Default Risk in the Automotive Supply Network

by

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Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in the Department of Economics
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Abstract

The goal of this dissertation is to empirically investigate, model, and estimate which features of a car-part supplier's portfolio, including production capacity, buyer or component-sector specialization, and solvency risk, drive the formation of new business relationships between this car-part supplier and a car manufacturer. In this dissertation, I exploit a unique professional database listing suppliers for a set of car components at the car model level. After cleaning the data, I combine reduced-from evidence and structural analysis to shed light on how, along with operational factors, financial risks are internalized by firms in the car-part supply network in their decisions to form new business relationships. Choosing to be agnostic about the process of contract-offer arrivals to a supplier from car manufacturers, I first use reduced-form evidence to exhibit the pattern of network externalities in the supply network, and investigate whether these patterns changed in the aftermath of the collapse and debated bailout of General Motors and Chrysler in 2009. In a second place, I provide and estimate a one-sided model of buyer-supplier agreements in the car-part industry in which a supplier exogenously receives contract offers overtime from its buyers and endogenously accepts a new contract as a function of the risk and operational benefits that this new business generates. Armed with this model, I assess the impact of an exit of GM or Chrysler on the probability that a supplier accept a new contract from another buyer.

What do you possess that you have not received? But if you have received it, why are you boasting as if you did not receive it? (1 Cor. 4:7)

To my parents and grand-parents.

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1

Introduction

This chapter gives an overview of the automotive industry in North America and Europe in the past fifteen years, with a focus on the car-part supplier network. The goal of this chapter is to provide the reader with the contextual, institutional, and data background necessary for reading of the next chapters.

First, in Section 1.1, I highlight the transformation trends that the industry has undergone during this period, during which an unprecedented crisis hit the whole industry in the years 2008 and 2009. This part gives a big picture of the operational transformations happening in the automotive industry in two major production regions (USA and Canada, and Western Europe) and their growing neighbors (Mexico and Eastern Europe). The goal is to depict the context in which the story I am going to tell about the car-part supply network takes place.

Second, I provide a description of the supplier-buyer network in the car-part industry from three different points of view: operational (production, R&D), legal (contracting conditions), and risk (financial shock or natural-disaster shock spreading through the network). This is the main topic of Section 1.2.

These industry facts are the motivation behind this dissertation. In Section 1.3, I describe the *Who Supplies Whom?* database, a dataset listing suppliers for a number of automotive parts at the car model level. This database gives a partial but fair view of the car-part supply network overtime and can be of great interest to anyone studying business relationships between car manufactures and their suppliers. I use this unique dataset in the analyses of Chapter 2 and Chapter 3.

Finally, in Section 1.4, I discuss the key structural assumptions that I will use in the model of Chapter 3.

1.1 An industry on the Move

In this section, I give a snapshot of the automotive industry in North America and Europe in the past fifteen years, with a focus on production. The goal of this chapter is to provide the reader with a big picture of the operational transformation happening in the automotive industry in two leading but contested regions of production, namely USA and Canada on the one hand, and Western Europe on the other hand, and in their growing neighboring regions, namely Mexico and Eastern Europe.

1.1.1 The 2008-2009 crisis in an already changing industry

Figure A.1 shows the aggregate statistics of car production in North America and Europe. Production in measured in 100k-units. Unsurprisingly, the 2008-2009 crisis shows a heavy drop in production in US, Canada, and Western Europe, with a smaller drop in magnitude in their growing neighbors, Mexico and Eastern Europe. A couple of years after the crisis, US and Canada seem to have recovered their level of production pre-crisis, unlike Western Europe. If the crisis has also hit their southern and eastern neighbors, the drop of production does not seem to have broken the upward trend in production. Furthermore, this shock in production happened in a context of steady decline in the number of active plants in US, Canada, and Western Europe. However, the stagnating trends of Eastern Europe and Mexico suggest that the portfolio of models produced in Europe and North America is concentrating overtime. As a matter of comparison, production in Far-Eastern Europe (Russia, Belarus, and Ukraine) and Central Asia (Kazakhstan and Uzbekistan) shows very dissimilar patterns: Unlike other regions, it shows a strong increase of models and active assembly lines overtime, and to some extent, of active plants as well.

Figure A.2 shows the aggregate statistics of car production at the plant level. To some extent, it offers a similar picture than that of Figure A.1. However, it also reveals that, with the heavy crisis hitting major manufacturers, especially in US, Canada, and Western Europe, both Mexico and Eastern Europe saw their average production per plant overtaking that of their larger neighbors. Both regions show cheaper labor costs, an already well-grounded automotive industry, and a trade agreement with their neighbors. These factors likely led major manufacturers to relocate production. Furthermore, Mexico and Eastern Europe show similar trend in production in 2007-2008, whereas Mexico seems to enjoy an increasing upward trend in the wake of the crisis (2010-2012), unlike Eastern Europe, whose trend seems to go back to something closer to that of 2007-2008. These observations suggest that Mexico has benefited more amply from the 2008-2009 crisis which hit the automobile industry in US and Canada, than Eastern Europe was able to capitalize on the turmoil in Western Europe.

1.1.2 A shift southward of American production after the crisis

Building upon the above observations, I plot in Figure A.3 estimates from the following regression of per-plant production on region-year-specific fixed effects:

$$Q_{pt} = \alpha_{rt} + \varepsilon_{pt}, \tag{1.1}$$

where α_{rt} is the effect of year t in region r on per-plant production. Figure A.3 clearly shows the common trend before 2009 in Mexican and Eastern-European productions, and the unchanged trend of Eastern-European production after 2009. In Figure A.4, I plot estimates from model (1.1) including plant fixed effects:

$$Q_{pt} = \alpha_p + \alpha_{rt} + \varepsilon_{pt},$$

Even though plant fixed effects shifted Mexican coefficients upward, Figure A.4 shows similar trends in per-plant production as in Figure A.3. These results suggest that, unlike Eastern Europe, the Mexican automotive industry enjoyed a boost in the aftermath of the collapse of its neighbor's automotive industry, as previously mentioned.

A more systematic and rigorous investigation of this question, including the impact on various outcome in the Mexican economy (e.g., labor), is beyond the goal of this section and left to future work.[1]

1.2 Supplier-Buyer Relations in the Automotive Industry

This section offers a snapshot of supplier-buyer relations in the automotive industry from three different points of view: operational, legal, and risk. It is based on existing literature and on anecdotal evidence based on discussions with engineers or former engineers at Ford and PSA-Peugeot-Citroën.

1.2.1 On the engineering side

Suppliers are chosen based on criteria including partnership, trust, quality, technology, cost, and flexibility. Since the nineties, technical collaboration has become prominent in buyer-supplier relationships. Firms collaborate on product development, part design, assistance and improvement of production processes. To minimize transaction costs and optimize allocation of engineering resources, an automaker chooses the same supplier for assembling a whole component system (e.g., a gearbox).

[1] This question of the impact of the bailout on the Mexican automotive industry is increasingly studied but still nascent. See, e.g., Alvarez-Medina and Carrillo (2014); Covarrubias et al. (2011) or, from an operational perspective, the technical report by Friedrich-Ebert-Stiftung (2017).

Preproduction heuristic development is critically important to the evolution of many vehicle parts. This process generates production as well as design knowledge (Monteverde and Teece, 1982a,b).[2] The know-how acquired during development makes supplier-switching costs very high to the automaker. As a consequence, automakers usually have a set of *preferred* suppliers for any component system and switch only when technology requires it.

When an automaker needs a part for a new model, it calls suppliers in its portfolio of preferred options and discusses with each the feasibility of the design and production of the part. The design and certification of the part in collaboration with the chosen supplier can take multiple months. It may also require heavy transaction-specific investments in the production line. When production has started, the automaker sends engineers specialized in process optimization to the supplier firm to help it reduce its costs (and lower its price). This ample bilateral activity makes it costly and technically risky to the automaker to work with an unknown supplier. It has no incentive to fail a supplier. In line with these industry facts, Dyer (1996b, 1997) finds that *a high level of human co-specialization will outperform a loosely integrated production network characterized by low levels of inter-firm specialization.*[3] Finally, if buyer-supplier co-location largely decreases transaction costs (Rosenbaum, 2013; Bernard et al., 2015) and increases component quality (Bray et al., 2016), Schmitt and Van Biesebroeck (2013) shows that geographical proximity and cultural proximity, such as a supplier R&D center in the buyer's home country, *should be interpreted as outcomes of a sourcing strategy, not as predictors for sourcing success.* Rosenbaum (2013) models this location decision for suppliers.

[2] See also, e.g., Dyer and Hatch (2004).

[3] See also Dyer and Nobeoka (2000).

1.2.2 On the legal side

A car is a complex product requiring large investments in human as well as physical durable relationship-specific assets. This high level of joint investments makes the hold-up problem a major concern to car manufacturers. In response to this risk of hold-up and to avoid limitations from vertical integration, such as increasing managerial costs and loss of high-powered incentives (Lafontaine and Slade, 2007), automakers separated the decision to vertically integrate (i.e., to internalize production) from the question of ownership of physical assets. In the case of transaction-specific physical assets, ownership eliminates the hold-up problem by internalizing the quasi-rents that it would generate for the supplier (Masten et al., 1989).

Contracts are the primary tool used to address the risk of hold-up. Ben-Shahar and White (2006) provide a detailed picture of a car-part contract and list the contractual techniques for deterring hold up. A contract is allocated through competitive bidding. Given the operational benefits from close relationships described in Section 1.2.1, the winning supplier likely belongs to the buyer's set of *preferred* suppliers. Furthermore, when winning a bid, a supplier usually brings in capital investment in R&D and production assets. A contract starts at the beginning of the production of the model and ends ten to fifteen years after the end of production (four to eight years) to account for after-sale services. A contract is only a long-term sourcing agreement. Prices and quantities are renegotiated on a short-run basis by the buyer. Contract terms seek to protect the buyer against a supplier hold-up. They cover termination rights (the buyer can unilaterally break the contract), tooling (the buyer owns most of the relationship-specific production assets), intellectual property rights (in technological innovations), and service parts (e.g., the supplier cannot set higher prices in the post-production period).

1.2.3 On the risk side

Automakers have low inventory and are highly connected through their supply network (Atalay et al., 2011). As emphasized in Section 1.2.1, these connections tend to be very strong, and as such, very strategic and critical to the survival of firms in the supplier-buyer network (Goolsbee and Krueger, 2015). Supply-chain disruption is a major concern for automakers because the failure of a supplier can block the entire production line of an automaker. This was the main fear of Ford in Fall 2008, when, foreseeing Chrysler's collapse, it ended its relationships with suppliers that it shared with Chrysler.[4] If legally possible in practice (see Section 1.2.2), such a move is exceptional in practice (see Section 1.2.1). Paradoxically, it is for the same reason - this aversion for supply-chain disruption - that a buyer has no incentive to fail a (longstanding and faithful) supplier in difficulty. Goolsbee and Krueger (2015) qualitatively argue that *it was essential to rescue General Motors to prevent an uncontrolled bankruptcy and the failure of countless suppliers, with potentially systemic effects that could sink the entire auto industry.*

Starting from the 2008-2009 events, Acemoglu et al. (2012) and Baqaee (2016) theoretically show how shocks can propagate in cascade in the economy through production networks. On the empirical side, Carvalho et al. (2014) quantify the spillover effects of the Great-East Japan earthquake on the supply-chain network of Japanese firms. They show that both suppliers and buyers in the supply chain outside of the earthquake zone were negatively impacted by the earthquake shock, revealing significant spillovers on the overall production network. Automakers favor geographically close suppliers not only because of lower transportation costs or easier R&D cooperation, but also to reduce natural risks of supply-chain disruption.

[4] Ford also reduced its exposure to suppliers which were highly leveraged or had a too diversified buyer portfolio. These series of precautions, taken in cahoots with Honda and Toyota, is commonly referred as Project Quark.

A vast literature has explored the cost of financial distress (Andrade and Kaplan, 1998; Almeida and Philippon, 2007; Berk et al., 2010) for car manufacturers in particular (Hortaçsu et al., 2011, 2013). However, few has been done to empirically investigate how automakers and their suppliers account for this financial-risk exposure when forming the supplier-buyer network. This dissertation is a stylized step in this direction.

1.3 A Dataset of Supplier-Buyer Relations

In this section, I describe the main dimensions of the IHS *Who Supplies Whom?* database, a professional database listing suppliers for a set of car-parts at the car model level.

1.3.1 The Who Supplies Whom? database

The IHS *Who Supplies Whom?* (WSW) database allows to partially reconstruct the supplier-buyer network in the automotive industry. It is a list of supplier-model-part combinations collected by IHS directly from the suppliers (to whom they send monthly surveys) and covering most car models assembled in North-America and Europe since 2001. For each combination, I see the sector of the part, as well as the start and end dates (month and year) of production of the model that it corresponds to. The database is built from the suppliers' point of view. As such, it is informative about the suppliers' buyer portfolios. However, some major suppliers are missing, and the set of suppliers of a carmaker cannot be faithfully recovered. In Section 1.3.2, I describe in details the cleaning of the raw data.

In the following chapters, I conduct the empirical analysis from the suppliers' point of view because the data are built from this perspective. I also restrict the database to the twelve largest buyers in North-America and Europe, namely BMW, Chrysler, Daimler, Fiat, Ford, GM, Honda, Hyundai-Kia, PSA Peugeot-Citroën, Renault-Nissan, Toyota, and VW. They represent about ninety percent of the car production in Europe and North-America. I separate Chrysler from Daimler before 2008 (DaimlerChrysler regrouped the two firms from 1998 to 2007), and from Fiat after their takeover (FCA regroups Fiat and Chrysler). On the other hand, I do not separate Hyundai and Kia or Renault and Nissan either, because their alliances were formed before 2005 and were still holding at the end of 2011, 2005-2011 being the time span I focus on in the next two chapters.

I also choose to conduct the analysis at the model level. It is a higher level than that of a car part. However, it is also a variable with smaller measurement error. A car can contain up to ten thousands parts. A quick look at the data show that the whole set of parts in a given model cannot be faithfully recovered, even partially. Working at the model level (i.e., considering whether supplier S supplies to a new model of buyer B, instead of considering whether S supplies to n parts in a new model of B) mechanically reduces measurement errors.

The set of suppliers in the database shows a steady decline overtime. This is partially due to firm exiting through liquidation or sale, but mostly to attrition among the surveyed suppliers. It is the reason why I choose to restrict the study to the 2005-2011 time window. I ignore the other years because they are more poorly populated. Before 2004, the set of surveyed cars is too incomplete and the construction of the database is still in a transitory phase of growth. After 2011, a change in IHS' marketing strategy has lead a consequent number of suppliers to end their subscription to a number of IHS services. As a consequence, these suppliers stopped providing information to IHS. Finally some suppliers exit because their customers demand that they do not reveal details of their business relationships. In the next chapter, for simplicity, I also assume that the merger of two suppliers is seen here as two exits and one entry. Likewise, a partial divestment, the sale of the whole company, or the acquisition of another one give birth to a new supplier. In the third chapter, I ignore mergers and divestments, and sales and liquidations are seen as exits.

Table A.1 to Table A.3 summarize the main aggregate statistics of the cleaned WSW database, which spans from 2005 to 2011. Table A.1 shows a small decrease of the total number of suppliers overtime, but an increase in the number of models reported in the database. Table A.2 shows that the average number of observed parts per model has an upward trend overtime but is far below the actual number of parts in a car model. Finally, Table A.3 shows the average number of models that a supplier supplies per buyer is around three, a very low number. However, this number is a lower bound as it does not account for the fact that a supplier does not necessarily work with all the buyers. Furthermore, standard deviation is of the same order than the mean, suggesting substantial variation across suppliers.

1.3.2 Cleaning the raw database

In this section, I describe how I treated and supplemented the raw network data from IHS.

The raw WSW database is a list of supplier-model-part combinations collected by IHS directly from surveyed suppliers and covering most car models assembled in North-America and Europe since 2001.[5] I use the 2005-2011 time span in this paper. For each combination, I see the sector and subsector of the part and its description, as well as the start and end dates (month and year) of production of the model that it corresponds to.

Recall that the database is built from the suppliers' point of view. However, the absence of a supplier-model-part combination does not necessarily mean that this supplier does not supply this part to this model: The data exhaustivity depends on the quality of suppliers' responses to the surveys. Furthermore, the supplier to a

[5] Asia, South-America, and Africa have been added along the way but are not used here.

model may not be reported in the database. The observed buyer-supplier network is likely a subset of the true one (See also IHS-SupplierBusiness (2014) for more details about the construction of the database). This partial information on the buyer-supplier network may bias the analysis. For example, if a supplier S reports all its buyers but underreports contracts, I may underestimate the magnitude of the relationship between S's probability of signing a new contract with a buyer B and the business intensity between S and its other buyers. I make the assumption that suppliers faithfully fill in surveys.

Many variables of interests were poorly populated. Suppliers in the data are not identified with unique ids or numerical labels. They are identified with their names, which is more subject to reporting errors. I had to check one by one all the names, correcting orthographical mistakes or abbreviations (e.g., Rhodia and Rodhia are the same firm. The same goes for Illinois Tool Works and ITW). I also pooled together suppliers which are subsidiaries of a same mother company (e.g., Benecke-Kaliko is a division of Continental). When a firm is a joint venture between two companies, I add the information of the venture to both mother companies and then drop the firm (e.g., Eurofit was launched as a joint venture between Michelin and Continental; so I add the observations of Eurofit to both Michelin and Continental and drop Eurofit in the data). Likewise, the model start- and end-of-production dates, which I use as my start and end dates of contracts, show a lot of missing observations. I manually supplemented the missing values for all the models concerned.

Finally, the data sort parts into areas, sectors, and sub-sectors. A part can belong to multiple areas (e.g., interior, exterior, powertrain, electronics) and sectors (e.g., actuators, airbags, axles, battery, fasteners, fluids, glass, metal parts), but belongs to only one sub-sector (e.g., actuators for airbag modules, actuators for braking systems, brake disc, brake pad). In the next two chapters, I choose the sector classification for my analysis because, unlike the area classification, it is detailed enough to be informative of the number of technologies and car dimensions that a supplier covers. In the meantime, this sector classification groups parts into systems (e.g., brake sector includes break drums and pads). It makes this classification fine enough since systems (e.g., braking system or gear-shift system) are usually designed and developed by the same supplier (see Section 1.2.1).

1.4 The *Preferred-Supplier* Assumption

In this section, I explain the suitability of the *Preferred-Supplier* assumption. It is a key assumption in my one-sided model of contract agreements in the car-part industry developed in the last chapter of the dissertation.

1.4.1 Beginning with an agnostic contract-offer process

In Chapter 2, I empirically explore which features of S's buyer portfolio, including capacity, specialization, and solvency risk, drive the formation of new business relationships between S and a car manufacturer. The reduced-form analysis follows the roadmap that this institutional description of supplier-buyer relations in the car-part industry naturally draws. The analysis remains purposely agnostic about the process of contract-offer arrivals to a supplier S. S can potentially receive offer from any active buyer. In this agnostic framework, results show a positive and significant relationship between the probability that S and B sign a new contract and the fact that S and B are already in an ongoing relationship. S and B are more likely to enter a new business relationship whenever S and B are already working together. This result is in line with the description of the car-part industry given in Section 1.2.1.

1.4.2 Being a preferred supplier

However, a quick look at the data at times of model launchings reveals that in more than 86 percent of the time when B and S sign a new contract, S is already in an ongoing relationship with B (i.e., S supplies parts to some models of B which are under production at the time of contract signature). The remaining percents cover cases wherein a supplier has a discontinued relationship with a buyer (e.g., S supplies parts to some models of B until t, does not from t to $t + \Delta$, and does it again from $t + \Delta$ on). In the meantime, Section 1.2.1 underlines how strong and longstanding relationships between a buyer and its suppliers are a major characteristic of the car-part industry. It follows that these discontinued cases are unlikely in practice and are in part due to survey misreporting. At first sight, the case in Section 1.2.3 of Ford willing to break all relationships with suppliers linked to Chrysler seems to be contradicting this point. On the contrary, it reveals (i) how tight are relationships between a buyer and its suppliers, and (ii) how a tight relationship with a buyer for a supplier can be detrimental to its relationship with another buyer.

The goal of Chapter 3 is to quantitatively assess the profitability of new supplier-buyer relationships in function of the shape of the supplier's customer portfolio. This goal makes the requirements on the data sample twofolds: (i) I need a dataset of which information tells something about the effect of one supplier's portfolio externalities on its profitability. As a consequence, I drop suppliers working with only one buyer. (ii) I need a dataset of which variation in the supplier characteristics are not only due to exogenous moves (e.g., the credit score of a buyer is downgraded by one notch, or the production of a model is terminated), but also to agreement decisions taken by the supplier. As a consequence, I drop suppliers for which I do not observe *enough* agreements. I choose to keep suppliers which supply to one or more new models per year on average. This selection criterion is strong: By excluding from the analysis suppliers which poorly report in the survey, I mechanically excludes suppliers which are also less likely to have resources to fill in the survey faithfully (e.g., firms with a more reduced administrative staff). Naturally, many of the smaller suppliers get excluded from the sample. It refocuses the analysis on large and highly connected suppliers. The ongoing-relationship percentage rises from 86 up to more than 88 percent whenever I focus on this set of suppliers, that is, the subset of non-exclusive suppliers which supply to one or more new models per year on average in the data.

In line with Section 1.2.1 and with the reduced-form results, I make the following assumption when I move to the structural model in the last chapter: I assume that carmakers have *preferred* suppliers with which they work and that observed relationships (or links) between a buyer and its *preferred* suppliers are continued overtime. In such a framework, a supplier receives contract offers only from buyers of which it is a *preferred* supplier and a supplier S is assumed to be a *preferred* supplier of buyer B if I observe some contract between S and B in the data. This *preferred-supplier* assumption is not so binding because the selection criterion imposed to the sample already shifted the analysis towards large and highly connected suppliers. That is, most suppliers in the selected sample are preferred suppliers to most of the twelve major car manufacturers.

1.5 A Foretaste of What Is Next

In Chapter 2, I empirically explore which features of a supplier's buyer portfolio, including capacity, specialization, and solvency risk, drive the formation of new business relationships between this car-part supplier and a car manufacturer. The reduced-form analysis reflects the institutional description of supplier-buyer relations in the car-part industry, described in Section 1.2.

In Chapter 3 I develop a one-sided model of buyer-supplier agreements in the car-part industry. A supplier exogenously receives contract offers overtime from its buyers and endogenously accepts a new contract in function of the risk and operational benefits that this new business generates. Nevertheless, this model is informative of buyers' preferences in the risk profile of their suppliers: The value generated to the supplier by an additional contract reflects how much the buyer is willing to pay for working again with this supplier. The model is built upon a key simplifying assumption, alleviating numerical optimization. This assumption rules out opportunities for a supplier to sign new contracts with a buyer of which it is not a *preferred* supplier. This *preferred-supplier* assumption, describe in Section 1.4, is motivated by the institutional depiction of supplier-buyer relations in the car industry, together with the conclusions of the reduced-form analysis.

2

Externalities in the Car-Part Supply Network

In this chapter, I empirically explore which features of a supplier's buyer portfolio, including capacity, specialization, and solvency risk, drive the formation of new business relationships between this car-part supplier and a car manufacturer. The analysis suggests that, when signing new contracts, the supplier and the car manufacturer internalize (i) two trade-offs in productive-factor allocation and in buyer-supplier specialization, as well as (ii) the exposure to financial risk of other firms in the buyer-supplier network. The pattern of these network externalities changes after 2009, hinting that firms shifted their criteria for signing new contracts in the aftermath of the collapse and bailout of GM and Chrysler. In particular, the probability that a buyer and a supplier sign a new contract becomes negatively correlated with the number of other buyers in the supplier's portfolio, in spite of the bailout of GM and Chrysler that signaled that industry flagships are too big to fail. From then on, better safe than sorry.

2.1 Introduction

As emphasized in Section 1.2.3, car manufacturers are highly interconnected through their supply network. The link between the formation of business relationships and geography, quality, transaction and know-how costs, or productivity has been amply documented for the automotive industry.[1] In the meantime, automakers' response to prevent supply disruptions during the 2008-2009 automobile crisis suggests that, when a supplier and a buyer sign a new contract, they also internalize some network externalities rising from the anatomy of the supplier's buyer portfolio. For example, foreseeing Chrysler's collapse, Ford ended in Fall 2008 its relationships with suppliers that it shared with Chrysler to safeguard its production from disruption and eventually to ensure its survival. At the same time, Ford and major Japanese automakers jointly advocated for the bailout of Chrysler and GM.[2] In the steps of the vast literature on financial distress (Almeida and Philippon, 2007; Hortaçsu et al., 2011, 2013), a goal of this chapter is to empirically investigate how automakers and their suppliers account for solvency-risk exposure when forming the supplier-buyer network.

From this viewpoint, the buyer-supplier network becomes the outcome of a game wherein one's decisions depend on others': Supplying to some buyer may hinder the prospects of supplying another manufacturer in the future. Similarly, a manufacturer may benefit from choosing a supplier working with another manufacturer (economies of scale, know-how spillovers) or suffer from it (production capacity constraint, scat-

[1] See, e.g., Rosenbaum (2013), Bray et al. (2016), Levitt et al. (2013), Carvalho et al. (2014), Bernard et al. (2015), Schmitt and Van Biesebroeck (2013), Monteverde and Teece (1982a,b), Masten et al. (1989), Foster et al. (2008), Gonzalez et al. (2004), Dyer (1996a), Clark and Fujimoto (1991), and Medina (2014).

[2] Ford also broke its contracts with too leveraged or not specialized enough suppliers. For further details, see Goolsbee and Krueger (2015) and *Inside Ford's Fight to Avoid Disaster*, The Wall Street Journal, March 8, 2012. Furthermore, in March 2009, right before Chrysler and GM file for bankruptcy protection, US Treasury announced *Auto Supplier Support Program*, to mitigate supplier failures.

tered engineering resources, indirect exposure to competitor's risk). In this chapter, I investigate these questions: Does the buyer-supplier network in the automotive industry drive the formation of new business relationships between car manufacturers and car-part suppliers? And, in particular, which features of a supplier's buyer portfolio (including production capacity, customer or sector specialization, and financial risk) affect the probability of a new contract to be signed between a buyer and this supplier?

To explore these questions, I use the IHS *Who Supplies Whom?* database. It is a continuous-time panel dataset, which includes at the car-part level, the suppliers to most of the models assembled in North-America and Europe. I estimate the probability that a supplier S will sign a new part contract with a buyer B in year t (provided that B launches some new models) as a function of some characteristics of S's buyer portfolio at the beginning of year t, before any contract has been signed in this year. For example, I define the number of ongoing contracts between S and B as the number of contracts (i) signed between S and B before year t starts and (ii) which are still ongoing in year t (i.e., these contracts supply to car models that have not been discontinued yet). To estimate this probability, I use a linear-probability model with fixed effects. Results suggest multiple mechanisms and trade-offs at play in the formation of the buyer-supplier network.

I find that S and B are more likely to sign a new contract when (i) S is already a supplier to B in multiple component sectors, (ii) S has a limited number of other ongoing buyers, and (iii) S has, on average, a limited number of large-scale-production ongoing contracts with its other buyers. An explanation to these patterns in the formation of new business relationships between S and B relates to the trade-offs faced by S in the profile of its customer portfolio: On the one hand, a supplier who signs new contracts with multiple buyers today may signal for cutting-edge technologies and quality,[3] and yield economies of scale, lower prices, and know-how spillovers. This can benefit the supplier as much as all of its buyers. On the other hand, a large buyer portfolio today requires to allocate resources to some obsolete parts and uncertain demand tomorrow. It also requires tailor-made engineering scattered across customers with specialized needs and, as such, higher transaction costs.[4]

On the risk side, I find that S is more likely to supply to some B's new model, (i) the smaller the number of other buyers and the average number of models supplied to them, and (ii) when its other buyers have a low probability of collapse. These correlations suggest that a diversified buyer portfolio is not necessarily detrimental to new business relationships, provided that the average buyer $\tilde{B}$ is financially strong and that S's exposure to $\tilde{B}$ is concentrated on a reduced number of models (and of production lines).

Empirical results also confirm what Ford claimed to do in anticipation of the collapse of Chrysler: In 2009, Ford is not likely to sign anew with a supplier linked to Chrysler. Furthermore, a year-specific analysis reveals that these externalities in suppliers' customer portfolio described above emerge from the 2008-2009 turmoil, that is, after GM's and Chrysler's descent to hell. Unlike before the crisis, S and B are less likely to sign anew after when S has a large number of other ongoing buyers. It suggests that firms shifted their criteria for signing new contracts in the aftermath of the collapse and bailout of GM and Chrysler. From then on, better safe than sorry.

2.2 A Toy Model of Supplier Contracting Trade-Offs

In this section, I build upon industry facts described in Section 1.2 and hypothesize about suppliers' contracting trade-offs. The goal is not to build a realistic model of

[3] See, e.g., Langfield-Smith and Greenwood (1998).

[4] See, e.g., Dyer (1996b, 1997).

suppliers' decisional environment, but rather to introduce in a simple but systematic fashion the empirical analysis that I will develop in Section 2.4.

I build the toy mechanism upon the main operational and risk features of the empirical analysis: In this model, I assume that a buyer B and a supplier S are more likely to sign a new contract when (i) B and S are already in an ongoing business relationship (S and B know each other) and S has a limited number of other buyers (S does not scatter its engineering resources across too many buyers), (ii) B and S's other buyers are financially healthy (that is, they have a low probability of default), and (iii) S supplies to a large number of models of B but to a small number of models of its other buyers. In this simple setting, I ignore production quantity. Production characteristics are summarized in the number of models only.

These features of the model introduce possibly negative or positive externalities on the relationship between S and B from the rest of S's portfolio: S may benefit (suffer) from having another buyer if this buyer is financially healthy (risky). I also allow for economies of scales. This feature introduces another layer of possibly negative or positive externalities on the relationship between S and B from the rest of S's portfolio: More contracts and more buyers may imply lower costs but also more scattered engineering resources across highly specialized and mutually exclusive projects, a possible source of inefficiency (see Section 1.2.1). These externalities naturally create a trade-off for the supplier in the formation of new business relationships: Supplying to a new model today may generate positive as well as negative externalities on future business prospects tomorrow.

2.2.1 Setting

Suppose that there are three buyers, labelled by $B \in \{B_1, B_2, B_3\}$. In each period t, B is endowed with a risk level θ_B^t randomly drawn from an i.i.d. standard uniform distribution: $\theta_B^t \overset{\text{i.i.d.}}{\sim} U[0,1]$. $\theta_B^t = 1$ means that B is risk-free at t. The smaller

θ_B^t, the riskier B. I also assume that the lifetime of a new model is equal to one period length, that is, if B releases a new model at the beginning of period t, it is terminated at the end of t.

Let V be the utility enjoyed by a supplier S from supplying to a new model of some risk-free buyer B over the course of one period. When S and B have already worked together in the past, this utility increases because, e.g., of the know-how acquired by S in past joint cooperation with B. Let $W = \alpha V$, where $\alpha > 1$, be this utility. Likewise, when S has been working with another buyer, this net present value V varies (it may increase through, e.g., know-how spillovers, or decrease through, e.g., scattered engineering resources). Let $U = \rho V$, where $\rho > 0$, be this utility. I also define the utility from signing with B when its risk score is $\theta_B^t < 1$, as $\theta_B^t V$ (or $\alpha\theta_B^t V$, $\rho\theta_B^t V$).[5] I denote by β the discount factor.

I now define the contract requirements of B when it makes an offer to S: B makes an offer to S if and only if (i) the risk of S's other-buyer portfolio is low *enough*, i.e., its risk score (defined as the minimum of individual scores) is above some threshold $T \in (0, 1)$, (ii) S has less than two other buyers, and (iii) S has on average signed no more than once with its other buyers. Notice that $\mathbb{P}(\theta_B^t > T|B, t) = 1 - T$, for any (B, t). T may be a function of the number of other buyers or ongoing models, of ρ or α.

I consider a two-period model. I denote these periods t and $t+1$. At the beginning of t, some arbitrary buyer B has already made an new offer to S and S must choose to sign or not. In the beginning of $t + 1$, some arbitrary B (which may be the same but not necessarily) decides whether to make a new offer to S (given what happened at t), and S responds. I denote by a and o respectively S's acceptance and B's submission of an offer. I tag their complementary actions with $\bar{a}$ and $\bar{o}$ respectively.

[5] A high score θ_B^t means that B is in good financial conditions. A low rating score signals a higher risk to fail at honoring and repaying contracts signed with a supplier.

Notice that accepting any offer in the last period is a dominant strategy for S.

I exhibit the trade-off faced by S for three different sets of initial conditions and buyer-offer sequences.[6] Moreover, the goal of this section is only to set out in a simple fashion the trade-offs faced by S under different conditions. Figures B.1, B.2, and B.3 show the path trees of these scenarios.

2.2.2 First scenario

In this scenario, S already supplies to one model of B_1 at the beginning of t and receives an offer from B_2. In the beginning of $t+1$, B_3 decides whether to make a new offer to S, and S responds.

At t, if S decides to supply to B_2, B_3 will not make an offer to S at $t+1$ because S will be supplying to *too many* buyers already (two buyers B_1 and B_2). If S decides not to supply to B_2, S can expect an offer from B_2 in the next (and last) period with probability $1-T$. It is the probability that (its current buyer) the risk score of B_1 will be above threshold T at $t+1$. At t, the expected risk score of B_3 at $t+1$ is equal to half. Further, when accepting an offer, S's utility is multiplied by a factor ρ since S already supplies B_1. The utilities derived from playing a and $\bar{a}$ are respectively given by:

$$u_a = \rho\theta_2^t V \qquad \text{and} \qquad u_{\bar{a}} = \beta(1-T)\rho\frac{1}{2}V.$$

S chooses to accept the offer of B_2 at t (i.e., play a) if and only if $u_a > u_{\bar{a}}$, that is:

$$\theta_2^t > \frac{1}{2}\beta(1-T).$$

Here, the operational benefit from signing with another buyer is the same to S, whether to play a or $\bar{a}$. In both cases, it would enjoy (or suffer) a multiplier of

[6] For simplicity, I do not formally show that initial conditions in these scenarios are likely events on nonzero-probability paths in a bigger decision problem.

magnitude ρ. S is willing to sign with B_2 at t only if B_2's rating score θ_2^t is high enough, relative to B_3's expected risk at $t+1$ (weighted by (i) the probability of actually receiving an offer from it at that period and (ii) the discount rate from having to wait one period before generating new revenues). Naturally, the more risk-averse (a high T) the buyers, the less likely they are to make an offer tomorrow to S if it has other buyers, and the more likely S to accept an actual offer from a risky buyer today.

2.2.3 Second scenario

In this scenario, S already supplied to one B_1's model at the beginning of t and receives an offer from B_1. In the beginning of $t+1$, B_2 decides whether to make an offer to S and S responds.

At t, if S decides to supply to B_1, B_2 will not make an offer to S at $t+1$ because S will be agreed to supply to *too many* models (two models) to B_1. If S declines B_1's offer, S can expect an offer from B_2 at $t+1$. Further, when accepting B_1's offer, S's utility is multiplied by α since S already supplied B_1. When accepting B_2's offer, it is multiplied by ρ. Then:

$$u_a = \alpha\theta_1^t V \qquad \text{and} \qquad u_{\bar{a}} = \beta(1-T)\rho\frac{1}{2}V.$$

S chooses to accept B_2's offer at t (i.e., play a) if and only if $u_a > u_{\bar{a}}$, that is:

$$\theta_1^t > \frac{1}{2}\beta(1-T)\frac{\rho}{\alpha}.$$

S is willing to sign at t with a riskier B_1 (a low θ_1^t) if the operational benefits α from working with an already well-known buyer compensate the loss from its high risk. The larger α (and the lower ρ, i.e., working with many buyers is operationally detrimental to S), the more willing S would be to keep working with B_1 when it has a high risk level.

2.2.4 Third scenario

In the third scenario, S has no buyer yet at the beginning of t and receives an offer from B_1. In the beginning of $t+1$, B_2 decides whether to make an offer to S and S responds.

At t, if S decides to supply B_1, B_2 will make an offer to S at $t+1$ with probability $T-1$. If S declines B_1's offer, B_2 would make an offer at $t+1$ with probability one. Then:

$$u_a = \theta_1^t V + \beta(1-T)\rho\frac{1}{2}V \qquad \text{and} \qquad u_{\bar{a}} = \beta\frac{1}{2}V.$$

S chooses to accept B_2's offer at t (i.e., play a) if and only if $u_a > u_{\bar{a}}$, that is:

$$\theta_1^t > \frac{1}{2}\beta\big[1-(1-T)\rho\big].$$

The larger ρ, the more willing S would be to sign with a risky B_1 at t because the benefits expected at $t+1$ from working with multiple buyers are high (e.g., through know-how spillovers). Instead, if working with multiple buyers requires to scatter engineering resources and lowers the value from a business relationship, the more willing S would be to wait for an offer from a *safer* buyer tomorrow.

2.3 Description of the Data

In this section, I describe additional data sources that I use along with the WSW database described in Section 1.3 and provide a description of the variables that I use in the empirical analysis of this chapter. In Section 1.4, I describe the risk of misreporting in the WSW database. As a consequence, I choose to focus the analysis on observations (S, B, t) such that I observe some ongoing or new business at t for S. I drop observations (S, B, t) such that S is supposed to be an alive supplier but shows no activity at all at t (S does not have any ongoing link or form any new link either at t).

2.3.1 Adding production and risk variables

I supplement the network dataset described in Section 1.3 with yearly per-model production quantities, measured in units of assembled cars. The production data are also provided by IHS. The final dataset is a list of supplier-buyer-year combinations. For each observed triplet (S, B, t), the dataset consists in the main features of the supplier's portfolio, seen from the buyer's viewpoint. These features include (i) whether S is already an ongoing supplier to B in year t, (ii) the number of ongoing contracts between S and B in year t (signed before t), (iii) the number of sectors that are covered by these ongoing contracts, (iv) the aggregate production that these ongoing contracts represent in year t (in 100k-units),[7] (v) whether S has other ongoing buyers, (vi) the number of S's ongoing buyers other than B in year t, (vii) the average number of ongoing contracts per other ongoing buyers in year t, (viii) the average number of sectors covered by these ongoing contracts, and (ix) the average aggregate production that these ongoing contracts represent per other buyer in year t (in k-units). (ii), (iii), and (iv) are conditional on (i) being true. Likewise, (vi) to (ix) are conditional on (v) being true. In Table B.2, I show the yearly summary statistics of these characteristics. In Table B.4, I show the cross-sectional summary statistics of these characteristics, conditional on whether S and B sign a new contract together in year t or not. Notice that over the 2005-2011 time window, more than 14 percent of the possible supplier-buyer-year combinations (S, B, t) in the data are

[7] Suppose that S supplies respectively one and three parts to B's models M_1 and M_2 and that in year t, B assembles Q_1 units of M_1 and Q_2 units of M_2. Then the aggregate production that these ongoing contracts represent in year t is equal to $Q_1 M_1 + 3Q_2 M2$.

such that S and B signed one new contract or more in year t.

Finally, I construct a risk score for the twelve major car manufacturers, based on their credit-rating scores by Moody's Analytics. These scores measure the ability of a firm to meet its financing obligations and its probability of default. By convention, a high score signals a small risk. Table B.3 shows the time-series of yearly averages of these scores for these firms. It reveals how compromised the financial position of Chrysler and GM was between 2008 and 2010. In contrast, strong foreign competitors such as BMW, Honda, Toyota, or VW, show steady high scores. The mapping between Moody's global long-term rating scale and the rating scale in Table B.3 works as follows: {Obligations with low credit risk: Aaa, Aa1, Aa2, Aa3, A1, A2, A3} → 5; {Obligations with moderate credit risk: Baa1, Baa2, Baa3} → 4; {Obligations with substantial or high credit risk, speculative: Ba1, Ba2, Ba3, B1, B2, B3} → 3; {Obligations with very high credit risk, highly speculative: Caa1, Caa2, Caa3} → 2; {Obligations near or typically in default, highly speculative with little prospect of recovery: Ca, C} → 1; {Default: D} → 0. See Moody's (2011, 2016) for more details on the rating scale.

2.3.2 Seeing Ford's Fall-2008 move in the data

In the introduction, I motivated the goal of this paper by invoking Ford's decision to reduce its risk of supply-chain disruptions by reducing its exposure to Chrysler, of which it was betting on the collapse. To assess the quality of the data, I want to test whether the data reveal Ford's decision. I write the baseline model as follows:

$$y_{SBt} = \alpha_S + \alpha_{Bt} + \delta_1 \tilde{l}_{SBt} + \delta_2 \tilde{l}_{S\text{Chrysler}t} + \delta_3 \tilde{l}_{S\text{GM}t} + \delta_4 \tilde{l}_{S\text{Other}Bt} + \varepsilon_{SBt},$$

where (i) y_{SBt} is an indicator variable that takes the value of one if S and B sign one or more new contracts in year t and zero otherwise, and (ii) $\tilde{l}_{SBt}$ is an indicator variables that takes the value of one if S and B are in an ongoing relationship at t. Similarly, $\tilde{l}_{S\text{Other}Bt}$ takes the value of one if S is linked to any buyer other than

B, Chrysler, and GM. I add a supplier fixed effect (α_S) and a buyer-year fixed effect (α_{Bt}). Standard errors are clustered at the supplier level. I also include time-varying coefficients $\tilde{l}_{S\text{Chrysler}t}$ and $\tilde{l}_{S\text{GM}t}$, depending on whether $t < 2009$, $t = 2009$, or $t > 2009$. Note that buyers Chrysler and GM are excluded from the analysis since the purpose of the above model is to investigate the relationship between working with Chrysler or GM and the probability of signing a new contract with someone else.

Figure B shows the time-specific estimates of (i) δ_1, (ii) Ford- and other-buyers-specific δ_2 and δ_3, and (iv) δ_4. Figure B also includes 95%-confidence intervals. Results reveal some interesting network patterns. First, data shows Ford's Fall-2008 decision with respect to Chrysler: In 2009, the probability that Ford signs a new contract with a supplier linked to Chrysler decreases by twenty percentage points! In the same period, the probability that Ford signs a new contract with a supplier linked to GM increases by more than twenty percentage points. This mechanical transfer from Chrysler to GM is explained by the historical high level of clustering in the Big Three's supply network in the Midwest. Betting on the collapse of Chrysler but not of GM (too big to fail), Ford mechanically redirected its new business relationships towards its other *preferred* suppliers which were not linked to Chrysler. Historically, many of them were also linked to GM. This effect disappears after 2009, that is, after GM and Chrysler were bailed out. From then on, firms in the network know that automakers are too big to fail, and risk seems no more a decision criterion in forming new business relationship. These results also signal the quality of the data, despite all the limitations described in Section 2.3.

Second, results also show taste for longstanding relationships in the industry (left-hand-side figure). It is consistent with the industry facts described in Section 1.2. Finally, the right-hand-side figure shows that, from 2009 on, the probability that S and B sign a new contract at t is negatively correlated to whether S is linked to other buyers. This result suggests that, if risk does not matter after the crisis, firms in the network are unwilling to expose themselves to a large number of business partners, unlike before the crisis. These results suggest a shift in firms' decision criteria for signing new contracts in the wake of the collapse and bailout of GM and Chrysler, and hint at the externalities from S's customer portfolio explored in the toy model of Section 2.2. Based on this set of motivating evidence, the next section offers a more thorough empirical strategy to investigate the relationship between forming new buyer-supplier business relationships and the shape of the supplier's portfolio.

2.4 Empirical Strategy

In this section, I investigate the hypothesis that, through the channel of a supplier's buyer portfolio, the buyer-supplier network drive the formation of new business relationships between this supplier and a car manufacturer. In particular, I examine the relationship between the probability that a new contract will be signed between a supplier S and a buyer B in year t (provided that B launches some new models) and the different characteristics of S's buyer portfolio at the beginning of t. These characteristics cover production capacity, customer or sector specialization, and financial risk, as described in Section 2.3.

I conceptualize a supplier's buyer portfolio as having three main components: (i) the network (N), which includes the links to major buyers, (ii) the operational component (O), which includes the number of contracts and of covered sectors, and production with buyers, and (iii) the risk component (R), which includes the financial riskiness of buyers. The variables of interests in these three categories are defined in Table B.5. The outcome of interest I denote by P_{SBt}, which is the probability of a new contract to be signed between a supplier S and a buyer B in year t. The baseline model can write in the following form:

$$y_{SBt} = \alpha + \delta' N_{SBt} + \pi' O_{SBt} + \phi' R_{SBt} + \theta' F_{SBt} + \mu' D_t + \varepsilon_{SBt},$$

where (i) y_{SBt} is an indicator variable that takes the value of one if S and B sign one or more new contracts in year t and zero otherwise, (ii) N_{SBt}, O_{SBt}, and R_{SBt} are defined as in Table B.5, (iii) F_{SBt} is a vector of firm control variables (including the size of S and B in t measured in total production units at $t-1$ and the number of new models that B launches in year t), and (iv) D_t is a vector of demand and five-year demand forecast indicators. Finally, the analysis is conditional to buyers launching new models because the probability that S and B sign a new contract in year t is mechanically equal to zero if B does not release a new car in t. As a consequence, I drop observations (S, B, t) such that B launches no new car in t.

2.4.1 Production operations

I begin with investigating the relationship between P_{SBt} and (i) direct operational characteristics of the relationship between S and B, and (ii) indirect externalities that S and B are exposed to through S's other-buyer portfolio. To examine these relationships, I write the baseline model as follows:

$$\begin{aligned} y_{SBt} = \alpha &+ \tilde{l}_{SBt} \times (\delta_0 + \pi_0 \tilde{n}_{SBt} + \pi_1 \tilde{m}_{SBt} + \pi_2 \tilde{q}_{SBt}) \\ &+ \tilde{l}^{\star}_{SBt} \times (\delta_1 + \delta_2 \tilde{z}^{\star}_{SBt} + \pi_3 \tilde{n}^{\star}_{SBt} + \pi_4 \tilde{m}^{\star}_{SBt} + \pi_5 \tilde{q}^{\star}_{SBt}) \\ &+ \theta' F_{SBt} + \phi' R_{SBt} + \mu' D_t + \varepsilon_{SBt}. \end{aligned} \tag{2.1}$$

The first four variables describe the shape of the relationship between S and B at t based on the contracts signed before t, in network (δ) and operational (π) terms. The next five ones describe the network (δ) and operational (π) externalities generated by S's other-buyer portfolio. I also control for unobserved heterogeneity by including buyer, supplier, and year categorical effects, as well as risk (R_{SBt}) and demand controls (D_t).

As described in Section 1.2, a car is a complex product and supplier-automaker relationships tend to be strong and longstanding. As a consequence, a fair guess is that the sign of bilateral coefficients, $(\delta_0, \pi_0, \pi_1, \pi_2)$, will be positive. However, the sign of externality coefficients, $(\delta_1, \delta_2, \pi_3, \pi_4, \pi_5)$, is not as straightforward. On the one hand, a supplier who signs new contracts with multiple buyers may signal for quality and cutting-edge technologies and yield economies of scale, lower prices, and know-how spillovers. This can benefit the supplier as much as all buyers in its portfolio. On the other hand, a large buyer portfolio today requires to allocate a large production capacity to some obsolete parts tomorrow. It also requires to scatter tailor-made engineering across customers with very specialized needs, and then higher transaction costs. Both the supplier and the buyer can suffer from a supplier having too many *outside* contracts to honor. It follows that, when the buyer launches a new model, both firms seem to face a trade-off in the decision to sign a contract together. These trade-offs emerge from the network externalities generated by the supplier's buyer portfolio at the time firms consider to sign a contract.

2.4.2 Financial risk

Next, I investigate the relationship between P_{SBt} and the indirect financial risk generated by S's other-buyer portfolio in year t. I have risk scores for the 12 largest automakers. I write the baseline model as follows:

$$
\begin{aligned}
y_{SBt} = \alpha &+ \tilde{l}_{SBt} \times (\delta_0 + \phi_0 \tilde{r}_{SBt}) \\
&+ \tilde{l}^{\star}_{SBt} \times (\delta_1 + \delta_2 \tilde{z}^{\star}_{SBt} + \phi_1 \tilde{r}^{\star}_{SBt}) \\
&+ \theta' F_{SBt} + \pi' O_{SBt} + \mu' D_t + \varepsilon_{SBt},
\end{aligned} \tag{2.2}
$$

The first two variables describe the shape of the relationship between S and B at t based on the contracts signed before t, in network (δ) and financial-risk (ϕ) terms. The next three ones describe the network (δ) and financial-risk (ϕ) externalities generated by S's other-buyer portfolio. I also try different combinations of buyer, supplier, and year categorical effects, and of operational controls (O_{SBt}).

Model (2.2) enables me to test whether B and S are more likely to sign a new contract at t when the financial risk of S's other ongoing buyers is high ($\phi_0^\star > 0$ since a high score means that the firm is strong). If this were not statistically rejected, it would give credits to the hypothesis that when assessing the possibility of a new contract with S, B takes into account the risk to which it exposes itself by forming such a new business relationship. If S has some fragile buyers in its portfolio, B may fear a higher risk of supply disruption: The collapse of a major buyer would result in a drop in revenues for S, an increase in costs (e.g., by diseconomies of scales), and as a consequence, a higher risk to fail at honoring contracts with other buyers.[8]

I also run the following model

$$\begin{aligned} y_{SBt} = \alpha &+ \tilde{l}_{SBt} \times (\delta_0 + \phi_0 \mathbb{1}\{\tilde{r}_{SBt} < 2\}) \\ &+ \tilde{l}^\star_{SBt} \times (\delta_1 + \delta_2 \tilde{z}^\star_{SBt} + \phi_1 \mathbb{1}\{\tilde{r}^\star_{SBt} < 2\}) \\ &+ \theta' F_{SBt} + \pi' O_{SBt} + \mu' D_t + \varepsilon_{SBt}, \end{aligned} \tag{2.3}$$

where r_{SBt} and $r^\star_{SBt}$ r_{SBt} and $r^\star_{SBt}$ are replaced by indicators taking value one when respectively B and any of the other buyers in S's portfolio are rated below two. I choose two as my threshold of interest because any smaller rating signals that the rated firm is either highly speculative and near to default (rating one), or already defaulted (rating zero). This specification simply replaces the risk scale by a risk threshold.

2.4.3 Time-specific coefficients

Finally, I test whether there are differences in the network (N_{SBt}), operational (O_{SBt}) and financial-risk (R_{SBt}) determinants of the probability that S and B sign a new

[8] This was Ford's concern in Fall 2008.

contract, before and after the crisis. This analysis would provide supporting evidence for the hypothesis that the pattern of these network externalities changes after 2009, which hints that firms shifted their criteria for signing new contracts in the aftermath of the collapse and bailout of GM and Chrysler.

2.5 Results

My findings support the hypothesis that (i) a buyer B and a supplier S account for the externalities generated by the latter's buyer portfolio when signing a new contract and (ii) the pattern of these network externalities changes after 2009, that is, in the aftermath of the collapse and bailout of Chrysler and GM. On the operational side, I find that S and B are more likely to sign a new contract when they have already been working together and S has large-scale-production relationships with a limited number of other buyers. On the risk side, I find that S is more likely to supply to some of B's new model when S has a narrow number of financially safe other buyers to whom S is not *too* exposed in terms of number of models supplied (i.e., of production lines).

I show results from operation model (2.1) and risk model (2.2) in Tables B.6 and B.7, respectively. In each table, column 1 presents results for the baseline operation and risk models, without any controls. In column 2, I extend the model to control for demand (D_t), firm (F_{SBt}), and risk (R_{SBt}) characteristics in operation model (2.1), and for demand (D_t), firm, and operation (O_{SBt}) characteristics in risk model (2.2). From column 2 on, Tables B.6 and B.7 present results for the same model. Table B.6 shows the estimated coefficients for network and operation variables, controlling for risk characteristics, while Table B.7 shows the estimated coefficients for network and risk variables, controlling for operation variables. Column 3 in both tables add year fixed effects, to better account for demand for car or other changes happening during the year that could explain variations in the likelihood that S and B would sign a new contract (e.g., raw material prices). Column 3 also includes buyer fixed effects to account for unobserved time invariant buyer characteristics (e.g., reputation, quality, or nationality). I show my preferred model in column 4, which adds supplier fixed effects to also control for time-invariant supplier characteristics (e.g., reputation, quality, or nationality again). I include results from all specifications for completeness, but only discuss results from the preferred model in the last column.

For ease of exposition, I now denote by P_{SBt} the probability that S and B sign a new contract at t.

2.5.1 Network variables

After including the full set of controls, P_{SBt} increases by 5.5 percentage points (pp) when S and B are already in an ongoing relationship (column 4 in Tables B.6 and B.7). As a matter of comparison, fourteen percent of the possible combinations (S, B, t) in the data are such that S and B sign a new contract in t.

Column 4 also shows that, once I account for supplier fixed effects, whether S has ongoing links with other buyers increases P_{SBt} by another 5.4 pp. However, if S has ongoing contracts with other buyers, one additional ongoing buyer reduces P_{SBt} by almost one pp. These results suggest that S and B are more likely to sign anew when S is not too connected. This relationship becomes negative when S is exposed to too many different buyers.

These results are consistent with the industry description of Section 1.2, in particular that the design and production of a car model require a heavy engineering cooperation between the automaker and its suppliers. What matters is that S and B *know each other* and *are linked*, and that S, while gaining know-how from projects with different buyers, does not scatter its engineering resources across a large number of them.

2.5.2 Operation variables

Column 4 (in Table B.6) shows that a unit increase in the numbers of ongoing models and of sectors supplied to B by S increases P_{SBt} by 1.6 pp and 0.5 pp respectively. Likewise, a 100k-unit increase in the number of models produced by B for which S is a supplier increases P_{SBt} by 0.8 pp.

Interestingly, column 4 also shows that the anatomy of S's other-buyer portfolio is a significant but ambiguous predictor of the probability that S and B sign a new contract. A unit increase in the average number of ongoing models per other buyer decreases P_{SBt} by 2.4 pp whereas a 100k-unit increase in the average number of models produced by S's other buyers for which S is a supplier increases P_{SBt} by 1.5 percent. In Section 2.5.1, I have shown that P_{SBt} is negatively correlated with S's number of other buyers; however, the potential externality generated by S's other-buyer portfolio on P_{SBt} can have a positive effect when these other buyers work with S on a concentrated number of models with large-scale production. The economies of scales generated by the latter can compensate all (or part) of the costs of working with a supplier that scatters its engineering resources across multiple buyers or production lines (models).

These results are consistent with some of the industry facts that I have discussed in Section 1.2. Buyers have a narrow set of preferred suppliers and they do not have incentives to fail them by entering into relationships that could jeopardize the position of the supplier. The design and production of a car model require a close engineering cooperation between the automaker and its suppliers. S and B working together on a broad range of models and component sectors likely generates efficiency gains in the engineering process (e.g., know-how spill-overs) and lower transaction costs. On the contrary, scattering engineering resources across buyers and multiple production lines (or models) may generate higher transaction costs. At the same time, buyers would tend to favor situations where they can enjoy economies of scales from working with suppliers having large-scale production relationships with other buyers.

These results suggests the hypothetical trade-off described in Section 2.4.1 and formalized in Section 2.2: On the one hand, S may benefit from having ample business relationships (in terms of models supplied) with multiple buyers provided that they represent a *large enough* production. As such, S may signal quality or efficient engineering resources, and enjoy economies of scales. This virtuous combination may also reduce transaction costs, foster know-how spillovers, and, as a consequence, benefit the buyers in S's portfolio. On the other hand, S may suffer from having a portfolio *too diversified*. As described in Section 1.2, S has no control on the production levels, which are fixed in the short-run by its buyers. Signing contracts today does not guarantee a large-scale production tomorrow. As such, it increases the risk to scatter tailor-made engineering across buyers for small-scale and more costly production levels. This vicious combination of S's production factors may also harm its buyers.

2.5.3 Financial risk variables

The risk rating of B is a significant predictor of P_{SBt} only when S and B are in an ongoing relationship Column 4 (in Table B.7) shows that a unit increase in the risk rating of the buyer increases the probability of a new contract by 0.9 pp.

When S has contracts with other buyers, P_{SBt} increases by 0.8 pp for each unit increase in the lowest risk rating among all other buyers that have a relationship with S. In Section 2.5.1, I have shown that P_{SBt} is negatively correlated with S's number of buyers other than B. However, if these other buyers are financially strong, the externality generated by S's other-buyer portfolio on P_{SBt} can become positive. A portfolio of buyers with a low default risk provides for reliability and can compensate all (or part) of the costs of working with a supplier scattering its engineering resources across multiple buyers.

As I have already shown, if S is not in an ongoing relationship with B, it is less likely that they will sign a new contract together because S is not in the set of preferred suppliers of B. In this case, the risk rating of B does not matter for S. However, if S and B are in an ongoing relationship, then S is more likely to accept a contract offer from B, the lower B's financial riskiness. S internalizes the dynamic that, when it is too tied to a risky buyer, it may decrease its probability to supply to new models to its other buyers in the future. The model in column 4 (in Table B.7) controls for the *vitality* of B through the number of new models that it launches at t. In other words, the risk variable does not capture the idea that good financial conditions reflect good operational conditions, and as such, a larger propensity to launch new models (and to sign new contracts). Instead, it suggests that S is more likely to accept to supply B anew when B is in good shape. This hypothesis is also supported by the positive correlation between P_{SBt} and the minimum risk-rating score in S's other-buyer portfolio: S and B are less likely to sign anew when S has another weak buyer. On the other hand, having a strong relationship with a healthy buyer generates a positive externality on its business prospects with its other buyers.

These results suggest the following hypothetical trade-off: S may benefit from having ample business relationships with multiple buyers, provided that they are financially *strong enough*. As such, S may signal a higher solvency profile and a high likelihood that its business orders would be honored overtime, a guarantee for a sustainable production chain. On the contrary, S may suffer from having a portfolio *too diversified*. Not only S has no control on the production levels of its buyers, but S cannot control their financial health either. Signing contracts today does not guarantee a solvent buyer tomorrow.

Finally, Table B.8 shows the results of model (2.3). It is the same model as

(2.2) but r_{SBt} and $r^{\star}_{SBt}$ are replaced by indicators taking value one when respectively B and any of the other buyers in S's portfolio are rated below two. I choose two as my threshold of interest because any smaller rating signals that the rated firm is either highly speculative and near to default (rating one), or already defaulted (rating zero). This specification simply replaces the risk scale by a risk threshold. Results are qualitatively the same.

The next section explores in a before-after analysis whether these patterns changed in the aftermath of the collapse and bailout of GM and Chrysler.

2.5.4 Year-specific analysis: A shift after the crisis?

In Table B.9, I show the risk-externality results of model (2.3) with time-specific coefficients.[9] I group years in two categories: pre-2010 and post-2009. I choose this categorization because the bailout of Chrysler and GM happened in the course of 2009. Results suggest that risk from other buyers in the portfolio of S was a significant predictor of P_{SBt} before the crisis. This relationship disappears with the bailout. Equally important is the change after the crisis in the relationship between the number of other ongoing buyers and the probability that S signs a new contract with B. This change suggests that the result shown in Section 2.5.1 sayng that S and B are more likely to sign anew when S is not too connected, is a pattern that emerges in the aftermath of the crisis.

I now push this time-specific analysis a step further. Figures B.5, B.6, and B.7 plot the estimates of model (2.2) with buyer, supplier, and year fixed effects. Figures also include 95%-confidence intervals (standard errors clustered at the supplier level). The plots compare the estimated coefficients of model (2.2) to their year-specific counterparts. I group years in three categories: pre-2008, 2008-2009, and post-2009.

[9] For ease of exposition, I omit in the table to show other variables. I also choose to focus on the externalities generated by the risk of other buyers in the supplier's portfolio.

I choose these categorization because, as suggested above, 2009 was a decisive year in which both GM and Chrysler collapsed, filed for bankruptcy protection, and were rescued with public money.[10] I also choose to go back from model (2.3) to model (2.2) because, prior to 2009, I do not observe any buyer B with a rating smaller than two. Before 2009, $\mathbb{1}\{\tilde{r}_{SBt} < 2\}$ and $\mathbb{1}\{\tilde{r}^{\star}_{SBt} < 2\}$ are always equal to zero.

Figures B.5 shows results for network characteristics of the supplier's portfolio. Specifically, the left-hand-side figure shows that during the crisis, being in an ongoing relationship did not matter for forming new business relationships. This change from pre-2009 level suggests that at times of crisis, prioritizing ongoing relationships is not as important as diminishing exposure to potentially risky partners. Once the crisis is over, having an ongoing relationship goes back to being an important determinant of signing new contracts. However, equally important is the relationship that a supplier S has with other buyers. The figure in the middle shows that the P_{SBt} increases when S is connected to other ongoing buyers. While this pattern was not significantly affected by the crisis, the right-hand-side figure shows that the larger the number of ongoing buyers the lower the probability of signing a new contract post-crisis. I hypothesize this is a strategy adopted by buyers to reduce their exposure to potentially risky suppliers, which, as previously noted, is consistent with the strategy adopted by Ford.

Figure B.6 shows results for risk characteristics. The left-hand-side figure suggests that the risk rating of B was a significant predictor of P_{SBt} before the crisis, regardless of whether there were an ongoing relationship between S and B. This positive relationship disappears with the crisis. The figure in the middle shows that, when S and B are in an ongoing relationship, the risk rating of B was a strong predictor of P_{SBt} only during the crisis. Likewise, the right-hand-side figure shows that a

[10] President Bush signed the first executive order to enable the transfer of public money to GM and Chrysler on December 19, 2008. President-elect Obama continued to fund the rescue of the US automobile once in office.

positive correlation between P_{SBt} and the minimum risk-rating score in S's other-buyer portfolio during the crisis. The risk of S's buyer portfolio matters because the solvency risk of the buyers in the portfolio is a strong predictor of the attractiveness of a supplier: A supplier working with a near-to-default buyer is more likely to face contract disruptions and to generate supply-chain disruptions for its other buyers. I hypothesize that the 2008-2009 crisis revealed to automakers the risk of supply-chain disruptions and collapse stemming from being indirectly connected to insolvent companies through the supply network. However, risk characteristics matter no more after the crisis because the mere fact of being too connected is in itself heavily penalized, in spite of the bailout of GM and Chrysler that signaled that industry flagships are too big to fail. The bailout seems to have been received more as a serious warning rather than as a blank check. I hypothesize the surge of an increased taste for more buyer-specialized suppliers in the wake of the collapse and bailout of Chrysler and GM: A buyer prefers a supplier that (i) is not exposed to disruption through too many channels (i.e., too many other buyers), and (ii) is a supplier to these other buyers for a concentrated number of large-scale production models (see Figure B.7). From then on, better safe than sorry.

2.5.5 Causality of the results

In this section, I briefly assess the causality of the above results. I list some potential sources of endogeneity in the explanatory variables and discuss how the inclusion of some fixed effects or controls clear them.

Risk score may capture the fact that good financial conditions reflect good operational conditions, and as such, a larger propensity to launch new models (and to sign new contracts). This is why I control for the operational *vitality* of B through the number of new models that it launches at t. The risk of B may also capture the demand for B's model: A poor rating may reflect poor sales. This is why I control for demand and demand forecast (common to all buyers) with year and buyer fixed effects. I do not include buyer-year fixed effects because they would capture some of the variation I am interested in (such as Ford's decision in Fall 2008 to break its links with its suppliers linked to Chrysler). Nevertheless, the buyer fixed effect captures some reputation effect and is, as such, already very useful: For example, the fixed effect of GM captures its reputation for not building fuel-efficient cars, a weakness in the marketing image at times of high gas prices, like in 2008, and which may be detrimental to the sale of GM's more fuel-efficient models, as much as to the sale of its fuel-inefficient models.

The number of other buyers and the average number of models per other buyers are clearly endogenous: When ignoring suppliers' unobserved permanent heterogeneity, adding another ongoing buyer to S's portfolio increases P_{SBt}. Likewise, increasing the average number of contracts per other buyer by one unit increases P_{SBt}. When adding supplier fixed effects, these relationships become negative. Supplier fixed effects capture some longstanding size or reputation effect. For example, an automaker signs new contracts with Michelin not because Michelin is highly connected, but because it is a global firm with a high quality reputation. As a consequence, Michelin happens to be highly connected. I choose not to add supplier-year fixed effects because they would capture some of the variation I am interested in. For example, because of the preferred-supplier characteristic of buyer-supplier relationships in the automotive industry, suppliers show little variation overtime in their set of customers. Adding a supplier-year fixed effect would capture most of the network effect on S's portfolio on P_{SBt}. Likewise, I do not include buyer-supplier fixed effects.

2.6 Concluding Remarks

This paper explores the different trade-offs that automakers and suppliers face from the externalities generated by suppliers' buyer portfolio when forming new business relationships. Results suggest that, when signing new contracts, the supplier and the automaker internalize (i) two trade-offs in production allocation (allocation of engineering resources across contracts) and in customer-supplier specialization (*idem* across buyers), as well as (ii) the exposure to financial risk of other firms in the buyer-supplier network. Interestingly, the analysis suggests that, if suppliers seem *engineering-capacity constrained*, they are not production-capacity constrained: The more models S is a supplier of to its other buyers, the less likely B is to sign with it; but the more S produces with its other buyers, the more likely B is to sign anew with it.

This paper shows that the hypothesis that strategic interactions drive the formation of the buyer-supplier network in the automotive industry cannot be rejected. In particular, results strongly suggest that buyers' financial risk levels may be a meaningful driver to the formation of new business relationships in the network. This paper leaves wide open the avenue to a more in-depth investigation of this question. A structural model, internalizing trade-offs into the decision preferences of the firms like in the toy model of this paper, is a natural next step.

Finally, the pattern of these network externalities changes after 2009, hinting that firms shifted their criteria for signing new contracts in the aftermath of the collapse and bailout of GM and Chrysler. The public bailout of GM and Chrysler signaled that industry flagships are too big to fail. But the bailout seems to have been received more as a serious warning rather than as a blank check. From now on, better safe than sorry seems to be the new guideline.

3

On Being a Car-Part Supplier: A Risk Perspective

This chapter offers a one-sided model of buyer-supplier agreements in the car-part industry. A supplier exogenously receives contract offers overtime from its buyers and endogenously accepts a new contract as a function of the risk and operational benefits that this new business generates. This model is informative of buyers' preferences in the risk profile of their suppliers: The value generated to the supplier by an additional contract reflects how much the buyer is willing to pay for working again with this supplier. I find that a supplier is ready to compensate its buyers for working with another buyer near to default, and to enjoy lower profits from safe buyers. Under low and high demand scenarios, a supplier working with a failed GM (Chrysler) is more than 15 and 21 percent (8 and 17 percent) less likely to sign a new contract with other buyers. These results support the view that a collapse of a major Detroit manufacturer could have had negative effects on the profitability of suppliers to accept new offers, on their ability to meet their risk costs, and as a natural consequence, on the viability of the supply network. However, results also show that the bailout did not make it easier to suppliers to accept contract offers as it came together with substantial changes in suppliers' profit function shape. In particular, the presence of a risky other buyer no longer matters after the crisis, but the mere fact of being connected to other buyers in now less profitable to suppliers. The crisis seems to have simply replaced the set of pre-bailout risk requirements and costs by another set of equally, if not more, stringent contract conditions.

3.1 Introduction

Motivated by Ford's response to the risk of supply-chain disruption during the crisis, the previous chapter empirically investigates whether automakers and their suppliers account for solvency-risk exposure when forming the supplier-buyer network. The analysis supports the hypothesis that strategic interactions drive the formation of the buyer-supplier network in the automotive industry. In particular, results strongly suggest that the solvency risk of other buyers in one supplier's portfolio may be a meaningful driver to the formation of a new business relationship between a buyer and this supplier. However, the analysis leaves wide open the avenue to a more in-depth investigation of the mechanisms behind. It is the main *raison d'être* of the structural model in the present chapter.

The buyer-supplier network can be seen as the outcome of strategic interactions wherein one's decisions depend on others': Supplying to some buyer may hinder the prospects of supplying another manufacturer in the future. Similarly, a manufacturer may benefit from choosing a supplier working with another manufacturer (economies of scale, know-how spillovers) or suffer from it (production capacity constraint, scattered engineering resources, indirect exposure to competitor's risk). In this chapter, I walk in the shoes of a car-part supplier and explore which features of its buyer portfolio affect its profitability. These features include operational variables (such as the numbers of buyers and of models supplied to each, and production levels) and risk variables (such as the solvency-risk level of each buyer).

I build a single-agent optimization problem in which a supplier receives contract offers overtime from a fixed set of buyers that it usually works with. The supplier endogenously accepts to supply to a new contract as a function of the risk and operational benefits that this new business generates. I assume that the arrival process of contract offers is exogenous and independent of the supplier's characteristics. Nevertheless, the buyer's preferences in the profile of its suppliers can still be inferred from the supplier's profit function: The value generated to the supplier by an additional contract is indeed informative of how much the buyer is willing to pay for working on its new model with this supplier.

In the model, the decision maker is the supplier. In practice, when a carmaker needs a new part, it undergoes extensive discussions with its preferred suppliers, bilaterally assesses with each whether it meets its technical demands, and then picks the cheapest one. The 2008-2009 crisis also revealed that risk could be part of the buyer's requirements. The final decision of the supplier to accept or decline an offer can be seen as the outcome of these discussions and joint assessment process. In this context, turning down a contract offer means that it is too costly to the supplier to meet all the demands of the buyer for this specific contract, at the time it is being offered.

I bring this model to the data, using the IHS *Who Supplies Whom?* database. It is a continuous-time panel dataset reporting at the car-part level, the suppliers to most of the models assembled in North-America and Europe. This database is built from the suppliers' viewpoint and offers a fair view of the buyer portfolio of the suppliers present in the data. However, some major suppliers are missing, and the set of suppliers of a carmaker cannot be faithfully recovered. The structural model described above is built from the supplier's point of view because of this major data limitation.

Results from these paper show that buyer-supplier dynamics in the car-part industry are simultaneously determined by the individual characteristics of the suppliers and the buyers as well as by the features of the other buyers in the supplier's portfolio, including their risk profile. When a supplier has a defaulted or speculative buyer in its portfolio, it is exposed to a greater risk of collapsing in the wake of its defaulted buyer. As a consequence, it has to compensate its other buyers for the increased risk of disrupting their supply chain. Consistent with this result, a supplier receives smaller profits when working with a safe buyer. A compensation paid to a safe buyer for being more attractive to other buyers and more connected. I also show that the bailout is an inflection point switching or tuning some patterns in the link formation. After the crisis, the presence of a risky other buyer does not matter as much for two reasons: First, the mere fact of being connected to other buyers in now penalized. And, second, governments signaled that they would bailout automakers whose collapse would be considered a systemic risk to the economy. Interestingly, this change in the profitability of being a highly connected supplier happened, in spite of the bailout. By rescuing GM and Chrysler, American and Canadian governments signaled that industry flagships are too big to fail. A decision debated for the risk of increasing moral hazard among firms. Contrary to what many considered a likely unintended consequence of the bailout, the rescue of Chrysler and GM seems to have been received more as a serious warning rather than as a blank check. From now on, better safe than sorry appears to be the new guideline.

Using the estimated CCP's, I am able to explore the hypothetical case of a GM or Chrysler collapse on new-contract signatures. I show that both under low and high demand scenarios, a supplier working with a failed GM (Chrysler) is more than 15 and 21 percent (8 and 17 percent) less likely to sign a new contract with other buyers. Working with a defaulted buyer decreases the willingness of other buyers to work with the supplier and naturally decreases the extra value generated to the supplier by accepting the contract. The marginal effect of an exit of GM is negatively correlated to the degree of exposure to GM that is faced by the supplier. This pattern does not hold for Chrysler. During the debate on whether Chrysler and GM should be rescued, the main concern would come from GM, a much larger company than Chrysler. It was acknowledged that the American economy could absorb the collapse of Chrysler. Much more debated was the question of GM. When making an offer to the supplier, other manufacturers would then naturally be tougher when it is linked to Chrysler, independently of its degree of exposure, because Chrysler was naturally more likely to exit than GM. These results support the view that a collapse of a major Detroit manufacturer could have had negative effects on the profitability of suppliers to accept new offers, on their ability to meet their risk costs, and as a natural consequence, on the viability of the supply network.

However, the bailout of Chrysler and GM seems to have led to another unintended consequence, opposite to that of an increased risk of moral hazard: The analysis suggests that buyers have become far more cautious after the crisis, in reaction to the disaster that was narrowly avoided. Once bitten, twice shy. The bailout did not make it easier to suppliers to accept contract offers. The crisis seems to have simply replaced the set of pre-bailout risk requirements and costs by another set of equally, if not more, stringent conditions. It sheds light on the hundreds of supplier liquidations that followed the bankruptcy of Chrysler and GM, in spite of their bailout (and of the multi-billion Auto Part Support Program launched by the Obama administration).

This chapter contributes to the literature that investigates formation of supplier-buyer networks by going beyond reduced form evidence and by uncovering some of the mechanisms that drive relationship formation. More importantly, this paper sheds light on the effects of government bailouts on network formation in an industry where buyers and suppliers are highly interconnected. This chapter supports the view that a collapse of a major Detroit manufacturer would have been a threat to the viability of the supply network. However, it also shows that the bailout did not make it easier to suppliers to accept contract offers. A possible explanation to the hundreds of supplier collapses that followed the bankruptcy of Chrysler and GM, in spite of their bailout. While the analysis I conduct is particular to the automotive industry, it can still provide useful information for the study of other government interventions.

3.2 Description of the Data

In this section, I continue the description of the WSW database provided in Section 1.3 and of the variables used in the empirical analysis of this chapter. Following Section 1.3 and to be consistent with the perspective of Chapter 2, I restrict the database to the twelve largest buyers in North America and Europe[1] and construct for these twelve major companies a risk score based on their credit-rating scores by Moody's Analytics. These scores measure the ability of a firm to meet its financing obligations and its probability of default. By convention, a high score signals a small risk. The construction of these scores is described in Section 2.3.

3.2.1 Sample selection

Recall that the goal of this chapter is to assess the profitability of new supplier-buyer relationships in function of the shape of the supplier's customer portfolio. Following Section 1.4, I make the *preferred-supplier* assumption and drop exclusive suppliers and suppliers for which I do not observe *enough* agreements. I choose to keep suppliers which supply to one or more new models per year on average. Table C.1 shows yearly aggregate statistics of the final dataset in parallel to those of the dataset used in Chapter 2. Table C.2 shows yearly statistics of the main features of the supplier's portfolio, seen from the buyer's viewpoint. These features include

[1] Namely, I consider BMW, Chrysler, Daimler, Fiat, Ford, GM, Honda, Hyundai-Kia, PSA Peugeot-Citroën, Renault-Nissan, Toyota, and VW. They represent about 90 percent of the car production in Europe and North-America. I separate Chrysler from Daimler before 2008 (DaimlerChrysler regrouped the two firms from 1998 to 2007), and from Fiat after their takeover (FCA regroups Fiat and Chrysler). On the other hand, I do not separate Hyundai and Kia or Renault and Nissan either, because their alliances were formed before 2005 and were still holding at the end of 2011.

(i) whether S is already an ongoing supplier to B in year t, (ii) the number of ongoing models of B that S supplies to in year t (contracts signed before t), (iii) the production that these models represent, (iv) whether S has other ongoing buyers, (v) the number of ongoing buyers other than B in S's portfolio in year t, (vi) the average number of ongoing models that S supplies to in year t per other ongoing buyers, and (vii) the average production per other buyer that these models represent. (ii) and (iii) are conditional on (i) being true. Likewise, (v) to (vii) are conditional on (iv) being true. An active supplier or buyer in year t is one which signs a new contract (or, equivalently for buyer, launches a new model) at t. An ongoing model is one whose production started before year t and which is still being assembled at t.

3.2.2 Summary statistics

As expected, suppliers in the final sample are larger and more connected than in the original sample. As a consequence, the story to be told *on being a car-part supplier* would hold first and foremost for large ones, such as Delphi, Denso, Johnson Controls, Michelin, Pirelli, or Valeo, just to cite a few commonly known ones. I emphasize this point because sample selection on the size upper tail of suppliers could likely induce a shift in the average production capacity and in the shape of the production function, as well as in the average risk management. Section 3.3 addresses the risk of potential biases in the portfolio externalities generated by sample selection by running the reduced-form empirical analysis on both the restricted final sample and the unrestricted sample used in Chapter 2.

As for the analysis in Chapter 2, Table B.3 shows the yearly time-series of the risk scores for the twelve major carmakers. Again, it reveals the descent to hell of Chrysler and GM from 2008 to 2010, in contrast to the steady high scores of strong foreign competitors such as BMW, Honda, Toyota, or VW.

Finally, Table C.3 shows summary statistics of the supplier's portfolio characteristics at the time it signs a new contract. Again, one can see that the selected suppliers are highly interconnected through the big twelve buyers: A supplier has on average nine buyers out of twelve. It follows that selected suppliers expose their customer to other buyers' risk through a large number of channels. However, the intensity of these links vary more greatly across suppliers, showing a varying degree of bilateral cooperation across buyer-supplier pairs.

3.3 Empirical Evidence: Externalities in the Supply Network

In this section, I investigate the relationship between the probability that a supplier S and a car manufacturer B sign a new contract in year t and the indirect financial risk generated by S's other-buyer portfolio in year t. I explore this relationship using a yearly panel linear-probability model, in which I remain agnostic on the offer arrival process and assume that a supplier can potentially receive contract offers from any possible buyer. I run the analysis on two different datasets: (i) the unrestricted dataset of Chapter 2 and (ii) the subset used in the structural model under the preferred-supplier assumption. The comparison of the two analyses will show whether and how sample selection and the preferred-supplier assumption change the shape of externalities.

In line with Chapter 2, results support the hypothesis that a buyer and a supplier account for the externalities generated by the risk level of the latter's buyer portfolio when signing a new contract.

3.3.1 Linear-probability model

Chapter 2 suggests that, when signing a new contract, a car-part supplier and a car manufacturer internalize (i) two trade-offs in productive-factor allocation and in buyer-supplier specialization, as well as (ii) the exposure to financial risk of other firms in the buyer-supplier network. Building upon these observations, I estimate the following linear-probability model:

$$
\begin{aligned}
y^B_{St} = \alpha + \phi_0 r^B_{St} + & \\
& l^B_{St} \times \Big[\delta_0 + \pi_0 n^B_{St} + \pi_1 Q^B_{St} + \phi_1 r^B_{St}\Big] + \\
& l^{B\star}_{St} \times \Big[\delta_1 + \delta_2 z^{B\star}_{St} + \pi_2 n^{B\star}_{St} + \pi_3 Q^{B\star}_{St} + \phi_2 \mathbb{1}\Big\{ \min_{\tilde{B}\neq B}\{r^{\tilde{B}}_{St}\} < r^* \Big\}\Big] + \\
& \theta' C^B_t + \varepsilon^B_{St},
\end{aligned} \tag{3.1}
$$

where (i) y^B_{St} is equal to one if S and B sign one or more new contracts in year t and to zero otherwise, (ii) C^B_t is a vector of control variables (including the number of new models that B launches in year t, and demand and demand forecast variables), and (iii) the explanatory variables are defined as in Table C.4. They cover different characteristics of S's buyer portfolio at the beginning of year t. Conditional on being in a relationship, the four variables in row two describe the shape of the relationship between S and B at the beginning of year t based on the contracts signed before t, in network (δ), operational (π), and financial-risk (ϕ) terms. Conditional on S having other buyers, the next row describes the network (δ), operational (π), and risk (ϕ) externalities generated by the other buyers present in the portfolio of S. I also control for unobserved heterogeneity through α by trying different combinations of buyer, supplier, and year categorical effects. I also allow for time specific (year $t > 2009$ versus $t \leqslant 2009$) to have a sense of how patterns change after the collapse and bailout of Chrysler and GM.

Under the preferred-supplier assumption and in the structural sample, l^B_{St} and $l^{B\star}_{St}$ are always equal to one. With this dataset, I cannot estimate δ_0 and δ_1. I drop them.

3.3.2 Results of the linear-probability model

In the steps of Chapter 2, my findings support the hypothesis that a buyer B and a supplier S account for the externalities generated by the latter's buyer portfolio when signing a new contract. I run (3.1) on three specifications: (i) without any control and on the structural dataset (built under the two constraints of sample selection and that a supplier only receives offers from buyers of which it is a *preferred* supplier), (ii) with buyer, year, and supplier controls, and on the same dataset, (iii) with buyer, year, and supplier controls on the whole dataset of Chapter 2 (no sample selection) and without the assumption that a supplier only receives offers from buyers of which it is a *preferred* supplier (no preferred-supplier assumption). Results are in Table C.5 and Table C.6.

Table C.6 shows that sample selection and the preferred-supplier assumption have no major impact on the pattern of operational variables. To most extent, the same goes for network and risk variables, as shown in Table C.5. Results vary by magnitude and statistical significance but, for the most part, the effects still go in the same direction.

There are differences when comparing patterns before and after 2009. In terms of network variables, an increase in the number of ongoing buyers after the crisis significantly reduces the probability that a new contract will be signed (columns 1 and 3). After the crisis I also see that suppliers do not react as much to the risk rating of the buyers, in particular when I look at results for the unrestricted sample (column 3). These results hold even when I look at the restricted sample, once I account for supplier, buyer and year fixed effects. After the crisis, risk characteristics matter no more because the mere fact of being a *too connected* supplier is in itself heavily penalized. These findings are in line with Chapter 2: I hypothesize the surge of an increased taste for more buyer-specialized suppliers in the wake of the collapse and bailout of Chrysler and GM: A buyer prefers a supplier that (i) is not exposed to disruption through too many channels (i.e., too many other buyers; see Table C.5), and (ii) is a supplier to these other buyers for a concentrated number of large-scale production models (see Table C.6). The goal of the structural model of Section 3.4

is to investigate these patterns from the suppliers' point of view.

Note that in the baseline specification with sample selection and under the preferred-supplier assumption, the probability that S and B sign anew is negatively correlated to the credit score of B. It seems prima facie counterintuitive since it suggests that S would be more likely to accept another offer from B when B is near to default (see column 1 in Table C.5). This negative relationship arises from the fact that GM and Chrysler, rated 0 in the aftermath of their collapse and during the whole period of restructuring, are actively launching models in the meantime. It naturally biases the relationship between B's risk and the probability that S and B sign anew. Controlling for unobserved heterogeneity wipes out this surprising result.

3.4 A Dynamic Model of Supplier-Buyer Agreements

This section aims at building a tractable model capturing buyers' strategic interactions in choosing which suppliers to allocate contracts to from the suppliers' point of view. The model will feature (i) a random continuous-time process through which the supplier receives contract offers that it either accepts or rejects, depending on the current shape of its portfolio and the consequent costs of accepting the offer; and (ii) a stylized mechanism controlling for the supplier's risk of exit through liquidation.

3.4.1 Choosing suppliers as independent decision makers

In modeling the supply network dynamics, I choose the suppliers as the decision makers over the buyers because the data are built from the suppliers' point of view. However, I observe hundreds of suppliers, in contrast with the buyer side where there are no more than 12 major players. To make the model tractable, I turn it into a single-agent optimization problem: The crucial assumption here is that strategic interactions take place on the buyers' side but not on the suppliers'. A supplier individually optimizes overtime, accounting for its buyers' taste for operational or risk externalities generated by its customer portfolio. However, the supplier's decisions do not depend on other suppliers' decisions. In other words, other suppliers' decisions or characteristics do not affect its profit function. This assumption is credible for at least two reasons: (i) Many suppliers, even large ones, are much smaller than buyers and have little control on contracting conditions (Ben-Shahar and White, 2006), and (ii) buyers have preferred sets of suppliers that they have chosen in house and to whom they directly make offers.[2]

3.4.2 Markov setting

The model follows the single-agent continuous-time discrete-choice setting of Arcidiacono et al. (2016). It is the continuous-time version of Rust (1987, 1996) or Hotz and Miller (1993). In line with the literature, I assume that suppliers optimize a Markov dynamic decision problem. That is, they condition their action on the current state of the world, not on the full history of play.

In the current setting, I assume that supplier S's state at time t, ω_{St}, includes (i) the set of active buyers of which S is a preferred supplier, $\mathcal{A}_{St}$, (ii) the number of ongoing models of B that S supplies to, n^B_{St}, (ii) B's risk rating, r^B_t, and (iii) B's average number of cars produced per model supplied by S, $\bar{Q}^B_{St}$, for all possible active buyers $B \in \mathcal{A}_{St}$, as well as (iv) demand for cars, D_t, and (v) whether governments already bailed out a carmaker, K_t. K_t signals whether public authorities are willing to save national industrial flagships from collapse ($K_t = 1$) or not ($K_t = 0$). Demand is high ($D_t = 1$) when average GDP growth in OECD countries is above its time trend. Demand is low ($D_t = 0$) otherwise.

The number of active buyers is equal to the twelve world largest carmakers, as described in Section 3.2. It does not vary overtime since the defaulted ones were

[2] Carmakers are very involved with their suppliers: Many car parts are jointly developed and carmakers help their suppliers to design efficient assembly lines in order to align the suppliers' car-part production costs with their willingness to pay for the part.

bailed out and did not exit the market. Then, at time t, the set of all active buyers is $\mathcal{A}_t = \mathcal{A}$. Under the constraint that a buyer has a preferred set of supplier, S's set of buyers from which it can receive an offer is a subset of $\mathcal{A}$: $\mathcal{A}_{St} = \mathcal{A}_S \subseteq \mathcal{A}$. Finally,

$$\omega_{St} = \left\{ \left\{ n_{St}^B, r_t^B, \bar{Q}_{St}^B \right\}_{B \in \mathcal{A}_S}, D_t, K_t \right\}.$$

I also denote by $\mathcal{B}_{St} = \{B \in \mathcal{A}_S : n_{St}^B > 0\} \subseteq \mathcal{A}$, S's set of buyers with which S is currently operationally active with at t. $\mathcal{B}_{St}$ is already implicitly defined in ω_{St}.

3.4.3 Receiving a contract offer

In practice, a car manufacturer develops ample bilateral activity with each of its suppliers, involving large investments in human as well as physical durable relationship-specific assets. This joint collaboration (in R&D, production, design, etc...) makes it costly and technically risky to the automaker to work with an unknown supplier. As a consequence, automakers have a set of preferred suppliers for any component system and switch only when technology requires it. Together with the continuous-time perspective of the data, it suggests that suppliers are very unlikely to receive contracts from buyers they are *unknown* to. Instead, especially given that this chapter does not study entry, I assume that suppliers receive offers from a narrower set of car makers with whom they are used to work.

The offer arrival process works as follows: At some rate $\lambda_t = \lambda(D_t)$, B launches a new model and offers S to supply to this new model. If S is not a preferred supplier of B, then S never receives an offer from B (i.e., $\lambda = 0$).

In this setting, the number of contracts between B and S at t is equal to the number of B's models that S supplies to. Furthermore, from S's point of view, λ is exogenous and can be estimated beforehand.

3.4.4 Markov notation

From now on, I drop or replace t by ω whenever possible, because suppliers follow Markov strategies (what matters is not that S plays at time t, but that S plays in state ω). For example, n^B_{St} and $\mathcal{B}_{St}$ become $n^B_{S\omega}$ and $\mathcal{B}_{S\omega}$ respectively. Likewise, I drop S subscripts whenever unnecessary because this model is a single-agent problem (S plays independently of other suppliers).

3.4.5 Accepting a contract offer

When it receives a contract offer (i.e., when it receives an offer to supply to a new model), S evaluates it taking into account how supplying the contract would affect its net present value. Signing a contract today with B may change the risk index of S's portfolio tomorrow. It will also eat some of its production capacity. In state ω, S enjoys some flow profits π_ω.

S endogenously accepts to supply to a new contract in function of the risk and operational benefits that this new business generates. The arrival process of contract offers is exogenous and independent of the characteristics of S. Nevertheless, B's preferences in the profile of its suppliers can still be inferred from S's profit function: The value generated to S by an additional contract with B is indeed informative of how much B is willing to pay for working on its new model with this supplier.

In the model, the decision maker is the supplier. In practice, when a carmaker needs a new part, it undergoes extensive discussions with its preferred suppliers, bilaterally assesses with each whether it meets its technical demands, and then picks the cheapest one. The 2008-2009 crisis also revealed that risk could be part of the buyer's requirements. The final decision of the supplier to accept or decline an offer can be seen as the outcome of these discussions and joint assessment process. Then, turning down a contract offer means that it is too costly to the supplier to meet all the demands of the buyer for this specific contract.

When it receives a contract offer from B, S can either accept it (S plays a) or decline it (S plays d). In state ω, S accepts B's offer if and only if

$$\varepsilon_{\omega}^{B\mathrm{a}} + \psi^{\mathrm{a}} + V_{\sigma(B,\omega)} > \varepsilon_{\omega}^{B\mathrm{d}} + V_{\omega},$$

where (i) ψ^{a} is the instantaneous cost of accepting buyer B's offer,[3] (ii) ε is a vector of instantaneous choice-specific payoff shocks, and (iii) $\sigma(B,\omega)$ is the new state resulting from S playing a (accepting B's offer) in state ω. State $\sigma(B,\omega)$ is equal to previous state ω, except that the number of B's models supplied by S is now increased by one: $n^{B}_{\sigma(B,\omega)} = n^{B}_{\omega} + 1$.

3.4.6 Ending a contract

I assume that this termination process is exogenous. In reality, the end date of a model is known when the offer is accepted, and the contract lasts until the model stops being produced. However, for simplicity, I do not endogenize the characteristics of the offer and simply assume that the model stops being produced at some exogenous rate q^{s}. Usually, the buyer can unilaterally break a contract, as seen in Section 1.2.2. Even if this situation rarely happens (e.g., at times of crisis, like Chrysler and GM that terminated a range of models and closed down a number of brands in the aftermath of their collapse), it motivates the fact that the termination process can be seen as exogenous for suppliers.

Let $\sigma^{\mathrm{s}}(B,\omega)$ be the state resulting from B stopping a model. $\sigma^{\mathrm{s}}(B,\omega)$ is equal to ω, except that the number of B's models supplied by S is now decreased by one: $n^{B}_{\sigma^{\mathrm{s}}(B,\omega)} = n^{B}_{\omega} - 1$.

3.4.7 Quantities

As explained in Section 1.2.2, a contract is only a long-term sourcing agreement. Quantities and prices are renegotiated over the lifetime of the contract, according to

[3] Assessing B's offer may be costly; accepting it may imply further engineering, legal or investment costs.

the needs of the buyer. From the supplier's point of view, it follows that that the average quantity of cars produced per model can be modeled as varying exogenously and independently of the timing of the signing of new contracts and of the termination of models.

I build five levels for the average production of a model by splitting the distribution of the number of car produced per model at its quintiles. I then set each level at the mean production between two quintiles. The average production per model that a supplier supplies to buyer B exogenously increases (decreases) by k production levels at some rate $q^{\mathrm{q}}_{\uparrow k}$ ($q^{\mathrm{q}}_{\downarrow k}$).

Let $\sigma^{\mathrm{q}\uparrow}(B, \omega, k)$ be the state resulting from the average production level per model of B increasing by k levels. $\sigma^{\mathrm{q}\uparrow}(B, \omega, k)$ is equal to ω, except that B's average production level per model is now increased by k levels. Similarly, I define $\sigma^{\mathrm{q}\downarrow}(B, \omega, k)$, the state resulting from the average production level per model of B decreasing by k levels.

I do not observe prices.

3.4.8 Buyer credit risk

I assume that one buyer's risk rating r exogenously upgrades (downgrades) by k rating notches at some rate $q^{\mathrm{r}}_{\uparrow k}$ ($q^{\mathrm{r}}_{\downarrow k}$). I construct this risk rating as a discrete function of credit-ratings scores awarded by Moody's Analytics, a major notation agency. As such, my risk score is a function of financial long-term solvency ratios.[4] By convention, a high grade r^B_ω signals a small risk and

$$r^B_\omega \in \{\underline{r}, ..., \overline{r}\},$$

where a risk score equal to $\underline{r}$ means that B is in default. In practice, I use the same rating scale as described in Section 2.3.1, that is, $\underline{r} = 0$ and $\overline{r} = 5$.

[4] Long-term solvency ratios include total or long-term debt to equity or capital, and total liabilities to total assets. These ratios measure the ability of a firm to meet its financing obligations. They are widely used metric for evaluating capital-intensive industries, such as the car industry.

Let $\sigma^{\mathrm{r}\uparrow}(B,\omega,k)$ be the state resulting from upgrading B's risk rating by k notches. $\sigma^{\mathrm{r}\uparrow}(B,\omega,k)$ is equal to ω, except that B's risk rating is now increased by k notches: $r^B_{\sigma^{\mathrm{r}\uparrow}(B,\omega)} = r^B_\omega + k$. Similarly, I define $\sigma^{\mathrm{r}\downarrow}(B,\omega,k)$, the state resulting from downgrading B's risk rating by k notches: $r^B_{\sigma^{\mathrm{r}\downarrow}(B,\omega,k)} = r^B_\omega - k$. Whenever B is downgraded to $\underline{r}$, that is, whenever B is in default, B is assumed to exit. It follows that it cannot be upgraded anymore or release any new model either.

This assumption holds until the bailout happens. After the bailout takes place, suppliers know that their buyers are too big to fail: Chrysler and GM, after falling into default, do not exit the market and continue releasing new models. It follows that for any buyer $B \in \mathcal{A}$ of which the supplier is a preferred one,[5]

$$\lambda^B_\omega = \lambda(D_\omega) \times \left[\mathbb{1}\{r^B_\omega > 0\} \times \mathbb{1}\{K_\omega = 0\} + \mathbb{1}\{K_\omega = 1\}\right].$$

There exists a mapping between the rating scale and the rate of default of rated firms. I assume that suppliers expect a buyer with a rating score r to default within a year at a rate $\delta(r)$.

I set up/downgrading rates $q^{\mathrm{r}}_{\uparrow/\downarrow k}$ and default rate $\delta(r)$ to the average within-a-year up/downgrading and default rates estimated by Moody's Analytics over period 1983-2008. Table C.7 shows the mapping between Moody's rating scale and the scale I use in the model. Table C.8 shows Moody's yearly transition rates from one grade to another and to default. Table C.9 shows the transition and default rates I choose in the model, based on Moody's estimates. I assume that a supplier uses services offered by experts such as Moody's in their problem optimization. When I estimate the model, I then take these risk-score rates as given and equal to Moody's estimated values.

Let $\sigma^{\mathrm{e}}(-B,\omega)$ be the state resulting from the exit of B. $\sigma^{\mathrm{e}}(-B,\omega)$ is equal to ω, except that now the supplier cannot receive anymore offer from B and B's production

[5] Recall that K_ω is a dummy variable signaling whether a bailout of a car manufacturer by public authorities already happened or not. See Section 3.4.10.

level in S's portfolio is set to zero.[6]

3.4.9 Supplier exit

The 2008-2009 turmoil revealed the fear of cascading failures in the wake of the collapse of a limited number of nodes in the supply network. Section 1.2 also stresses the critical interdependence of car manufacturers and their suppliers. Many suppliers defaulted because their customers could not honor and repay their contracts signed with their suppliers. According to the definitions explained in Section 2.3.1, a rating score of zero means that the buyer is in full default, and a rating score of one means that it is speculative and highly unlikely to be able to settle its debts. As a consequence, I naturally model the risk-of-default rate of a supplier S as a weighted average of the sum of the default ($r = 0$) and highly speculative ($r = 1$) rates of its buyers:

$$\delta_\omega^{\mathrm{e}} = \frac{1}{N_\omega} \sum_B n_\omega^B \times \left[\delta(r_\omega^B) + q_{\downarrow r-1}^{\mathrm{r}}\right].$$

I assumed that whenever a buyer exits, it cannot launch any new model, and as such, a supplier cannot receive any new contract offer from it. However, I account for the inertia of being exposed to a defaulted buyer overtime as follows: Whenever a buyer B is defaulted, n_ω^B can no longer increase but keeps decreasing at rate q^{s} overtime. Likewise, B's share of S's exit rate decreases overtime. As such, if a supplier S had a lot of business in common with a defaulted (exited) buyer B, S's suffering consequences of his high exposure to B's default is carried overtime in a discounting way.

Ford's decision to break links with suppliers working with Chrysler while betting on the bailout of GM showed that the collapse of only one buyer suffices to generate failures in the supply chain of other buyers interconnected with the failed firm. A

[6] In the current model, I assume that there is no impact on production levels of other buyers when one of them exits.

natural specification for the supplier's exit rate is then to equate it to the exit rate of the riskiest buyer in its portfolio. I also condition this rate on S having ongoing business with this failing buyer, to capture the exposure to the defaulted buyer overtime.

$$\delta^{\mathrm{e}}_{\omega} = \max_{B} \Big\{ \mathbb{1}\{n^{B}_{\omega} > 0\} \times \big[\delta(r^{B}_{\omega}) + q^{\mathrm{r}}_{\downarrow r-1}\big] \Big\}. \tag{3.2}$$

At rate $\delta^{\mathrm{e}}_{\omega}$, the supplier faces the risk of exiting the market. Practically speaking, one can say that the supplier files for bankruptcy at rate $\delta^{\mathrm{e}}_{\omega}$ and investigates whether to liquidate or to reorganize and stay in. The supplier exits if and only if

$$\varepsilon^{\mathrm{out}}_{\omega} + \psi^{\mathrm{out}} + V_{\mathrm{out}} > \varepsilon^{\mathrm{in}}_{\omega} + V_{\omega},$$

where (i) ε is a vector of instantaneous payoff shocks associated with the decision of exiting or staying in, and (ii) ψ^{out} is the instantaneous cost of exiting. I also normalize the value of exiting, V_{out}, to zero.

3.4.10 Bailout intervention

At times of low demand and before governments saved car manufacturers from collapse, suppliers expect that a public bailout of their endangered buyers is a probable event. It happens at rate q^{bo}_{ω}, which I set equal to one (i.e., a bailout intervention happens on average once a year) when demand is low ($D_{\omega} = 0$) and when no intervention ever happened before (i.e., suppliers do not know whether governments would save industry flagships: $K_{\omega} = 0$). I set it equal to zero otherwise because when demand is high ($D_{\omega} = 1$), buyers are in good shape, and when an intervention already happened ($K_{\omega} = 1$), governments have signaled their willingness to support weak buyers. It follows that firms know that in case of another collapse happens, the endangered firm will be bailed out and

$$q^{\mathrm{bo}}_{\omega} = \mathbb{1}\{K_{\omega} = 0\} \times \mathbb{1}\{D_{\omega} = 0\}.$$

When $K_\omega = 1$, suppliers know that a defaulted buyer is financially supported. In my model, it means that the firm does not exit and keep producing cars, launching new models, and offering new contracts to its preferred suppliers. Finally, the defaulted buyer, now owned and restructured by the state, goes back to being a publicly listed company on stock markets at some rate q^{mkt}. Going back to being traded is a sign of being solvent again. When it goes back onto stock markets, the car manufacturer is awarded an average grade equal to three. It is what happened for Chrysler and GM in 2011.

Let $\sigma^{\text{bo}}(\omega)$ be the state resulting from having a first bailout intervention, and $\sigma^{\text{mkt}}(B, \omega)$ be the state resulting from having B, a collapsed and bailed-out car manufacturer, going back onto stock markets.

3.4.11 Dynamic formulation of the supplier problem

I assume that payoff shocks ε, are all independent of each others. In state ω, a supplier's value is solution to the following Bellman equation:

$$V_\omega = \frac{\pi_\omega + \sum\limits_{\omega' \neq \omega} q_{\omega\omega'} V_{\omega'} + \sum\limits_B \lambda_\omega^B \mathbb{E}\left[\max\left\{\varepsilon_\omega^{B\text{a}} + \psi^{\text{a}} + V_{\sigma(B,\omega)}; \varepsilon_\omega^{B\text{d}} + V_\omega\right\}\right]}{\rho + \sum\limits_{\omega' \neq \omega} q_{\omega\omega'} + \sum\limits_B \lambda_\omega^B + \delta_\omega^{\text{e}}}$$
$$+ \frac{\delta_\omega^{\text{e}} \mathbb{E}\left[\max\left\{\varepsilon_\omega^{\text{out}} + \psi^{\text{out}}; \varepsilon_\omega^{\text{in}} + V_\omega\right\}\right]}{\rho + \sum\limits_{\omega' \neq \omega} q_{\omega\omega'} + \sum\limits_B \lambda_\omega^B + \delta_\omega^{\text{e}}}, \quad (3.3)$$

where (i) ρ is the exogenous discount rate and (ii) $q_{\omega\omega'}$ is the exogenous transition rate from ω to ω' (q includes buyers' risk-rating and default rates, changes in demand and production levels, bailout intervention, and model-discontinuation rate). Arcidiacono et al. (2016) show that a solution $V : \omega \mapsto V_\omega$ exists to the above fixed-point problem.[7]

[7] See also the working-paper version, Arcidiacono et al. (2013b).

I choose not to detail the construction of the continuous-time Bellman equations. The derivation of (3.3) from a discrete-time setting closely follows that of Doraszelski and Judd (2012), Arcidiacono et al. (2016), or Ambrus and Lu (2015).

3.4.12 Parameterizing the shocks

Following the literature, I further assume that shocks ε are (i) i.i.d. across time and across choices, (ii) independent of the state of the world and (iii) Type-I generalized extreme value (GEV) random variables (see, e.g., Rust (1987)). Equation (3.3) rewrites as follows:

$$V_\omega = \frac{\pi_\omega + \sum\limits_{\omega' \neq \omega} q_{\omega\omega'} V_{\omega'} + \sum\limits_{B} \lambda_\omega^B \Big[\text{ec} - \ln P(\text{d}|\omega, B) \Big] + \delta_\omega^{\text{e}} \Big[\text{ec} - \ln P(\text{in}|\omega) \Big]}{\rho + \sum\limits_{\omega' \neq \omega} q_{\omega\omega'}}, \tag{3.4}$$

where (i) ec is the Euler constant, (ii) $P(\text{d}|\omega, B)$ is the conditional choice probability (CCP) that S declines B's offer in state ω, and (iii) $P(\text{in}|\omega)$ is the CCP that S stays in the market when assessing exit in state ω:

$$\begin{aligned} P(\text{d}|\omega, B) &= \Big[1 + \exp\left(\psi^{\text{a}} + V_{\sigma(B,\omega)} - V_\omega \right) \Big]^{-1}, \\ P(\text{in}|\omega) &= \Big[1 + \exp\Big(\psi^{\text{out}} - V_\omega \Big) \Big]^{-1}. \end{aligned}$$

This more concise expression of the Bellman equations directly follows from Arcidiacono et al. (2016)'s Proposition 2 and Proposition 3. They extend Hotz and Miller (1993)'s to continuous-time settings.

3.5 Estimation Strategy

In this section, I describe the estimation strategy. It follows Arcidiacono et al. (2016)'s two-step maximum likelihood technic. First, I separately estimate exogenous rates q and λ. Second, I non-parametrically estimate the CCP's. Together with the presence of a terminal action in the model (exiting), this stage allows to skip solving the fixed point given by (3.3), by plugging CCP's into (3.4). Third, I recover structural parameters π. In this section, I also address the challenges and limitations imposed by the data, the model, and the chosen estimation strategy. I also explain why I chose the latter over a strategy wherein I fully solve the fixed point instead of bypassing the obstacle with CCP's.

3.5.1 Unpacking compact notations

To begin with, I clarify the meaning of some compact notations used in Bellman equation (3.3). An exogenous state transition from ω to ω' at rate $q_{\omega\omega'}$ can either be (i) a model discontinuation, (ii) a risk downgrading or upgrading of a buyer B, (iii) the exit of B, (iv) a change in the average production level of B, (v) a flip in demand, (vi) the public decision to bailout a collapsing car manufacturer, or (vii) the come-back onto stock markets of a bailed-out car manufacturer:

$\sigma(1-D,\omega)$	at rate	q^{d}	(Demand flips)
$\sigma^{\mathrm{bo}}(\omega)$	at rate	q^{bo}_{ω}	(First bailout happens)
$\sigma^{\mathrm{r}\downarrow}(B,\omega,k)$	at rate	$q^{\mathrm{r}}_{\omega\downarrow k}$	(B's risk rating decreases by k notches)
$\sigma^{\mathrm{r}\uparrow}(B,\omega,k)$	at rate	$q^{\mathrm{r}}_{\omega\uparrow k}$	(B's risk rating increases by k notches)
$\sigma^{\mathrm{e}}(-B,\omega)$	at rate	$\delta(r^B_{\omega})$	(B exits)
$\sigma^{\mathrm{q}\downarrow}(B,\omega,j)$	at rate	$q^{\mathrm{q}}_{\omega\downarrow j}$	(B's production level decreases by j levels)
$\sigma^{\mathrm{q}\uparrow}(B,\omega,j)$	at rate	$q^{\mathrm{q}}_{\omega\uparrow j}$	(B's production level increases by j levels)
$\sigma^{\mathrm{s}}(B,\omega)$	at rate	q^{s}_{ω}	(# of models supplied to B decreases by one)
$\sigma^{\mathrm{mkt}}(B,\omega)$	at rate	$q^{\mathrm{mkt}}_{\omega}$	(B goes back onto stock markets)

Subscript ω stands for conditions such as (i) $n^B_{\omega} > 0$ for the termination of a model of B to happen, (ii) $r^B_{\omega} > \underline{r}$ (B is not defaulted) for a change in B's production level, or (iii) $K_{\omega} = 0$ and $D_{\omega} = 0$ (no bailout ever happened and demand is low) for the first bailout to happen.

Other state transitions come from the supplier's accepting a contract or exiting the market:

$$\begin{array}{llll} \sigma(B,\omega) & \text{at rate} & \lambda_\omega^B P(\mathrm{a}|\omega,B) & \text{(receiving and accepting an offer)} \\ \text{out} & \text{at rate} & \delta_\omega^{\mathrm{e}} P(\mathrm{out}|\omega) & \text{(supplier exits)} \end{array}$$

where (i) $P(\mathrm{a}|\omega,B)$ is the CCP that the supplier accepts B's offer in state ω, (ii) $P(\mathrm{out}|\omega)$ is that of exiting, and (iii) and subscript ω stands for conditions such as $r_\omega^B > \underline{r}$ (B is not defaulted) for the launching of a new model.

3.5.2 Constructing the likelihood

I build the likelihood, using the fact that the data are continuously observed overtime. For each supplier, I observe the months and years of when a supplied model starts and ends. I assume that these model start- and end-of-production dates correspond to the contract start- and end-of-production dates.[8] Whenever two events happen the same day, I randomly assign one after the other.

It follows that the total rate at which the state leaves ω to another one is given by:

$$\begin{aligned} h_\omega =& q^{\mathrm{d}} + q_\omega^{\mathrm{bo}} + \\ & \sum_B \left\{ \sum_k \left[q^{\mathrm{r}}_{\omega\downarrow k} + q^{\mathrm{r}}_{\omega\uparrow k} \right] + \sum_j \left[q^{\mathrm{q}}_{\omega\downarrow j} + q^{\mathrm{q}}_{\omega\uparrow j} \right] + \delta(r_\omega^B) + q_\omega^{\mathrm{mkt}} + q_\omega^{\mathrm{s}} \right\} + \\ & \sum_B \lambda_\omega^B P(\mathrm{a}|\omega,B) + \delta_\omega^{\mathrm{e}} P(\mathrm{out}|\omega). \end{aligned} \tag{3.5}$$

The probability that the state leaves ω within an interval of τ units of time writes as the cumulative distribution function of an exponential distribution of rate h_ω: $1-\exp\left(-\tau \times h_\omega\right)$. Then the density of the event that next state transition occurs in τ units of time is then given by $h_\omega \times \exp\left(-\tau \times h_\omega\right)$. Conditional on the state leaving ω, the probability that this change is due to the supplier accepting an offer from B

[8] In practice, suppliers commit to keep the production line active for an extra 10-to-15-year extension after the model is discontinued. It guarantees the buyer to have parts available for after-sale service and maintenance. However this production is much lower in terms of quantities.

(the state moves to $\sigma(B,\omega)$) is $\lambda_\omega^B P(\mathrm{a}|\omega,B)/h_\omega$. The likelihood that the state moves from ω to $\sigma(B,\omega)$ in τ units of time is the product of the two above objects:

$$\lambda_\omega^B P(\mathrm{a}|\omega,B) \times \exp\big(-\tau \times h_\omega\big).$$

Likewise, I can compute the likelihood that the next state transition occurs in τ units of time and is due to an exogenous change or to the supplier's exit.

Now let's consider a supplier over a period of length $\bar{T}$ during which state changes M times. Let ω_m and t_m be respectively the state prior to the m^{th} transition and the time at which this transition happens. I also define $\tau_m = t_m - t_{m-1}$ (for $m \leqslant M$), the duration time that the supplier stays in state ω_{m-1}. The log-likelihood associated with this sequence of states writes as follows:

$$\begin{aligned} l = \sum_{m=1}^{M} \Bigg[\sum_B \Bigg\{ & \ln\Big[q^{\mathrm{s}}\Big]^{\mathbb{I}_m^{B\mathrm{s}}} + \ln\Big[\delta(r_\omega^B)\Big]^{\mathbb{I}_m^{B\mathrm{e}}} + \ln\Big[q_{\omega_m}^{\mathrm{mkt}}\Big]^{\mathbb{I}_m^{B\mathrm{mkt}}} \\ & + \sum_k \bigg(\ln\Big[q_{\omega_m\downarrow k}^{\mathrm{r}}\Big]^{\mathbb{I}_m^{B\mathrm{r}\downarrow k}} + \ln\Big[q_{\omega_m\uparrow k}^{\mathrm{r}}\Big]^{\mathbb{I}_m^{B\mathrm{r}\uparrow k}} \bigg) \\ & + \sum_j \bigg(\ln\Big[q_{\omega_m\downarrow j}^{\mathrm{q}}\Big]^{\mathbb{I}_m^{B\mathrm{q}\downarrow j}} + \ln\Big[q_{\omega_m\uparrow j}^{\mathrm{q}}\Big]^{\mathbb{I}_m^{B\mathrm{q}\uparrow j}} \bigg) + \ln\Big[\lambda_{\omega_m}^B P(\mathrm{a}|\omega_m,B)\Big]^{\mathbb{I}_m^{B\mathrm{a}}} \Bigg\} \\ & + \ln\Big[q^{\mathrm{d}}\Big]^{\mathbb{I}_m^{\mathrm{d}}} + \ln\Big[q_{\omega_m}^{\mathrm{bo}}\Big]^{\mathbb{I}_m^{\mathrm{bo}}} + \ln\Big[\delta_{\omega_m}^{\mathrm{e}} P(\mathrm{out}|\omega_m)\Big]^{\mathbb{I}_m^{\mathrm{e}}} - \tau_m \times h_{\omega_m} \Bigg], \end{aligned} \tag{3.6}$$

where $\mathbb{I}_m^{\mathrm{d}}$, $\mathbb{I}_m^{\mathrm{bo}}$, $\{\mathbb{I}_m^{B\mathrm{s}}, \mathbb{I}_m^{B\mathrm{r}\downarrow k}, \mathbb{I}_m^{B\mathrm{r}\uparrow k}, \mathbb{I}_m^{B\mathrm{q}\downarrow j}, \mathbb{I}_m^{B\mathrm{q}\uparrow j}, \mathbb{I}_m^{B\mathrm{e}}, \mathbb{I}_m^{B\mathrm{mkt}}\}$, $\mathbb{I}_m^{B\mathrm{a}}$, and $\mathbb{I}_m^{\mathrm{e}}$ indicate whether the m^{th} state transition comes from (i) a flip in demand, (ii) governments signaled that they will support weak buyers, (iii) B's model termination, risk rating change, production level change, exit, or come-back onto stock markets, (iv) the supplier accepts an offer from B, and (iv) the supplier exits. Given that suppliers face independent decision problems, the overall likelihood simply writes as the sum of all the individual likelihoods.

3.5.3 Estimation challenges

My goal is to estimate the set of rate and structural parameters, using maximum-likelihood technic. However, I need to know the suppliers' value function V to be able to evaluate the likelihood. The value function $V : \omega \mapsto V_\omega$ is solution to a fixed-point problem, given by equation (3.3). When the number of possible states ω is large, solving this fixed point becomes computationally challenging, if not impossible. This is the so-called curse of dimensionality. I explored two ways to address this problem. A first solution is to make use of the presence of a terminal action to apply the trick of Arcidiacono et al. (2016) and express all the value terms in (3.4) as a function of CCP's. A second solution is to fully solve the fixed point given by (3.4).

The advantage of the first method is that it avoids the second one! However, it requires to observe enough terminal actions (here, exit). In my data, I observe only nine liquidations out of the more than three hundreds observed suppliers. These liquidations happens both before and after the bailout of GM and Chrysler (when K_ω turns to one in the model).[9] It follows that I have only a very limited number of observed exits before the bailout. It forces me to estimate the model with all the observations. For example, I cannot confidently estimate the model with pre-bailout data (when $K_\omega = 0$) and then run counterfactuals with the post-bailout observations.[10]

The advantage of the second method is that it does not require to observe many exits. I could estimate the model with pre-bailout data and then run counterfactuals

[9] I set the date of this event at March 29th, 2009, when the Obama administration decided to bail out the collapsing manufacturers. In December 2008, President Bush had already passed an executive action to lend money to GM and Chrysler. But it was more in the view of playing for time and hand the situation over the incoming administration in the least bad conditions, rather than a proper bailout plan.

[10] A solution would be to (manually) search for all the bankruptcy filings of the suppliers observed in the data and consider reorganizations (the firm did not liquidate) as an exit opportunity wherein the firm decided to stay in. It would substantially increase the number of observed exit opportunities as bankruptcy is rather frequent in the car-part industry. This is left to future work.

with post-bailout observations. However, given the large number of states, I need to approximate V. Following a modified version of Arcidiacono et al. (2013a)'s Sieve Value Function Iteration (SVFI) algorithm, I tried to approximate V with a nonparametric sieve function.[11] For a chosen sieve space Φ_n (typically a polynomial space), I seek an approximation ϕ_n of V, that is:

$$V_\omega \approx \phi_n(\omega).$$

Given a state vector ω and our chosen sieve space Φ_n, the sieve approximation writes as follows:

$$\phi_n(\omega) = W_n(\omega) \times \phi = \phi_1 w_1(\omega) + \phi_2 w_2(\omega) + \cdots + \phi_n w_n(\omega),$$

where (i) $W_n(\omega) = (w_1(\omega), ..., w_n(\omega))$ is the vector of monomials in sieve space Φ_n corresponding to state ω and (ii) ϕ is the vector of coefficients associated with the sieve basis of the sieve space. By construction, $\omega \mapsto \phi_n(\omega)$ approximately solves the system of equations defined by (3.3). Unfortunately, in this model setting, results are extremely sensitive to the choice of the sieve basis W_n and of the convergence criterion. For a given vector of structural parameters, the algorithm converges to the approximated fixed point extremely slowly as I decrease discount rate ρ (i.e., suppliers are more and more forward looking).[12]

Given these limitations, I choose the first method to estimate structural parameters with CCP's. I also include per- and post-bailout specific parameters ($K_\omega = 0$ versus $K_\omega = 0$) to see how suppliers' value change when firms know that car manufacturers are too big to fail.

Another numerical challenge here is the large number of parameters to estimate. Following the literature, I break the estimation into multiple steps and try to estimate as many parameters as possible outside of the likelihood: (i) I estimate λ

[11] I directly approximate the value function, $V : \omega \mapsto V_\omega$, whereas Arcidiacono et al. (2013a) approximate the integrated value function, $EV : \omega \mapsto \mathbb{E}[V_{\omega'}|\omega]$, where ω' is the next state.

[12] For a model with less than ten structural parameters to estimate and a discount rate equal to 0.1, I need some ten thousands iterations to find the fixed point for some choices of sieve basis.

with the observed sequence of model release at times of high and low demand; (ii) likewise, I estimate q^{s} with the observed sequence of model termination; (iii) upgrading, downgrading, and default rates are assumed to be given and based on Moody's estimates; (iv) the bailout rate has already been set to one and I get the rate of going back onto stock markets from Moody's by setting it equal to the rate of moving from $r = 1$ (the firm is close to default) to $r = 3$; (v) with all these parameters at hand, I can estimate structural parameters π and ψ with likelihood maximization.

3.5.4 Terminal actions

In Section 3.4, I model the possibility of a firm to exit. There exits a vast literature on bankruptcies strategies covering this topic (See, e.g., Mazur (2015)). It is beyond the scope of this paper. Here, exposure to buyers' risk of default generates a risk to exit for the supplier. When bankruptcy occurs, the firm, the court, or its debtors decide whether the firm reorganizes and stays in or liquidates and exits. With this decision, the model features a terminal action. Proposition 4 in Arcidiacono et al. (2016) shows that, when the decision-maker has a terminal action (e.g., the exiting choice here), any state value can be rewritten in terms of the CCP's. Here, algebra yields the following relationship between V_ω and the probability of exiting:

$$V_\omega = \psi^{\text{out}} + \ln P(\text{in}|\omega) - \ln P(\text{out}|\omega).$$

This feature of the model allows to directly use Arcidiacono et al. (2016)'s two-stage maximum likelihood strategy without solving the fixed-point: In the first stage, rates (here, q, λ, and the rate of exit opportunities) are estimated and CCP's are non-parametrically estimated. This first-stage estimates allow to approximate the supplier's value function without having to solve the fixed point. Given this approximation, structural parameters (π) of the model are recovered in the second stage.

3.5.5 A two-stage estimation strategy

As explained above, the estimation strategy follows Arcidiacono et al. (2016). I proceed in two steps, given the exogenous rates that I estimated beforehand: (i) I non-parametrically estimates the CCP's; (ii) I plug these estimates into (3.4) and estimate the structural parameters in a second step. Both steps use maximum likelihood technic.

The CCP's are non-parametrically approximated with logit-sieve functions:

$$P(\mathrm{a}|\omega, B) \simeq \Big[1 + \exp\big(\kappa_{\mathrm{a}}(\omega, B)\big)\Big]^{-1} = P_{\omega}^{B\mathrm{a}}(\kappa),$$

where κ_{a} is a flexible polynomial functions of the state variables. Likewise, I define sieve function κ_{out} and logit-sieve function $P_{\omega}^{\mathrm{out}}(\kappa)$.

For the choice of sieve basis $\kappa_{\mathrm{a}}(\omega, B)$, I run a principal component analysis (PCA) on some aggregate statistics of the state variables computed from the perspective of the bilateral relationship between the supplier and buyer B. These statistics include the number of models in common, the production level that these models represent, B's risk rating, the number of buyers other than B, the average number of models per other buyer, the average production level per other buyer, the minimum rating score among other buyers, and their interaction monomials up to degree three. After rotating this basis according to the PCA, I keep all the terms of which the cumulated variance explains 95 percent of the total observed variation. Given that I observed a limited number of exits, I follow the same strategy to choose $\kappa_{\mathrm{out}}(\omega, B)$ but run the PCA on a narrowed set of aggregate statistics of the supplier's portfolio. They include the total number of buyers, the average number of models supplied per buyer, the average production level per buyer, the average risk score per buyer, and their monomial interactions up to degree two.

With these sieve basis κ_{a} and κ_{out} at hand, I replace $P(\mathrm{a}|\omega, B)$ and $P(\mathrm{out}|\omega)$ in the likelihood function given in (3.6) with their approximated non-parametric counterparts, $P_\omega^{B\mathrm{a}}(\kappa)$ and $P_\omega^{\mathrm{out}}(\kappa)$. I then maximize this approximated likelihood (3.6) over parameters κ.

In the second stage, I estimate structural parameters ψ and π with the first-stage parameter estimates $\hat{\kappa}$ taken as state variables. For a given set of profit and cost parameters, π and ψ, I approximate CCP's with estimated sieve parameters $\hat{\kappa}$ and then V_ω in (3.4) with: $\hat{V}_\omega(\pi,\psi) = V_\omega(\pi,\psi|\hat{\kappa})$. With this value-function estimate at hand and the draw of structural parameters (π,ψ), I can approximate again CCP's $P(\mathrm{a}|\omega,B)$ with

$$\hat{P}_\omega^{B\mathrm{a}}(\pi,\psi|\hat{\kappa}) = \left[1 + \exp\left(\hat{V}_\omega(\pi,\psi|\hat{\kappa}) - \hat{V}_{\sigma(B,\omega)}(\pi,\psi|\hat{\kappa}) - \psi^{\mathrm{a}}\right)\right]^{-1}.$$

Likewise, I can get $\hat{P}_\omega^{\mathrm{exit}}(\pi,\psi|\hat{\kappa})$. Then, I replace $P(\mathrm{a}|\omega,B)$ and $P(\mathrm{out}|\omega)$ in the likelihood function given by (3.6) with $\hat{P}_\omega^{B\mathrm{a}}(\pi,\psi|\hat{\kappa})$ and $\hat{P}_\omega^{\mathrm{exit}}(\pi,\psi|\hat{\kappa})$. I then maximize this approximated likelihood (3.6) over parameters (π,ψ).

3.5.6 Identification analysis

First, model release and termination rates are identified from the continuously observed data of launch and termination of models. Suppliers' conditional choice probabilities are identified from the continuously observed data of contract agreements.[13] Second, the value function and the structural parameters are together identified from (i) the explicit relationship between V and CCP's under the Type-I GEV shock assumption and (ii) the parametric restrictions imposed to cost and profit functions.

I keep the analysis brief here as it closely follows that of Blevins (2014a) and Arcidiacono et al. (2016).

[13] See also Blevins (2014b) and Billingsley (1961) for more details on the identification of parameters of continuous-time data generating processes.

3.6 Results of the Structural Model

In this section, I describe the specification of the profit function and then provide a qualitative interpretation of the estimated structural parameters. The section ends with the focus on the marginal effects of the exit of GM or Chrysler on the probability that the supplier accepts a new offer from another buyer.

3.6.1 Specifications of the profit function

A supplier enjoys flow profits π_ω which vary with the riskiness and size of its buyer portfolio. The specification of the profit function must be such that portfolios with similar operational profiles (in terms of buyer portfolio, number of models supplied, and quantity levels) but with different risk profiles generate different benefits to the supplier. I choose a reduced-from specifications for the profit function that captures the trade-offs faced by a supplier when signing anew with a buyer B: one more business line with B may foster the supplier's relationship with B. It may also have a positive or negative impact on subsequent business opportunities with other buyers. I write the main specification of the reduced-form profit function of a supplier as follows:

$$\pi_\omega = \pi_0 + \sum_B Q_\omega^B \times \Bigg[\pi_1 + \pi_2 n_\omega^B + \pi_3 r_\omega^B + Q_\omega^B \times \Big(\pi_4 + \pi_5 \sum_{\tilde{B}} Q_\omega^{\tilde{B}}\Big) + \pi_6 z_\omega^{B\star} + \pi_7 n_\omega^{B\star} + \pi_8 r_\omega^{B\star} + Q_\omega^{B\star} \times \Big(\pi_9 + \pi_{10} \sum_{\tilde{B}} Q_\omega^{\tilde{B}}\Big)\Bigg],$$

where (i) $Q_\omega^B = n_\omega^B \times \bar{Q}_\omega^B$, (ii) n_ω^B, r_ω^B, and $\bar{Q}_\omega^B$ are the state variables defined in Section 3.4.2, and (iii) other variables are defined in Table C.4. This specification allows to capture the trade-off faced by a supplier in choosing to supply another model to buyer B. π_1 to π_5 capture how the shape of the relationship with B changes the profitability of having a new contract with B, while π_6 to π_{10} capture how the shape of the rest of the supplier's portfolio indirectly affects profits.

Portfolios with different degrees of buyer specialization and risk profiles generate different benefits to the supplier. π_2 and π_3 capture how profitability varies with, respectively, the size of the operational relationship between S and B, and the riskiness of B. For example, a positive π_2 means that, for a given level of production, it is more profitable to supply to a large number of models of B. π_6 captures how much the spreading of engineering resources across different buyers is profitable to the supplier and as such, valued by B. π_8 captures the impact of the riskiness of buyers other than B: A negative π_8 means that if S has at least one very risky other buyer, it has to compensate B for the increased risk in supply chain disruption coming from the presence of this risky buyer in its portfolio.

To see how the supplier enjoys economies of scales in its relationship with B, one can rewrite the above expression as follows:

$$\pi_\omega = \tilde{\pi}^0_\omega + \tilde{\pi}^1_\omega Q_\omega + \tilde{\pi}^2_\omega Q^2_\omega + \tilde{\pi}^3_\omega Q^3_\omega, \tag{3.7}$$

where

$$\tilde{\pi}^0_\omega = \pi_0,$$

$$\tilde{\pi}^1_\omega = \sum_B \alpha^B_\omega \times \left(\pi_1 + \pi_2 n^B_\omega + \pi_3 r^B_\omega + \pi_6 z^{B\star}_\omega + \pi_7 n^{B\star}_\omega + \pi_8 r^{B\star}_\omega\right),$$

$$\tilde{\pi}^2_\omega = \sum_B \alpha^B_\omega \times \left(\pi_4 \alpha^B_\omega + \pi_9 \sum_{\tilde{B}\neq B} \frac{\alpha^{\tilde{B}}_\omega}{z^{B\star}_\omega}\right),$$

$$\tilde{\pi}^3_\omega = \sum_B \alpha^B_\omega \times \left(\pi_5 \alpha^B_\omega + \pi_{10} \sum_{\tilde{B}\neq B} \frac{\alpha^{\tilde{B}}_\omega}{z^{B\star}_\omega}\right).$$

π_4, π_5, π_9, and π_{10} capture how the supplier enjoys economies of scale, as a function of the operational shape of its portfolio. The cubic specification also allows for regions in the production level wherein the supplier enjoys either economies or diseconomies of scales.

Finally, I set π_1 to π_{10} to be K_ω-specific, that is, specific to before or after the bailout was approved by public authorities.

3.6.2 Comments on the structural-parameter estimates

In this section, I provide a qualitative interpretation of the estimated structural parameters. Whenever a parameter has a magnitude or a sign that seems counterintuitive, I give the interpretation of what would have been expected instead, in light of the industry facts described in Section 1.2. I then explore the reasons and possible solutions to unexpected signs or magnitudes. Table C.11 shows the result estimates of the structural model when the exit rate of a supplier, $\delta^{\mathrm{e}}_\omega$ is given by (3.2).

Naturally, both reduced-form and structural analysis show that a large number of models supplied to B at a large production level increases the profits that S enjoys from B. In the profit function expressed as a cubic polynomial in Q_ω in (3.7), one can see that a large Q^B_ω directly enhances economies of scale (square coefficient π_4 is negative but cubic coefficient π_5 is positive). Less intuitive is the result that that S receives lower profits when B is less risky. A possible reason could be that S must compensate B for working with a safe buyer. Later on, I show that S enjoys larger profits from B when the other buyers in its portfolio are safe. The negative coefficient on r^B_ω can be seen as the compensation to pay to B for being more attractive to other buyers. However, the model may omit some variable or fail to capture some unobserved heterogeneity in the firms' characteristics (whether buyer or supplier). The analysis of the reduced-form results in Section 3.3.2 shows that firm fixed effects are necessary to get a more robust estimate of the relationship between B's risk and the probability that S and B sign anew. It suggests that the current model is not specific enough. Adding firm-specific heterogeneity is outside the scope of this paper and left to future work. It is interesting to see that the risk parameter has increased in magnitude after the bailout. It mimics the baseline reduced-form specification of

Table C.11. The analysis of this pattern in the reduced-form results given at the end of Section 3.3.2 holds again here. It can also be said that, in the aftermath of the bailout of Chrysler and GM, governments signaled that they would not let an industry flagship collapse, incentivizing suppliers to work with defaulted (but bailed out) buyers.

Before the collapse of GM and Chrysler, supplier S enjoys larger profits with buyer B the larger the number of other buyers in its portfolio. After the bailout, a large number of other buyers results in lower profits with B. This result is consistent with other suggestive evidence.[14] The reduced-form analysis shows indeed a negative relationship after 2009 between the probability that S and B sign anew and the number of buyers other than B working with S, even in the baseline analysis ignoring endogeneity (Table C.5). Consistent with the reduced-form analysis, Table C.11 shows that the benefits of having a large number of other buyers becomes substantially negative after the bailout ($K_\omega = 1$). S no longer benefits from having a large buyer portfolio in the aftermath of the crisis. In the post-crisis period, B prefers to engage with more specialized suppliers supplying large production levels on a concentrated number of models to a small number of other buyers. A point consistent with Ford's strategic supply decision taken in the eve of the collapse of its fellow Detroiters (see Section 2.1).

Consistent with reduced-form analysis of Chapter 2, Table C.5, and Table C.6, this post-crisis change in the supply network dynamics also goes together with (i) an increase in the importance of the strength of the relationship between S and B

[14] Before pushing further the analysis, it should first be recalled that the structural model adopts the supplier's point of view. As such, it is less agnostic than the reduced-form analysis. The structural model views the forces and mechanisms at play in the contract-agreement process from the point of view of the supplier. Nevertheless, the buyer's preferences in the risk and operational profile of its suppliers can still be inferred from the supplier's profit function: To some extent, the value generated to the supplier by an additional contract is indeed informative of how much the buyer is willing to pay for working on its new model with this supplier. On the contrary, the reduced-form analysis encompasses indifferently the supplier's and buyer's preferences.

in the profits that S enjoys from B, and (ii) a decrease in the importance of the risk factors generated by the presence of buyers other than B in S's portfolio: First, it is no longer profitable after the bailout to supply to a large number of models of B (π_2 significantly decreases but remains positive). S also substantially benefits in its working with B from having a strengthened relationship with B in terms of production level (π_1, π_4, and π_5 increase). Second, S's profits are less penalized after the bailout by the presence of a near-to-default other buyer in its portfolio This result suggests that, before the crisis, B would compensate for S's exposure to many other buyers by rewarding more S when its portfolio was *healthier*. After the crisis, the presence of a risky other buyer does not matter as much for two reasons: First, the mere fact of being connected to other buyers in now less profitable to S. And, second, governments signaled that they would bailout automakers whose collapse would be considered a systemic risk to the economy (Goolsbee and Krueger, 2015). Interestingly, this change in the profitability of being a highly connected supplier happened, in spite of the bailout. By rescuing GM and Chrysler, American and Canadian governments signaled that industry flagships are too big to fail. A decision debated for the risk of increasing moral hazard among firms. Contrary to what many considered a likely unintended consequence of the bailout, the rescue of Chrysler and GM seems to have been received more as a serious warning rather than as a blank check. From now on, better safe than sorry appears to be the new guideline.

Lastly, note that both before and after the collapse, the impact of S's production level with other buyers on profits from B shows a pattern different from that of B's production level (cubic coefficient π_{10} is negative). A larger average level of production with other buyers directly penalizes S's profits from B (scattered resource across non-substitute buyers). On the other hand, it increases total production level Q_ω, which has a positive impact on profits from B (economies of scales). The magnitude of this pattern changes after the bailout. Unlike before the collapse, S's profits with B can increase in the production that S has with other buyers (square coefficient π_9 becomes positive after the bailout). A fact not shown in the reduced-form analysis. Furthermore, the negative cubic coefficient has decreased in magnitude after the bailout. It suggests that, after the bailout, B values the presence of operationally strong relationships with a narrowed number of other buyers in the portfolio of its supplier S. A consequence of these patterns is that the impact on S from working with B is ambiguous. A strong relationship with B may boost or hinder S's profits with another buyer.

In the next section, I study the effect of an exit of GM or Chrysler on the probability that a supplier accepts a contract from another buyer in the wake of the exit. The goal is to shed light on how risk in the supplier's portfolio changes its ability to accept an offer and to give a first measure of the impact of a buyer exit on the supply network.

3.6.3 What is the effect of a collapse of GM or Chrysler on contract signature?

In this section, I explore the marginal effect of the exit of GM (or Chrysler) before the bailout on the CCP of accepting an offer from another buyer. I begin with GM. More precisely, I study how an exit changes this CCP both in absolute and relative terms:

$$\Delta^B_{\mathrm{GM}}(\omega) = P(\mathrm{a}|\sigma^{\mathrm{e}}(-\mathrm{GM}, \omega), B) - P(\mathrm{a}|\omega, B),$$

$$\Lambda^B_{\mathrm{GM}}(\omega) = \frac{\Delta^B_{\mathrm{GM}}(\omega)}{P(\mathrm{a}|\omega, B)} \times 100,$$

where $\Delta^B_{\mathrm{GM}}(\omega)$ and $\Lambda^B_{\mathrm{GM}}(\omega)$ are respectively the percentage-point and the percentage changes in the CCP consecutive to an exit of GM. Recall that $\sigma^{\mathrm{e}}(-\mathrm{GM}, \omega)$ is the state resulting from the collapse of GM in state ω. Results are shown in Table C.12 and Table C.13.

Table C.12 reads as follows: Column 1 shows the median of pre-bailout CCP's $P(\text{a}|\omega, B)$ ($K_\omega = 0$) generated by the model. Columns 2 and 3 show the medians of $\Delta^B_{\text{GM}}(\omega)$ and $\Lambda^B_{\text{GM}}(\omega)$ respectively. Column 4 shows the median of the pre-bailout CCP's in the aftermath of the exit of GM, $P(\text{a}|\omega, B) + \Delta^B_{\text{GM}}(\omega)$. Columns 5, 6, and 7 read as columns 2, 3, and 4, except that it is now Chrysler that exits. Finally, column 8 shows the median of the post-bailout CCP's ($K_\omega = 1$) generated by the model.

The main take away of these tables is that the probability that a supplier accepts an offer from a buyer other than GM in the aftermath of the collapse of GM shrinks by more than fifteen percent at the median at times of low demand, and by more than twenty-one percent at times of high demand. Intuitively, if S lost a customer, it would transfer its production capacity and engineering resources to its other buyers and should be more likely to accept a contract from them. Here, results suggest the contrary. Recall that, even if the model is built from the supplier's point of view, the extra value generated by accepting a new contract with a buyer B reflects the willingness of B to work with S. In this setting, one can see the final decision of S to accept or decline an offer from B as the outcome of the bilateral discussions undertaken by S and B to assess whether S meets the operational and risk requirements of B (see Section 1.2.1). When B makes an offer to S, it makes S pay for its exposure to a defaulted buyer (here GM) and the risk that it generates to B (supply chain disruption through the exit of S). As a consequence, the extra value generated to S by accepting B's offer is smaller in the aftermath of the collapse of GM than when GM was in the market. This point does not contradict the first intuition given. For ease of exposition, I focus here on the median and mean of CCP changes. However, a closer look at the upper tail distribution of $\Lambda^B_{\text{GM}}(\omega)$ or $\Delta^B_{\text{GM}}(\omega)$ shows that the exit of GM can yield a nonnegative change in the CCP of accepting a new offer from another buyer.

Furthermore, a quick look at the data shows a negative relationship between $\Delta^B_{\mathrm{GM}}(\omega)$ and the exposure of S to GM (Table C.14). That is, the less S is exposed to GM, the larger $\Delta^B_{\mathrm{GM}}(\omega)$, and the more S is exposed to GM, the smaller (more negative) $\Delta^B_{\mathrm{GM}}(\omega)$. Depending on the risk externality that its portfolio generates to B, S may benefit from the exit of GM in its business relationship with B. However, the distribution of $\Lambda^B_{\mathrm{GM}}(\omega)$ or $\Delta^B_{\mathrm{GM}}(\omega)$ is substantively skewed towards the negatives. It suggests that the mere fact of being linked to collapsing GM is a threat. A last note on GM: The effect of the exit of GM on the probability of signing with another buyer is larger at times of high demand because production levels are larger. It follows that the magnitude of the disruption in manufacturers' supply chains would be larger too.

In the wake of the exit of smaller Chrysler, changes in the CCP's are in general smaller in magnitude than those shown in the GM case. Table C.14 also shows that these percentage-point changes in the CCP's are not negatively correlated with the exposure of the supplier to Chrysler. I hypothesize that this difference in patterns between Chrysler and GM comes from the substantial gap in size between the two manufacturers. During the debate on whether Chrysler and GM should be rescued, the main concern was GM, a much larger company than Chrysler. It was acknowledged that the American economy could absorb the collapse of Chrysler. Much more debated was the question of what would be the ramifications of a collapse of GM (Goolsbee and Krueger, 2015). When making an offer to S, other manufacturers would then naturally be tougher when S is linked to Chrysler, independently of its degree of exposure, because Chrysler was naturally more likely to exit than GM.

Ford shows much smaller effects than other buyers because it is historically very interconnected with GM and Chrysler. If it got *too tough* with all its suppliers linked to either GM or Chrysler, it would find itself with a more narrow set of alternative suppliers than other European or Japanese manufacturers. Most of the above analysis done at the median holds at the mean, as shown in Table C.13. Interesting is the fact that at times of low demand, that is, when production levels are low, an exit of Chrysler would have had on average no impact on the percentage-point change in the CCP of signing new contracts with Ford. A fact consistent with Ford's decision in late 2008 to reduce its exposure to Chrysler.[15]

Finally, columns 4 in Table C.12 and columns 3 in Table C.13 show that the median and the mean of the penalized CCP's resulting from the exit of GM are lower than those of the CCP's before the collapse (column 1). This results does not hold for Chrysler: For some buyers, such as Ford or Renault-Nissan (at times of low demand), the median and the mean of the penalized CCP's resulting from the exit of Chrysler (column 7 in Table C.12 and column 5 in Table C.13) are larger than those of the CCP's before the collapse. A reason is that the states in which S was already very likely to accept an offer from B, the exit of Chrysler, a buyer representing small production volumes, did not penalize the relationship. If S has a large probability of accepting an offer from B in a state where Chrysler is near to default, the actual default would not penalize the relationship.

3.6.4 Did the bailout achieve its purpose?

The above results support the view that a collapse of a major Detroit manufacturer could have had negative effects on the profitability of suppliers to accept new offers and on their ability to meet their risk costs. Furthermore, Table C.17 suggests the vicious circle in which a supplier can be trapped: The table shows that the structural model yields a probability of accepting an offer from a buyer which is negatively correlated to the probability of choosing to exit when S is given the opportunity. The more S is likely to exit, the tougher will be a buyer when it makes an offer to compensate for the risk of supply disruption, and the less likely S will accept the

[15] Demand for cars was low in late 2008 and 2009.

offer. As a natural consequence, a collapse of a major Detroit manufacturer could have threatened the viability of the supply network itself by trapping suppliers in this vicious circle.

However, the median and mean probabilities of accepting offers in the post-bailout regime (last column in Table C.12 and Table C.13) are in general substantially lower than their counterparts in the pre-bailout regime (first column in Table C.12 and Table C.13), even when penalizing pre-bailout CCP's by their drop following the collapse of a buyer (columns 4 and 7 in Table C.12, and columns 3 and 5 in Table C.13).[16]

The estimated structural parameters explained in Section 3.6.2 show that the bailout comes together with substantial changes in suppliers' profit function shape (Table C.11). In particular, after the crisis, the presence of a risky other buyer no longer matters, but the mere fact of being connected to other buyers in now less profitable to S. This change in the profitability happened, in spite of the bailout and of the multi-billion Auto Part Support Program (APSP) launched by the Obama administration. The rescue of GM and Chrysler was amply debated for the risk of increasing moral hazard that the bailout could possibly generate. Contrary to what many considered a likely unintended consequence, the bailout of Chrysler and GM seems to have led to another opposite unintended consequence: The negative impact on profitability with buyer B of working with a large number of other buyers and the lower CCP's in the post-regime period suggest that buyers have become far more cautious after the crisis, in reaction to the disaster that was narrowly avoided. Once bitten, twice shy. It is consistent with Ford's anticipated decision in Fall 2008 to

[16] However, data show that production levels after the crisis are lower than before. To wipe out the possible bias that it may generate in the production-level distribution before and after the bailout, I double the 1200 observations used to compute the distribution for each case (K_ω, D_ω) with the 1200 observations of $(1-K_\omega, D_\omega)$, where I replace $1-K_\omega$ by K_ω. The medians and means obtained from these new datasets of 2400 observations marginally differ from those shown in Table C.12 and Table C.13. Finally, a focus on suppliers' states right before the bailout or around this period does not change this observation either: CCP's are lower in the post-bailout regime.

work with more buyer-specialized suppliers.

As a consequence of this change in profitability, the bailout did not make it easier to suppliers to accept contract offers. The crisis seems to have simply replaced the set of pre-bailout risk requirements and costs by another set of equally, if not more, stringent conditions. Another suggestive evidence of this point is the hundreds of supplier liquidations that followed the bankruptcy of Chrysler and GM, in spite of their bailout and of APSP (Medina, 2014). Likewise, Table C.17 show that the magnitude of the negative relationship between the probability of accepting an offer and that of exiting is substantively larger after the bailout than its magnitude before.

It would be unfair to paint an entirely gloomy picture of the bailout: Interesting is the fact that, at times of high demand, the median and mean penalized CCP's when $K_\omega = 0$ are smaller than the median and mean CCP's post-bailout for BMW, Daimler, Toyota, and VW, four manufacturers renowned for their financial strength. It suggests that the bailout improved the position of suppliers to accept offers from less risky buyers, that is, buyers who would have been very demanding otherwise (see Section 3.6.2).[17] A positive fact to be credited to the bailout intervention.

Although the analysis of these results does not fully answer the question of what would have happened to buyer-supplier relationships in the event of the collapse of GM or Chrysler and no bailout, results support the hypothesis that buyers reacted to the collapse more than to the bailout. Finally, consistent with the lower median and mean CCP's of accepting an offer after the bailout in Table C.12 and Table C.13, the post-2009 time trend of the ratio of new models of B launched in year t that S supplies to is smaller than that of before (see Table C.16). This result holds for both the unrestricted dataset of Chapter 2 and the restricted one of the present chapter, but its magnitude is larger in the latter case. After the crisis, large suppliers supply

[17] Perhaps more surprising is that GM also benefited from the bailout (at times of high demand again).

to a smaller share of new models of their buyers.

3.7 Concluding Remarks

Using the estimated CCP's, I am able to explore the hypothetical case of a GM or Chrysler collapse on new-contract signatures. I show that both under low and high demand scenarios, a supplier working with a failed GM (Chrysler) is more than 15 and 21 percent (8 and 17 percent) less likely to sign a new contract with other buyers. Working with a defaulted buyer decreases the willingness of other buyers to work with the supplier and naturally decreases the extra value generated to the supplier by accepting the contract. The marginal effect of an exit of GM is negatively correlated to the degree of exposure to GM that is faced by the supplier. This pattern does not hold for Chrysler. During the debate on whether Chrysler and GM should be rescued, the main concern would come from GM, a much larger company than Chrysler. It was acknowledged that the American economy could absorb the collapse of Chrysler. Much more debated was the question of GM. When making an offer to the supplier, other manufacturers would then naturally be tougher when it is linked to Chrysler, independently of its degree of exposure, because Chrysler was naturally more likely to exit than GM. These results support the view that a collapse of a major Detroit manufacturer could have had negative effects on the profitability of suppliers to accept new offers, on their ability to meet their risk costs, and as a natural consequence, on the viability of the supply network. I test what happens to CCP's of accepting an offer under two scenarios: bailout and collapse. I show that CCP's post-bailout are smaller and that in the event of a collapse of GM (or Chrysler), CCP's are also smaller but larger that in post-bailout regime. These results support the hypothesis that buyers reacted to the collapse more than to the bailout.

The bailout indeed came together with substantial changes in suppliers' profit function shape. In particular, after the crisis, the presence of a risky other buyer does not matter as much, but the mere fact of being connected to other buyers in now less profitable to S. This change in the profitability happened, in spite of the bailout. The rescue of GM and Chrysler was amply debated for the risk of increasing moral hazard, that the bailout could possibly generate. Instead, the bailout of Chrysler and GM seems to have led to another opposite unintended consequence: The analysis suggests that buyers have become far more cautious after the crisis, in reaction to the disaster that was narrowly avoided. Once bitten, twice shy. The bailout did not make it easier to suppliers to accept contract offers. The crisis seems to have simply replaced the set of pre-bailout risk requirements and costs by another set of equally, if not more, stringent conditions. It sheds light on the hundreds of supplier liquidations that followed the bankruptcy of Chrysler and GM, in spite of their bailout (and of the multi-billion Auto Part Support Program launched by the Obama administration).

This chapter contributes to the literature that investigates formation of supplier-buyer networks by going beyond reduced-form evidence and by uncovering some of the mechanisms that drive relationship formation. More importantly, this paper sheds light on the effects of government bailouts on network formation in an industry where buyers and suppliers are highly interconnected. While the analysis I conduct is particular to the automotive industry, it can still provide useful information for the study of other government interventions. This paper supports the view that a collapse of a major Detroit manufacturer could have had negative effects on the profitability of suppliers to accept new offers, on their ability to meet their risk costs, and as a natural consequence, on the viability of the supply network. However, it also shows that the bailout did not make it easier to suppliers to accept contract offers.

This chapter has a number of limitations. First, due to data constrains in the model I adopt the perspective of the supplier where it accepts or rejects offers. In reality, agreements in the automotive industry involve bilateral negotiations between a buyer and a suppliers to mutually decide a new contract and the role of the buyer is determinant in the process. Second, the model may fail to capture some firm-specific unobserved heterogeneity, which should be taken into account in future extensions of this paper. Third, the analysis is conducted at the model level, not a the part level, and without exact prices and quantities. Finally, trying different profit function specifications would allow to check the robustness of risk patterns that the present model exhibits. Finally, trying different profit function specifications, introducing firm heterogeneity, controlling for the change in production levels of other buyers in the wake of an exit, or specifying the buyer exit rate as a function of its size before the bailout would allow to check the robustness of risk patterns that the present model exhibits.

Appendix A

Appendix of Chapter 1

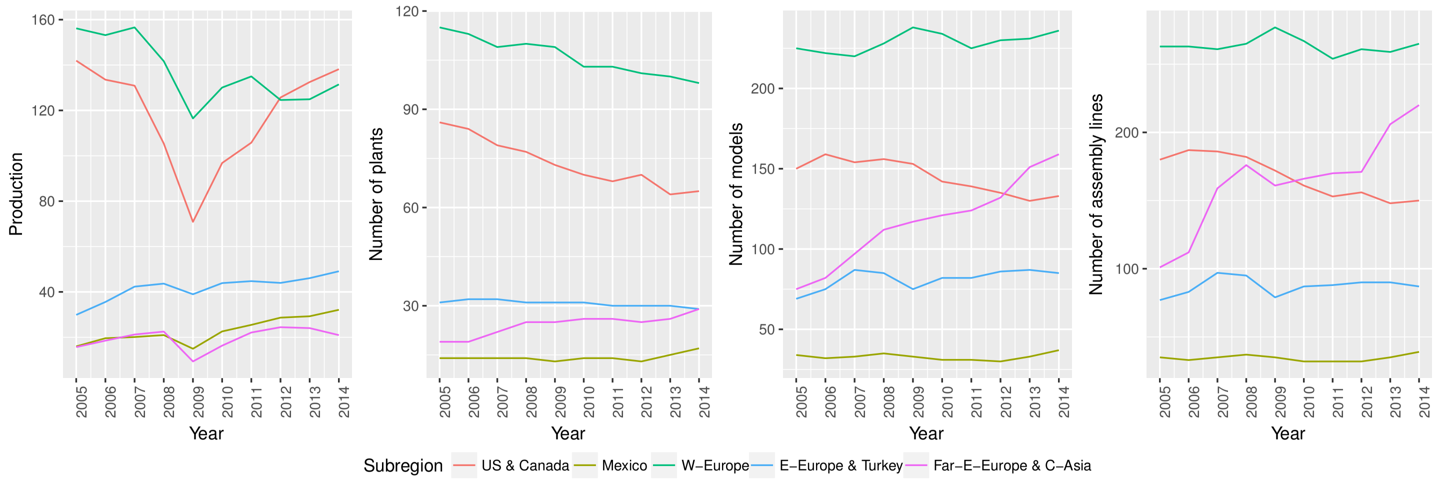

FIGURE A.1: Aggregate statistics of car production in North America and Europe (in 100k-units)

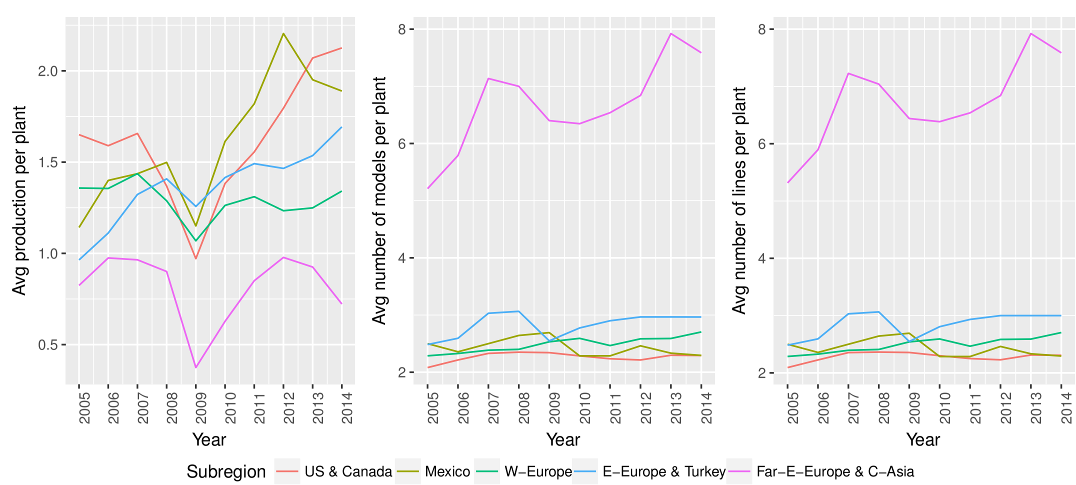

FIGURE A.2: Aggregate statistics per plant of car production in North America and Europe (in 100k-units)

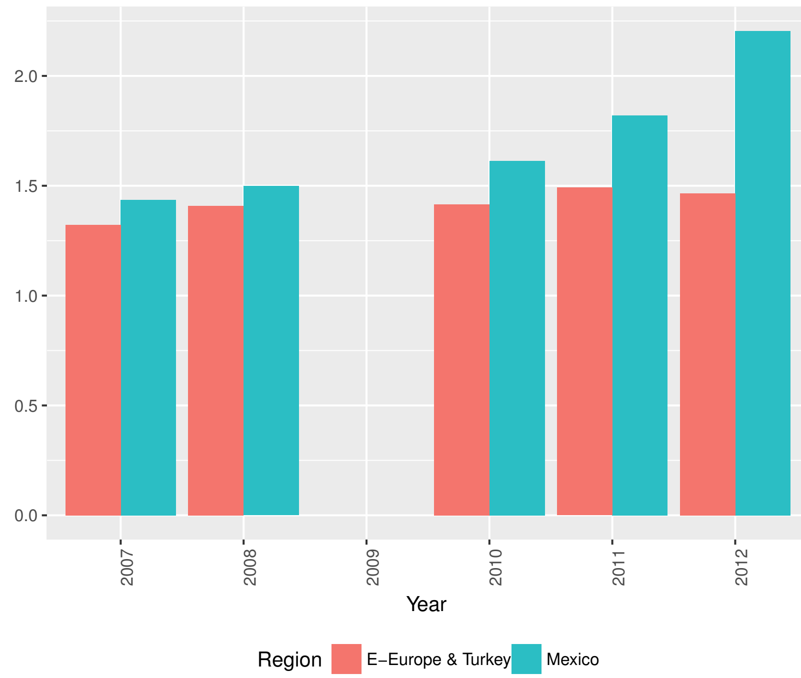

FIGURE A.3: Common trend in per-plant production before 2009

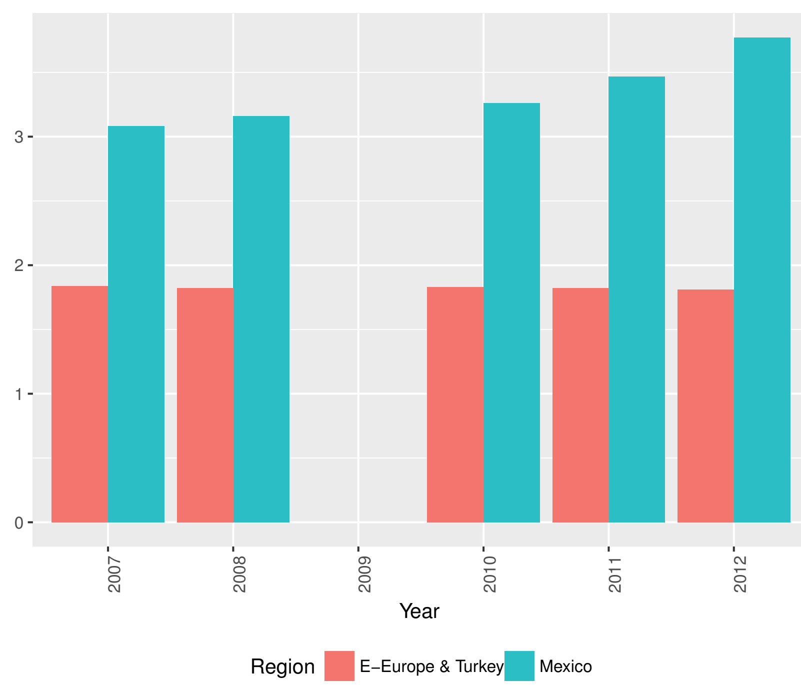

FIGURE A.4: Common trend in per-plant production, with plant fixed effects

Table A.1: Aggregate statistics of the cleaned WSW database

	Total number of							
	suppliers	buyers	models	new models	parts	subsectors	sectors	areas
2005	899	12	248	49	17,871	486	50	7
2006	921	12	292	59	21,491	489	50	7
2007	871	12	308	37	22,728	495	50	7
2008	846	12	318	45	24,394	497	50	7
2009	800	12	328	37	25,322	498	50	7
2010	719	12	325	38	25,283	495	50	7
2011	670	12	307	33	24,222	491	50	7

Table A.2: Aggregate statistics per model

	Per-model number of							
	parts		subsectors		sectors		areas	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2005	162.747	112.925	96.964	49.021	35.676	11.174	6.627	1.240
2006	170.668	113.546	100.888	48.018	36.525	10.485	6.664	1.171
2007	179.265	113.163	105.657	46.529	37.634	9.600	6.750	1.021
2008	187.324	117.069	108.945	46.950	38.338	9.085	6.785	0.940
2009	184.650	112.273	108.238	46.030	38.339	8.784	6.787	0.914
2010	185.227	108.374	108.738	45.996	38.067	8.954	6.784	0.920
2011	185.420	110.032	108.363	46.464	38.004	8.822	6.802	0.857

Table A.3: Aggregate statistics per supplier

	Per-supplier per-buyer number of											
	models		parts		subsectors		sectors		areas		new models	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2005	2.314	2.322	5.096	8.579	1.878	1.095	1.878	1.095	1.878	1.095	1.771	0.833
2006	2.522	2.636	5.499	9.498	1.891	1.102	1.891	1.102	1.891	1.102	1.675	0.774
2007	2.770	2.915	6.007	10.326	1.936	1.141	1.936	1.141	1.936	1.141	1.619	0.691
2008	2.956	3.092	6.475	11.092	1.957	1.150	1.957	1.150	1.957	1.150	1.670	0.670
2009	3.140	3.297	6.849	11.716	1.983	1.163	1.983	1.163	1.983	1.163	1.710	0.760
2010	3.369	3.404	7.432	11.965	2.051	1.178	2.051	1.178	2.051	1.178	1.745	0.854
2011	3.360	3.225	7.517	11.662	2.056	1.183	2.056	1.183	2.056	1.183	1.635	0.647

Appendix B

Appendix of Chapter 2

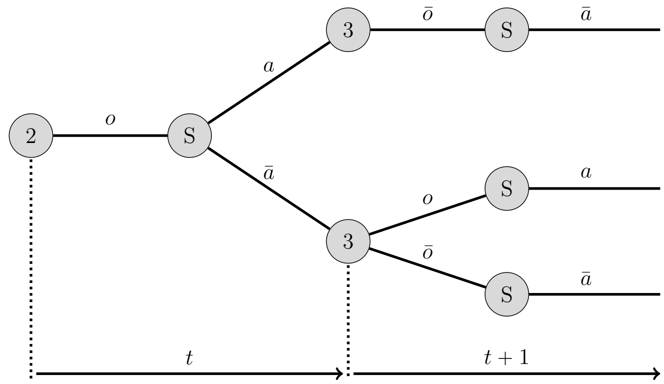

FIGURE B.1: Scenario 1 (S already supplies to one B_1's model at the beginning of t)

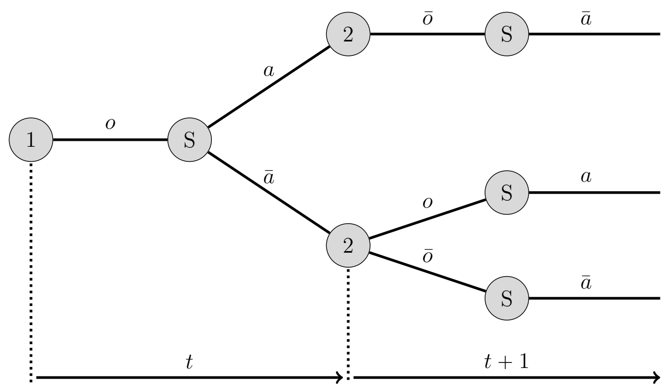

FIGURE B.2: Scenario 2 (S already supplies to one B_1's model at the beginning of t)

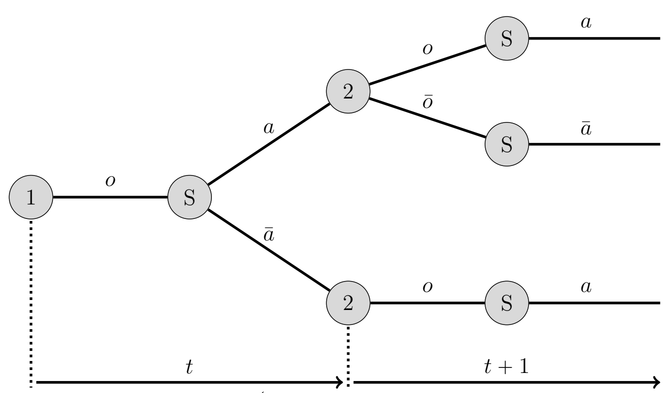

FIGURE B.3: Scenario 3 (S has no buyer at the beginning of t)

Table B.1: Yearly aggregate statistics

	Number of					
	present		ongoing	active		new
	suppliers	buyers	models	suppliers	buyers	models
2005	842	12	248	308	11	49
2006	866	12	292	336	12	59
2007	844	12	308	297	11	37
2008	821	12	318	320	11	45
2009	781	12	328	287	12	37
2010	704	12	325	284	11	38
2011	663	12	307	232	10	33

Table B.2: Yearly production statistics for supplier-buyer-year combinations (S, B, t)

	# obs	Sample Mean of								
		Indicator variables		*conditional on being in an ongoing relationship*			*conditional on having other ongoing buyers*			
		ongoing buyer	other ongoing buyers	# ongoing		ongoing		# ongoing		ongoing
				models	sectors	prod	other buyers	models	sectors	prod
								per other buyer		
2005	9,262	0.270	0.963	11.029	3.592	5.137	3.107	2.191	2.684	3.164
2006	10,392	0.285	0.964	12.326	3.651	5.481	3.254	2.421	2.772	3.349
2007	9,284	0.323	0.965	14.286	3.782	5.814	3.446	2.695	2.812	3.477
2008	9,031	0.325	0.965	15.304	3.846	5.830	3.466	2.876	2.867	3.404
2009	9,372	0.323	0.969	16.113	3.896	4.547	3.669	3.117	2.964	2.673
2010	7,744	0.342	0.967	17.365	4.012	6.035	3.811	3.308	3.021	3.487
2011	6,630	0.337	0.970	16.484	3.960	5.662	3.976	3.390	3.058	3.800

Note: Production is in $100k$-units ($\times 10^5$).
A model is equivalent to a contract here.

Table B.3: Risk score time-series of the 12 major car manufacturers

	BMW	Chrysler	Daimler	Fiat	Ford	GM	Honda	Hyundai Kia	PSA	Renault Nissan	Toyota	VW
2005	5	5	5	3	3.67	3.67	5	4	5	4	5	5
2006	5	4.83	4.83	3	3	3	5	4	5	4	5	5
2007	5	3.58	4.25	3	3	3	5	4	4.08	4.25	5	5
2008	5	2.67	5	3.58	2.75	2.67	5	4	4	4.58	5	5
2009	5	0.33	5	3.17	2.08	0.42	5	3.33	4	4.17	5	5
2010	5	0	5	3	3	0.5	5	3.25	4	4	5	5
2011	5	1.75	5	3	3	3	5	4	4	4	5	5

Table B.4: Cross-sectional statistics for supplier-buyer-year combinations (S, B, t)

	S and B sign a new contract in t					S and B do not sign any new contract in t				
	Mean	SD	1D	Med.	9D	Mean	SD	1D	Med.	9D
Network variables										
Relationship indicators:										
ongoing buyer	0.869	0.338	0	1	1	0.232	0.422	0	0	1
other ongoing buyers	0.983	0.130	1	1	1	0.963	0.188	1	1	1
Conditional on the supplier having other ongoing buyers:										
# other ongoing buyers	7.457	3.174	2	8	11	2.918	2.565	1	2	7
Risk variables										
Conditional on being in an ongoing relationship:										
buyer rating	3.922	1.268	2.667	4.167	5	3.902	1.244	2.667	4	5
Conditional on the supplier having other ongoing buyers:										
min of other-buyer ratings	1.985	1.429	0	3	3	2.951	1.563	0	3	5
Operation variables										
Conditional on being in an ongoing relationship:										
# ongoing models	8.348	7.367	1	6	19	2.796	3.069	1	2	6
prod ongoing models	9.701	8.984	1.130	7.290	22.142	3.209	3.935	0.117	1.869	7.891
# ongoing sectors	5.569	5.391	1	4	13	2.867	2.825	1	2	6
Conditional on the supplier having other ongoing buyers:										
avg # other ongoing models	6.544	4.615	1.500	5.333	13.636	2.264	2.129	1	1.333	4.800
avg other ongoing prod	7.759	5.180	1.939	6.699	15.862	2.653	2.781	0.157	1.846	6.166
avg # ongoing sectors	4.757	4.083	1.167	3.400	9.818	2.591	2.095	1	2	5
# observations			7,821					53,894		

Note: Production is in 100k-units ($\times 10^5$).

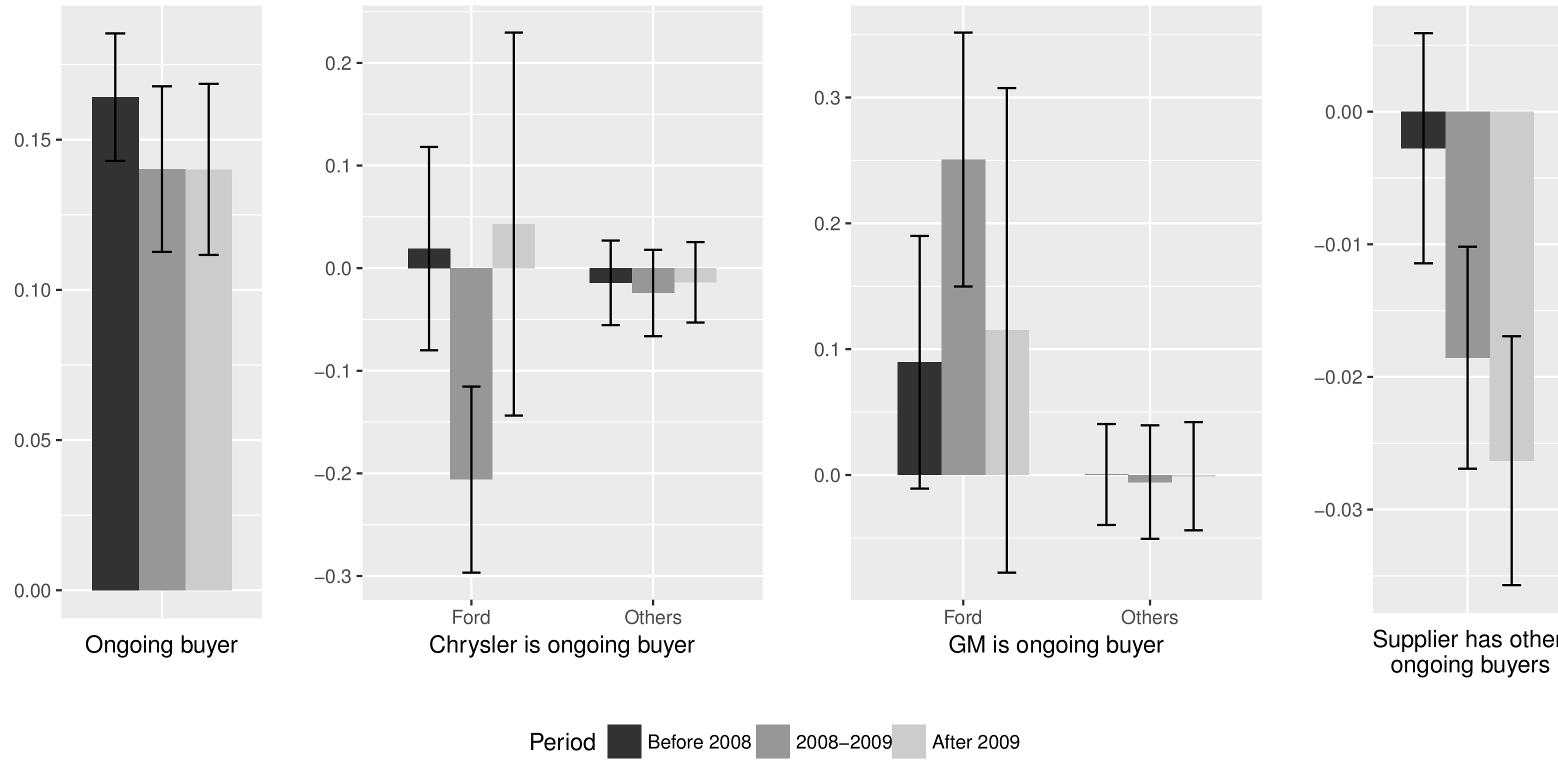

FIGURE B.4: Supportive evidence of Ford CEO's strategy

Table B.5: Symbols and definitions of portfolio variables, N_{SBt}, R_{SBt}, and O_{SBt}

Network variables N_{SBt}	
Relationship indicators:	
$\tilde{l}_{SBt}$	equal to one if B is already an ongoing buyer of S at t
$\tilde{l}^{\star}_{SBt}$	equal to one if S has some ongoing buyers other than B at t
Conditional on the supplier having other ongoing buyers:	
$\tilde{z}^{\star}_{SBt}$	number of S's ongoing buyers other than B at t
Risk variables R_{SBt}	
Conditional on being in an ongoing relationship:	
$\tilde{r}_{SBt}$	risk rating score of B at t
Conditional on the supplier having other ongoing buyers:	
$\tilde{r}^{\star}_{SBt}$	minimum risk rating score of S's ongoing buyers other than B at t
Operation variables O_{SBt}	
Conditional on being in an ongoing relationship:	
$\tilde{n}_{SBt}$	number of ongoing models of B that S supplies to at t
$\tilde{q}_{SBt}$	production of ongoing models of B that S supplies to at t
$\tilde{m}_{SBt}$	number of sectors in ongoing models of B that S supplies to at t
Conditional on the supplier having other ongoing buyers:	
$\tilde{n}^{\star}_{SBt}$	average number of ongoing models that S supplies to at t per other buyer
$\tilde{q}^{\star}_{SBt}$	average production of ongoing models that S supplies to at t per other buyer
$\tilde{m}^{\star}_{SBt}$	average number of sectors in ongoing models that S supplies to at t per other buyer

Table B.6: Results of operation model (2.1)

		Dependent variable:			
		$y_{SBt} = \mathbb{1}\,[S \text{ and } B \text{ sign anew at } t]$			
		(1)	(2)	(3)	(4)
Network variables	N_{SBt}				
Relationship indicators:					
ongoing buyer	$\tilde{l}_{SBt}$	0.113***	0.089***	0.081***	0.055***
		(0.009)	(0.014)	(0.014)	(0.013)
other ongoing buyers	$\tilde{l}^{\star}_{SBt}$	0.070***	0.041***	0.038***	0.054***
		(0.012)	(0.014)	(0.014)	(0.015)
Conditional on the supplier having other ongoing buyers:					
# other ongoing buyers	$\tilde{z}^{\star}_{SBt}$	0.014***	0.018***	0.018***	−0.009**
		(0.002)	(0.002)	(0.002)	(0.004)
Operation variables	O_{SBt}				
Conditional on being in an ongoing relationship:					
# ongoing models	$\tilde{n}_{SBt}$	0.019***	0.020***	0.020***	0.016***
		(0.002)	(0.002)	(0.002)	(0.002)
prod ongoing models	$\tilde{q}_{SBt}$	0.010***	0.009***	0.009***	0.008***
		(0.001)	(0.001)	(0.001)	(0.001)
# ongoing sectors	$\tilde{m}_{SBt}$	0.002	0.002	0.002	0.005***
		(0.002)	(0.002)	(0.002)	(0.002)
Conditional on the supplier having other ongoing buyers:					
avg # ongoing models per other buyer	$\tilde{n}^{\star}_{SBt}$	−0.001	0.007***	0.007***	−0.024***
		(0.002)	(0.003)	(0.003)	(0.004)
avg prod ongoing models per other buyer	$\tilde{q}^{\star}_{SBt}$	0.012***	0.009***	0.009***	0.015***
		(0.002)	(0.002)	(0.002)	(0.002)
avg # ongoing sectors per other buyer	$\tilde{m}^{\star}_{SBt}$	−0.004***	−0.004***	−0.004***	0.003
		(0.001)	(0.001)	(0.001)	(0.003)
Demand controls	D_t		X		
Firm controls	F_{SBt}		X	X	X
Risk controls	R_{SBt}		X	X	X
Year dummy				X	X
Buyer dummy				X	X
Supplier dummy					X
Observations		61,715	61,715	61,715	61,715
R^2		0.385	0.396	0.398	0.469
Adjusted R^2		0.385	0.396	0.397	0.459

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered at the supplier level.

Table B.7: Results of risk model (2.2)

		Dependent variable:			
		$y_{SBt} = \mathbb{1}\,[S \text{ and } B \text{ sign anew at } t]$			
		(1)	(2)	(3)	(4)
Network variables	N_{SBt}				
Relationship indicators:					
ongoing buyer	$\tilde{l}_{SBt}$	0.234***	0.089***	0.081***	0.055***
		(0.016)	(0.014)	(0.014)	(0.013)
other ongoing buyers	$\tilde{l}^{\star}_{SBt}$	0.039**	0.041***	0.038***	0.054***
		(0.016)	(0.015)	(0.015)	(0.016)
Conditional on the supplier having other ongoing buyers:					
# other ongoing buyers	$\tilde{z}^{\star}_{SBt}$	0.039***	0.018***	0.018***	−0.009**
		(0.002)	(0.002)	(0.002)	(0.004)
Risk variables	R_{SBt}				
Unconditional on being in an ongoing relationship:					
buyer rating	$\tilde{r}_{SBt}$	−0.002**	−0.001*	0.002	0.003
		(0.001)	(0.001)	(0.002)	(0.002)
Conditional on being in an ongoing relationship:					
buyer rating	$\tilde{r}_{SBt}$	−0.003	0.004	0.007**	0.009***
		(0.004)	(0.003)	(0.003)	(0.003)
Conditional on the supplier having other ongoing buyers:					
min other-buyer ratings	$\tilde{r}^{\star}_{SBt}$	0.016***	0.003*	0.004**	0.008***
		(0.002)	(0.002)	(0.002)	(0.002)
Demand controls	D_t		X		
Firm controls	F_{SBt}		X	X	X
Operation controls	O_{SBt}		X	X	X
Year dummy				X	X
Buyer dummy				X	X
Supplier dummy					X
Observations		61,715	61,715	61,715	61,715
R^2		0.304	0.396	0.398	0.469
Adjusted R^2		0.304	0.396	0.397	0.459

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered at the supplier level.

Table B.8: Results of risk model (2.3)

		Dependent variable:			
		$y_{SBt} = \mathbb{1}\left[S \text{ and } B \text{ sign anew at } t\right]$			
		(1)	(2)	(3)	(4)
Network variables	N_{SBt}				
Relationship indicators:					
ongoing buyer	$\tilde{l}_{SBt}$	0.222***	0.108***	0.109***	0.094***
		(0.009)	(0.009)	(0.009)	(0.009)
other ongoing buyers	$\tilde{l}^{\star}_{SBt}$	0.102***	0.054***	0.053***	0.088***
		(0.013)	(0.012)	(0.012)	(0.012)
Conditional on the supplier having other ongoing buyers:					
# other ongoing buyers	$\tilde{z}^{\star}_{SBt}$	0.038***	0.018***	0.018***	−0.008**
		(0.002)	(0.002)	(0.002)	(0.003)
Risk variables	R_{SBt}				
Unconditional on being in an ongoing relationship:					
is buyer risky?	$\mathbb{1}\{\tilde{r}_{SBt} < 2\}$	0.008**	0.011***	−0.009	−0.008
		(0.004)	(0.004)	(0.006)	(0.006)
Conditional on being in an ongoing relationship:					
is buyer risky?	$\mathbb{1}\{\tilde{r}_{SBt} < 2\}$	0.006	−0.020	−0.023*	−0.034***
		(0.014)	(0.013)	(0.013)	(0.013)
Conditional on the supplier having other ongoing buyers:					
is any other buyer risky?	$\mathbb{1}\{\tilde{r}^{\star}_{SBt} < 2\}$	−0.058***	−0.032***	−0.034***	−0.051***
		(0.008)	(0.007)	(0.008)	(0.007)
Demand controls	D_t		X		
Firm controls	F_{SBt}		X	X	X
Operation controls	O_{SBt}		X	X	X
Year dummy				X	X
Buyer dummy				X	X
Supplier dummy					X
Observations		61,715	61,715	61,715	61,715
R^2		0.305	0.397	0.398	0.469
Adjusted R^2		0.305	0.396	0.398	0.460

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered at the supplier level.
I choose rating 2 as my threshold because any rating below is either speculative and near to default (1) or default (0).

Table B.9: Risk-externality results of risk model (2.3) with time-specific coefficients

			Dependent variable:
			$y_{SBt} = \mathbb{1}\,[S$ and B sign anew at $t]$
			(1)
Network variables	N_{SBt}		
Conditional on the supplier having other ongoing buyers:			
# other ongoing buyers	$\tilde{z}^{\star}_{SBt}$	$(t \leqslant 2009)$	−0.003
			(0.003)
		$(t > 2009)$	−0.018***
			(0.004)
Risk variables	R_{SBt}		
Conditional on the supplier having other ongoing buyers:			
is any other buyer risky?	$\mathbb{1}\{\tilde{r}^{\star}_{SBt} < 2\}$	$(t \leqslant 2009)$	−0.049***
			(0.006)
		$(t > 2009)$	0.011
			(0.009)
Firm controls	F_{SBt}		X
Operation controls	O_{SBt}		X
Year dummy			X
Buyer dummy			X
Supplier dummy			X
Observations			61,715
R^2			0.474
Adjusted R^2			0.465

Notes: *p<0.1; **p<0.05; ***p<0.01
Standard errors clustered at the supplier level.
Included in the model but not shown are other variables in Table B.8, interacted with time.

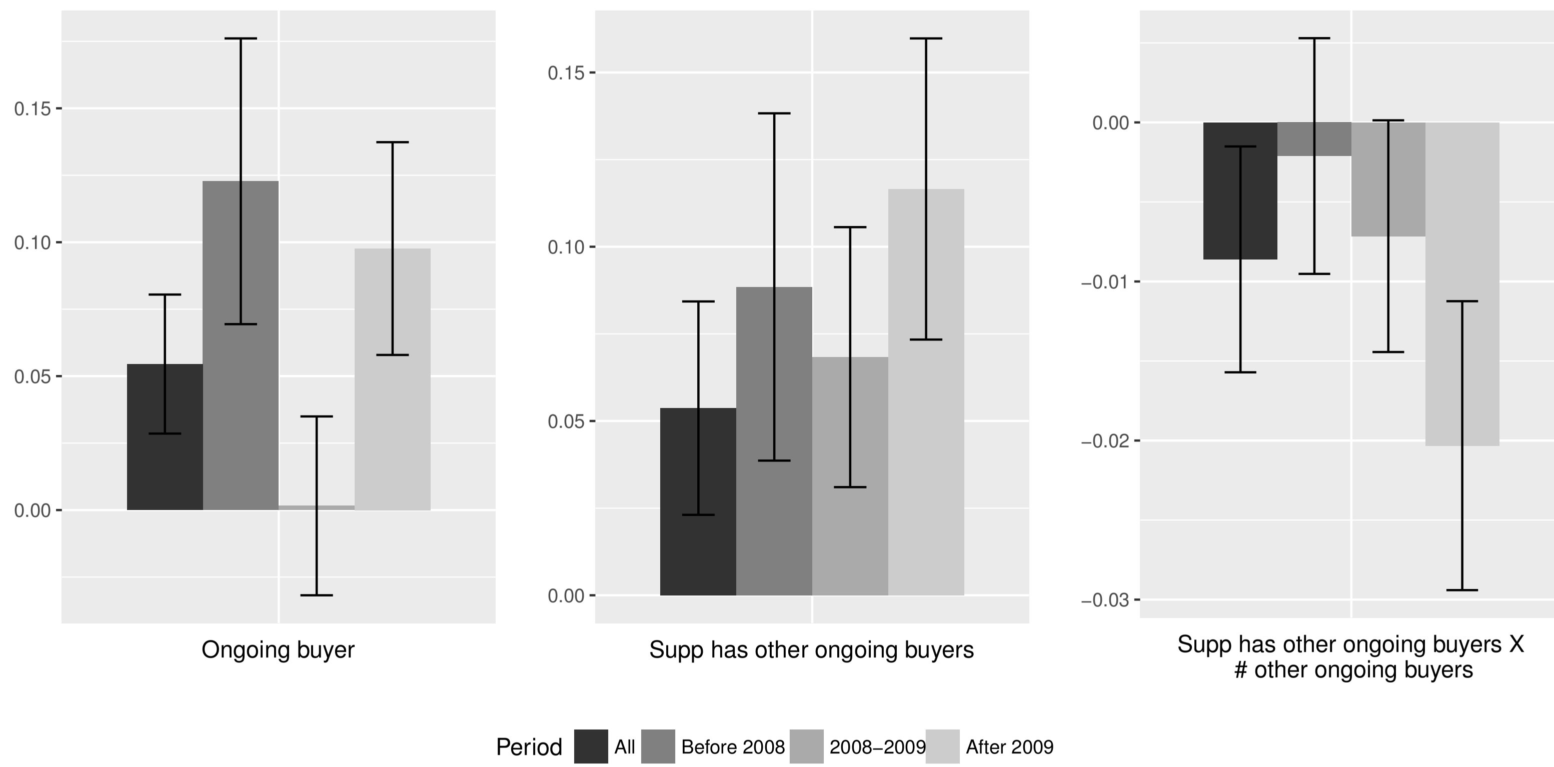

FIGURE B.5: Results of model (2.2) with time-specific coefficients: Network variables

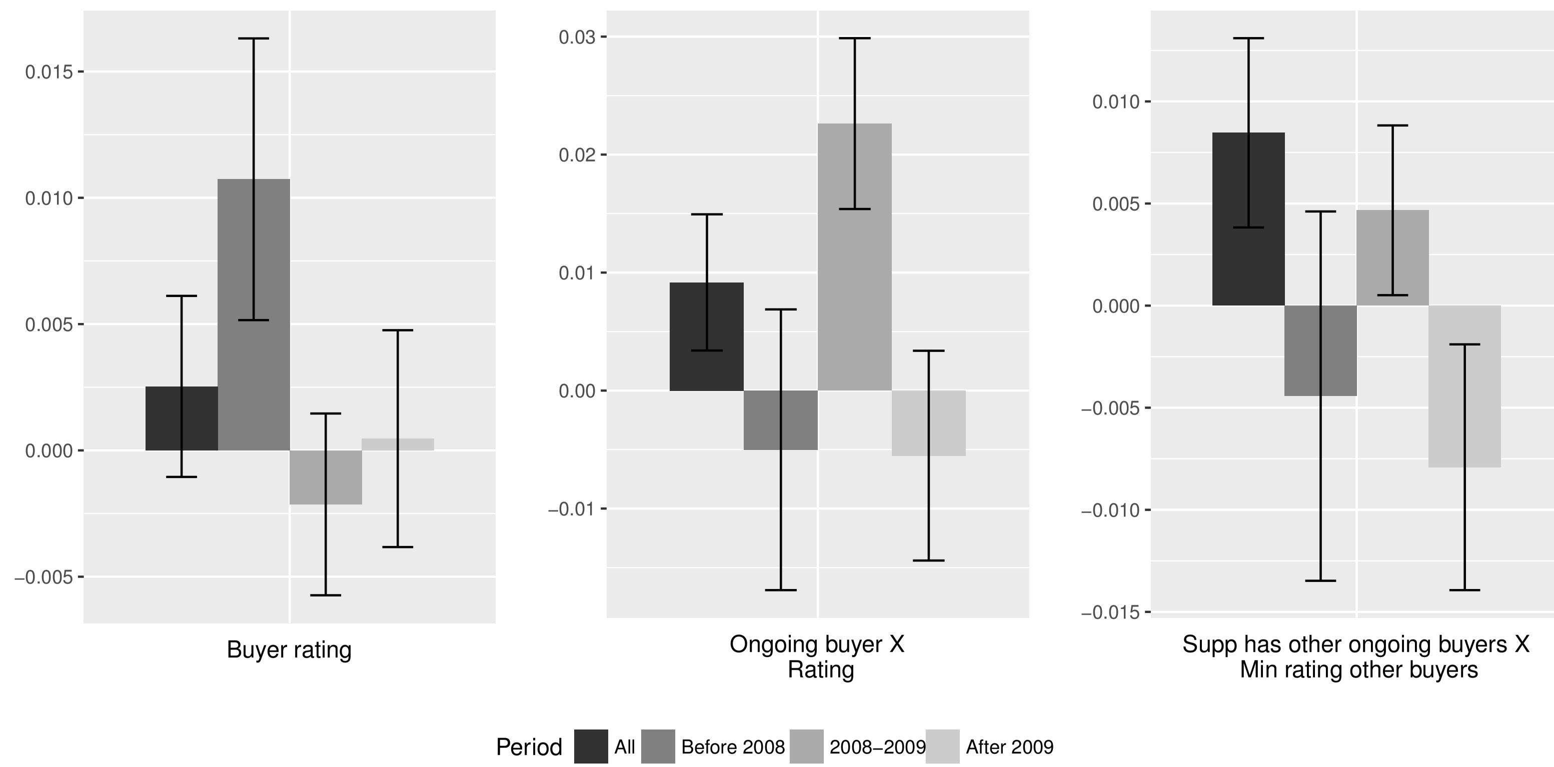

Figure B.6: Results of model (2.2) with time-specific coefficients: Risk variables

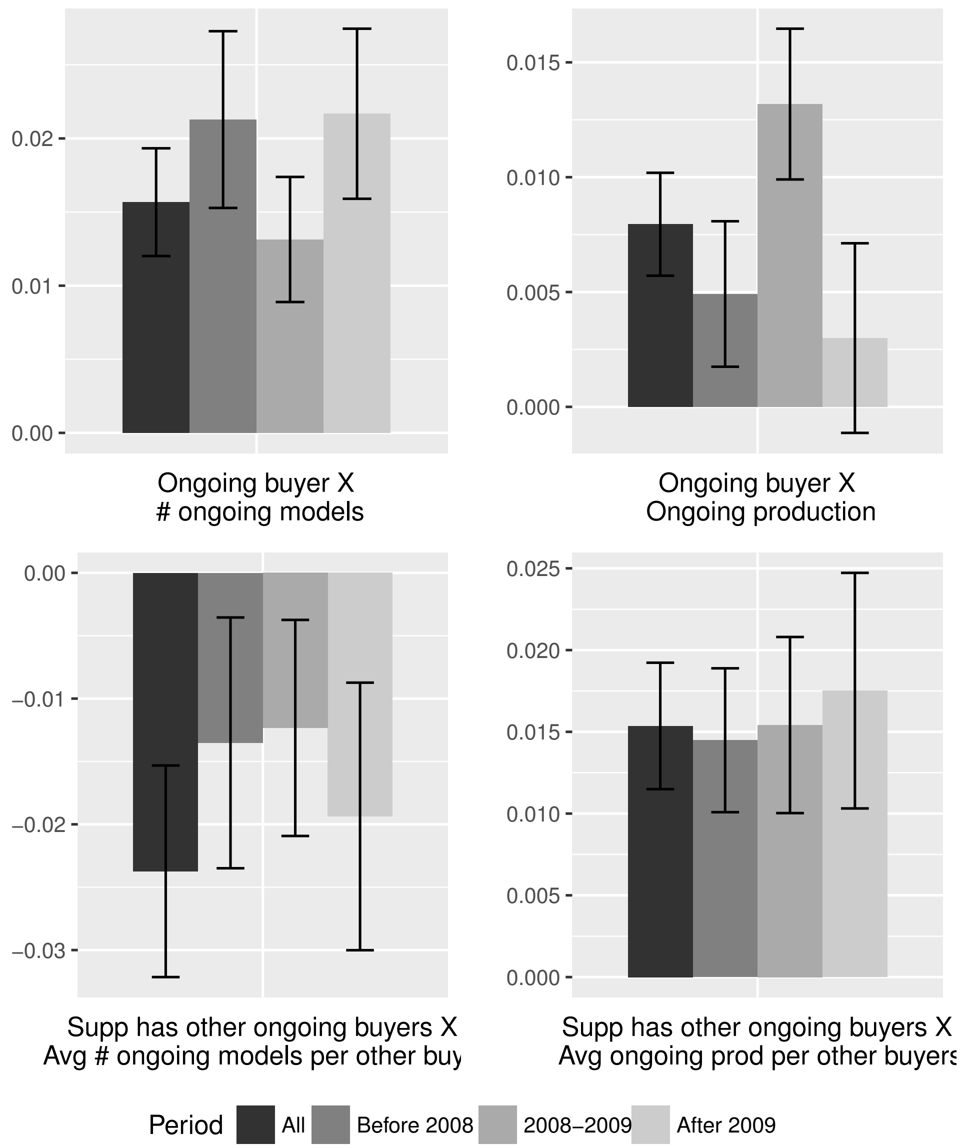

FIGURE B.7: Results of model (2.2) with time-specific coefficients: Production variables

Appendix C

Appendix of Chapter 3

Table C.1: Yearly aggregate statistics

	Number of					
	present		ongoing	active		new
	suppliers	buyers	models	suppliers	buyers	models
Unrestricted dataset:						
2005	842	12	248	308	11	49
2006	866	12	292	336	12	59
2007	844	12	308	297	11	37
2008	821	12	318	320	11	45
2009	781	12	328	287	12	37
2010	704	12	325	284	11	38
2011	663	12	307	232	10	33
Restricted dataset:*						
2005	285	12	247	247	11	49
2006	309	12	291	284	12	59
2007	321	12	308	265	11	37
2008	323	12	318	283	11	45
2009	326	12	328	255	12	37
2010	321	12	324	248	11	37
2011	321	12	306	206	10	33

Note: *Dataset restricted to non-exclusive suppliers with an annual average of one or more contracts signed.

Table C.2: Yearly production statistics for supplier-buyer-year combinations (S, B, t)

	# obs	Sample Mean of						
		Indicator variables		*conditional on* (1) *true*		*conditional on* (2) *true*		
		(1)	(2)					
		B is an ongoing buyer of S	S has other ongoing buyers	# ongoing models	ongoing prod	# ongoing other buyers	# ongoing models per other buyer	ongoing prod per other buyer
Unrestricted dataset:								
2005	9,262	0.270	0.963	11.029	5.137	3.107	2.191	3.164
2006	10,392	0.285	0.964	12.326	5.481	3.254	2.421	3.349
2007	9,284	0.323	0.965	14.286	5.814	3.446	2.695	3.477
2008	9,031	0.325	0.965	15.304	5.830	3.466	2.876	3.404
2009	9,372	0.323	0.969	16.113	4.547	3.669	3.117	2.673
2010	7,744	0.342	0.967	17.365	6.035	3.811	3.308	3.487
2011	6,630	0.337	0.970	16.484	5.662	3.976	3.390	3.800
Restricted dataset:								
2005	2,139	0.678	0.983	16.039	6.928	5.949	4.172	5.927
2006	2,485	0.737	0.984	17.511	7.352	6.292	4.754	6.436
2007	2,431	0.814	0.990	19.598	7.657	6.719	5.275	6.683
2008	2,427	0.839	0.993	20.333	7.568	6.849	5.627	6.772
2009	2,524	0.887	0.998	20.481	5.689	7.173	6.191	5.425
2010	2,315	0.895	0.997	21.200	7.310	7.224	6.214	6.773
2011	1,980	0.910	0.998	19.572	6.704	7.425	6.236	7.260

Note: Production is in $100k$-units ($\times 10^5$).

Table C.3: Shape of the portfolio of S from B's viewpoint at time S and B sign anew

	Before bailout					After bailout				
	Mean	SD	1D	Med.	9D	Mean	SD	1D	Med.	9D
Conditional on being in an ongoing relationship:										
# ongoing models of B S supplies to	8.676	7.442	1	7	19	11.072	9.046	2	9	25
Ongoing prod of B S supplies to	33.491	42.493	1.766	17.664	81.265	42.345	44.551	3.533	26.495	104.298
Risk score of B	4.023	0.983	3	4	5	3.465	1.857	0	4	5
Conditional on the supplier having other ongoing buyers:										
# other ongoing buyers	8.060	2.952	3	9	11	8.390	2.921	4	9	11
Avg # ongoing models per other buyer	6.653	4.219	1.857	5.750	13	7.911	4.603	2.500	7	14.991
Avg ongoing prod per other buyer	26.722	18.427	6.213	22.841	53.508	25.420	15.637	7.066	22.568	48.212
Min risk score of other buyers	2.864	0.570	2	3	3	0.949	1.421	0	0	3
Whether this min risk score < 2	0.055	0.227	0	0	0	0.686	0.464	0	1	1
Observations	$10,540$					$4,692$				

Note: Recall that in the dataset S and B are always (i) in an ongoing relationship at the time of signing a new contract, and (ii) non-exclusive relationship.
Production levels are in $10k$-units ($\times 10^4$). 5 levels s.t. level k is the mean of kth quintile.

Table C.4: Symbols and definitions of portfolio variables

Network variables	
Conditional on the supplier having other ongoing buyers:	
$z_{St}^{B\star}$	number of S's ongoing buyers other than B at t
Risk variables	
Conditional on being in an ongoing relationship:	
r_{St}^{B}	risk rating score of B at t
Conditional on the supplier having other ongoing buyers:	
$r_{St}^{B\star}$	$\mathbb{1}\Big\{\min_{\tilde{B}\in\mathcal{A}_S\setminus\{B\}}\{r_{St}^{\tilde{B}}\} < r^*\Big\}$
Operation variables	
Conditional on being in an ongoing relationship:	
n_{St}^{B}	number of ongoing models of B that S supplies to at t
$\bar{Q}_{St}^{B}$	average production per model that S supplies to at t
Q_{St}^{B}	$n_{St}^{B}\bar{Q}_{St}^{B}$
Conditional on the supplier having other ongoing buyers:	
$n_{St}^{B\star}$	average number of ongoing models that S supplies to at t per other buyer
$\bar{Q}_{St}^{B\star}$	average production per model that S supplies to at t per other buyer
$Q_{St}^{B\star}$	$\frac{1}{z_{St}^{B\star}}\sum_{\tilde{B}\neq B} Q_{St}^{\tilde{B}} = \frac{1}{z_{St}^{B\star}}\sum_{\tilde{B}\neq B} n_{St}^{\tilde{B}}\bar{Q}_{St}^{\tilde{B}}$

Note: In the reduced-form panel-data analysis, t is yearly.
In the structural analysis, t is continuous and St is replaced by ω.
In the reduced-form panel-data analysis, production is not defined in levels as in Table C.3, and is in $100k$-units.
In the structural analysis, production is defined in levels as in Table C.3.
In practice, r^* is set to two.

Table C.5: Linear-probability model: Network and risk variables

			Dependent variable: $y_{SBt} = \mathbb{1}[S$ and B sign anew at $t]$		
			(1)	(2)	(3)
Sample Selection			X	X	
Preferred-Supplier Assumption			X	X	
Network variables					
Conditional on the supplier having other ongoing buyers:					
# other ongoing buyers	$z_{St}^{B\star}$	$(t \leqslant 2009)$	0.014***	0.020***	−0.003
			(0.004)	(0.006)	(0.003)
		$(t > 2009)$	−0.013**	0.002	−0.018***
			(0.005)	(0.008)	(0.004)
Risk variables					
Conditional on being in an ongoing relationship:					
buyer rating	r_{St}^{B}	$(t \leqslant 2009)$	0.008*	0.017***	0.015***
			(0.004)	(0.006)	(0.003)
		$(t > 2009)$	−0.015***	−0.008	−0.005
			(0.005)	(0.008)	(0.005)
Conditional on the supplier having other ongoing buyers:					
whether other buyers very risky	$r_{St}^{B\star}$	$(t \leqslant 2009)$	−0.141***	−0.032	−0.051***
			(0.017)	(0.031)	(0.006)
		$(t > 2009)$	0.109***	0.054*	0.012
			(0.027)	(0.031)	(0.009)
Relationship indicators					X
Yearly number of model release by buyer				X	X
Year dummy				X	X
Buyer dummy				X	X
Supplier dummy				X	X
Observations			16,301	16,301	61,715
R^2			0.180	0.285	0.474
Adjusted R^2			0.179	0.269	0.464

Notes: *p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the supplier level.

$r_{St}^{B\star} = \mathbb{1}\left\{ \min_{\tilde{B} \in \mathcal{A}_S \setminus \{B\}} \{r_{St}^{\tilde{B}}\} < r^* \right\}$

Relationship indicators include whether (i) B is an ongoing buyer and (ii) S has other ongoing buyers. These indicators are always equal to one under the *preferred-supplier* assumption. In (3), I also control for B's rating, unconditionally on whether S supplies it. Production is not defined in levels (as in Table C.3) and is in $100k$-units.

Table C.6: Linear-probability model: Operation variables

			Dependent variable: $y_{SBt} = \mathbb{1}[S \text{ and } B \text{ sign anew at } t]$		
			(1)	(2)	(3)
Sample Selection			X	X	
Preferred-Supplier Assumption			X	X	
Operation variables					
Conditional on being in an ongoing relationship:					
# ongoing models	n^B_{St}	$(t \leqslant 2009)$	0.020***	0.019***	0.019***
			(0.002)	(0.002)	(0.002)
		$(t > 2009)$	0.022***	0.024***	0.024***
			(0.003)	(0.003)	(0.003)
prod ongoing models	Q^B_{St}	$(t \leqslant 2009)$	0.006***	0.008***	0.008***
			(0.001)	(0.001)	(0.001)
		$(t > 2009)$	0.004*	0.002	0.003
			(0.002)	(0.002)	(0.002)
Conditional on the supplier having other ongoing buyers:					
avg # ongoing models per other buyer	$n^{B\star}_{St}$	$(t \leqslant 2009)$	−0.007	−0.013	−0.012***
			(0.005)	(0.008)	(0.004)
		$(t > 2009)$	−0.015*	−0.022**	−0.019***
			(0.009)	(0.011)	(0.005)
avg prod ongoing models per other buyer	$Q^{B\star}_{St}$	$(t \leqslant 2009)$	0.013***	0.026***	0.015***
			(0.004)	(0.005)	(0.002)
		$(t > 2009)$	0.027***	0.030***	0.017***
			(0.009)	(0.009)	(0.003)
Relationship indicators					X
Yearly number of model release by buyer				X	X
Year dummy				X	X
Buyer dummy				X	X
Supplier dummy				X	X
Observations			16,301	16,301	61,715
R^2			0.180	0.285	0.474
Adjusted R^2			0.179	0.269	0.464

Notes: *p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the supplier level.

$r^{B\star}_{St} = \mathbb{1}\left\{ \min_{\tilde{B} \in \mathcal{A}_S \setminus \{B\}} \{r^{\tilde{B}}_{St}\} < r^* \right\}$

Relationship indicators include whether (i) B is an ongoing buyer and (ii) S has other ongoing buyers. These indicators are always equal to one under the *preferred-supplier* assumption. In (3), I also control for B's rating, unconditionally on whether S supplies it. Production is not defined in levels (as in Table C.3) and is in $100k$-units.

Table C.7: Mapping between Moody's rating scale and model's rating scale

Scale	Score									
Moody's	Aaa	Aa	A	Baa	Ba	B	Caa	Ca	C	D
Model		5		4	3		2	1		0

Table C.8: Average rating within-a-year transition rates (in percentage points) based on Moody's estimates

Scale	5	4	3	2	1	0
5	-	5.275	0.647	0.038	0.004	0.040
4	5.02	-	4.946	0.203	0.021	0.163
3	0.64	6.024	-	5.639	0.681	5.249
2	0.63	0.222	9.412	-	3.589	13.122
1	0	0	3.121	9.446	-	30.033
0	0	0	0	0	0	-

Note 1: Entry (i, j) reads as follows: Rating scores transitions from rating $r(i)$ to rating $r(j)$ within a year at rate given in entry (i, j).

Note 2: Ratings are computed as in the following example: Transition rate from 5 to 3 is equal to the sum of transition rates from Aaa, Aa, or A, to Ba or B as shown in Exhibit 32 of Moody's (2009).

Table C.9: Transition rates (in percentage points) in the model scale

Scale	5	4	3	2	1	0
5	-	5.275	0	0	0	0
4	5.02	-	4.946	0	0	0
3	0	6.024	-	5.639	0	5.249
2	0	0	9.412	-	3.589	13.122
1	0	0	3.121	9.446	-	30.033
0	0	0	0	0	0	-

Note: I set to zero rates below one pp.

Table C.10: Other rates used in the estimation

Rate		Value			
Arrival rate of offers					
High D	$\lambda(1)$	3.635			
Low D	$\lambda(0)$	3.279			
Demand flip rate	q^{d}	0.286			
Model termination rate	q^{s}	2.607			
Production jump rates					
		$\downarrow 4$	$\downarrow 3$	$\downarrow 2$	$\downarrow 1$
High D	$q^{\mathrm{q}}_{\downarrow k}(1)$	0.001	0.003	0.043	0.463
Low D	$q^{\mathrm{q}}_{\downarrow k}(0)$	0.002	0.013	0.074	0.657
		$\uparrow 1$	$\uparrow 2$	$\uparrow 3$	$\uparrow 4$
High D	$q^{\mathrm{q}}_{\uparrow k}(1)$	0.519	0.042	0.017	0.003
Low D	$q^{\mathrm{q}}_{\uparrow k}(0)$	0.572	0.035	0.009	0.002

Table C.11: Structural model: profit parameters

	Variable	Coefficient	
Before or after bailout		$K_\omega = 0$	$K_\omega = 1$
Variables interacted with production	$Q^B_\omega \times$		
Network variables			
Conditional on being in an ongoing relationship:			
Constant	1	−2.208***	−0.447
		(0.4168)	(0.3673)
Conditional on the supplier having other ongoing buyers:			
# other ongoing buyers	$z^{B\star}_\omega$	0.080***	−0.174***
		(0.0269)	(0.0257)
Risk variables			
Conditional on being in an ongoing relationship:			
buyer rating	r^B_ω	−0.154**	−0.372***
		(0.0761)	(0.0907)
Conditional on the supplier having other ongoing buyers:			
whether other buyers very risky	$r^{B\star}_\omega$	−4.730***	−0.283
		(0.6562)	(0.1821)
Operation variables			
Conditional on being in an ongoing relationship:			
# ongoing models	n^B_ω	1.776***	0.867***
		(0.0765)	(0.0570)
ongoing prod	Q^B_ω	−0.178***	−0.062***
		(0.0096)	(0.0084)
ongoing prod × tot prod level / 10,000	$Q^B_\omega \times Q_\omega$	0.215***	0.252***
		(0.0380)	(0.0561)
Conditional on the supplier having other ongoing buyers:			
avg # ongoing models per other buyer	$n^{B\star}_\omega$	0.164***	−0.328***
		(0.0723)	(0.0504)
avg ongoing prod per other buyer	$Q^{B\star}_\omega$	−0.040**	0.031***
		(0.0181)	(0.0124)
avg ongoing prod per other buyer × tot prod level / 10,000	$Q^{B\star}_\omega \times Q_\omega$	−0.179***	−0.125***
		(0.0369)	(0.0585)
Other variables			
Instantaneous cost variables			
Conditional on exiting:			
Exiting costs	ψ^{out}	−0.178	
		(1.3325)	
Conditional on accepting an offer:			
Agreement costs	ψ^{a}	−1.745***	
		(0.0582)	
Intercept		19.291***	
		(3.5978)	
Observations		50,060	

Notes: *p<0.1; **p<0.05; ***p<0.01
Bootstrapped standard errors. Production in levels.

Table C.12: Median change of a collapse of GM or Chrysler on CCP of accepting an offer

	Median of							
	$K_\omega = 0$							$K_\omega = 1$
		If GM collapses:			If Chrysler collapses:			
	$P(\mathrm{a}\|B,\omega)$	$\Delta^B_{\mathrm{GM}}(\omega)$	$\Lambda^B_{\mathrm{GM}}(\omega)$	$P(\mathrm{a}\|B,\omega)$ $+\Delta^B_{\mathrm{GM}}(\omega)$	$\Delta^B_{\mathrm{Ch}}(\omega)$	$\Lambda^B_{\mathrm{Ch}}(\omega)$	$P(\mathrm{a}\|B,\omega)$ $+\Delta^B_{\mathrm{Ch}}(\omega)$	$P(\mathrm{a}\|B,\omega)$
When demand is low ($D_\omega = 0$)								
BMW	0.304	-0.093	-29.139	0.211	-0.089	-23.395	0.245	0.195
Chrysler	0.299	-0.043	-14.789	0.258	-	-	-	0.133
Daimler	0.259	-0.116	-42.236	0.171	-0.114	-37.629	0.194	0.177
Fiat	0.309	-0.057	-15.478	0.269	-0.046	-8.882	0.323	0.191
Ford	0.258	-0.017	-7.203	0.243	-0.008	-2.238	0.268	0.141
GM	0.474	-	-	-	-0.068	-13.491	0.410	0.348
Honda	0.225	-0.037	-17.871	0.192	-0.029	-11.349	0.206	0.124
Hyundai-Kia	0.198	-0.045	-23.194	0.160	-0.040	-19.264	0.169	0.122
Renault-Nissan	0.268	-0.044	-9.427	0.254	-0.025	-4.759	0.270	0.171
PSA	0.270	-0.045	-11.388	0.250	-0.024	-5.317	0.270	0.167
Toyota	0.259	-0.080	-30.359	0.186	-0.075	-23.014	0.211	0.147
VW	0.672	-0.054	-7.509	0.584	-0.035	-4.438	0.642	0.336
All	0.284	-0.050	-15.184	0.231	-0.034	-8.943	0.255	0.158
When demand is high ($D_\omega = 1$)								
BMW	0.321	-0.169	-50.191	0.179	-0.159	-49.999	0.176	0.242
Chrysler	0.330	-0.065	-18.596	0.294	-	-	-	0.180
Daimler	0.329	-0.148	-48.377	0.184	-0.145	-45.382	0.206	0.233
Fiat	0.378	-0.075	-17.016	0.358	-0.064	-12.295	0.440	0.172
Ford	0.324	-0.040	-10.576	0.294	-0.013	-4.451	0.352	0.145
GM	0.349	-	-	-	-0.135	-37.400	0.329	0.388
Honda	0.242	-0.051	-21.041	0.197	-0.037	-12.688	0.253	0.135
Hyundai-Kia	0.207	-0.025	-9.361	0.199	-0.066	-21.980	0.213	0.137
Renault-Nissan	0.572	-0.070	-14.286	0.484	-0.043	-9.533	0.516	0.141
PSA	0.382	-0.076	-19.529	0.311	-0.042	-12.445	0.332	0.170
Toyota	0.217	-0.118	-52.468	0.119	-0.143	-46.902	0.166	0.166
VW	0.648	-0.091	-18.454	0.489	-0.064	-8.594	0.696	0.521
All	0.325	-0.079	-21.852	0.253	-0.067	-17.042	0.290	0.177

Notes: Medians are based on distinct subsets of 1,200 states randomly picked among observed states ω conditional on D_ω and K_ω.

Table C.13: Mean change of a collapse of GM or Chrysler on CCP of accepting an offer

	Mean of					
	$K_\omega = 0$					$K_\omega = 1$
		If GM collapses:		If Chrysler collapses:		
	$P(\mathrm{a}\mid B,\omega)$	$\Delta^B_{\mathrm{GM}}(\omega)$	$P(\mathrm{a}\mid B,\omega)$ $+\Delta^B_{\mathrm{GM}}(\omega)$	$\Delta^B_{\mathrm{Ch}}(\omega)$	$P(\mathrm{a}\mid B,\omega)$ $+\Delta^B_{\mathrm{Ch}}(\omega)$	$P(\mathrm{a}\mid B,\omega)$
When demand is low ($D_\omega = 0$)						
BMW	0.364	-0.094	0.271	-0.079	0.296	0.220
Chrysler	0.364	-0.042	0.322	-	-	0.142
Daimler	0.330	-0.108	0.225	-0.091	0.255	0.266
Fiat	0.399	-0.050	0.352	-0.026	0.390	0.255
Ford	0.286	-0.021	0.267	0.001	0.296	0.143
GM	0.512	-	-	-0.078	0.473	0.421
Honda	0.247	-0.040	0.207	-0.012	0.232	0.128
Hyundai-Kia	0.230	-0.054	0.176	-0.022	0.207	0.128
Renault-Nissan	0.360	-0.039	0.325	-0.020	0.352	0.175
PSA	0.349	-0.040	0.312	-0.021	0.339	0.187
Toyota	0.304	-0.083	0.222	-0.062	0.252	0.176
VW	0.609	-0.067	0.549	-0.053	0.582	0.362
All	0.374	-0.058	0.302	-0.043	0.343	0.225
When demand is high ($D_\omega = 1$)						
BMW	0.359	-0.150	0.207	-0.148	0.251	0.319
Chrysler	0.378	-0.046	0.343	-	-	0.201
Daimler	0.381	-0.140	0.246	-0.116	0.282	0.340
Fiat	0.436	-0.059	0.402	-0.022	0.464	0.240
Ford	0.380	-0.034	0.348	-0.009	0.384	0.153
GM	0.435	-	-	-0.132	0.406	0.475
Honda	0.265	-0.039	0.226	0.0003	0.295	0.151
Hyundai-Kia	0.227	0.045	0.268	-0.034	0.269	0.166
Renault-Nissan	0.552	-0.059	0.497	-0.024	0.516	0.201
PSA	0.442	-0.067	0.385	-0.031	0.401	0.210
Toyota	0.260	-0.103	0.164	-0.114	0.215	0.201
VW	0.590	-0.094	0.506	-0.049	0.611	0.525
All	0.401	-0.072	0.331	-0.064	0.378	0.274

Notes: Medians are based on distinct subsets of 1,200 states randomly picked among observed states ω conditional on D_ω and K_ω. I do not show means of $\Lambda^B_{\mathrm{GM}}(\omega)$ and $\Lambda^B_{\mathrm{Ch}}(\omega)$ because of outliers.

Table C.14: Relationship between percentage-point change in CCP of GM exit and supplier's exposure to GM

		Dependent variable: $\Delta^{B}_{\tilde{B}}(\omega) = P(\mathrm{a}\vert\sigma^{\mathrm{e}}(-\tilde{B},\omega),B) - P(\mathrm{a}\vert\omega,B)$			
		(1)	(2)	(3)	(4)
Ratio of prod supplied to $\tilde{B}$	$\frac{Q^{\tilde{B}}_{\omega}}{Q_{\omega}}$	-0.162^{***}	-	-	-
		(0.029)			
Ratio of # of models supplied to $\tilde{B}$	$\frac{n^{\tilde{B}}_{\omega}}{n_{\omega}}$	-	-0.064^{**}	-	-
			(0.031)		
Ratio of prod supplied to Chrysler	$\frac{Q^{\mathrm{Chrysler}}_{\omega}}{Q_{\omega}}$	-	-	-0.081	-
				(0.067)	
Ratio of prod supplied to GM	$\frac{Q^{\mathrm{GM}}_{\omega}}{Q_{\omega}}$	-	-	-0.167^{***}	-
				(0.030)	
Ratio of # of models supplied to Chrysler	$\frac{n^{\mathrm{Chrysler}}_{\omega}}{n_{\omega}}$	-	-	-	0.010
					(0.050)
Ratio of # of models supplied to GM	$\frac{n^{\mathrm{GM}}_{\omega}}{n_{\omega}}$	-	-	-	-0.103^{***}
					(0.032)
Ratio of prod supplied to B		X		X	
Ratio of # of models supplied to B			X		X
# of buyers other than B and $\tilde{B}$		X	X	X	X
Demand		X	X	X	X
Buyer-Exiter dummy (B)		X	X	X	X
Observations		27,418	27,418	27,418	27,418
R^2		0.261	0.235	0.262	0.237
Adjusted R^2		0.260	0.235	0.261	0.236

Note: *p<0.1; **p<0.05; ***p<0.01

Standard errors are clustered at the buyer-exiter level. Exiter $\tilde{B} \in \{\mathrm{GM}, \mathrm{Chrysler}\}$, buyer $B \notin \{\mathrm{GM}, \mathrm{Chrysler}\}$.

Table C.15: Relationship between percentage-point change in CCP when exiter exits and CCP of accepting an offer from a buyer other than exiter, before the bailout.

		Dependent variable: $\Delta^{B}_{\tilde{B}}(\omega)$
CCP of accepting an offer from $B \neq$ Chrysler	$P(\mathrm{a}\vert\omega,B)\times \mathbb{1}\{\tilde{B} = \mathrm{Chrysler}\}$	-0.051^{**} (0.021)
CCP of accepting an offer from $B \neq$ GM	$P(\mathrm{a}\vert\omega,B)\times \mathbb{1}\{\tilde{B} = \mathrm{GM}\}$	-0.094^{***} (0.029)
Demand		X
Buyer-Exiter dummy		X
Observations		27,418
R^2		0.195
Adjusted R^2		0.194

Notes: *p<0.1; **p<0.05; ***p<0.01

Table C.16: Time trend of the ratio of new models of B launched in year t that S supplies to.

		Dependent variable: $\frac{\text{\# new models of } B \text{ that } S \text{ supplies to}}{\text{\# new models of } B \text{ at } t}$	
		(1)	(2)
Sample Selection			X
Preferred-Supplier Assumption			X
Year	$t \times \mathbb{1}\{t < 2009\}$	0.002**	0.011***
		(0.001)	(0.004)
	$t \times \mathbb{1}\{t > 2009\}$	−0.019***	−0.057***
		(0.003)	(0.009)
Period dummy		X	X
Buyer dummy		X	X
Supplier dummy		X	X
Observations		61,715	16,301
R^2		0.426	0.296
Adjusted R^2		0.416	0.281

Notes: *p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at the supplier level.
Reference period is year 2009.

Table C.17: Relationship between CCP that the supplier exits and CCP that the supplier accepts an offer from a buyer.

		Dependent variable: $P(\text{exit}\|\omega)$
When demand is low before bailout ($D_\omega = 0$ and $K_\omega = 0$)		
CCP of accepting an offer from B	$P(\text{a}\|\omega, B)$	−0.026***
		(0.009)
When demand is high before bailout ($D_\omega = 1$ and $K_\omega = 0$)		
CCP of accepting an offer from B	$P(\text{a}\|\omega, B)$	−0.063***
		(0.006)
When demand is low after bailout ($D_\omega = 0$ and $K_\omega = 1$)		
CCP of accepting an offer from B	$P(\text{a}\|\omega, B)$	−0.165***
		(0.019)
When demand is high after bailout ($D_\omega = 0$ and $K_\omega = 1$)		
CCP of accepting an offer from B	$P(\text{a}\|\omega, B)$	−0.126***
		(0.008)
Demand		X
Post-bailout dummy		X
Buyer dummy		X
Observations		47,449
R^2		0.058
Adjusted R^2		0.058

Notes: *p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered at the buyer level.

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Biography

Nicolas-Aldebrando Benelli was born in Paris, France, in 1989. He earned a master's degree in telecommunication engineering from Télécom ParisTech (formerly known as École Nationale Supérieure des Télécommunications de Paris) in 2011, and a master's degree in economics from the Toulouse School of Economics in 2012. He then completed his PhD in economics at Duke University. In the Fall of 2017, Nicolas will go back to France to take part in the one-year propaedeutic program of the Roman Catholic Archdiocese of Paris, to discern his call to priesthood in the Catholic Church and decide upon his entry to seminary the next year.