, a_{-fht}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) = \sum_{j \in J_{fht}} \frac{1}{N} \sum_n \frac{1}{M} \sum_m \pi_{jt}^*(\boldsymbol{\tau_t}, \mathbf{I_t^n}, \mathbf{e_t^m}, \cdot)$$

For each firm-transmission pair, there are also K state variables. I label them as $\epsilon_{fht}(a_{fht})$ which are private information to each firm-transmission pair for each action. These are the idiosyncratic sources of profitability that 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 firms have private information.[27] 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 is 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 forms 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 beliefs of the other rivals' strategies 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:

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

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.[28]

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

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

[28]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.

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

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

3.2.3 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 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.[29] The expected profit of each upstream s for each transmission type h is as follows:

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

Upstream firms set prices τ_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 with whom upstream firm s has signed a contract with for each transmission type h. $ED_{jt}^{O*}(\mathbf{a_t}, \tau_t, \sigma_t, \cdot)$ is the expected equilibrium outsourcing demand (quantity) at a given action vector $\mathbf{a_t}$.[30]

The equilibrium transmission prices τ_t satisfy the vector of first-order conditions listed below. Increasing input prices would have three separate effects. First, doing so 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 $ED_{jt,\tau}^{O*}$. The first-order condition also indicates that upstream firms' prices respond to demand volatility σ_t, and downstream firms' outsourcing strategies $\mathbf{Pr_t}$:

$$FOC = \sum_{f \in F_{sht}} \sum_{j \in J_{fht}} \sum_{\mathbf{a_t}} ED_{jt}^{O*}(\mathbf{a_t}, \tau_t, \sigma_t, \cdot) Pr_t^*(\mathbf{a_t}, \tau_t, \sigma_t, \cdot)$$

$$+ (\tau_{sht} - mc_{sht}) \sum_{f \in F_{sht}} \sum_{j \in J_{fht}} \sum_{\mathbf{a_t}} ED_{jt}^{O*}(\mathbf{a_t}, \tau_t, \sigma_t, \cdot) \frac{dPr(\mathbf{a_t}, \tau_t, \sigma_t, \cdot)}{d\tau_{sht}}$$

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

[30]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.

$$+ (\tau_{sht} - mc_{sht}) \sum_{f \in F_{sht}} \sum_{j \in J_{fht}} \sum_{\mathbf{a_t}} ED_{jt,\tau}^{O*}(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) Pr_t^*(\mathbf{a_t}, \boldsymbol{\tau_t}, \boldsymbol{\sigma_t}, \cdot) \tag{7}$$

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 B.

In my setup, the transmission prices are set by the upstream firms instead of through bilateral bargaining.[31] 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.[32] Finally, 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.[33] It is consistent with the supply contact in the industry that only a unit price is specified for demand risk transfer. Further, 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).[34] In addition, to explore changes in market primitives, it is necessary to solve counterfactuals under different circumstances. The assumption of linear contract reduces the contract space and keeps the problem computationally tractable.

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[31]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).

[32]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.

[33]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.

[34]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.

3.2.4 Equilibrium

An equilibrium in this model is a set of upstream prices τ_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 τ_t, $\mathbf{Pr_t}$, and the realization of $\mathbf{e_t}$, prices of J_t products are uniquely determined in a Nash-Bertrand price equilibrium by solving the downstream firms' first-order conditions as specified in Equation 4.

2. Given τ_t, the equilibrium outsourcing strategies $\mathbf{Pr_t}$ best respond to each other based on 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. τ_t satisfies 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 $\theta^d = (\beta, \alpha, \beta_v^0, \beta_d^p)$, 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,

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

The expression $\delta_{jt} = f(\mathbf{D_t}, \mathbf{p_t}, \beta_v^0, \beta_d^p)$ represents the utility of product j. Berry (1994) proves that δ_{jt} can be obtained by contraction mapping. 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:

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

$(\mathbf{D_t}, \mathbf{p_t})$ are correlated with ξ_{jt}, which is not observed. Instruments for $(\mathbf{D_t}, \mathbf{p_t})$ are used to identify the non-linear parameters β_v^0 and β_d^p. The number of instruments should be greater 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 are assumed to have been determined prior

to the realization of ξ_{jt} in my model and since 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. The expression $d^{\hat{p}}_{jt,j'}$ represents the difference in the predicted price between product j and j', where the projection is based on exogenous variables like characteristics and cost shifters. I also add the Bureau of Labor Statistics estimate of the production wage in the MSA where each vehicle model is assembled to proxy for the factory wage rate.(Wollmann, 2018)[35] According to 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 minimal variations in characteristics. I use the sample variance of the demand shock realization to estimate the variance:

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

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

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[35]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 US dollars using Purchasing power parity (PPP).

ative 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 parametrize the cost function of in-house production by a flexible third-order polynomial. 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.[36] To further reduce the number of parameters needed to be estimated, I fit a second order polynomial of each upstream firm's price as $\tau_{st} = \tau_s + \tau_s^{trend}t + \tau_s^{trend_2}t^2$.[37] Therefore, instead of estimating s*t number of fixed cost, I just need to estimate 3*s number of parameters. According to the model's timing assumption, product characteristics (X_{jt}) and the decisions of outsourcing (I_{jt}) are determined before the realization of supply-side shocks.

However, the output, demand which enters into the cost of producing a transmission in-house, is an equilibrium object depending on the unobserved marginal cost shock ω_{jt}. I construct a similar instrument in the spirit of Gandhi and Houde (2019). Instead of using exogenous product characteristics to predict prices, I use these product characteristics to predict the demand variable D_{jt} via Lasso. Belloni et al. (2012) show that IV estimator based on using Lasso or Post-Lasso in the first stage is root-n consistent and asymptotically normal. Therefore, the standard inference procedures can be applied. In addition, Belloni et al. (2012) 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 the difference between c_1 and τ_s is identified.

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[36] To reduce the number of parameters to estimate and the equilibrium upstream firms' prices to compute in the counterfactuals, I 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) provided 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 compared with a ZF six-speed."(EPA/FEV 2011)

[37] The expression t is the number of years from the first year in my data sample: t=year-2009

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 B. Since I use only four upstream firms and ten years, I don't 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 this is not a key focus of my paper.

The major challenge of estimating the model is solving the discrete game the vehicle manufacturers employ when making outsourcing decisions. Since the industry is populated with many firms, each with many actions, the full solution method is 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 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 B. 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.[38]

Adding information on the outsourcing choice of downstream firms would increase efficiency. Since the model cannot be fully solved, it also introduces misspecification errors when using SMLE. In addition, the relatively shorter time period covered by my data sample prevents the use of a two-stage Conditional Choice Probability (CCP) method because the conditional choice probability cannot be estimated 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 C 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 state industry-level average behaves poorly.

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

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. SUVs have a premium of $5217 compared to sedans. There are also significant differences in transmissions. Transmissions made by ZF have a higher premium of $10961, and cars equipped with ZF transmissions are, on average, of better product quality. Therefore, the premium consists of the transmission premium and other potential complementarities between ZF transmission and the vehicle. The heterogeneity on the outside option is also significant. The standard deviation is about 60% of the mean. It captures the dispersion in the consumer's outside option value. Accounting for this consumer heterogeneity implies more flexible substitution patterns and more sensible markups.

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 5, more expensive products have less elastic demand since they target wealthier households. In addition, the product competition is concentrated on 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 2018 data sample in Figure 6. In general, more expensive vehicle models also have higher marginal costs, reflecting their quality differences.

Table 5 reports the estimates of the supply system of downstream firms. Since larger horsepower, bigger size, and higher fuel efficiency all add 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 heterogene-

Figure 5: Own-Price Elasticity of Products in Year 2018
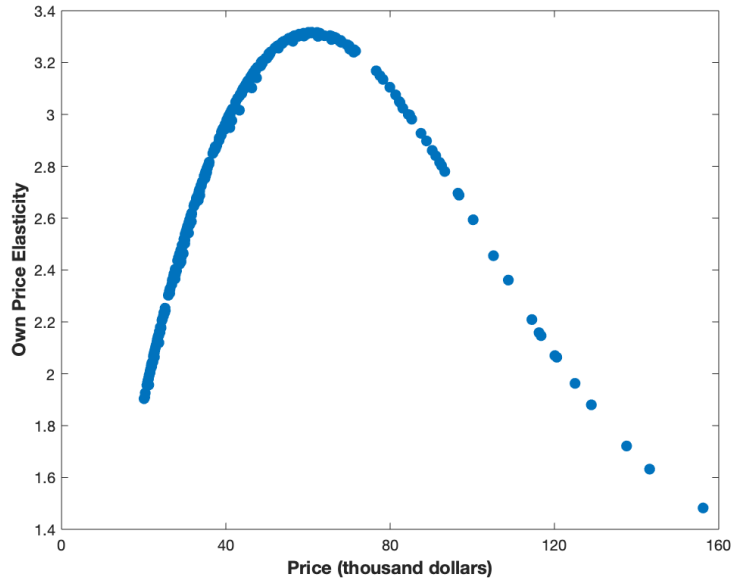
Notes: This figure shows own price elasticity of the products sold in year 2018. Each data point is a model-transmission-year. Price elasticity is the percentage change in a product's sales in a year over a one percentage change in MSRP price.

Figure 6: Marginal Cost of Products in Year 2018
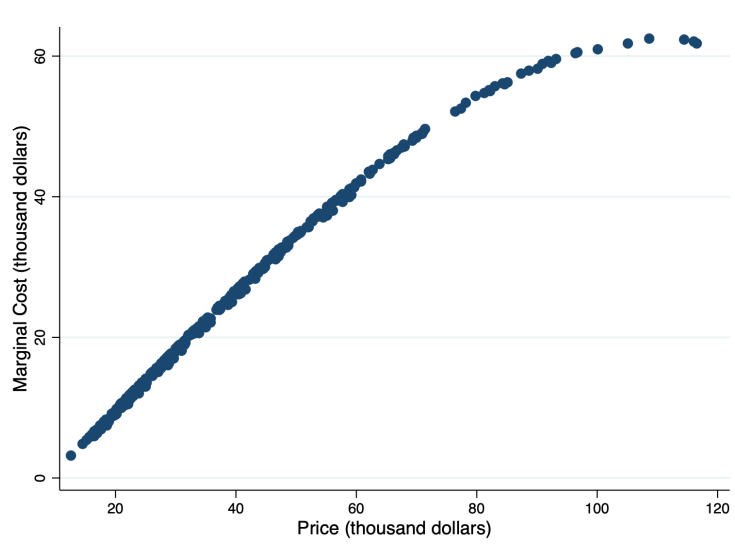
Notes: This figure shows marginal cost products sold in year 2018. Each data point is a model-transmission-year. The marginal cost of each product is inverted out from the downstream firms' first-order condition after demand estimation.

Table 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, in parentheses, are clustered at the product level. For the 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 is the same as Dubé et al. (2012).

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

ity in downstream firms. According to the data pattern, Daimler, Honda, Hyundai, and Volkswagen have significantly large in-house production portions, which 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 character-

istics 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 unreasonably large coefficient estimates. The results also show that weak IV can lead to inconsistent estimates.

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

Figure 7 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 the types of transmission products they offer. ATs and CVTs, which are produced mainly by Aisin, ZF and JATCO, are more expensive than MT. The price differences are also significant at a 10% significance level.

Figure 8 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, by 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 9, I plot the differences in the marginal cost of each upstream firm from 2009 to 2018 and compare these with the marginal cost of the other-supplier group in

Figure 7: Transmission Prices Differences Across Years
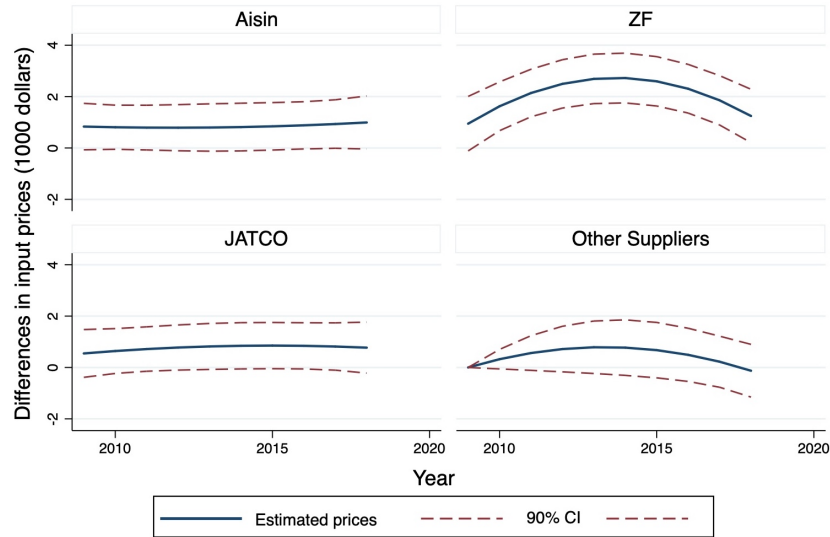
Notes: This figure shows the transmission price differences compared to τ_O charged by upstream firms. Estimated transmission prices are computed as $\tau_{st} = \hat{\tau}_s + \tau_s^{\widehat{trend}}t + \tau_s^{\widehat{trend_2}}t^2$.

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 those of 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 the other three upstream firms in the "other-supplier" category, the variations in marginal cost are probably due to a change in the composition of the upstream firm and it products. There is also a positive correlation between the profit margin and industry level HHI across time.[39]

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[39]For the full set of stimulation specifications I use for computing the marginal cost, please refer to Appendix B Table A2.

Figure 8: Transmission Cost Differences: In-house Versus Outsourcing
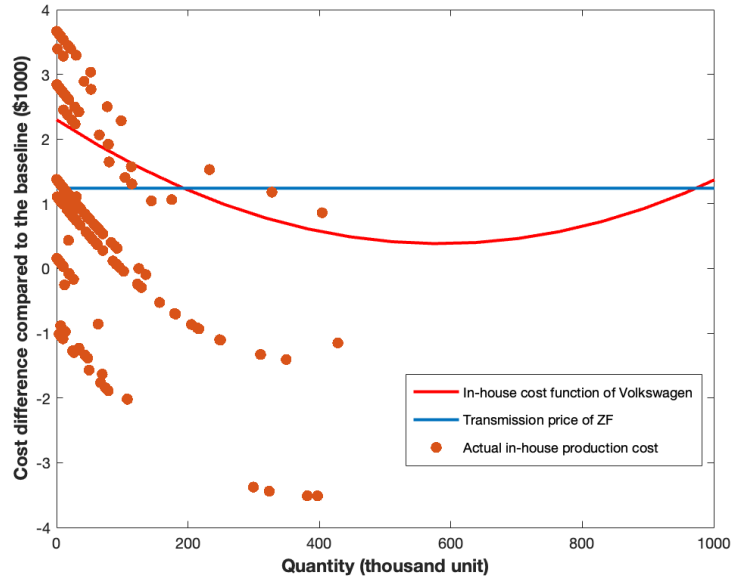
Notes: This figure plots the cost difference between the in-house and the outsourced transmission of selected downstream manufacturers. The red curve is drawn from the cost function of Volkswagen. Actual in-house production cost are computed using the estimates and realized equilibrium demand. The blue horizontal line is the equilibrium price of ZF in 2018.

Figure 9: Upstream Firms' Marginal Cost Differences
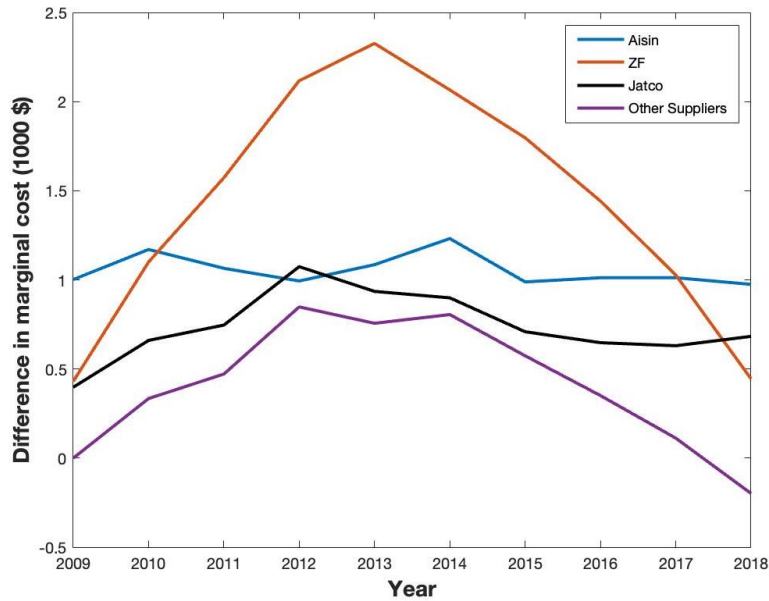
Notes: This figure plots the relative marginal cost because the transmission prices are using other-supplier group's prices in year 2009 as a base group. The marginal costs of upstream firms are inverted from Equation 7 and I use the estimated equilibrium upstream prices and parameter primitives of each year to back out the marginal cost.

6 Counterfactuals

In this section, I analyze how quantitatively important demand shocks and upstream market structure are in shaping 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 recent pandemic has had a drastic impacts on the US automobile industry. Especially in the first few months of the pandemic, travel was discouraged, dealers' showrooms were closed, and the demand for new vehicles collapsed.[40] From Figure 2, one can see that sales dropped by almost 50% in early 2020. Many manufacturers significantly decreased the number of shifts or even temporarily shut down some plants. To mimic the economic bust, I consider shrinking the size of the downstream market 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.[41] During an economic bust, the demands for vehicles and the input demand for transmissions decrease. 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.[42] 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. As indicated in Figure 10, 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, which is 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 they face a shrinking demand. However, outsourcing enables downstream firms to transmit some in-house cost disadvantages to the upstream and attenuates the profit loss. As is shown

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[40] 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."

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

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

Figure 10: Changes in Transmission Cost During an Economic Bust
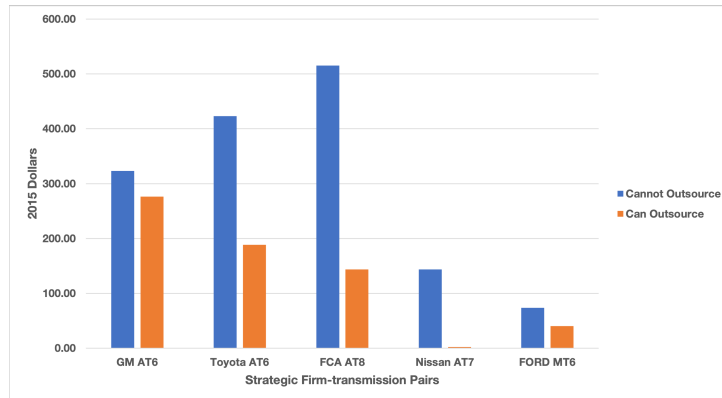
Notes: This figure shows the increase in unit transmission cost in a negative shock when the market size is decreased by 1/3. The blue bars represent changes in the first scenario when downstream firms cannot outsource. The orange bars represent changes in the second scenario when strategic downstream firms optimally outsource without upstream firms' prices fixed at the equilibrium without the negative shock.

in Figure 11, the loss in expected profit is mitigated for most of the strategic firm-transmission pairs. For the strategic firm-transmission pairs, outsourcing helps to avoid a total loss in profit equal to $527 million. The attenuation is most significant for the FCA AT6 and Toyota AT6 divisions; this is due to a substantial cost saving in outsourcing and is reflected in Figure 10. The expected profit is also affected by the amount of competition faced by each firm-transmission pair. The cost savings due to outsourcing are not as significant for the GM AT6 and Ford MT6 divisions; they experience a moderate decrease in expected profits because their competitors have a cost advantage in transmission when outsourcing is allowed. Since outsourcing brings down the cost of transmission, it also reduces the negative-shock-induced consumer welfare loss by $1.24 billion.

According to Table 6 column (1), most strategic firm-transmission pairs increase their outsourcing propensities to transfer unfavorable shocks to the upstream firms.[43] The new equilibrium transmission prices of the four upstream firms all increase in response to the rise in their market shares, and hence the weighted average price increases by $137.18.[44] Table 7 shows that 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 eco-

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[43]For GM AT6, the quantity outsourced is roughly 93,000. Therefore a 2% change in outsourcing is approximately 2000 units.

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

Figure 11: Differences in Profit Loss with and without Outsourcing
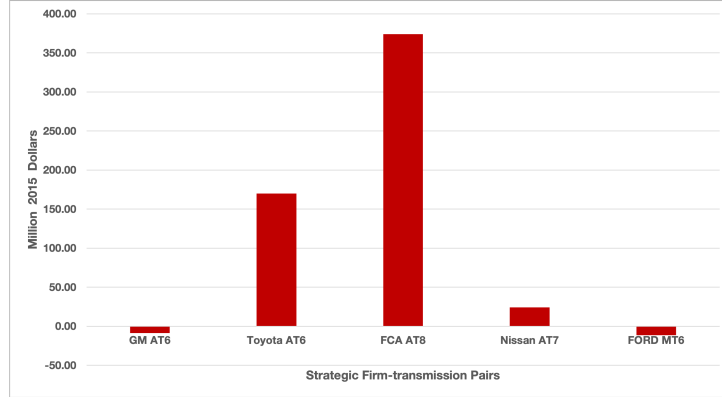
Notes: This figure shows the differences in strategic downstream firms' profit loss under the two scenarios in a negative shock when the market size decreases by 1/3 (profit loss=expected profit loss with outsourcing-expect profit loss without outsourcing).

nomic bust. Due to the increase in the equilibrium upstream prices, downstream firms decrease their outsourcing propensities, but the magnitudes depend on the changes they face in upstream firms' prices. Similar to the case where the upstream price is fixed, the expected downstream profit is also affected by the downstream competition.

Table 6: Changes in Outsourcing Propensities and Expected Downstream Profit in an Economic Bust (4 Upstream Firms)

Firm-transmission Pairs	Before τ adjust		After τ adjust	
	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. The upstream market still have 4 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 7: 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 8 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

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market power exacerbates an economic bust. Compared with a perfectly competitive state when upstream firms are only allowed to charge their marginal cost, the change in total welfare is very significant. Even though upstream firms don't have profit, the consumer surplus and downstream profits increase significantly because of a much lower transmission price.

Table 8: 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 profit, 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) compares the welfare change to a perfectly competitive market where upstream firms charge their marginal 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

The previous analysis has shown that the 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, the sourcing behaviors of downstream firms, the expected profit of the upstream and downstream firms, 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 took effect in July 2020 and will be phased in over four years. Because my data extends only through 2018, to quantify the potential impact I consider a case in which Aisin is a monopoly in the upstream sector. 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 also need to 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 has only 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 $2,247.73, 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 serves the purposes well. However, the increasing upstream prices lead to a decrease in consumer surplus and downstream profit. The total welfare loss is $13.21 billion as shown in Table 9, column (1). 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. In an economic bust, the

price rise for upstream firms occurs because of downstream firms' outsourcing incentives. In addition, a more concentrated upstream further increases the Aisin's price by 8% (231.10/214.16-1) and increases 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: Table 9, Columns (2) and (3) 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 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 9: 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 profit, and downstream profit . Column 1 is a comparison before and after the upstream market power change. Columns 2 and 3 are welfare changes due to increasing upstream prices under different upstream market structure during an economic bust. All prices are 2015 dollars.

Downstream firms intend to expand outsourcing when facing a cost disadvantage of in-house production during an 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 firms become more concentrated, their 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 upstream prices and the firm boundaries of downstream firms. Even though the surviving firm, Aisin, gains substantial profit after the policy, the downstream firms become more vulnerable in times of a major economic bust. Furthermore, 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 farther away from an efficient allocation.

6.3 A Propagation of Idiosyncratic Demand Uncertainty in the Production Network

Finally I 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 price. Furthermore, the changes in transmission prices also depend on the upstream market structure. When the upstream is more concentrated, it can pool together idiosyncratic shocks, 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.[45]

Own Demand Uncertainty Increase: In a process similar to that described in 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 cost estimates for in-house production, 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. The expected downstream profit also increases with demand uncertainty due to the convexity in demand function. However, an increase in idiosyncratic demand uncertainty imposes 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. Figure 12 shows that Toyota and FCA are affected most significantly.

Next I analyze the role of upstream, which affects the transmission cost differently from the negative result reported in the demand shock case. For the GM AT6 division, it is more efficient to produce in-house since the increase in demand uncertainty drives down the in-house production cost. For the other firm-transmission pairs, the upstream firms can provide a stable price. As a result, except for the GM AT6 division, all other firm-transmission pairs reduce their in-house production quantity as shown in Table 10, column (1). The expected profit for the other firm-transmission pairs also decreases less due to the existence of upstream, as shown in Figure 13.

Upstream firms respond to their expected demand and adjust their prices. As reported in Table 11, the price drop of Aisin is most significant ($\sim 7\%$) because of the increasing in-house cost advantage of GM AT6 and GM's intention to produce in-house. 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

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[45]I choose Aisin because all the impacts will have a larger magnitude. Doing so also allows for comparison with the later exercise. The analysis can be repeated for other upstream firms or even downstream firms with in-house production.

Figure 12: Changes in Transmission Cost with Demand Uncertainty Increase
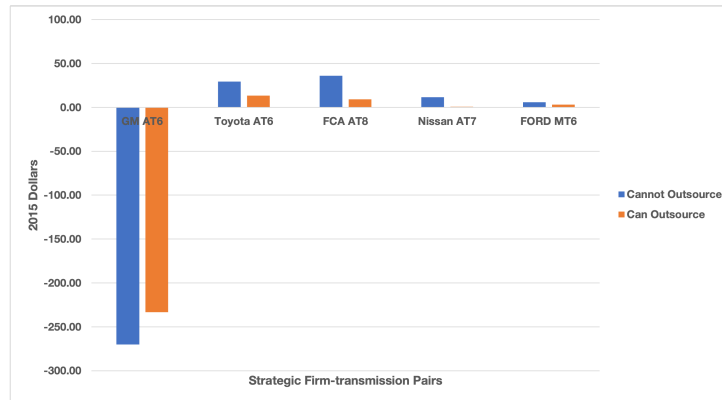
Notes: This figure shows the increase in unit transmission cost when the variance of the demand shock of GM 6AT division increases. The blue bars represent changes in the first scenario when downstream firms cannot outsource. The orange bars represent changes in the second scenario when strategic downstream firms optimally outsource without upstream firms' prices fixed at the equilibrium without the negative shock.

Figure 13: Differences in Profit Loss with and without Outsourcing with Demand Uncertainty Increase
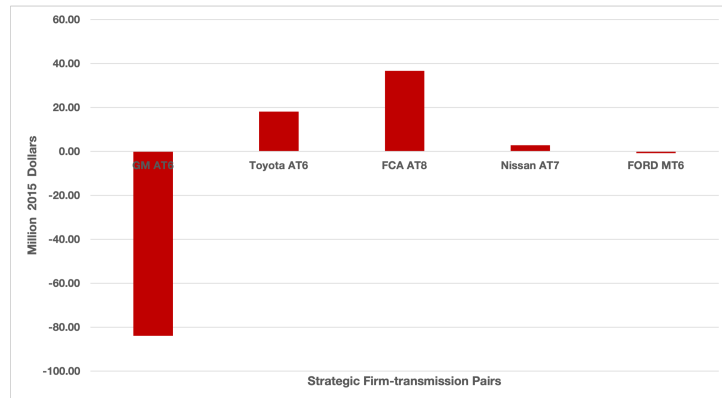
Notes: This figure shows the differences in strategic downstream firms' profit loss under the two scenarios when the demand uncertainty of the GM 6AT division increases (profit loss=expected profit loss with outsourcing-expect profit loss without outsourcing).

increasing demand uncertainty of the GM AT6 division, the other upstream firms all witness a profit decrease due to an impact from the downstream though its magnitude is minimal. Aisin's profit also decreases due to the increasing in-house production of GM AT6 and its negative impact on the other competitors using Aisin transmissions. In Table 10, column (3) and (4) indicates that the profit loss of all other strategic firm-transmission pairs is narrowed because of a decrease in upstream prices in the new equilibrium. However, the GM AT6 division loses some competitive advantage in transmission cost and its profit decreases as well.

Table 10: Changes in Transmission Cost and Expected Downstream Profit with Increasing Idiosyncratic Demand Uncertainty (4 Upstream)

Firm-transmission pair	Before τ adjust		After τ adjust	
	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 the GM 6AT division doubles and there are four upstream firms. The prices here are in 2015 dollars.

Table 11: 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 the GM AT6 division doubles and there are four upstream firms. The prices here are in 2015 dollars.

Finally I examine the impact of upstream firms on the producer surplus and consumer surplus with an idiosyncratic demand shock. As shown in Table 12, 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 price of transmissions, benefiting both downstream firms and consumers. Outsourcing allows the upstream to partly absorb the downstream volatility. Even though the upstream firms' profit loss is larger in a new equilibrium, it is partly offset by the the total welfare gain to the industry.

Table 12: 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 profit, and downstream profit when the demand uncertainty changes. In columns (1) and (2), I double the demand uncertainty of GM AT6 division. In columns (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.

Increase in Competitors' Demand Uncertainty : According to the inhouse-production patterns, my dataset includes firms, such as Tata Group and Geely, that never produce transmissions in-house. I double the demand uncertainty of downstream firms that use Aisin transmissions and that do not change outsourcing strategies, and study their impact on the strategic firms and the transmission prices. This counterfactual is also used to understand the role of upstream market structure in the propagation of idiosyncratic shocks.

Table 13 shows the changes in upstream prices when Asian's non-strategic downstream firms face increasing demand uncertainty. The volatile demand of downstream firms drives up Aisin's price in two ways. First, when the demand is more volatile, the expected downstream profit increases, thus driving up the demand of Aisin's transmis-

sion. Second, the strategic firm-transmission pairs like the GM AT6 and Toyota AT6 divisions increase their outsourcing propensities and further drive up prices.[46] The demand uncertainty of Aisin's downstream firms affects the competition among the downstream firms and thereby affects other upstream firms. 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 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 13: 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 transmissions are doubled. The prices here are in 2015 dollars.

Table 12, columns (3) and (4) show the effect of idiosyncratic shock in the industry. Consumer surplus and expected total downstream profit are driven up by the increasing demand uncertainty of nonstrategic Aisin consumers. Unlike previous case, the new equilibrium transmission price of Aisin increases. Due to Aisin's price increase, consumer surplus and downstream profit are both smaller. I further decompose the expected downstream profit. Strategic downstream firms like GM AT6 and Toyota AT6, which outsourced from Aisin, are negatively affected by the downstream competition and Aisin's new equilibrium price. Aisin also drives up the total upstream profit. The other upstream firms suffer from a profit loss because their downstream firms are less competitive.

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, 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

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[46]The increase in in-house production cost is similar to that is described in Section 6.1 because of a fiercer downstream competition.

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.

References

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012). The network origins of aggregate fluctuations. *Econometrica 80*(5), 1977–2016.

Acemoglu, D., S. Johnson, J. Robinson, and Y. Thaicharoen (2003). Institutional causes, macroeconomic symptoms: volatility, crises and growth. *Journal of Monetary Economics 50*(1), 49–123.

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi (2017). Microeconomic origins of macroeconomic tail risks. *American Economic Review 107*(1), 54–108.

Antràs, P., T. C. Fort, and F. Tintelnot (2017). The margins of global sourcing: Theory and evidence from us firms. *American Economic Review 107*(9), 2514–64.

Arkolakis, C. and F. Eckert (2017). Combinatorial discrete choice. *Available at SSRN 3455353.*

Bajari, P. and S. Tadelis (2001). Incentives versus transaction costs: A theory of procurement contracts. *The RAND Journal of Economics 32*(3), 387–407.

Barrot, J.-N. and J. Sauvagnat (2016). Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks. *The Quarterly Journal of Economics 131*(3), 1543–1592.

Belloni, A., D. Chen, V. Chernozhukov, and C. Hansen (2012). Sparse models and methods for optimal instruments with an application to eminent domain. *Econometrica 80*(6), 2369–2429.

Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica 63*(4), 841–890.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics 25*(2), 242–262.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives 28*(2), 153–76.

Bresnahan, T. and J. Levin (2012). *Vertical Integration and Market Structure*, pp. 853–890. Princeton University Press.

Carlton, D. W. (1979). Vertical integration in competitive markets under uncertainty. *The Journal of Industrial Economics 27*(3), 189–209.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi (2020). Supply Chain Disruptions: Evidence from the Great East Japan Earthquake*. *The Quarterly Journal of Economics 136*(2), 1255–1321.

Chipty, T. and C. Snyder (1999). The role of firm size in bilateral bargaining: A study of the cable television industry. *The Review of Economics and Statistics 81*(2), 326–340.

Council, N. R. (2015). *Cost, Effectiveness, and Deployment of Fuel Economy Technologies for Light-Duty Vehicles*. Washington, DC: The National Academies Press.

Crawford, G. S., R. S. Lee, M. D. Whinston, and A. Yurukoglu (2018). The welfare effects of vertical integration in multichannel television markets. *Econometrica 86*(3), 891–954.

Crawford, G. S. and A. Yurukoglu (2012). The welfare effects of bundling in multi-channel television markets. *The American Economic Review 102*(2), 643–685.

di Giovanni, J. and A. Levchenko (2009). Trade openness and volatility. *The Review of Economics and Statistics 91*(3), 558–585.

Dubé, J.-P., J. T. Fox, and C.-L. Su (2012). Improving the numerical performance of static and dynamic aggregate discrete choice random coefficients demand estimation. *Econometrica 80*(5), 2231–2267.

Eizenberg, A. (2014). Upstream Innovation and Product Variety in the U.S. Home PC Market. *The Review of Economic Studies 81*(3), 1003–1045.

Espin-Sanchez, J.-A., A. Parra, and Y. Wang (2021). Equilibrium uniqueness in entry games with private information. Cowles Foundation Discussion Papers 2126R, Cowles Foundation for Research in Economics, Yale University.

Forbes, S. J. and M. Lederman (2009). Adaptation and vertical integration in the airline industry. *American Economic Review 99*(5), 1831–49.

Forbes, S. J. and M. Lederman (2010). Does vertical integration affect firm performance? evidence from the airline industry. *The RAND Journal of Economics 41*(4), 765–790.

Gandhi, A. and J.-F. Houde (2019). Measuring substitution patterns in differentiated-products industries. Working Paper 26375, National Bureau of Economic Research.

Garetto, S. (2013). Input sourcing and multinational production. *American Economic Journal: Macroeconomics 5*(2), 118–51.

Goldberg, P. K. and F. Verboven (2001). The Evolution of Price Dispersion in the European Car Market. *The Review of Economic Studies 68*(4), 811–848.

Gowrisankaran, G., A. Nevo, and R. Town (2015). Mergers when prices are negotiated: Evidence from the hospital industry. *American Economic Review 105*(1), 172–203.

Green, J. R. (1986). *Vertical Integration and Assurance of Markets*. MIT Press.

Grennan, M. (2013). Price discrimination and bargaining: Empirical evidence from medical devices. *American Economic Review 103*(1), 145–77.

Grennan, M. and A. Swanson (2020). Transparency and negotiated prices: The value of information in hospital-supplier bargaining. *Journal of Political Economy 128*(4), 1234–1268.

Grieco, P. L. E., C. Murry, and A. Yurukoglu (2021). The evolution of market power in the us auto industry. Working Paper 29013, National Bureau of Economic Research.

Head, K. and T. Mayer (2019). Brands in motion: How frictions shape multinational production. *American Economic Review 109*(9), 3073–3124.

Ho, K. and R. S. Lee (2017). Insurer competition in health care markets. *Econometrica 85*(2), 379–417.

Jia, P. (2008). What happens when wal-mart comes to town: An empirical analysis of the discount retailing industry. *Econometrica 76*(6), 1263–1316.

Klein, B. (1988). Vertical integration as organizational ownership: The fisher body-general motors relationship revisited. *Journal of Law, Economics, Organization 4*(1), 199–213.

Klein, B. (2000). Fisher—general motors and the nature of the firm. *The Journal of Law and Economics 43*(1), 105–142.

Klein, B., R. G. Crawford, and A. A. Alchian (1978). Vertical integration, appropriable rents, and the competitive contracting process. *The Journal of Law Economics 21*(2), 297–326.

Lafontaine, F. and M. Slade (2007). Vertical integration and firm boundaries: The evidence. *Journal of Economic Literature 45*(3), 629–685.

Langlois, R. N. and P. L. Robertson (1989). Explaining vertical integration: Lessons from the american automobile industry. *The Journal of Economic History 49*(2), 361–375.

Lind, N. and N. Ramondo (2018). Trade with correlation. Working Paper 24380, National Bureau of Economic Research.

Loertscher, S. and M. H. Riordan (2019). Make and buy: Outsourcing, vertical integration, and cost reduction. *American Economic Journal: Microeconomics 11*(1), 105–23.

Long, J. B. and C. I. Plosser (1983). Real business cycles. *Journal of Political Economy 91*(1), 39–69.

Masten, S. E., J. W. Meehan, and E. A. Snyder (1989). Vertical integration in the u.s. auto industry: A note on the influence of transaction specific assets. *Journal of Economic Behavior Organization 12*(2), 265–273.

Mathewson, G. and R. Winter (1984). An economic theory of vertical restraints. *RAND Journal of Economics 15*(1), 27–38.

Monteverde, K. and D. J. Teece (1982). Supplier switching costs and vertical integration in the automobile industry. *The Bell Journal of Economics 13*(1), 206–213.

Mueller, F., K. O. Stahl, and F. Wachtler (2008). Upstream relationships in the automotive industry: A contractual perspective. *University of Mannheim*.

Nocke, V. and N. Schutz (2018). Multiproduct-firm oligopoly: An aggregative games approach. *Econometrica 86*(2), 523–557.

Nosko, C. (2011). Competition and quality choice in the cpu market.

Nurski, L. and F. Verboven (2016). Exclusive Dealing as a Barrier to Entry? Evidence from Automobiles. *The Review of Economic Studies 83*(3), 1156–1188.

Petrin, A. (2002). Quantifying the benefits of new products: The case of the minivan. *Journal of Political Economy 110*(4), 705–729.

Ramey, V. A. and D. J. Vine (2006, December). Declining volatility in the u.s. automobile industry. *American Economic Review 96*(5), 1876–1889.

Rust, J. (1994). Structural estimation of markov decision processes. *Handbook of econometrics 4*, 3081–3143.

Schmalense, R. (1981). Monopolistic two-part pricing arrangements. *The Bell Journal of Economics 12*(2), 445–466.

Seim, K. (2006). An empirical model of firm entry with endogenous product-type choices. *The RAND Journal of Economics 37*(3), 619–640.

Spence, M. (1976). Product differentiation and welfare. *The American Economic Review 66*(2), 407–414.

Stigler, G. J. (1951). The division of labor is limited by the extent of the market. *Journal of Political Economy 59*(3), 185–193.

Taylor, C. R. and S. N. Wiggins (1997). Competition or compensation: Supplier incentives under the american and japanese subcontracting systems. *The American Economic Review 87*(4), 598–618.

Villas-Boas, S. B. (2007). Vertical relationships between manufacturers and retailers: Inference with limited data. *The Review of Economic Studies 74*(2), 625–652.

Walker, G. and D. Weber (1984). A transaction cost approach to make-or-buy decisions. *Administrative Science Quarterly 29*(3), 373–391.

Weintraub, G. Y., C. L. Benkard, and B. Van Roy (2008). Markov perfect industry dynamics with many firms. *Econometrica 76*(6), 1375–1411.

White, L. J. (2013). *The automobile industry since 1945*. Harvard University Press.

Wollmann, T. G. (2018). Trucks without bailouts: Equilibrium product characteristics for commercial vehicles. *American Economic Review 108*(6), 1364–1406.

Yang, C. (2020). Vertical structure and innovation: A study of the soc and smartphone industries. *The RAND Journal of Economics 51*(3), 739–785.

Appendix A: A Simple Model with Linear Demand

Here I consider a simple linear demand case to illustrate the key features of my model. In this system, there are four downstream firms and two upstream firms. Each firm will produce one product. Firms 1 and 2 choose in-house produce or not. Firms 3 and 4 always outsource to make sure that upstream firms have positive input demand. Firms 1 and 3 are linked with Supplier 1 and Firms 2 and 4 are linked with Supplier 2.
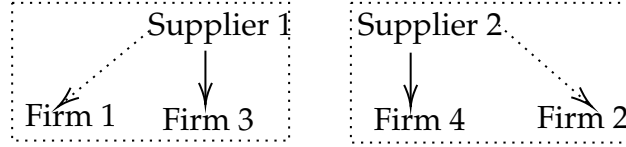
I follow Spence (1976) to formulate the inverse demand function. The price depends on the quantity of other products and the effect is homogeneous.

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

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 governing the shape of the in-house production cost and I omit $(\mathbf{mc}, \mathbf{X}, \alpha, \eta)$ which will be held fixed throughout the exercise.

In stage 2, Firm 1 and 2 play a discrete-choice game with private information and there are four sets of action combinations $\{(0, 0), (1, 0), (0, 1), (1, 1)\}$. 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:

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

I further assume that both players know the distribution of the private information ϵ 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 $Pr(I_2 = 1)$ denote Firm 1's belief of the probability that Firm 2 will produce in-house. The expected profit of Firm 1 choosing in-house production is:

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

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

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

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

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

First, I derive some comparative statics of how the in-house production cost θ_c, the upstream firms' prices ($\boldsymbol{\tau}$), 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.

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

The sign would depend on how demand uncertainty σ affects the expected profit of Firm 1 under in-house or outsourced conditional on the action of Firm 2. The overall effect will be an average weighted by the belief in Firm 2's strategy. Since the outsourc-

ing strategy Pr is an equilibrium outcome, it is also affected by σ.

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

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.[47]

Theorem 1 (Comparative Statics of in-house production cost, upstream prices, and demand uncertainty)
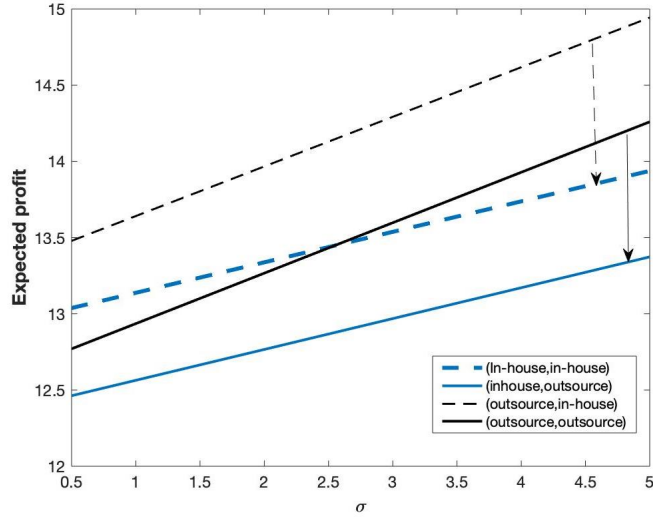
1. *Given $(c(q_i), \sigma)$, when τ increases, downstream firms increase in-house production.*

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 14. 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 the profit function is convex in ζ. 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.

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

Notes: This figure shows the expected profit of Firm 1 at different demand uncertainty levels. The solid lines are the expected profit of Firm 1 when Firm 2 chooses outsourcing. The dashed lines are the expected profit of 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, and demand uncertainty)

1. $c_2 > 0$, *there is decreasing returns to scale of in-house production*
   - *Given σ, when $c(q_i)$ is more convex, equilibrium τ increases.*
   - *Given $c(q_i)$, when σ increases, equilibrium τ 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 τ decreases.*
   - *Given $c(q_i)$, when σ increases, equilibrium τ 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 15, the equilibrium upstream prices, which are determined by the intersection of the dashed line, are higher when the cost function of producing in-house is more convex. The equilibrium upstream prices will increase when demand uncertainty rises by Figure 16. 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 the incentive to outsource.

Figure 15: Equilibrium Upstream Prices at Different $c(q)$
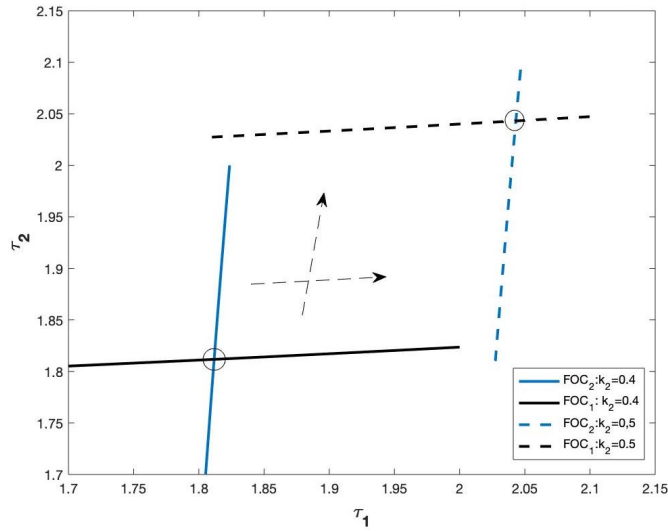
Notes: This figure shows the upstream prices at different costs. The solid lines are when $c_2 = 0.4$ and dash lines are when $c_2 = 0.5$. The blue lines are the best response of Firm 2 to Firm 1's prices. The black lines are the best response of Firm 1 to Firm 2's prices.

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 outsourcing incentives by increasing their prices.

Figure 16: Equilibrium Upstream Prices at Different Uncertainty Levels
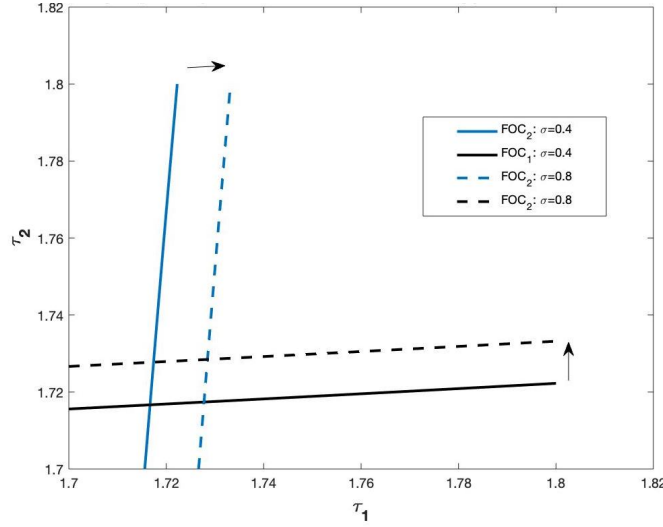
Notes: This figure shows the upstream prices at different uncertainty levels. The solid lines are when $\sigma = 0.4$ and dash lines are when $\sigma = 0.8$. The blue lines are the best response of Firm 2 to Firm 1's prices. The black lines are the best response of Firm 1 to Firm 2's prices.

Appendix B: Algorithm for Solving the Model

Timing:

- Stage 1: Each upstream supplier s competes 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:

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

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

Profit equation:

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

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The marginal cost of each product:

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

The inhouse production cost function:

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

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

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

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

In matrix form:

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

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 $\mathbf{I}$. Since the equilibrium prices $\mathbf{p_t}$ is very sensitive to extreme values, I additionally try a two-step iterative method(F is the equation (B2)) to allow for a smooth update:

$$y_k = p_k - F'(p_k)^{-1}F(p_k)$$

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

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

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

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

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

$$D_j^I (2c_2 N + 6c_3 N^2 g_j).$$

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

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

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

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

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

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

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

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 σ. 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:

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

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

I additionally compute the expected profit of each action vector:

$$E\pi_j^*(\mathbf{p}^*, \tau, \mathbf{a}, \cdot) = \frac{1}{M} \sum_m \frac{1}{N} \sum_n (p_j^*(\tau, \mathbf{I^n}, \mathbf{e^m}, \cdot) - cost(g_j^*(\mathbf{p}^*, \mathbf{e^m}, \cdot), \mathbf{I_j^n})) N g_j^*(\mathbf{p}^*, \mathbf{e^m}, \cdot)$$

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

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

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

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

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

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

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

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

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

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:

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

$$FOC = \sum_{f \in F_s} \sum_{j \in J_f} \sum_{\mathbf{a}} ED_j^{O*}(\mathbf{a}, \boldsymbol{\tau}, \cdot) Pr^*(\boldsymbol{\tau}, \mathbf{a}, \cdot)$$

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

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

Eg_τ^{O*} is defined before. As for:

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

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 is 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 that 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 the 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 C: 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 on 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 actions:

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

Downstream firm-transmission pairs' profits are based on the steady-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 the competitor's action distribution at a specific strategy profile. This indicates the number of type l firm-transmission pairs 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, and the 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 **?**, 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 Bayes Nash 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 introduces approximation errors with little gains in computation.