Essays in Industrial Organization and Environmental Economics

by

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Bryan Bollinger

Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in the Department of Economics
in the Graduate School of Duke University

2020

ABSTRACT

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Abstract

This dissertation is comprised of three chapters in industrial organization and environmental economics. Chapter 2 examines the mechanism of cost efficiency following mergers of U.S. freight railroads and uncovers the sources. Efficiency is generally cited as the primary reason why mergers are good for consumers, yet there is little evidence showing the sources of cost efficiency. In this chapter, I first provide reduced-form result showing that following mergers, average shipment price significantly decreases, and the price effect of the merger is greater where railcars must be switched between two companies. However, given that markets are interdependent in railroad networks because of routing and investment decisions, merger efficiency cannot be measured simply by comparing individual markets. I addresses this with a structural model of firm pricing, routing, and investment decisions. Model estimates allow simulations that reveal sources of cost efficiency to include elimination of interchange costs, routing and consolidation of traffic, and re-optimization of investment. Welfare impacts show a great deal of geographic heterogeneity across markets.

Chapter 3 studies R&D spill-over in the in the Korean electric motor industry. In joint work with Daniel Yi Xu, we develop and estimate a dynamic industry equilibrium model of R&D, R&D spill-overs, and productivity evolution of manufacturing plants in the Korean electric motor industry from 1991 to 1996. We use a Simulated Method of Moments estimator to estimate the cost of R&D, the magnitude of the R&D spill-over, adjustment costs of physical investment, and the distribution of plant scrap values. Counterfactual experiments of two policies are implemented. The results show that increasing the elasticity of substitution between products increases plant innovation incentives and the plant turnover. In contrast, a lower entry cost does not change industry productivity. Although the market selection effect is

strengthened by higher firm turnover, the plant's incentives to invest in R&D are reduced.

Chapter 4, in joint work with James Roberts, Christopher Timmins, and Ashley Vissing, analyzes mortgage lenders' behavior with respect to shale gas risk during the period of the U.S. shale gas boom, which coincided with the U.S. housing market rise, collapse and subsequent increase in lending industry scrutiny. The results show that lenders did indeed increase the weight they place on shale risk relative to income risk in mortgage pricing behavior after 2010. This effect is particularly evident for groundwater dependent properties, indicating that lenders view shale activities as placing the residential value of these properties at greater risk. We find that insurers, on average, lose around $2,394.9, or 1.2% of profit earned on an average mortgage.

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I am indebted to my committee members, Allan Collard-Wexler, Daniel Yi Xu, Christopher D. Timmins, James W. Roberts, and Bryan Bollinger. Although I have not achieved anything yet, I could not have reached where I am today without their help. I want to thank my advisors Allan and Daniel for their invaluable advising and continuous support throughout my Ph.D. study. My apprenticeship with them was the most rewarding and precious experience in my school life. More importantly, they not only showed me how to be a great researcher, but how to be a great person. What I have seen, and what I have learned from them will continue to guide me for many years to come. I am also grateful to my committee member, Christopher Timmins, for his tremendous help and great encouragement for me. Whenever I needed help, he was always there. I would also like to thank my committee member James Roberts, for his great advice and valuable comments for my dissertation. I have appreciated and enjoyed all our discussions and conversations.

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Chapter 1

Introduction

Increased efficiency is generally cited as the primary reason why mergers are good for both consumers and industry, but there is typically little evidence showing the mechanisms driving these efficiencies and how they interact with incentives to raise prices. In Chapter 2, I study the mechanism of cost efficiency following railroad mergers. The U.S. freight railroad industry witnessed a wave of merger activity between 1980 and 2005, reducing the number of active firms from 38 to 7. Unlike many other industries, metrics of efficiency can be directly observed in railroad transport. Using detailed waybill data, I first use reduced-form evidence to suggest that the average shipment price decreases significantly following a merger and that the effect is greater where railcars must be switched between two companies. However, the interdependent nature of railroad networks means that merger efficiency cannot be fully understood by comparing individual markets in a simple regression. Instead, I estimate a structural model that endogenizes firm pricing, routing, and investment decisions. Counterfactual simulations based on that model decompose the sources of cost efficiency into elimination of interchange costs, routing and consolidation of traffic, and reoptimization of investment. The results show how the relative importance of these three sources changes with features of the merger and that there is tremendous heterogeneity in the welfare effects of mergers across different geographic markets depending on network ownership and the location of each market within the network.

Chapter 3, in joint work with Daniel Yi Xu, studies R&D spill-over in the in the Korean electric motor industry. We develop and estimate a dynamic industry equilibrium model of R&D, R&D spillovers, and productivity evolution of manufacturing plants in the Korean electric motor industry from 1991 to 1996. Plant-level decisions for R&D, physical capital investment, entry, and exit are integrated in an equilibrium model with an imperfectly competitive product market. We use a Simulated Method of Moments estimator

to estimate the cost of R&D, the magnitude of the R&D spillover, adjustment costs of physical investment, and the distribution of plant scrap values. The recent approximation method of Weintraub, Benkard, and Van Roy (2007) is applied. Counterfactual experiments of two policies are implemented. Increasing the elasticity of substitution between products increases plant innovation incentives and plant turnover. In contrast, a lower entry cost does not change industry productivity. Although the market selection effect is strengthened by higher firm turnover, the plant's incentives to invest in R&D are reduced.

Chapter 4, in joint work with James Roberts, Christopher Timmins, and Ashley Vissing, analyzes mortgage lenders' behavior with respect to shale gas risk during the U.S. shale gas boom, which coincided with the U.S. housing market rise, its subsequent collapse, and the ensuing increase in lending industry scrutiny. Shale gas operations may place affected houses into technical default such that GSEs (Fannie Mae and Freddie Mac) are unable to maintain them in their portfolios. We find that lenders do indeed increase the weight they place on shale risk relative to income risk in mortgage pricing behavior after 2010. This effect is particularly evident for groundwater-dependent properties, indicating that lenders view shale activities as placing the residential value of these properties at greater risk.

Chapter 2

Efficiency Gain from Mergers: Evidence from the U.S. Railroad Network

2.1 Introduction

In the past thirty years, a small number of firms have gained a very large share of the market in the United States, following mergers and consolidations. [Autor et al., 2017] document an upward trend over time that industries have become more concentrated on average. There is a large strand of literature documenting and analyzing mergers in multiple industries.[1] However, an open question is that are the efficiency gains of mergers small, large, or absent? In theory, on the one hand a merger gives the combined firm greater market power hence incentive to increase prices. On the other hand, a merger may generate efficiencies, reduce marginal costs, and give the combined firm an incentive to lower prices. Economists are aware of this trade-off since [Williamson, 1968], yet there is very little direct empirical evidence showing efficiency gain of mergers, and if it offsets the incentive to raise prices. This is largely because it is difficult to measure and quantify if mergers lower the marginal cost of production of the combined firm. The objective of this paper is to study the mechanism of cost efficiency after mergers in U.S. railroads, and evaluate if the

[1] In the airline industry, a wave of consolidation happened during a short period of time in the late 1980s ([Peters, 2006]); in the telecommunication industry, over 6,000 acquisitions occurred between 1996 and 2006 ([Leeper, 1999]; [Jeziorski, 2014]); a dozen global hard-disk manufacturers consolidated into only three in the last 20 years from 1996 to 2015 ([Igami, 2017]; [Igami and Uetake, 2016]); 190 hospital mergers occurred between 1989 and 1996 ([Dafny, 2009]; [Bazzoli et al., 2002]; [Dranove and Lindrooth, 2003]), and in the dialysis industry, more than 1,200 acquisitions occurred between 1998 and 2010 ([Eliason et al., 2018]).

efficiency gain offsets the incentive to raise prices. Moreover, I contribute to the merger analysis by proposing a novel way to study efficiency gain at a network industry where origin-destination markets are interdependent.

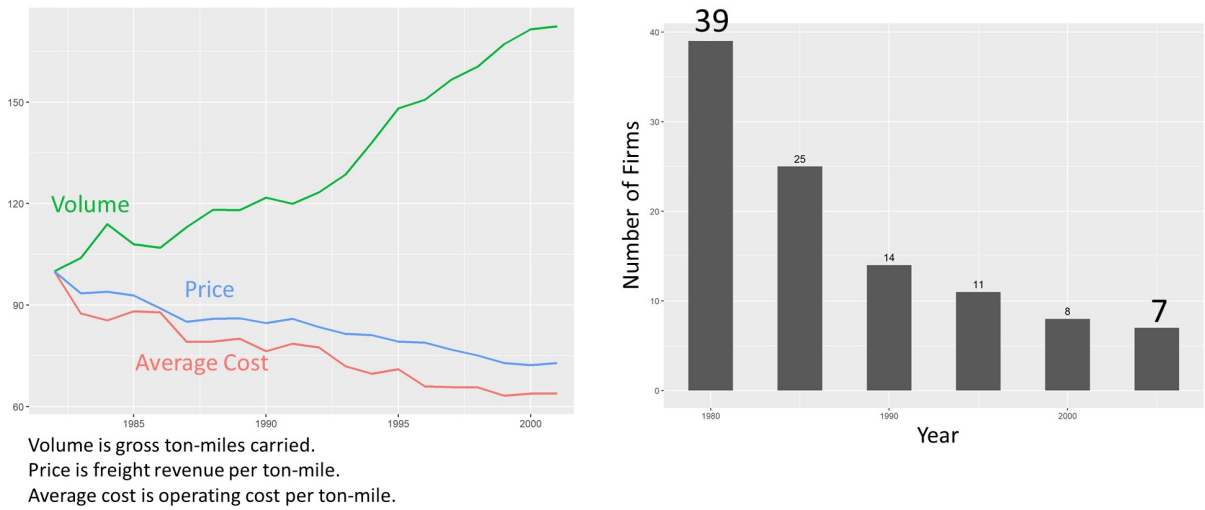
I do this by looking at the U.S. freight railroad industry. First, there was a series of merger from 1980 to 2005. The number of Class I railroads[2] dropped from 39 to 7, and market share of the top four firms increased from 66% to 94%. Although concentration has gone up in this industry, prices have decreased steadily. As illustrated in the left panel in Figure 2.1, from 1980 to 2005, prices per shipment have decreased by 20%, while the total volume of shipment has doubled. Given there is limited technological change in the studied period, the price reduction indicates that there might be efficiency gains following these railroad mergers. According to the Department of Transportation, in 2017, railroads are the second largest transport mode in providing freight service in the United States, carrying 1,675 billion ton-miles of freight, and accounts for around 30% of total freight transportation. According to the Association of American Railroads (AAR), in 2016 the railroads transported about 40% of intercity ton-miles, more than any other mode of transportation.[3] Unlike many other industries, metrics of efficiency can be directly observed in railroad transport. At individual route level, the combined firm can abandon the redun-

[2]Class I railroads are defined as "having annual carrier operating revenues of $250 million or more in 1991 dollars." According to AAR, Class I railroads account for more than 95% of revenues generated in the U.S. freight railroad industry in 2016.

[3]One evidence that shows limited technological change in the studied time period is that until the late 1990s, the vast majority of rail lines in the U.S. still relies on the human crew for complying with all safety rules. One accident that highlights this fact is the Big Bayou Canot rail accident, where a tow of heavy barges collided with the rail bridge and later caused the derailing of an Amtrak train on the CSXT Big Bayou Canot bridge with 47 people killed and 103 more injured. The accident happened partly because no technology was implemented to monitor the real-time condition of tracks and train movements, and the Amtrak engineer was not notified of the collision in time. Positive Train Control system that monitors and controls train movements was required by rail safety law in 2008, but full implementation is still underway and is supposed to be done by the end of 2020.

dant rail lines that serve the same origin and destination market. Also, the combined firm can eliminate the interchange cost where railcars need to be switched between two railroad companies before the merger. At network level, the combined firm can consolidate traffics and choose shorter efficiency-weighted routes that are not available before the merger.[4]

Figure 2.1: U.S. Freight Railroad Performance and Number of Class I Railroads



Source: AAR, Analysis of Class I Railroads Annual Issues

I use detailed shipment data on 12 million waybills to quantify the efficiency gain of mergers at both individual route level and network level. Railroad companies conduct point-on-point pricing, and the waybill data contains price information at firm-origin-destination level. The waybill data also contain detailed shipment information on such attributes as commodities carried, total billed weight, participating railroads, and origin, destination locations of each load. I begin my analysis by examining the price effect of mergers. By conducting reduced-form analysis at individual route level for each origin-destination market, I study how prices change before and after mergers. After controlling for observable characteristics and a rich set of fixed effects, I find that on average shipment prices have

[4]According to [Kwoka and White, 1997], efficiency gain of mergers include alleviation of capacity constraints, integration of track networks, reduction of mileage along major routes, and improved utilization of locomotives and railcars.

decreased by 9% after mergers. Then I open up the merger cases and examine the price effects for different route types. For route where railroad companies exchange railcars before the merger, the price effect of merger is 11%. For other types of route, the price effect of merger is only 6%. The results suggest that efficiency gain of mergers vary by route types, and elimination of interchange cost where railroad firms exchange railcars is an important source of cost efficiency. One concern regarding these price effects is that such price effects might be driven by competition from other transportation modes, instead of mergers. I address this concern by showing that these price changes occur both for commodities that are mostly transported by rail such as coal, and commodities that are also largely transported by other modes such as electrical machinery. The results suggest that the price effects are not driven by competition from other transportation modes.

I then provide motivating evidence to show that there is efficiency gain of mergers. I do this by examining changes of aggregate operational statistics at firm level, and also examine changes of operations at individual route level for each origin-destination market. At firm level, after controlling for observable characteristics, the reduced-form results show that on average the ratio of switching hours to road service hours has decreased by 11.5%, and length of haul has increased by 5.3% after railroad mergers. The results indicate that there is efficiency gain of mergers because the less time a train spends switching in yards the more efficient the operation is, and it is more fuel efficient for a train to run a longer distance. Results at individual route level also show that there is efficiency gain of mergers. By comparing the changes before and after mergers, I show that the number of interchanges has decreased following railroad mergers. Moreover, firms utilize more unit trains after mergers. A unit train is a train in which all railcars carry the same commodity and are shipped from the same origin to the same destination. The use of unit trains saves time and money. The combined firm can reoptimize routing and consolidate traffics to initiate more unit trains after the merger.

One challenge in quantifying merger effects in the freight railroad industry, however, is that origin-destination markets in a railroad network are interdependent. The shipment

cost from one origin to destination depends on the routing and investment decision, which depends on the location and demand of other markets in the railroad network. Therefore, looking only at changes at individual route level is insufficient for understanding mergers in this industry. To overcome this problem, I estimate a structural model that features firms pricing, routing, and investment decisions in multiple origin-destination markets based on the framework of [Galichon, 2016] and [Fajgelbaum and Schaal, 2017].

With the empirical evidence in mind, I propose an optimal transport network model that allows firms to choose pricing, routing, and investment for thousands of origin-destination markets. In the model, firms choose prices for the markets they serve, conditional on their perceived cost of operating there and the prices of competitors. Given the prices, the transportation service demanded for each firm in each origin-destination market is determined. Then firms jointly decide how to allocate infrastructure investment and make routing decisions in their network by minimizing the operational cost. Intuitively, firms allocate more resources to routes that carry larger volume of traffic, and choose the shortest efficiency-weighted routing to serve each origin-destination market. I model demand of transportation service using a nested logit model. Shippers choose between different railroad companies and an outside option which is trucking. Firms compete in prices, and in equilibrium, the perceived cost of operating at the pricing stage is consistent with the outcome from firms cost minimization problem. I consider the interdependence of markets in modeling routing and investment. Railroad firms can consolidate infrastructure investment into a small number of corridors, and then route traffic from multiple origins and destinations over these efficient corridors to reduce shipment cost. This allows operational cost to be dependent on topology of the network. For example, if origins and destinations locate near hubs, firms can consolidate traffics into a small number of routes through these hubs. If origins and destination locate in disperse regions, it is difficult to consolidate traffics from different origins and destinations into few efficient routes. I estimate the model using generalized method of moments, and the data moments are obtained from the detailed shipment data.

I then use the estimated parameters to conduct counterfactual simulations. Results of

counterfactual simulations show that shipment cost decreases by 32% after mergers, which leads to a model predicted price decreases of 10%. The counterfactual simulations also decompose sources of cost efficiency into elimination of interchange cost, reallocation of resources for investment, and re-optimization of routing. The results suggest that elimination of interchange cost is the predominant source, which accounts for 44% of the cost reduction. Network efficiency that comes from routing accounts for 36% of the cost reduction. In general, the level of cost efficiency from a merger depends on the number of interconnecting services provided by the two merging parties, and it also depends on how traffic can be consolidated between the two merging parties. Last, I use the model to examine the trade-off between efficiency gains and increased market concentration, and study the implied welfare changes in different geographic markets. On the one hand, the degree of overlap between the two networks determine the incremental of market power, because the number of firms providing freight service decreases in the overlapped regions. On the other hand, the topology of the network and distribution of demand affects how the traffics can be consolidated, hence affect the degree of efficiency gain. By combining these two forces, I show that there is a large degree of heterogeneity of welfare changes in different geographic markets, depending upon the location of each market within the network.

Contributions to the Literature. This paper adds to the literature on the effects of horizontal mergers by providing evidence of efficiency gain after mergers and uncovering the sources. First, the price effects of mergers are extensively studied in the literature. [Borenstein, 1990] and [Kim and Singal, 1993] analyze the effects of airline mergers, and [Kim and Singal, 1993] find that airfares increase by 9.44% on airline routes served by the merging firms. [Dafny, 2009] evaluates the impact of independent hospital mergers between 1989 and 1996 and finds evidence of sharp increases in rivals' prices of about 40% following a merger. In comparison, my paper finds that on average price decreases by 9% after a railroad merger, and price decreases by 11% for interconnecting routes. By contrast, the literature on the cost efficiency of mergers is sparse. One good exception is [Ashenfelter et al., 2015], the authors use panel scanner data and geographic variation

in the U.S. beer industry, and find that the average predicted increase in concentration leads to price increases of 2% but that this is offset at the mean by a nearly equal and opposite efficiency effect. Some other paper includes [McGuckin and Nguyen, 1995], which use an unbalanced panel of plants from the Longitudinal Research Database to examine the relation between ownership changes and productivity growth, and they find that plant productivity growth is positively related to a change in ownership.[5] My paper contributes to the literature on the cost efficiency by not only providing reduced-form evidence on improvement of metrics of efficiency and price reduction after mergers, but also uncovering the mechanism of efficiency gain and how it changes with features of the merger through a structural model.

This paper also contributes to the literature that studies the freight railroad industry. The existing literature on the freight railroad industry examines multiple aspects of the effect of deregulation and mergers. [Casavant et al., 2012] study the rail rate structure for agricultural commodities and compare it with rates for other commodities. [Friebel et al., 2014] investigate the restructuring of the U.S. freight railroad after deregulation and document both network reductions (the abandonment of redundant rail lines) and labor downsizing after mergers. [Prater et al., 2012] examine the sufficiency of rail freight competition and the effects of intramodal competition on rail rates. [Chapin and Schmidt, 1999] find that merged firms are larger than efficient scale. [McCullough, 2005] documents that changes in output composition along with line abandonment and a significant degree of industry consolidation lead to longer haul lengths and higher traffic densities. Event studies on special merger cases in the literature also provide explanations on the origination of merger

[5] Given the fact that direct metrics of efficiency is hard to define and measure, some other literature calculates cost savings through merger simulations. [Jeziorski, 2014] uses a dynamic oligopoly model to estimate the cost savings resulting from mergers in the U.S. radio industry, with the estimated resulting savings amounting to $1.2 billion per year. [Pesendorfer, 2003] examines mergers in the U.S. paper and paperboard industry, comparing equilibrium investment decisions before and after the merger wave and finding that total welfare increases by $583.5 million as a result of the mergers.

efficiency. [Kwoka and White, 1997] study the Union Pacific–Southern Pacific merger, and [Pittman, 2009] examines the Santa Fe and Southern Pacific merger proposal. However, most of the literature studies change of some aggregate cost or price index, or examine merger effect by looking at individual markets in a regression. Virtually no research looks at merger effect by considering the interdependent nature of railroad networks. My paper contributes to filling in this gap by considering the interaction of cost efficiency and incentives to raise prices in railroad network, and understanding welfare implications in different geographic markets.

In this paper, I jointly model firms pricing, investment, and routing decisions by employing an optimal transport network method, which is similar to the method used in [Fajgelbaum and Schaal, 2017]. I differ from their paper by adding competition and routing choices of each railroad company. My research is also broadly related to other papers that use spatial analysis in understanding distributional impact of economic activities, such as [Buchholz, 2015], [Donaldson, 2010], and [Brancaccio et al., 2017].[6] In both [Buchholz, 2015] and [Brancaccio et al., 2017], the network interdependence comes from the fact that once I drop somebody off, I end up in the location where I drop them off for future ride, which is more limited than the interdependencies in routing in railroads.

The remainder of the paper is organized as follows. Section 2 describes the industry background and explains sources of cost efficiency. Section 3 outlines the three datasets used in the paper. Section 4 provides reduced-form evidence on how shipment prices and metrics of efficiency change after railroad mergers. Section 5 constructs the structural model of firm pricing, routing and investment decisions in a rail network. Section 6 shows the estimation results and assesses the validity of the model. Section 7 shows the counterfactual simulations that decompose the sources of cost efficiency, and explains why there is

[6] [Buchholz, 2015] analyzes the dynamic spatial equilibrium of taxicabs and shows how common taxi regulations lead to substantial inefficiencies; [Donaldson, 2010] uses archival data from colonial India to investigate the impact of India's vast railroad network; [Fajgelbaum and Schaal, 2017] study optimal transport networks in spatial equilibrium; and [Brancaccio et al., 2017] use detailed data on vessel movements and shipping contracts to study world trade costs and trade flows.

tremendous heterogeneity of welfare changes after mergers in different geographic markets. Section 8 concludes.

2.2 Industry Background

2.2.1 Deregulation and Background

As explained in Section 2.1, the freight railroad industry plays a vital role in the U.S. economy. The railroad industry, however, has not always enjoyed financial success, and in recent decades it has undergone a remarkable evolution. Following a cycle of decline that began in the 1960s, many freight rail carriers faced liquidation.[7] At the start of 1980s, the U.S. railroad industry accounted for only a small proportion of total ton-miles of freight, around 20%, and carrying less than pipelines.[8]

In response, a series of laws to deregulate the industry followed in the years 1973–1980.[9] Among them, the 1980 Staggers Act formally deregulated the industry, by offering railroad companies much greater pricing and operating freedom. The deregulation sparks a wave of mergers of railroad companies: from 1980 to 2005, the number of Class I railroads decreased from 39 to 7. Figure 2.2 illustrates the network of current seven Class I railroads: the Burlington Northern and Santa Fe railway (BNSF) competes with the Union Pacific railway (UP) in the west, the CSX Transportation (CSXT) and the Norfolk Southern railway (NS) competes in the east. Two Canadian Class I railroads the Canadian Pacific railway (CP) and the Canadian National railway (CN) connect freight shipment between

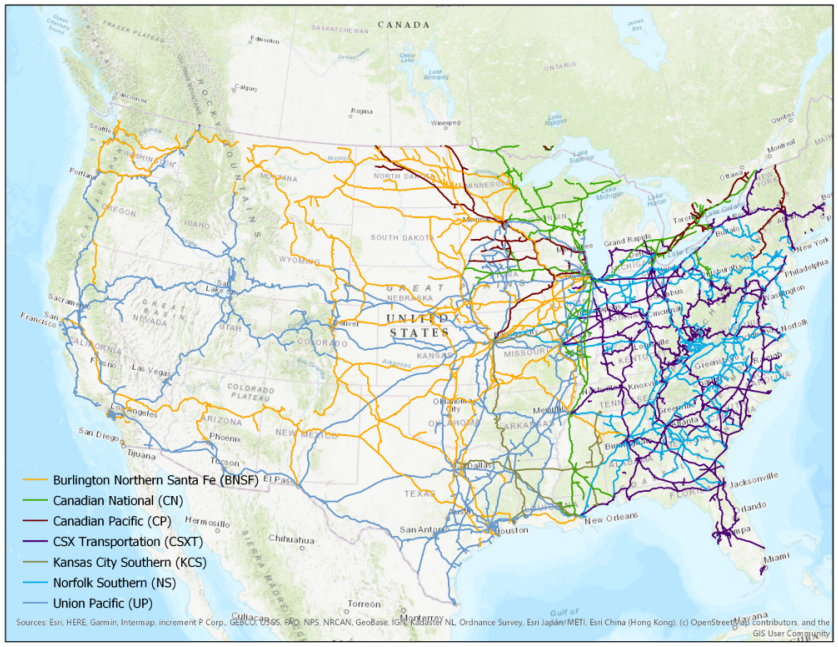
[7] In 1970 the nation's largest railroad Penn Central declared bankruptcy along with a dozen other northeastern railroads. See [Grimm and Winston, 2000] and [Gallamore and Meyer, 2014] for more discussions.

[8] Figure A.2 and A.3 plots the total ton-miles of freight carried by different mode of transport and how it changed from 1980 to 2011.

[9] Appendix A.3 provides details of regulation changes, and appendix A.1 shows a complete history of railroad mergers.

Canada and U.S., and the Kansas City Southern railway (KCS) locates in the south and connects freight shipment between Mexico and the United States.

Figure 2.2: U.S. Class I Railroads



Since the mergers, the U.S. freight railroad industry has enjoyed a renaissance, becoming not only self-sustaining but one of the most efficient freight railroad systems in the world. Proportion of total ton-miles of U.S. freight carried by rail increased after the deregulation of 1980. According to Department of transportation, in 2017, railroads are the second largest transport mode in providing freight service in the United States. Railroads carry 1,675 billion ton-miles of freight, accounting for 30% of total freight transportation.

A majority of the freight revenues in the U.S. freight railroad industry are generated by so called Class I railroads.[10] According to AAR, in 2012, the seven Class I railroads generate $67.6 billion freight revenues, which accounts for around 95% of the total freight revenues generated by railroad transport.[11] In this paper, I focus on mergers of Class I

[10]The Surface Transportation Board defines a Class I railroad as "having annual carrier operating revenues of $250 million or more in 1991 dollars", which is equivalent to $464 million in 2017 dollars.

[11]The rest of the revenues are generated by regional and short lines. Check Appendix A.2 for more

railroads.

The U.S. railroad industry ships various types of commodities, but the majority of carloads are generated by bulk shipments like coal, chemical, and farm products. According to AAR, in 2012, the top four commodities measured by share of total tonnage are coal (37%), chemicals (10%), non-metallic minerals (9%), and farm products (8%). If we look at share of revenues, each of these four commodities accounts for 17% (coal), 14% (chemicals), 5% (non-metallic minerals), 8% (farm products) of total freight revenues. Coal has been the most important commodity in freight railroad industry ("King Coal"), but the revenues generated by shipping coal are decreasing. Instead, the carloads of intermodal shipping[12] (Misc. mixed shipments such as containers) are increasing nowadays, and intermodal shipment accounts for 13% of total freight revenues in 2012.[13]

2.2.2 The Story of Train 9-698-21

To better explain sources of cost efficiency and my model in the later sections, here I introduce three concepts of railroading: interchange cost, interconnecting route versus competing route, and investment decisions regarding track maintenance and locomotives. I use the example of train 9-698-21 to explain these three concepts.[14]

details on regional and short lines.

[12]Intermodal is the use of two modes of freight, such as truck and rail.

[13]Check Appendix A.2 for more details on carloads originated by different types of commodities.

[14]Train 9-698-21 runs from Birmingham, Alabama to Los Angeles. To explain the concepts, I focus on the section between Los Angeles and Memphis, Tennessee. The original story provides more details on why interchange is costly and why coordination is a problem when two railroads are involved in a shipment.

Figure 2.3: Story of train 9-698-21

Source: Original story from *Trains* magazine "Twenty-four hours at Supai Summit"

Train 9-698-21 went from Birmingham to Los Angeles, and it begun with Burlington Northern via the Avard gateway in summer 1994. This was before the Burlington Northern railway and the Atchison, Topeka and Santa Fe railway discussed merging. The main customers of train 9-698-21 are UPS and J.B. Hunt, and the train is an express freight train and initiated to "reach downtown L.A. in time for UPS to deliver the next morning". The contract is for Santa Fe to be given haulage rights over BN to Memphis and Birmingham. Haulage rights means Santa Fe sold the service, then paid BN to run the trains east of Avard. However, according to Rollin Bredenberg, BNSF's vice president of transportation at that time, everything has not gone right with 9-698 though:

> *"It was very unreliable under the haulage agreement, pre-merger," reports Bredenberg, "BN's internal measurement of how well they ran trains did not include the performance of the Santa Fe haulage trains, so you can guess what happened." In an interview last year, Krebs (chairman of Santa Fe railway) said he finally had to tell key customers such as Hunt that they were free to go elsewhere until Santa Fe and BN could get their acts together.*

First, interconnecting and competing routes are both shown in this example. In Figure 2.3, the route from Los Angeles to Memphis is an example of an interconnecting route, because the train needs to ride both Santa Fe and Burlington Northern tracks. If a shipment originates in Claremore, Oklahoma, and is bound for Memphis, the owner has a choice of

riding the Union Pacific or the Burlington Northern line, which is an example of competing routes. Second, this example shows the micro-foundation of interchange cost. When train 9-698-21 arrives at Avard gateway in Oklahoma, it needs to exchange crews and rolling stocks (railcars and locomotives) between the Burlington Northern railway and the Santa Fe railway. However, because BN and SF have different priorities over this train, it usually results in delays to finish this process. Moreover, check the condition of railcars and exchange rolling stocks take time and efforts, which further add to the interchange cost.

Last, I want to introduce the investment decisions regarding track maintenance and locomotives. If more locomotives are available in the Avard gateway, the waiting time of train 9-698-21 will be shortened to finish the interchange. Meanwhile, adequate and constant maintenance of tracks is essential for railroad operation.[15] Regular track maintenance is costly,[16] and railroad companies decide on the frequencies of track evaluation in each region. In the example of train 9-698-21, if the railroad companies invest more in the route from Los Angeles to Memphis by allocating more locomotives and conducting more frequent track maintenance, the route efficiency from Los Angeles to Memphis will increase.

2.2.3 Sources of Cost Efficiency

I categorize sources of cost efficiency into route efficiency and network efficiency. Efficiency gain of mergers at individual route level is achieved by eliminating interchange cost and combining resources of the two merging firms in each individual market. Efficiency gain of mergers at network level is achieved by re-optimization of routing and consolidating traffics

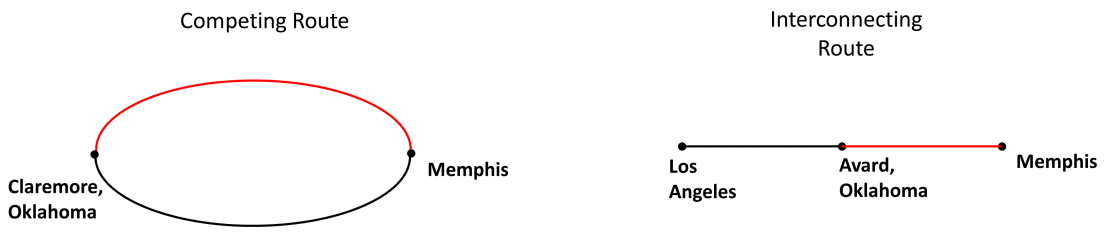
[15] To perform regular maintenance, railroad companies need to operate track evaluation cars to evaluate track geometry, performance based track geometry, rail wear etc and other things. Then the track evaluation cars will report the data for capital and maintenance planning.

[16] According to a Bloomberg report, a New Jersey Transit safety project costs more than $320 million, but the agency still fell behind on rail maintenance, let its ranks of train engineers dwindle and triggered a federal operations audit. https://www.bloomberg.com/news/articles/2018-10-18/how-nj-transit-s-lifesaving-rail-task-dragged-while-cost-doubled.

across markets. Network efficiency depends on the topology of network and location of each market.

Route Efficiency. There are two types of individual routes: interconnecting route and competing route, as illustrated below:

Figure 2.4: Route Efficiency



In the case of competing routes, both merging parties provide freight service serving the same market before the merger. After the merger, firms can consolidate resources to one of the parallel lines and abandon the other to achieve greater cost efficiency.[17] In other words, firm can get rid of redundant rail lines by combining resources of the two merging firms. Based on the story of train 9-698-21 in Section 2.2, interchange is costly. Besides the evidence provided in that story, interviews with Terminal Superintendent of Conrail and Terminal Operations manager of Lake State Railway Company confirm that interchange usually means more delays and higher operational cost. In the case of interconnecting route, the combined firm eliminates interchange costs following the merger.

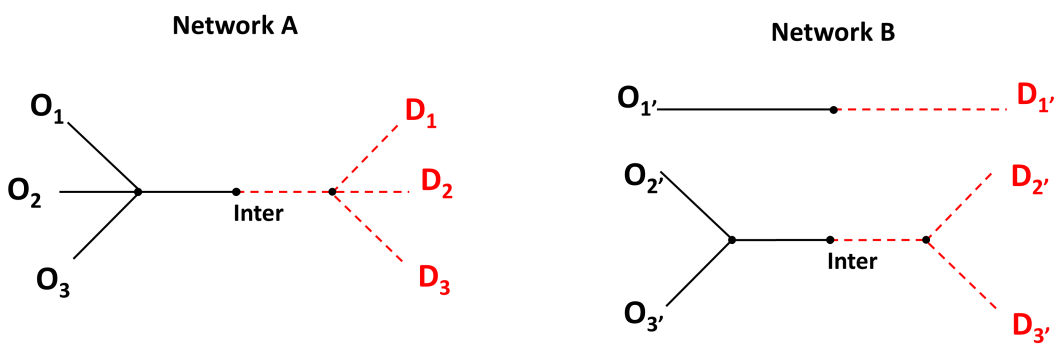
Network Efficiency. Firms can achieve greater cost efficiency by optimizing over routing and consolidating traffic after mergers. More specifically, railroad firms can consolidate infrastructure investment into a small number of routes, and then consolidate traffics from multiple origins and destinations over these efficient routes to reduce shipment cost. The Chief Operating Officer, Cindy Sanborn of CSXT states that "An essential feature of the operating plan is to consolidate traffic over a smaller number of efficient, high-volume

[17] In my model firms cannot physically abandon rail lines, but they can choose where to allocate the resources. Firms are allowed to allocate 0 resources to a rail line.

routes."[18] The idea of achieving greater cost efficiency by consolidating traffics is also supported by the former CEO of the Southern Pacific railway [Krebs, 2018] and the former CEO of the Canadian National railway [Harrison, 2005].

To elaborate how does topology of network affect efficiency gain of mergers, Figure 2.5 depicts two networks, network A and network B. Each network consists of three individual routes. There are two firms within each network, firm 1 owns all the black and solid lines, and firm 2 owns all the red and dashed lines. All three routes are interconnecting routes and are jointly served by firm 1 and firm 2. I further assume that for each individual route, such as route O_1 to D_1, the travel distance from O_1 to D_1 is exactly the same in network A as the travel distance from $O_{1'}$ to $D_{1'}$ in network B, and the total mass of demand of market O_1 to D_1 in network A is the same as the total mass of demand of market $O_{1'}$ to $D_{1'}$ in network B. Therefore, the only difference between these two networks are the topology of the network.

Figure 2.5: Network Efficiency



If merger effects only occur at individual route level, we should expect route O_1 to D_1 in network A and route $O_{1'}$ to $D_{1'}$ in network B have the same level of efficiency gain after merger, because the market characteristics of these two individual markets are exactly the same. However, given the topology that is different, resources will be consolidated more intensively into network A than network B after merger. Therefore, route O_1 to D_1 will

[18] Ex Parte No. 711 (Sub-No.1) Reciprocal Switching, Opening Comments of CSX Transportation INC.

have greater efficiency gain than route $O_{1'}$ to $D_{1'}$ after merger. That being said, cost efficiency depends on the topology of the network, and the location of each market within the network.

2.3 Data

I use three main datasets to document the changes in cost efficiency following railroad mergers. The confidential version of the Carload Waybill Sample provides detailed information on shipment price and corresponding shipment attributes; the Class I Railroad Annual Report R-1 dataset contains information on firm attributes and aggregate operational statistics; and a Department of Transportation database provides geographic information on all U.S. rail lines and their associated railroad companies. I also observe the ancestry of each rail line, which enables me to trace back to any given time between 1984 and 2010 and reconstruct the rail network for any particular period.

The Carload Waybill Sample is a sample of carload waybills for all U.S. rail traffic submitted to the Surface Transportation Board (STB) by those rail carriers terminating 4,500 or more revenue carloads annually.[19] The data contain detailed shipment information on such attributes as commodities carried, total billed weight, equipment used, participating railroads, and origin, destination, and interchange locations (BEA Economic Areas) of each load. Railroad companies conduct point-on-point pricing, and the price information I observe is at firm-origin-destination level. I obtain the confidential version of this dataset, which has price information and location of origins and destinations, from 1984 to 2010. Table 2.1 shows the summary statistics of variables used in the reduced-form analysis. The median of price per ton is $38, and the median of travel distance is 854 miles, which converts

[19]STB is an independent adjudicatory and economic-regulatory agency charged by Congress with resolving railroad rate and service disputes and reviewing proposed railroad mergers. STB is created on January 1, 1996 by the ICC Termination Act of 1995, the Board is the successor to the former Interstate Commerce Commission. More details about Carload Waybill Sample can be found at https://www.stb.gov/stb/industry/econ_waybill.html.

into a price of 4 cents per ton-mile. The number is comparable to the price per ton-mile reported by AAR in its annual reports.[20]

Table 2.1: Summary Statistics of Covariates

	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
Price Per Ton ($)	$ 62	$ 3,736	$ 19	$ 38	$ 70
Freight Revenue ($)	$ 14,369	$ 50,427	$ 762	$ 1,441	$ 3,645
Billed Weight (ton)	983	3,222	17	26	106
Number of Carloads	9	27	1	1	1
Travel Distance (miles)	1,045	773	404	854	1,647
Waybills (Carrier-Origin-Destination-Date)				12,113,581	

Source: STB, Carload Waybill Sample

Table 2.2 reports the descriptive statistics of selected commodities that are mainly shipped by rail. We can see that a large number of waybills involve shipment of coal. Meanwhile, railroad carries a lot of bulk shipment such as chemicals, agricultural products, and construction materials such as concrete and clay.[21] Table 2.2 also shows descriptive statistics of car ownership category. There are three categories of car ownership: privately owned, railroad owned, or trailer train. If a shipper uses its own railcars in a shipment (privately owned), railroad companies will give the shipper a discount. Trailer train is mostly used when shipping containers.

[20]In year 2001, according to AAR the average price per ton-mile in the U.S. is 2.32 cents.

[21]For full information of commodities shipped by rail, check Table A.3.

Table 2.2: Descriptive Statistics of Commodity Types and Car Ownership Category

	Number of Waybills	Percentage
Commodities		
Field Crops	466,584	3.85%
Coal	1,002,580	8.28%
Nonmetallic Minerals	371,109	3.06%
Lumber or Wood Products	487,386	4.02%
Chemicals	635,119	5.24%
Petroleum or Coal Products	158,794	1.31%
Clay, Concrete, Glass or Stone Products	323,923	2.67%
Primary Metal Products	354,360	2.93%
Containers	660,513	5.45%
Car Ownership Category		
Privately Owned	5,349,791	44%
Railroad Owned	3,621,221	30%
Trailer Train	2,202,838	18%
Non-Categorized	939,731	8%
Waybills (Carrier-Origin-Destination-Date)	12,113,581	

Source: STB, Carload Waybill Sample

Second, every Class I railroad operating within the United States must submit the Class I Railroad Annual Report R-1. This dataset contains information on financial statistics (income statement, balance sheet, total operating expense breakdown etc.), wage and equipment expenditures, and summary of operations (traffics, operating statistics etc). I use the dataset to document operational changes before and after mergers. The data ranges from 1981 to 2001.

I obtain geographic information from the Federal Transit Administration. The dataset contains the coordinates of rail lines and rail stations and provides information on the affiliation of each rail line and its ancestry, which permits me to geocode and reconstruct the rail network at any time between 1984 and 2010. I use the reconstructed network in the structural model to calculate the optimal routing of each origin-destination pair and

estimate the transportation cost.

2.4 Reduced-form Evidence

I first examine price effect of mergers by using detailed waybill data. Through comparing shipment prices before and after mergers, I show that on average shipment price has decreased by 9.4%. I further decompose these price effects by route types. As a robustness check, I examine these price changes for commodities that are mostly transported by rail such as coal, and commodities that are largely transported by other transportation modes such as food and kindred product. The robustness results show that these price effects are not driven by competition from other transportation mode like trucking. To better understand the sources of these price changes, I examine four measures of efficiency, which includes two aggregate operational statistics and two shipment attributes. The two aggregate operational statistics are the ratio of switching hours to road service hours and average length of haulage. The two aggregate operational statistics come from the Class I Railroad Annual Report R-1, which is data is at firm-year level. The two shipment attributes are number of interchanges and the use of unit trains. The shipment attributes are obtained from the confidential Waybill data, which is at carrier-origin-destination-date level. By examining all four metrics of efficiency, the results provide evidence of efficiency gain after mergers.

2.4.1 Price Changes

The regression model studying change in price is specified as:

$$\log P_{iodt} = \mu_{od} + \gamma_i + \lambda_t + \delta_1 D_{iod,t} + X'_{iodt}\beta + \epsilon_{iodt}$$

where γ_i : firm fixed effect

λ_t : year fixed effect

μ_{od} : route fixed effect (from origin o to destination d)

$D_{iod,t}$: indicator of if a merger has happened to firm i that carries shipment from o to d before or equal to time t

X_{iodt} : shipment attributes: commodities carried, ownership of railcars, total billed weight

Table 2.3 shows the estimation result of price effect of mergers. The result suggests that on average a railroad merger reduces the shipment price by 9.4%. By opening up the mergers and examining each individual merger, I find that the price effect is largely consistent across individual mergers.[22] Then, to further decompose the effect of railroad mergers on price changes by different route types, I interact the merge dummy with three route types: interconnecting, competing, and non-interconnecting, noncompeting. As explained in section 2.2, an interconnecting route is a route in which two firms conduct interchange and finish the shipment jointly. Results in column 2 of Table 2.3 show that the interconnecting routes have the largest price reduction among all route types, with price decreasing by 11% after mergers. In comparison, the other route types have a price reduction of about 6.5% following mergers.

[22] Table A.4 shows the robustness check results by looking at change of prices following each railroad merger.

Table 2.3: Effect of Mergers on Price Change (by Route Types)

	(1)	(2)
	Log Price	Log Price
Indicator of Merger	-0.0935***	
	(0.0142)	
Indicator of Merger × Indicator of Interconnecting Route		-0.107***
		(0.0178)
Indicator of Merger × Indicator of Competing Route		-0.0690***
		(0.0180)
Indicator of Merger × Non-interconnecting, Noncompeting Route		-0.0641***
		(0.0171)
N	12,110,107	12,110,107
Firm FE	Y	Y
Year FE	Y	Y
O-D Route FE	Y	Y
O-D Route Cluster	Y	Y

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Surface Transportation Board, Carload Waybill Sample

However, there might be concerns that these price effects are driven by competition from other transportation modes such as trucking, not from the effect of railroad mergers. Because comparable origin-destination-level shipment data for trucking is lacking, I cannot directly run the price regressions by controlling for competition of trucking. Instead, to address this concern, I examine the price effects of mergers for different types of commodities. The argument is that the shipment of different types of commodities faces different levels of competition from other transportation modes. Therefore, if the price effects are driven by changes in other transportation modes, the price effects should be greater for commodities

facing higher competition from other modes of transport. Table 2.4 summarizes the two commodities used in this analysis: the Commodity Flow Survey (CFS) of 2012 shows that coal is mainly shipped by railroads. Only 1.5% of coal is shipped by trucking, and 91.8% is shipped by rail. In comparison, food or kindred products are largely shipped by trucking. 62.37% of food or kindred products is shipped by trucking, and only 17.63% is shipped by rail.

Table 2.4: Summary Statistics of Coal and Food Shipment

	Coal (STCC 11)	Food or kindred products (STCC 20)
Total Ton-Miles in 2012 (Truck)	1.5%	62.37%
Total Ton-Miles in 2012 (Rail)	91.8%	17.63%

Source: U.S. Census Bureau, Commodity Flow Survey

Table 2.5 shows the estimation results of price effect of mergers for coal and food or kindred products respectively. The results show that railroad mergers have a significantly negative price effect for both coal and food or kindred products. Moreover, the price effect of mergers is greater for coal. This is contrary to the prediction of the hypothesis that the price effect is driven by changes in other transport modes.

The estimated price effect is comparable to other analysis of freight railroad mergers. In the Surface Transportation Board analysis of the Union Pacific and Southern Pacific merger, the shipment price of coal was found to decrease by 11%, and that of other commodities by 6% after the merger. The price effect of mergers found in the U.S. freight railroad industry is larger than the price effect of mergers found in some other industries. For example, [Ashenfelter et al., 2015] find that the estimated price reduction caused by merger efficiency is 2%. In comparison, I find a 9.4% overall shipment price reduction, and a 17.9% average price reduction for coal shipment, which suggests that cost efficiency following mergers is very important in this industry.

Table 2.5: Effect of Merger on Price Change (by Commodities)

	(1) Log Price (Coal)	(2) Log Price (Food or Kindred Products)
Indicator of Merger	-0.179***	-0.052***
	(0.028)	(0.014)
Log Billed Weight	-0.030	-0.212***
	(0.020)	(0.010)
Ownership of Railcar (Private)	-0.096***	-0.132***
	(0.027)	(0.008)
Ownership of Railcar (Trailer Train)	-0.021	-0.144***
	(0.071)	(0.016)
N	1,002,552	882,066
Firm FE	Y	Y
Year FE	Y	Y
O-D Route FE	Y	Y
O-D Route Cluster	Y	Y

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Surface Transportation Board, Carload Waybill Sample

As a robustness check of the price effect of mergers, I run the price regression for each type of commodity, and the results show that price reduction following railroad mergers is consistent across different types of commodities. If we look particularly at commodities that are largely shipped by rail, such as coal, chemicals, and construction materials (clay, concrete, etc.), there is a large and significant price reduction following railroad mergers.[23]

[23]Results are in Appendix A.4 and Table A.5.

2.4.2 Evidence from Aggregate Operational Statistics

To better understand the sources of price changes, and provide evidence for efficiency gain after mergers, I further examine four metrics of efficiency and how they change before and after mergers. I first look at the Class I Railroad Annual Report R-1 data, and examine the change of average length of haulage and total switching hours after mergers. The ratio of switching hours to road service hours measures proportion of train hours spent in sorting and switching in railyards. The less time a train spends switching in yards, the more efficient the operation is. Length of haul is another metric of efficiency, because it is more fuel efficient for a train to run a longer distance.

I run two types of regressions to evaluate the effect of mergers on aggregate operational statistics:

$$y_{it} = \gamma_i + \lambda_t + \delta_0 \cdot D_{i,t} + \epsilon_{it}$$

$$y_{it} = \gamma_i + \lambda_t + \sum_{k=-3}^{T=2} \delta_k \cdot \Delta_{i,t+k} + \epsilon_{it}$$

where: y_{it} : ratio of switching hours to road service hours of firm i at time t,

or average length of haulage of firm i at time t

γ_i : firm fixed effect, λ_t : year fixed effect

$D_{i,t}$: indicator of if a merger has happened to firm i before or equal to time t

$\Delta_{i,t}$: indicator of if a merger happens to firm i at time t

The lagged terms incorporated in the second specification are used to examine the pre-trend of changes before mergers.

Table 2.6 shows the results. In column 1, on average a merger results in an 11.5 percentage point decrease of the ratio of switching hours to road service hours. The median value of the ratio is 0.735, therefore, a 11.5 percentage point decrease of the ratio is equivalent to a 15% decrease of switching to road service hours. Column 3 of Table 2.6 does not show a pre-trend of reduction in the ratio of switching hours to road service hours before the mergers. As a robustness check, I examine the merger effect for each merger case. The

results in column 2 of Table A.1 show that in general mergers still generate a significant reduction of the ratio of switching hours to road service hours. However, the estimated effect varies among mergers, because the potential to reduce switching hours depends on the network size and network structure of each merging railroad. For some merger, the ability to re-optimize network operation and reduce switching hours is limited. In section 2.5, I will jointly consider the pricing decision and operation decision in a railroad network, and use the detailed Waybill data to uncover the exact relation between network structure and efficiency gain.

Column 2 of Table 2.6 shows the effect of mergers on the average length of haulage. The results indicate that on average a merger results in a 5% increase in haul length. Column 4 of Table 2.6 indicates that there is no pre-trend of increase in the average length of haulage before mergers. The merger effect is significantly positive but small right after the merger and becomes larger one year later, which may be because it takes time for different railroad companies to integrate their networks after the merger. As a robustness check, I also look at the merger effect case-by-case. The robustness check confirms that in general there is an increase of average length of haulage after mergers, and shows that small companies have a substantial increase in average length of haulage after being acquired by a large company.[24]

[24]Results of robustness check are in Appendix A.4.

Table 2.6: Effect of Merger on Metrics of Efficiency

	(1) Ratio of Switching Hrs to Road Service Hrs	(2) Log Average Length of Hauling	(3) Pre-Post Ratio of Switching Hrs to Road Service Hrs	(4) Pre-Post Log Average Length of Hauling
Indicator of Merger	-0.115**	0.052**	-0.068**	0.053*
	(0.051)	(0.023)	(0.024)	(0.026)
1 Year After Merger			-0.065*	0.147***
			(0.032)	(0.040)
2 Years After Merger			-0.027	0.060**
			(0.032)	(0.028)
1 Year Prior Merger			0.049*	0.045
			(0.026)	(0.028)
2 Year Prior Merger			0.021	0.040
			(0.022)	(0.028)
3 Years Prior Merger			0.055*	0.027
			(0.030)	(0.026)
Observations	208	208	208	206
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Firm Cluster	Y	Y	Y	Y

Robust standard errors in parentheses

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

Source: AAR, Analysis of Class I Railroads Annual Issues

In brief, analysis of aggregate operational statistics suggests that on average railroad mergers result in a 15% decrease in the ratio of switching to road service hours, and a 5% increase in the average length of haulage. However, there are certain limitations to studying the efficiency gain by looking only at firm-level aggregate statistics. The firm-level statistics cannot not reveal the details of efficiency gain of route operations. Especially in the case of a large railroad company acquiring a small railroad company, there may be efficiency gain in a portion of the network, but the outcome might not be revealed in the firm-level statistics because the acquired company is small. To solve these problems, I use the Confidential Waybill data to study the change of shipment attributes at finer scale.

2.4.3 Evidence from Shipment Data

Here I use detailed waybill data to examine number of interchanges and use of unit trains. A unit train is a train in which all railcars carry the same commodity and are shipped from the same origin to the same destination, without being split up or stored en route. The use of unit trains saves time and money by avoiding the complexities and delays that are involved with assembling and disassembling trains at railyards.

Former Southern Pacific Railroad president [Krebs, 2018] states "Every time you interchange with another railroad, you add to the cost and delay." Following this statement, combined with other descriptive evidence provided in Section 2, I propose that the more interchanges there are on a route, the higher the operational cost will be in carrying a shipment. Hence, reducing the number of interchanges will be a clear sign of efficiency gain from a merger. Table 2.7 shows the change in the number of waybills containing interchanges by comparing the numbers two years before and two years after each merger. The result shows a clear reduction in the number of waybills with interchanges following railroad mergers. For example, the percentage of waybills with interchanges decreases from 27.2% to 18.5% following the merger of the Burlington Northern and the Santa Fe railways, and the percentage of waybills with interchanges decreases from 50.7% to 30.3% following the merger of the Southern Pacific and Union Pacific railroads. The only exception is the merger of the Illinois Central with the Canadian National, where the percentage of waybills with interchanges increases from 44.4% to 51.5%. One explanation is that because the Canadian National is a Canadian Class I freight railway, a large fraction of the Canadian National's business in the United States involves interchanging with other large U.S. railroads, such as the Burlington Northern Santa Fe, Union Pacific, CSX Transportation, and Norfolk Southern.

Table 2.7: Comparing Number of Interchanges Before and After Mergers

	Number of Waybill with Interchange			Percentage of Waybill with Interchange		
	t-2	t+2	Difference	t-2	t+2	Difference
SBD	35,588	29,152	-6,436	50%	39%	-11%
BNSF	23,511	21,456	-2,055	27%	18%	-9%
LA	4,478	4,530	52	82%	67%	-14%
MSRC	3,614	3,875	261	74%	71%	-4%
IC	19124	11678	-7,446	44%	51%	7%
CNW	18,273	15,123	-3,150	51%	28%	-23%
MKT	8,072	7,807	-265	52%	48%	-4%
DRGW	8,543	8,848	305	86%	84%	-2%
SP	57,053	41,665	-15,388	51%	30%	-20%
SSW	14,803	19,565	4,762	85%	81%	-4%
WC	4,534	3,750	-784	50%	44%	-6%

Source: Surface Transportation Board, Carload Waybill Sample

Another efficiency measure is use of unit trains in carrying shipment. Table 2.8 shows the number of waybills with unit trains before and after each merger. I focus on coal shipments because unit trains are widely used only for such bulk commodities as coal, agricultural products, and petroleum, and because coal is the single largest commodity per revenue share of railroads.[25] Table 2.8 suggests that following most of the mergers, the number of waybills using unit trains increases. There is some heterogeneity in the change of number of unit trains because coal shipments occur only in certain geographic markets. Railroad companies conduct business in diverse geographic markets, and the flexibility of switching to unit trains varies among companies and markets. For example, Louisiana and Arkansas Railway (LA), Wisconsin Central Railway (WC), and MidSouth Rail Corporation (MSRC) have very few coal shipments, so there is no large increase of unit trains for those mergers. Moreover, the use of unit trains depends on geographic conditions, and therefore the total number of unit trains may not increase proportionally with respect to total shipments.

[25]For more on commodity share, see Appendix A.2.

Table 2.8: Comparing Usage of Unit Trains Before and After Mergers (Coal Shipment)

	Number of Waybill with Unit Train			Percentage of Waybill with Unit Train		
	t-2	t+2	Difference	t-2	t+2	Difference
SBD	2,562	4,404	1,842	19.4%	48.0%	28.6%
BNSF	7,079	8,195	1,116	86.1%	89.3%	3.3%
LA	384	333	-51	95.0%	96.8%	1.8%
MSRC	0	0	0	0.0%	0.0%	0.0%
IC	1,449	1,496	47	73.3%	98.6%	25.4%
CNW	3,371	5,045	1,674	94.2%	92.7%	-1.5%
MKT	1,248	1,518	270	95.9%	94.6%	-1.3%
DRGW	307	571	264	65.3%	79.2%	13.9%
SP	5,001	6,709	1,708	91.5%	90.8%	-0.6%
SSW	131	313	182	90.3%	89.2%	-1.2%
WC	236	66	-170	75.2%	46.2%	-29.0%

Source: Surface Transportation Board, Carload Waybill Sample

To sum up, in this section I show that prices decrease after mergers, and the price effect is greater for inter-connecting routes. To understand the sources of price changes, I examine four metrics of efficiency and the results show efficiency gain after mergers.

The Need for a Model. Examining individual routes only is insufficient for understanding mergers in this industry, however, because origin-destination railroad markets are interdependent. Furthermore, in this networked industry it is hard to find a clean control group for performing a difference-in-differences analysis. Efficiency changes in one part of the network will affect the routing and optimization problem of the whole network, thereby affecting the efficiency in another part of the network. To examine the mechanism of cost efficiency following railroad mergers, I therefore build a structural model to capture firms' endogenous decisions of routing, pricing, and investment in track maintenance and locomotives.

2.5 Model

In the model, I define a market as an origin-destination pair. Firms provide either single-line service or joint-line service to serve a market. Single-line service means that the shipment is carried by only one railroad firm, and joint-line service means that the shipment is carried by two railroad firms and an interchange is involved. Each firm owns a network, and each firm makes three decisions. First, firms simultaneously choose prices, conditional on their perceived cost of themselves and their rivals. For interconnecting routes, I assume that the firms participating in the joint-line service jointly determines the price of the joint-line service. Second, firms decide how to allocate infrastructure investment in their network. Third, firms make routing decisions for the transportation service demanded in each market. Firms make these three decisions simultaneously and compete in price. On the demand side, I assume a fixed amount of commodities needs to be shipped in each market. Consumers choose between railroad firms based on shipment price and firm characteristics. Consumers also face an outside option, which is shipping by trucks. In the subsections below, I will explain how I model demand and firm's problem in details.

2.5.1 Definition of Network

Following [Galichon, 2016], we define a network $\mathcal{N}$ as a directed graph $(\mathcal{Z}, \mathcal{A})$, where $\mathcal{Z}$ is a set of nodes and $\mathcal{A}$ is a set of arcs $\mathcal{A} \subseteq \mathcal{Z}^2$ which are pairs (x, y) where $x, y \in \mathcal{Z}$. In the model I define nodes as centroids of BEA regions[26] and arcs as rail lines that connect each BEA economic area.

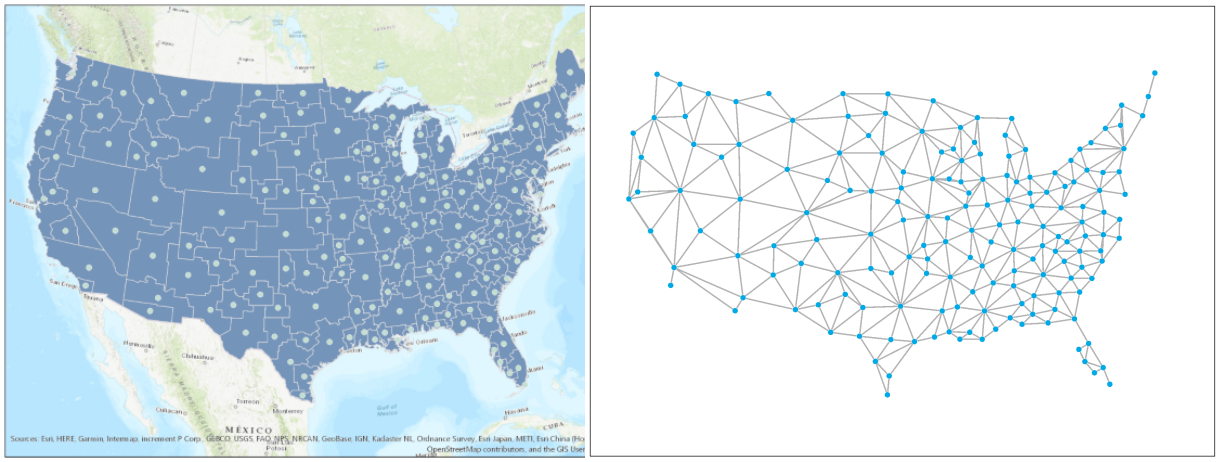
In order to project origin-destination shipment data to traffic in a rail network, I geocode the rail network and label the rail lines with affiliated railroad companies. I obtain detailed geographic information for each rail line and information about the ancestry of rail lines from the Federal Transit Administration. The geographic coordinates and historical infor-

[26]BEA Economic Areas are used by the STB to conduct economic analysis.

mation allow me to reconstruct the rail network back in time. For example, Burlington Northern (BN) merged with the Atchison, Topeka and Santa Fe (ATSF) Railway in December 1996. We can reconstruct the network of the BN and ATSF, respectively, in 1996. Figure 2.6 depicts the geocoded map of the current U.S. rail network.

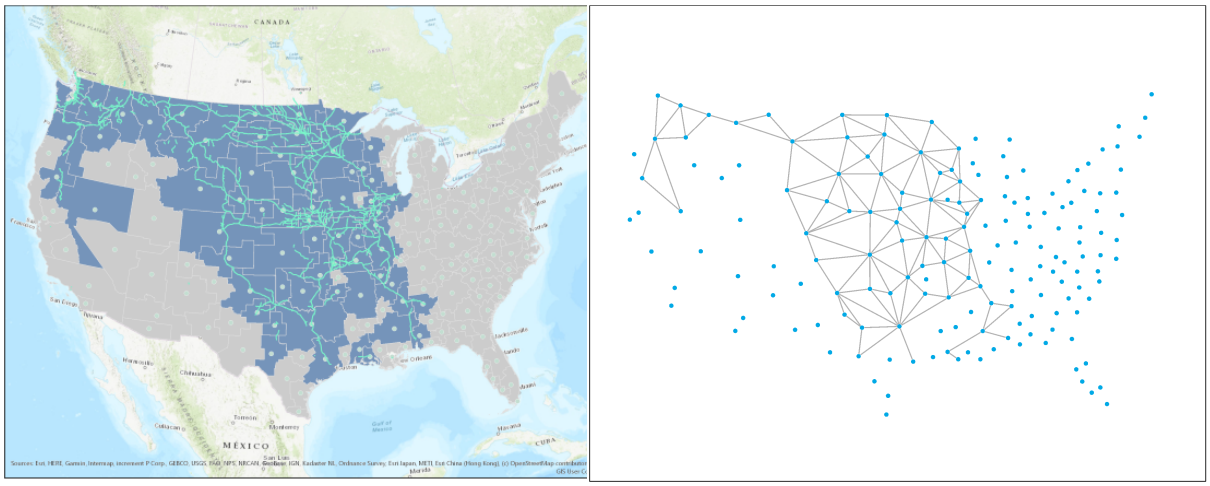
It shows all the BEA economic areas in the mainland U.S. and how they are converted into nodes and arcs in the virtual network for modeling.

Figure 2.6: U.S. Rail Network



Given the definition of arcs and nodes, I obtain network information for each firm. The left panel of Figure 2.7 shows the actual rail network of BN in 1994, and the right panel shows how the network is converted into nodes and arcs in the virtual network for analysis.

Figure 2.7: The Rail Network of BN



2.5.2 Demand

I follow the airline and the railroad literature ([Coublucq, 2013]; [Jourquin, 2018]; [Peters, 2006]) in modeling the demand of railroad shipment using a nested logit model ([Berry, 1994]). Demand is defined at service-origin-destination level. For example, consumer i chooses service s to ship from origin o to destination d. A service s is either a single-line service or a joint-line service. Single-line service means that shipment from origin o to destination d is only carried by one railroad firm. Joint-line service means that the shipment is carried by more than one railroad firm and interchanges are incurred. Information of services in each market and firms providing these services are obtained from the data and assumed to be exogenous.

I allow the railroad firms to be more substitutable among themselves, versus outside option which is trucking. The utility of consumer i depends on three components. The price of service s to ship from o to d, distance to customer's facility, which is measured by the logarithm of total miles of tracks of railroads, and the unobservable efficiency $\xi_{s,od}$.

The utility function is specified as:

$$u_{is,od} = \alpha \cdot \log p_{s,od} + \beta \cdot \log DistToFacility_{s,od} + \xi_{s,od} + (1-\sigma)\epsilon_{is,od}$$

where $\epsilon_{is,od}$ is the consumer-specific deviation from the mean utility. As σ approaches one, the within-group correlation of utility levels goes to one, and as σ approaches zero, the within-group correlation goes to zero. To control for unobservable efficiency that are constant within significant subsets of the data, I include fixed effects of services, time periods, and markets.[27] Mathematically,

$$\xi_{s,od} = \alpha_s \cdot \text{Service}_s + \alpha_t \cdot \text{Time}_t + \alpha_{od} \cdot \text{Mkt}_{od} + v_{s,od}$$

[27] I estimate demand parameters and cost parameters separately in section 2.6. In the demand estimation, I use the whole sample that ranges from 1984-2000. So, I control for time fixed effects in the demand estimation. However, because my model is static, to be consistent with other parts of the model, I do not put a subscript t in defining $u_{is,od}$ and $\xi_{s,od}$.

Given the probability of choosing service s among all the rail services, multiply it by the probability of choosing railroad over other transportation modes, I obtain the probability of choosing service s in the market from o to d. Given that the distribution of $\epsilon_{is,od}$ is an identically and independently distributed extreme value, the probability of choosing service s in market from o to d is derived as

$$\Pr\left(\text{choose service } s \text{ in market } od\right) =$$

$$\frac{e^{\mathfrak{u}_{s,od}/(1-\sigma)}}{\sum_{s'\in rail_{od}} e^{\mathfrak{u}_{s',od}/(1-\sigma)}} \cdot \frac{\left[\sum_{s'\in rail_{od}} e^{\mathfrak{u}_{s',od}/(1-\sigma)}\right]^{(1-\sigma)}}{\left[\sum_{s'\in rail_{od}} e^{\mathfrak{u}_{s',od}/(1-\sigma)}\right]^{(1-\sigma)} + \left[e^{\mathfrak{u}_{0,od}/(1-\sigma)}\right]^{(1-\sigma)}}$$

it also gives a market share of:

$$shr_{s,od} = \frac{e^{\mathfrak{u}_{s,od}/(1-\sigma)}}{\sum_{s'\in rail_{od}} e^{\mathfrak{u}_{s',od}/(1-\sigma)} + \left(\sum_{s'\in rail_{od}} e^{\mathfrak{u}_{s',od}/(1-\sigma)}\right)^{\sigma}}$$

where $\mathfrak{u}_{0,od}$ is the mean utility of choosing the outside option, and the value is normalized to 0. $\mathfrak{u}_{s,od}$ is the mean utility of choosing service s from o to d at time t and

$$\mathfrak{u}_{s,od} = \alpha \log p_{s,od} + \beta \log DistToFacility_{s,od} + \xi_{s,od}$$

$rail_{od}$ is the set of railroad services from o to d. Also, the total quantity of freight that railroad service s ships from o to d is denoted as:

$$Q_{s,od} = M_{od} \cdot \frac{e^{\mathfrak{u}_{s,od}/(1-\sigma)}}{\sum_{s'\in rail_{od}} e^{\mathfrak{u}_{s',od}/(1-\sigma)} + \left(\sum_{s'\in rail_{od}} e^{\mathfrak{u}_{s',od}/(1-\sigma)}\right)^{\sigma}} \tag{2.1}$$

M_{od} is the total population of shipment from origin o to destination d.[28] Having set out the basic demand model, we can now derive the analytical expression for mean utility levels:

$$\ln(shr_{s,od}) - \ln(shr_{0,od}) = \alpha \log p_{s,od} + \beta \log DistToFacility_{s,od} + \sigma \ln(\bar{shr}_{s,od/rail_{od}}) + \xi_{s,od}$$

[28] In my model the total population of shipment of each market is exogenously determined. The rationale behind this assumption is that under certain scenarios shippers have limited flexibility in choosing where to import and export certain commodities. This is especially true for bulk commodities like coal and agricultural products. Those commodities can only be produced in certain geographic markets, which limits shippers' freedom in choosing where to import the commodities.

where $\bar{shr}_{s,od/rail_{od}}$ is the within-group market share of service s among all railroad services that serve market from o to d.

Estimates of demand parameters α, β and σ will be obtained from a linear instrumental variables regression of difference in log market shares on firm presence, prices, and the log of the within-group share.

We can also derive the own-price-elasticity and cross-price-elasticity of demand which will be used in deriving the equilibrium conditions:

$$\frac{\partial Q_{s,od}}{\partial p_{s,od}} = M_{od}\frac{\alpha}{1-\sigma} shr_{s,od}\left[1 - \sigma \bar{shr}_{s,od/rail_{od}} - (1-\sigma) shr_{s,od}\right]$$
$$\frac{\partial Q_{s,od}}{\partial p_{s',od}} = -M_{od}\frac{\alpha}{1-\sigma} shr_{s,od}\left[\sigma \bar{shr}_{s',od/rail_{od}} + (1-\sigma) shr_{s',od}\right]$$

Given the utility of consumer i choosing railroad service s from o to d, we recover the consumer surplus from o to d as the expected utility specified in the formula below:

$$\begin{aligned} G_{i,od} &= \left(\sum_{s\in rail_{od}} \exp(\frac{u_{is,od}}{1-\sigma})\right)^{(1-\sigma)} + (exp(u_{i0,od})^{(1-\sigma)}) \\ &= \left(\sum_{s\in rail_{od}} \exp(\frac{u_{is,od}}{1-\sigma})\right)^{(1-\sigma)} + 1 \quad \text{(normalize } exp(u_{i0,od}) = 0 \text{ here)} \end{aligned}$$

Therefore total consumer surplus across all markets equals to:[29]

$$\begin{aligned} CS &= \frac{1}{\alpha}\sum_{o,d} \ln(G_{i,od}) \\ &= \frac{1}{\alpha}\sum_{o,d} \ln\left[\left(\sum_{s\in rail_{od}} \exp(\frac{u_{is,od}}{1-\sigma})\right)^{(1-\sigma)} + 1\right] \end{aligned}$$

[29] Actual consumer surplus equals to

$$CS = \frac{1}{\alpha}\sum_{o,d}(\ln(G_{i,od}) + C)$$

where C is an unknown constant.

2.5.3 Firm's Problem

Each firm j owns a network $\mathcal{N}_j$ with corresponding nodes $\mathcal{Z}_j$ and arcs $\mathcal{A}_j$. Firms make three types of decisions: pricing decision, routing decision, and allocation decision of investment. Firms choose prices $p_{s,od}$ for each service s, conditional on their perceived cost of themselves and their rivals. For interconnecting routes, I assume that firms participating in the joint-line service jointly determine the price of the joint-line service.[30] I also assume that firms do not consider the cannibalization between their own single-line service and joint-line service that they participate in for a given o-d market.[31] Then firms make routing and allocation decisions in their own network to minimize operation cost. Each firm j decides how to allocate investment $I_{j,ab}$ on each arc $(a, b) \in \mathcal{A}_j$. Each firm j also makes routing decisions $\mathcal{R}_{j,od_j(s)}$ for the transportation service demanded in each market. For a single-line service, firm j makes routing decision $\mathcal{R}_{j,od}$ from origin o to destination d. For a joint-line service, firm j makes routing decision $\mathcal{R}_{j,om}$ from origin o to interchange stations m if the firm serves the origin, or firm j makes routing decision $\mathcal{R}_{j,md}$ from interchange station m to destination d if the firm serves the destination. Routing $\mathcal{R}_{j,od_j(s)} \in \mathcal{A}_j$ is a subset of connected arcs that routes firm j from origin o_j to destination d_j. For interconnecting routes, I assume that the locations of interchange stations $m(s)$ and the firms participate in the joint-line service $J(s)$ are exogenous. By choosing the optimal routing and investment allocation decision, firms minimize their total operating cost. Firms make all decisions simultaneously and compete in prices. In equilibrium, the perceived cost of operating at the pricing stage is consistent with the outcome from firms cost minimization problem.

In summary, each firm j makes three kinds of decisions to maximize profit:

1. Price of service s from origin o to destination d, $p_{s,od}$

[30] I assume that there is no issue with double marginalization in the pricing of the interconnecting route based on findings from [Alexandrov et al., 2018].

[31] This assumption has little impact on the empirical results because in the data a firm rarely provides both single-line service and joint-line service in the same market.

2. Routing decisions, $\mathcal{R}_{j,od_j(s)} \subseteq \mathcal{A}_j$

   - Single-line service: from origin o to destination d, $\mathcal{R}_{j,od} \subseteq \mathcal{A}_j$
   - Joint-line service: (WLOG) from origin o to interchange station m, $\mathcal{R}_{j,om} \subseteq \mathcal{A}_j$

3. Amount of resources to allocate to each arc (a, b), $I_{j,ab}, (a, b) \in \mathcal{A}_j$

Pricing Firms choose price of each service s, conditional on their perceived cost of themselves and their rivals. For interconnecting routes, I assume that the firms participating in the joint-line service determine the price jointly. The optimization problem of pricing of each service s is denoted as:

$$\tilde{\pi}_s := \max_{p_{s,od}} \left[p_{s,od} - \tilde{C}_{s,od} \right] \cdot Q_{s,od}(p_{s,od}, p_{-s,od})$$

where $\tilde{C}_{s,od}$ is the perceived cost of providing service s to ship from origin o to destination d.[32] Firms compete in prices and the transportation service demanded in each market $Q_{s,od}$ is derived in equation 2.1. Then the first-order condition of price $p_{s,od}$ is calculated as

$$\begin{aligned} \frac{\partial \tilde{\pi}_s}{\partial p_{s,od}} &:= Q_{s,od} + (p_{s,od} - \tilde{C}_{s,od}) \cdot \frac{\partial Q_{s,od}}{\partial p_{s,od}} \\ &= Q_{s,od} + (p_{s,od} - \tilde{C}_{s,od}) \cdot Q_{s,od} \cdot \left[1 - \sigma \bar{shr}_{s,od/rail_{od}} - (1-\sigma) shr_{j,od} \right] \end{aligned} \tag{2.2}$$

where $\bar{shr}_{j,od/rail_{od}}$ is the within-group share of railroad services serving market from o to d. Conditional on firms perceived cost of operating in each market, and combine equation 2.1 with equation 2.2, I can get the equilibrium prices $\{\tilde{p}_{s,od}, \tilde{p}_{-s,od}\}$ that firms charge in each market. Plug these prices back into equation 2.1, I get the transportation service demanded $Q_{s,od}(\tilde{p}_{s,od}, \tilde{p}_{-s,od})$ for each service s in each market from o to d.

Transport Cost The per-unit transportation cost of a service $C_{s,od}$ depends on the routing decision $\mathcal{R}_{\cdot,od}$ and investment allocation decision $\boldsymbol{I}$. For single-line service, $C_{s,od}$ is specified as:

$$C_{s,od}(\boldsymbol{I_j}, \mathcal{R}_{j,od}) = \sum_{(a,b) \in \mathcal{R}_{j,od}} c_{j,ab}(\boldsymbol{I_j})$$

[32] In equilibrium, the perceived cost of operating at the pricing stage is consistent with the outcome from firms cost minimization problem.

where firm j is the firm that provides this single-line service from origin o to d, and $c_{j,ab}$ is the arc-level cost of firm j. The per-unit transportation cost $C_{s,od}$ is the summation of arc-level costs that firm j routes from o to d, and it depends on the routing decision $\mathcal{R}_{j,od}$, and investment allocation decision $\boldsymbol{I_j}$.

The per-unit transportation cost of joint-line service is specified as:

$$C_{s,od} = \sum_{(a,b)\in\mathcal{R}_{j,om}} c_{j,ab} + \sum_{(a',b')\in\mathcal{R}_{j',md}} c_{j',a'b'} + \eta$$

where η is the interchange cost, and m is the interchange station. Firm j carries the shipment from origin o to interchange station m, and firm j' carries the shipment from interchange station m' to destination d. The per-unit transportation cost of joint-line service $C_{s,od}$ is the summation of cost of firm j from o to m, and the cost of firm j' from m to d plus the interchange cost η.

I follow [Galichon, 2016] and [Fajgelbaum and Schaal, 2017] in defining the per-unit cost of transportation at arc level. The arc-level transportation cost of firm j at arc (a, b) is parameterized as:

$$c_{j,ab} = \frac{\delta_0 Dist_{j,ab}}{(1 + I_{j,ab})^{\gamma}}$$

The arc-level transportation cost $c_{j,ab}$ depends on the distance between a and b, and depends on the route efficiency $I_{j,ab}$. If firm j allocates more resources to arc (a, b), the route efficiency increases hence the arc-level transportation cost $c_{j,ab}$ decreases. For any arc (a', b') such that $(a', b') \notin \mathcal{A}_j$, the arc-level cost of transportation $c_{j,a'b'} = \infty$.[33]

[33]It is easy to enrich the model by adding geographic characteristics to the cost function such as in [Fajgelbaum and Schaal, 2017]; δ_0 in my model can be further parameterized as:

$$\delta_0 = \delta_1 \left(1 + |\Delta\text{Elevation}|_{ab}\right)^{\delta_2}$$

$$\text{or} \quad \delta_0 = \delta_1 \left(1 + |\Delta\text{Elevation}|_{ab}\right)^{\delta_2} \delta_3^{\text{CrossingRiver}_{ab}} \delta_4^{\text{AlongRiver}_{ab}}$$

What's more, I can add congestion in the cost function by modifying c_{ab} as a function of total traffics q_{ab} that go through arc (a, b). I choose not to include congestion in my model because it does not provide new insights into my story here, but it adds computational complexity because the routing problem is no longer a linear programming problem if congestion is included.

Given the arc-level transportation cost, the general form of transportation cost of service s from origin o to destination d is written as:

$$\begin{aligned} C_{s,od} &= \sum_{j \in J(s)} \sum_{(a,b) \in \mathcal{R}_{j,od_j(s)}} c_{j,ab} + \#_{interchanges} \cdot \eta \\ &= \sum_{j \in J(s)} \sum_{(a,b) \in \mathcal{R}_{j,od_j(s)}} \left[\frac{\delta_0 Dist_{j,ab}}{(1 + I_{j,ab})^{\gamma}} \right] + \#_{interchanges} \cdot \eta \end{aligned}$$

where $J(s)$ is the set of firms that provides service s. For a single-line service provided by firm j, $J(s) = \{j\}$, and for a joint-line service provided by firm j and j', $J(s) = \{j, j'\}$. $\#_{interchanges}$ is the total number of interchanges incurred in providing service s.

Routing and Investment Allocation Given the prices, the transportation service demanded in each market is determined. Given the transportation service demanded in each market $Q_{j,od}(\tilde{p}_{j,od}, \tilde{p}_{-j,od})$, firms make routing and allocation decision to minimize operating cost. Firms choose routing $\{\mathcal{R}_{j,od_j(s)}\}$ and investment allocation decision $\{I_{j,ab}\}$ in their own railroad networks $(\mathcal{Z}_j, \mathcal{A}_j)$, by solving the cost minimization problem and satisfying the constraint of capital allocation and balanced-flow constraints. The cost minimization problem of firm j is written as:

$$\min_{\{\mathcal{R}_{j,od_j(s)}\},\{I_{j,ab}\}} \sum_{s:j \in J(s)} C_{s,od_j(s)}(\boldsymbol{I_j}, \mathcal{R}_{j,od_j(s)}) \cdot Q_{s,od}(\tilde{p}_{s,od}, \tilde{p}_{-s,od}) \tag{2.3}$$

such that

Constraint of capital allocation:

$$\sum_{(a,b) \in \mathcal{A}_j} I_{j,ab} \leq K_j$$

Balanced-flow constraint, $\forall m' \in \mathcal{Z}_j$:

$$D_{j,m'} + \sum_{a \in \mathcal{Z}_j(m')} Q_{s,od} \cdot \mathbb{1}\{(a, m') \in \mathcal{R}_{j,od_j(s)}\} \leq \sum_{b \in \mathcal{Z}_j(m')} Q_{s,od} \cdot \mathbb{1}\{(m', b) \in \mathcal{R}_{j,od_j(s)}\}$$

The intuition of the capital allocation constraint is that each firm j has a fixed amount of capital K_j, that firm j can allocate to arcs in its network. The balanced-flow constraint

means that for each node m', the total inflow of traffic plus the net demand equals to the total outflow of traffic. $Q_{s,od} \cdot \mathbb{1}\{(a, m') \in \mathcal{R}_{j,od_j(s)}\}$ measures the total traffic that run through arc (a, m') of firm j. Then the total inflow of traffic into node m' is the summation of traffic from all the arcs (a', m') of firm j, such that a' is in the neighborhood of node m, $a' \in \mathcal{Z}_j(m)$. $D_{j,m'}$ is the net demand at node m'.[34]

Let us first look at the routing problem. Given prices $\{\tilde{p}_{j,od}, \tilde{p}_{-j,od}\}$ and fix firms investment allocation decisions, firm j's routing problem from origin o_j to destination d_j is written as:

$$\min_{\mathcal{R}_{j,od_j(s)}} \sum_{(a,b)\in\mathcal{R}_{j,od_j(s)}} c_{j,ab} \cdot Q_{s,od} \tag{2.4}$$

s.t. $\forall m' \in \mathcal{Z}_j$, the balanced-flow constraint is satisfied:

$$D_{j,m'} + \sum_{a\in\mathcal{Z}_j(m')} Q_{s,od} \cdot \mathbb{1}\{(a, m') \in \mathcal{R}_{j,od_j(s)}\} \leq \sum_{b\in\mathcal{Z}_j(m')} Q_{s,od} \cdot \mathbb{1}\{(m', b) \in \mathcal{R}_{j,od_j(s)}\}$$

where $D_{j,m'}$ is the net demand of firm j at node m', and $\mathbb{1}\{\cdot\}$ is the indicator function that has value 1 if the condition is true and 0 otherwise. Solving equation 2.4 is equivalent to solving the minimization problem:

$$\min_{\mathcal{R}_{j,od_j(s)}} \sum_{(a,b)\in\mathcal{R}_{j,od_j(s)}} c_{j,ab}$$

$$\Rightarrow \min_{\mathcal{R}_{j,od_j(s)}} \sum_{(a,b)\in\mathcal{R}_{j,od_j(s)}} \frac{\delta_0 Dist_{j,ab}}{(1 + I_{j,ab})^{\gamma}}$$

s.t. $\forall m' \in \mathcal{Z}_j$,

$$\mathbb{1}\{m' = o\} - \mathbb{1}\{m' = d\} + \sum_{a\in\mathcal{Z}_j(m')} \mathbb{1}\{(a, m') \in \mathcal{R}_{j,od_j(s)}\} \leq \sum_{b\in\mathcal{Z}_j(m')} \mathbb{1}\{(m', b) \in \mathcal{R}_{j,od_j(s)}\}$$

The intuition of the routing problem is that firm j chooses the shortest efficiency-weighted route to travel from origin o_j to destination d_j in its own railroad network. Firm j obtains

[34] $D_{j,m'} = \begin{cases} Q_{s,od} & \text{if } m' = o \\ -Q_{s,od} & \text{if } m' = d \\ 0 & \text{otherwise} \end{cases}$

the optimal routing for each market from o_j to d_j by solving a linear programming problem.[35]

The optimal allocation decision is obtained by solving the cost minimization problem in equation 2.3. By taking the derivatives with respect to $I_{j,ab}$ for each firm j and arc $(a,b) \in \mathcal{A}_j$, the optimal investment allocation decision is solved as:

$$\begin{aligned} I_{j,ab} &= \left[\frac{\gamma}{\lambda_j} \sum_{s:j \in J(s)} \left(\delta_0 Dist_{j,ab} \cdot Q_{s,od} \cdot \mathbb{1}\{(a,b) \in \mathcal{R}_{j,od_j(s)}\} \right) \right]^{\frac{1}{1+\gamma}} - 1 \\ &= \left[\frac{\gamma}{\lambda_j} \cdot \delta_0 Dist_{j,ab} \cdot q_{j,ab} \right]^{\frac{1}{1+\gamma}} - 1 \end{aligned} \tag{2.5}$$

where $q_{j,ab}$ is the total amount of traffics that run through arc (a,b), and λ_j is the Lagrangian multiplier of the capital constraint of firm j.[36] Therefore, for any non-zero $I_{j,ab}$ and $I_{j,a'b'}$,

[35] To represent a linear-programming problem, the routing problem from origin o to destination d can be written in vectors as:

$$\min_{\boldsymbol{q}} \boldsymbol{c} \times \boldsymbol{q}$$

$$\text{such that } \nabla \boldsymbol{q} = \boldsymbol{Q_s}, \text{ where } \boldsymbol{Q_s} = \begin{bmatrix} \cdots \\ -Q_{s,od} \\ 0 \\ 0 \\ Q_{s,od} \\ 0 \\ 0 \\ \cdots \end{bmatrix}$$

[36] Because the investment of track maintenance and locomotives cannot be negative, the optimal level of investment would be

$$I_{j,ab} = \max\{I_{j,ab}, 0\}$$

from equation 2.5 we know that:

$$\frac{I_{j,ab}+1}{I_{j,a'b'}+1} = \left[\frac{Dist_{j,ab}\cdot q_{j,ab}}{Dist_{j,a'b'}\cdot q_{j,a'b'}}\right]^{\frac{1}{1+\gamma}} \tag{2.6}$$

The intuition of the allocation problem is that firms will allocate more resources to arcs that carry larger volume of traffic. Conditional on optimal routing, and combine equation 2.6 with the capital constraint of firm j such that $\sum_{(a,b)\in\mathcal{A}_j} I_{j,ab} = K_j$, I can obtain the solution of the optimal investment allocation problem.

To sum up, given the transportation service demanded of each service $Q_{s,od}(\tilde{p}_{s,od}, \tilde{p}_{-s,od})$, firms make routing and allocation decision by solving the cost minimization problem in equation 2.3. The optimal routing of firm j chooses the shortest efficiency-weighted route to travel from origin o_j to destination d_j by solving a linear programming problem, and the optimal allocation is solved by allocating more resources to arcs that carry larger volume of traffics.

In equilibrium, firms choose prices conditional on their perceived cost of themselves and their rivals. Given the prices, the transportation service demanded for each service is determined. Then, given the transportation service demanded in each market, firms make routing and allocation decision to minimize operating cost. Last, the outcome from firms cost minimization problem is consistent with the perceived cost of operating at the pricing stage.

2.6 Estimation

2.6.1 Demand Estimation

The utility function in my model is specified as:

$$u_{is,od} = \alpha \log p_{s,od} + \beta \log DistToFacility_{s,od} + \xi_{s,od} + (1-\sigma)\epsilon_{is,od}$$

where the utility of consumer i depends on three components. The price of service s to ship from o to d, distance to customer's facility, which is measured by the logarithm of

total miles of tracks, and the unobservable efficiency $\xi_{s,od}$. $\epsilon_{is,od}$ is the consumer-specific deviation from the mean utility. I allow the railroad firms to be more substitutable among themselves, versus outside option which is trucking. Parameters that need to be estimated here are price coefficient α, coefficient on firm presence β, and within-group correlation parameter σ.

The demand estimation follows the procedure of [Berry, 1994], and estimates of α, β and σ are obtained from a linear instrumental variables regression.[37]

$$\ln(shr_{s,od}) - \ln(shr_{0,od}) = \alpha \log p_{s,od} + \beta \log DistToFacility_{s,od} + \sigma \ln(\bar{shr}_{s,od/rail_{od}}) + \xi_{s,od}$$

$shr_{s,od}$ is the market share of service s in serving market from o to d, $shr_{0,od}$ is the market share of the outside option, which is trucking in serving market from o to d, and $\bar{shr}_{s,od/rail_{od}}$ is the within-group market share of service s among all railroad services from o to d. I obtain the share of rail mode versus the share of truck mode from one region to another from the Commodity Flow Survey, which shows what the substitution to the outside option looks like.

In this application, shipment price $p_{s,od}$ and within-group market share $\bar{shr}_{s,od/rail_{od}}$ are likely to be endogenous. I instrument price $p_{s,od}$ by the number of competing railroads that serve the same market from o to d, and I instrument within-group market share $\bar{shr}_{s,od/rail_{od}}$ by characteristics of other railroads that serve the same market from o to d.

The intuition behind the expected correlation between the selected instruments and price $p_{s,od}$ is that, absent from perfectly collusive conduct, price will tend to fall with an increase in the number of competing railroads in the market from o to d. After controlling for market, firm, and time fixed effects of the unobservable efficiency $\xi_{s,od}$, I believe the instruments are uncorrelated with firms idiosyncratic efficiency shocks $v_{s,od}$. One concern is that market entry depends on firms idiosyncratic efficiency shocks $v_{s,od}$, therefore the

[37] It is more efficient to estimate demand parameters and cost parameters together using GMM. Given the level of complexity of the firm's problem in my model, however, I choose to estimate demand parameters and cost parameters separately.

instrument exogeneity assumption is violated. To address this concern, I define the number of competing railroads as number of railroads that have tracks connecting origin o to destination d. A firm that has tracks connecting origin o to destination d, may not necessarily choose to provide freight service in serving market from o to d.[38] The physical layout of rail in the United States was largely stable and unchanged in the time period under study. Therefore, the overall network structure is exogenous. Although firms endogenously choose which markets to serve, the number of railroad firms that have tracks connecting origin o to destination d in each market are assumed to be uncorrelated with firms idiosyncratic efficiency shocks $v_{s,od}$.

To instrument the within-group market share $s\bar{h}r_{s,od/rail_{od}}$, I use other firms characteristics in the origin o. The premise here is that shippers are more likely to choose a railroad to carry its shipment from the origin to the destination, if that railroad has longer tracks in the origin. This is because the longer miles of tracks a railroad has in a region, the more likely the railroad is closer to the shipper's facilities and easier to reach. The exogeneity assumption is satisfied because I assume the overall network structure is exogenous, hence the total miles of tracks of each firm in a region is fixed and orthogonal to firms idiosyncratic efficiency shocks $v_{s,od}$.

Table 2.9 reports the estimated parameters from the linear instrumental variables regression.

[38] Actively serving a market requires constant track maintenance, so firms may choose not to serve a market even if it has tracks connecting origin o to d.

Table 2.9: Demand Estimation Results

	(1) Difference of Log Shares
Log Price	-2.041***
	(0.328)
σ	0.700***
	(0.060)
β	0.592***
	(0.093)
Observations	109,011
Year FE	Y
Firm FE	Y
O-D Route FE	Y

First, all parameters are highly significant with the expected sign. Shipment price is negatively correlated with market share, and firm presence is positively correlated with market share. The within-group correlation σ is significantly different from 0, which indicates that it is important to allow for closer substitution between railroads compared to other transportation modes. A convenient feature of the nested logit model is that the aggregate elasticity in any origin-destination market is simple to compute. In our case, aggregate price elasticity equals -1.3. The estimated aggregate elasticity is comparable to the estimates found by other research. For example, [Ivaldi and McCullough, 2005] found the price elasticity of bulk shipment in freight railroad is -1.52.

Given the estimated demand parameters, I can write the transportation service demanded in each market $Q_{s,od}(p_{s,od}, p_{-s,od})$ as a function of firms prices according to equation 2.1. Then, I can solve the firms optimization problem and estimate the cost parameters.

2.6.2 Estimation of Cost Parameters

In section 2.5, the arc-level transportation cost of firm j at arc (a, b) is parameterized as

$$c_{j,ab} = \frac{\delta_0 Dist_{j,ab}}{(1 + I_{j,ab})^\gamma}$$

The arc-level transportation cost $c_{j,ab}$ depends on the distance between a and b, and depends on the amount of investment $I_{j,ab}$. The per-unit transportation cost of service s is:

$$\begin{aligned} C_{s,od} &= \sum_{j \in J(s)} \sum_{(a,b) \in \mathcal{R}_{j,od_j(s)}} c_{j,ab} + \#_{interchanges} \cdot \eta \\ &= \sum_{j \in J(s)} \sum_{(a,b) \in \mathcal{R}_{j,od_j(s)}} \left[\frac{\delta_0 Dist_{j,ab}}{(1 + I_{j,ab})^\gamma} \right] + \#_{interchanges} \cdot \eta \end{aligned}$$

Therefore, the cost parameters to be estimated are δ_0, γ, and η. δ_0 captures the average shipment cost per efficient mile, γ captures the effectiveness of investment, and η captures interchange cost.

I use simulated GMM to estimate δ_0, γ, and η. I target four data moments in estimating the parameters:[39]

[39] I obtain shipping expense from the data as follows: in the data we can observe the shipment price for each waybill. Given the estimated demand parameters and information on market competition in each origin-destination pair, we can thus derive the shipping expense as

$$Q_{s,od} + (p_{s,od} - C_{s,od}) \cdot \frac{\partial Q_{s,od}}{\partial p_{s,od}} = 0$$

$$\Rightarrow C_{s,od} = p_{s,od} + \delta^{-1} Q_{s,od}$$

Table 2.10: Targeted Data Moments

	Data Moments
Average shipping expense per actual mile	\$0.87
Change of average shipping expense per actual mile on total travel distance (per 100 miles)	\$-0.11
Percentage of non-minimum-distance routing	18.3%
Average difference of shipping expense between interconnecting route and non-interconnecting route	\$310

The identification argument is as follows: the first three moments jointly pin down the value of δ_0 and γ. The first and second moment measures the intercept and gradient of the effect that travel distance has on average shipping expense. Because δ_0 captures the average shipment cost per efficient mile, the larger the value of δ_0, the larger the value of average shipping expense per actual mile. γ captures the effectiveness of investment, and affects the conversion between shipping expense per efficient mile and shipping expense per actual mile. The value of δ_0 and γ jointly affects firms routing decisions, which in turn affects the gradient of the effect that travel distance has on average shipping expense. The value of γ largely affects the value of the third moment, percentage of non-minimum-distance routing. Route efficiency depends on investment allocation decisions $I_{j,ab}$ and the value of γ. Firms will trade travel distance with the efficiency of the route when making routing decisions. When the value of γ increases, firms have more incentive to choose routing that deviates from minimum-distance routing. Therefore, the value of γ largely affects the percentage of routes that deviate from minimum-distance routing. To sum up, the first three moments jointly identify δ_0 and γ. Conditional on the value of δ_0 and γ, the last moment the average difference of shipping expense between an interconnecting route and a non-interconnecting route identifies the interchange cost η. When the value of interchange cost η increases, the average shipping expense of an interconnecting route increases, hence the difference between average shipping expense of an interconnecting route and average

shipping expense of a non-interconnecting route increases.

Regarding the value of the data moments, average shipping expense per actual mile in the data is \$0.87. As a benchmark, according to AAR, in 2007 the average shipping expense per mile for a loaded car is \$1.2, which is comparable to the number I observe in my data here. In my data, if the total travel distance increases by 100 miles, the average shipping expense per mile decreases by \$0.11, which is equivalent to a 12% decrease of average shipping expense per mile. The average difference of shipping expense between an interconnecting route and a non-interconnecting route in the data is \$310 per loaded car. As a benchmark, in the data the average shipment price is \$1,500 per loaded car, which means that the interchange cost is equivalent to around 20% of average shipment price.

I estimate the cost parameters by minimizing the weighted distance between data and simulated moments. Table 2.11 shows the estimated results:[40]

Table 2.11: Estimation Result of Cost Parameters

	Point Estimate
δ_0	0.9
γ	0.7
η	290

The estimated value of γ is less than 1. It indicates that the marginal return of investment is decreasing. Therefore, railroad companies are more likely to spread out investment of infrastructure into multiple arcs, rather than stacking investment of infrastructure in only few arcs. Table 2.12 compares the data moments with simulated moments under the estimated cost parameters.

[40]The confidence intervals of the estimated parameters are obtained from bootstraps and coming in the future versions.

Table 2.12: Compare Simulated Moments with Data Moments

	Data Moments	Simulated Moments
Average shipping expense per car-mile	\$0.87	\$1.28
Change of average shipping expense per car-mile on total travel distance (per 100 miles)	\$-0.11	\$-0.10
Percentage of non-minimum-distance routing	18.3%	17.1%
Average difference of shipping expense between interconnecting route and non-interconnecting route	\$310	\$342

The model does well in matching the change in average shipping expense per car-mile on total travel distance, and the simulated moment approximates well the percentage of non-minimum-distance routing that we observe in the data. However, the simulated moment deviates from average shipping expense per car-mile in the data. This might be because conditional on routing, my model has a very restricted relation between travel distance and transportation cost. My model does not consider the topography such as elevation and ruggedness of the terrain. Therefore, the data moment might be different, because besides investment of infrastructure, other factors may also affect the average shipping expense per car-mile in the data. The simulated moment of average difference of shipping expense between interconnecting route and non-interconnecting route also deviates from the data moment. This might be because the simulated moment is capturing some of the systematic difference between interconnecting and non-interconnecting route. For example, interconnecting routes may have longer travel distance compared to non-interconnecting route, hence the average shipping expense captures the effect of longer travel distance.

2.6.3 Out-of-Sample Predictions

To validate the model, I perform out-of-sample predictions by comparing simulated moments with non-targeted data moments. First, I look at the average price reduction following mergers. In the data the average price reduces by 9.4% following mergers. The

simulated price change following merger in my model is 10.51%, which is comparable to the data moment. One reason that my simulated moment is larger than the price change in the data is because my model does not capture the increase in service quality. Moreover, firms conduct a Bertrand competition in my model and there is no space for collusion. Next, my model predicts which origin-destination pairs will have the largest price reduction following mergers. In the data I also observe which origin-destination markets have the largest price reductions after mergers. I compare the set of routes in my model with the set of routes in the data and examine whether my model correctly predicts which routes have the largest price reductions. For the top 10% markets with price reductions, my model has an accuracy of 62.7% of making the prediction.

Table 2.13: Compare Simulated Moments with Non-Targeted Data Moments

Moments	Data	Model
Average Price Reduction after Merger	-9.4%	-10.51%

If we look at the accuracy of prediction for each merger case, I find:[41]

[41]Due to confidentiality reasons, the names of the actual mergers are marked.

Table 2.14: Accuracy of Predicting the Top 10% Markets of Price Reduction

Merger ID	Number of O-D Markets	Accuracy of Predicting top 10% Price Reductions
1	597	54%
2	854	79%
3	1163	75%
4	1442	39%
5	1161	62%
6	11	100%
7	52	100%
8	192	100%
9	180	100%
10	40	50%
11	57	0%

The model does well in predicting the top 10% markets of price reduction. For large mergers that involve more than 500 origin-destination markets, the accuracy of prediction is above 50%. The only exception is merger #4, which has an accuracy of prediction of only 39%. This might be because these railroads encountered well-documented hurdles when integrating their networks after their merger. This may cause the price change in the data to deviate from the predicted price change in the model.

For some mergers the accuracy of prediction is 100%. This may be because those mergers involve only a small amount of origin-destination markets, and it is easier to predict price changes when the number of markets is small. One exception, However, is the railway that is involved in merger #10 and merger #11, for which the accuracy of prediction is 50% and 0%. This may be because the main business of that railway originates and ends in country outside the United States, which is not captured in my model. My model estimates demand only within the United States because the CFS covers the United States only.

Next, I conduct merger simulations by simulating the pricing decision, routing decision,

and investment decision following each railroad merger and examine the efficiency gain from each source along with welfare changes in each geographic market.

2.7 Results

My model allows markets to be interdependent in the cost minimization stage, and the model has rich implications in understanding the change of transportation cost after mergers. I conduct counterfactual simulations of mergers and calculate the change of cost. Then I decompose the sources of cost efficiencies by fixing the pricing as the new equilibrium pricing after merger, and change the cost component one by one. Last, I evaluate the welfare changes at different geographic markets, and look at how topology of the network affects such changes.

2.7.1 Sources of Cost Efficiency

First, I conduct counterfactual simulations of mergers and calculate cost changes. For example, I observe the mass of demand, and I observe the network of each incumbent railroad firm including the Burlington Northern railway (BN) and the Santa Fe railway (SF) before the merger. Using the value of the estimated demand and cost parameters, I solve for each firm's pricing, routing, and investment decision, and derive the equilibrium price and shipment cost of each firm in each origin-destination market before the merger. Then I evaluate the merger between BN and SF. I fix the mass of demand and the network of railroad firms other than BN and SF as what they are before the merger. Then I combine the network of BN and the network of SF, and assume the merged firm BNSF makes pricing, routing, and investment decision in the newly combined network. Next I solve for the new equilibrium price and shipment cost of firms after the merger. By comparing the change of costs and prices before and after mergers, I find what the merger effect is. I repeat this kind of analysis and conduct merger simulations for all the mergers in my studied period. I find that on average shipment cost decreases by 32% after mergers. The model predicted

price decrease from the merger simulations is 10.5%.

Second, I conduct other counterfactual simulations to decompose sources of cost efficiency, and I examine the importance of each source in determining efficiency gain following railroad mergers. In total there are three sources of efficiency gain: the elimination of interchange cost, the reallocation of resources for investment, and reoptimization of routing. First, I conduct a merger simulation by allowing for all three types of changes. The cost change after the merger is denoted as $\Delta C_{tot,od}$ for each origin-destination market. I then conduct a counterfactual by fixing the pricing as the new equilibrium pricing while holding routing and investment decisions the same as pre-merger routing and investment decisions. The cost changes under this counterfactual is denoted as $\Delta C_{inter,od}$. $\Delta C_{inter,od}$ measures the cost changes caused by elimination of interchange cost. Next, I conduct a counterfactual by fixing the pricing as the new equilibrium price, and holding the investment decisions the same as pre-merger investment decisions. The cost changes under this counterfactual is denoted as $\Delta C_{invest,od}$. The difference between $\Delta C_{invest,od}$ and $\Delta C_{inter,od}$ measures the cost changes caused by reallocation of resources for investment. Last, the rest of the change in cost (the difference between $\Delta C_{invest,od}$ and $\Delta C_{tot,od}$) is attributed to the reoptimization of routing.[42]

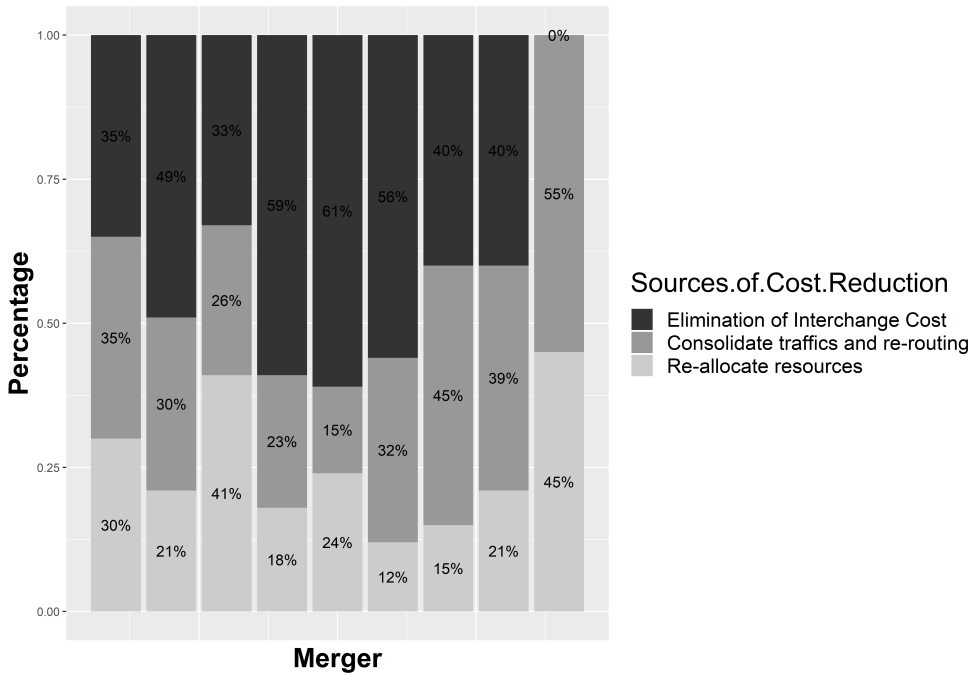
The counterfactual result shows that the reduction of interchange cost on average accounts for 44% of the cost reduction. The freedom to allocate resources on average accounts for 20% of the cost reduction, and the consolidation of traffic and reoptimization of routing on average accounts for 36% of the cost reduction. The result suggests, first, that the elimination of interchange costs play an important role in gaining efficiency following railroad mergers. Looking only at an individual market is not enough to understand mergers in this industry, however, because the reoptimization of routing and reallocation of resources also

[42]The three sources of efficiency interact with each other. For example, the routing decision depends on if the interchange cost is eliminated or not. Therefore, the exact decomposition of cost changes depends on the sequence of how I conduct the counterfactuals.

play key roles in cost reduction following railroad mergers.

I also look at how the decomposition changes across different mergers by repeating this analysis for mergers in my studied period. Figure 2.8 shows that sources of efficiency gain vary across mergers. The variation depends on the number of interconnecting lines involved in each merger and on the network structure of the firms. In general, the elimination of interchange costs is the most important source of efficiency gain.

Figure 2.8: Sources of Efficiency Gain Across Mergers

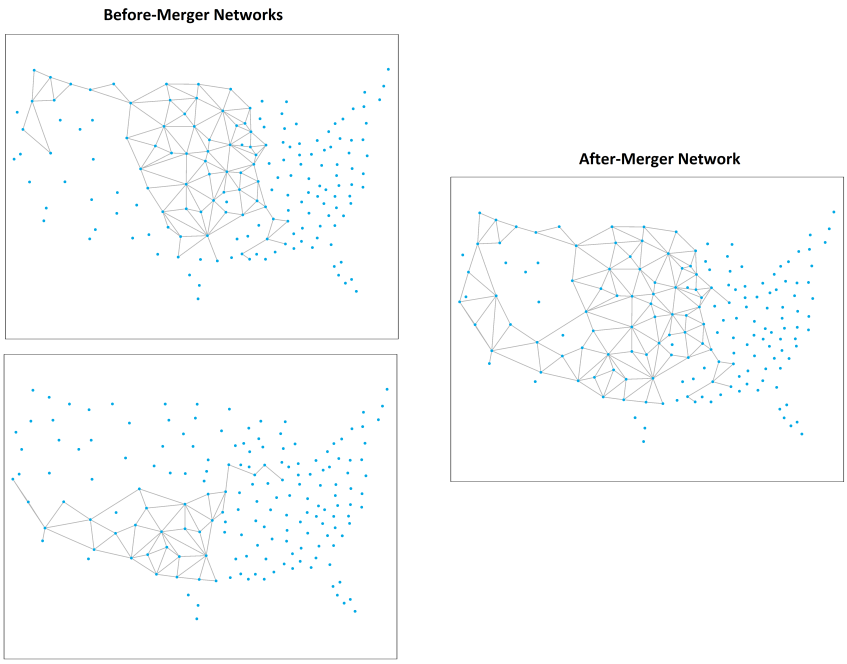


2.7.2 Heterogeneity of Welfare Changes

Given the sources of cost efficiency and how they change with features of the merger like ownership of network, next I analyze the trade-off of increased market power versus efficiency gain, and examine the magnitude of welfare changes in different geographic markets. To provide intuition on how topography of network affects the trade-off between increased market power and efficiency gain, here I look specifically at the merger of the Burlington Northern and Santa Fe railways.

Figure 2.9 illustrates the network of the Burlington Northern and the Santa Fe before and after their merger. The left panel shows the networks owned by the Burlington Northern (top) and the Santa Fe (bottom). The right panel shows merged network. Note that the network of the Burlington Northern and the Santa Fe overlaps in the central United States, including Colorado, Kansas, Oklahoma, and north Texas.

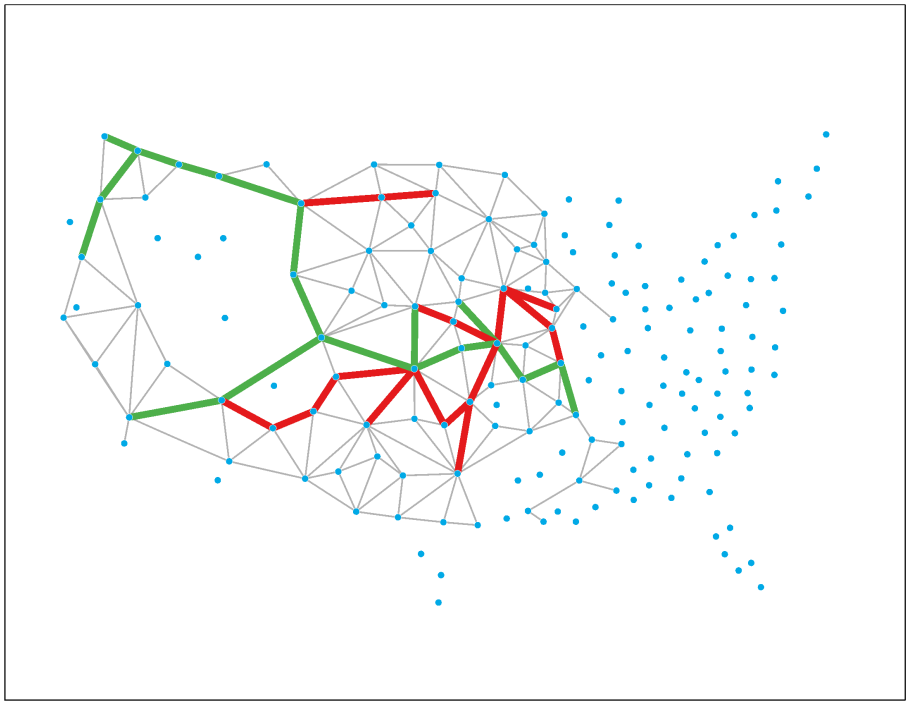
Figure 2.9: Rail Networks of Burlington Northern and Santa Fe



I first examine the efficiency gain following this merger. The merger simulation displays the firm's decision on routing and investment of track maintenance and locomotives in the new equilibrium. By comparing the investment decision before and after the merger, I show how the allocation of resources changes after the merger. The green lines in Figure 2.10 highlight regions where resources are consolidated. The red lines highlight regions where resources are lessened. The exact efficiency gain of each origin-destination market depends on its choice of routing, but a rule of thumb is that regions closer to the green lines are more likely to have an efficiency gain after the merger. Meanwhile, regions closer to the red lines are less likely to have an efficiency gain following the merger. One observation is that

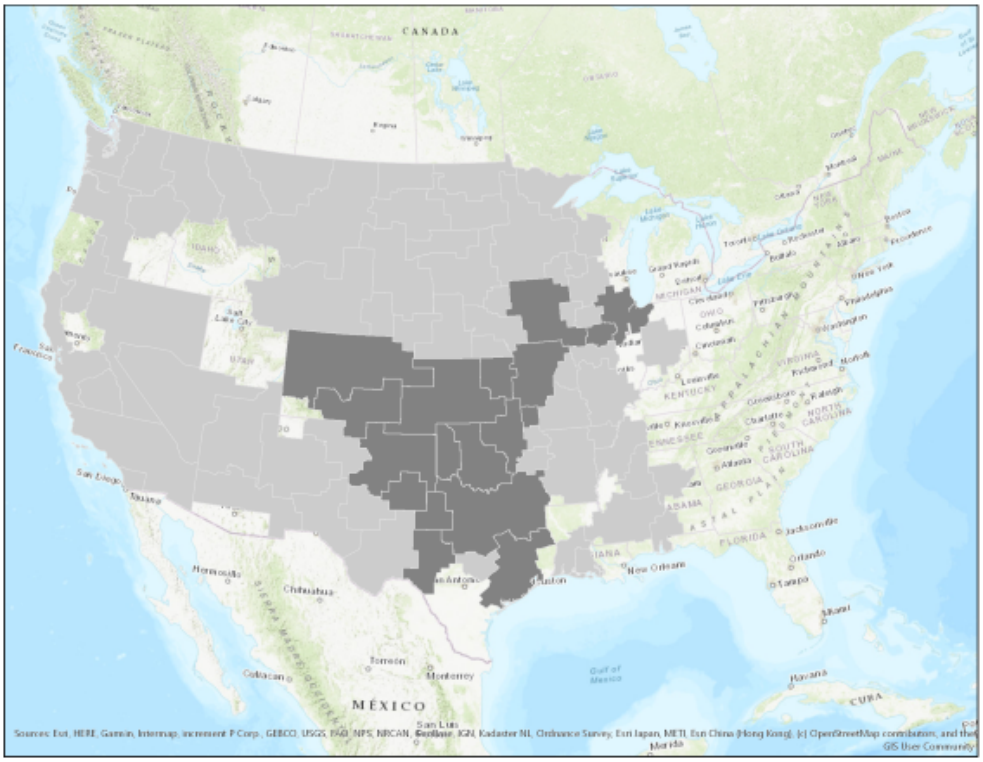
firms tend to enhance the connection of their networks after the merger. For example, more resources are allocated to regions where the network of the former Burlington Northern and Santa Fe railways connect, such as the central United States and West Coast.

Figure 2.10: Change of Investment Before and After Merger



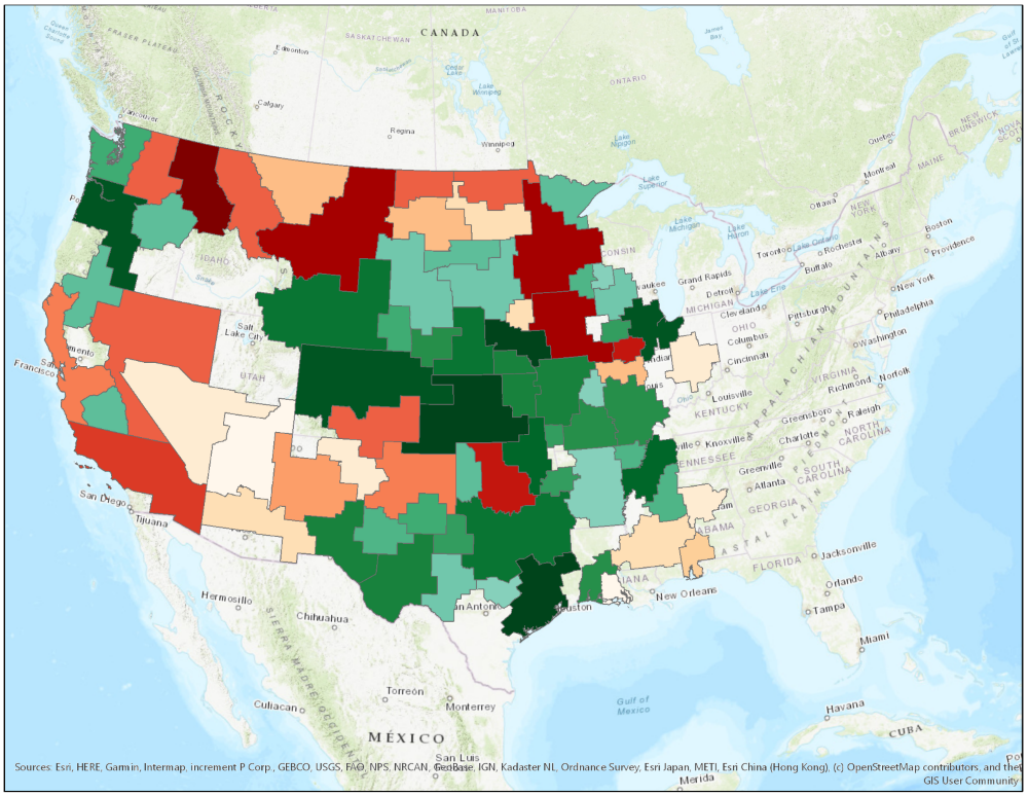
Next, I examine the change of market power in different geographic markets following the merger of the Burlington Northern and the Santa Fe. The gray areas in Figure 2.11 depict all regions affected by this merger. Light gray areas are regions where only one of the two companies provides freight service before the merger. Dark gray areas are regions where both firms provide freight service before the merger. Following the merger, therefore, the number of firms providing freight service remains the same in the light gray areas, whereas it decreases in the dark gray areas.

Figure 2.11: Change of Market Power Before and After Merger



The combined forces of change of market power versus cost efficiency results in a large degree of heterogeneity in welfare changes. For each BEA region, I calculate the change of consumer welfare by aggregating all the inbound and outbound traffic of that region. Figure 2.12 illustrates the change in consumer welfare after the merger in different regions. The green areas are places where consumer welfare increases following the merger, while the red areas are places where consumer welfare decreases after the merger. There is a large variation regarding the value of change in consumer welfare, ranging from -15% to 15%. The result suggests that in the merger of the Burlington Northern and the Santa Fe, the consumer welfare of regions in the periphery of the two networks is likely to decrease, while the consumer welfare of regions in the core of the merged network is likely to increase.

Figure 2.12: Change of Consumer Welfare Before and After Merger



2.8 Conclusion

I document evidence of improved cost efficiency following the wave of mergers in the U.S. railroad industry from 1980 to 2010. By conducting a reduced-form analysis with detailed route-level shipment data, I find that following the mergers, the ratio of switching hours to road-service hours decreases by 11% and the average haul length increases by 5%. Moreover, on average the number of interchanges decreases and use of unit trains increases following railroad mergers. Shipment prices decrease by 9.4% on average after the mergers, and interconnecting routes have the largest price reduction, 11%, of all the route types.

Using the reduced-form evidence and descriptive evidence from interviews and merger documents, I argue that looking solely at the effect of individual routes is not sufficient to

understand efficiency gain in this industry. This is because each origin-destination market in the network is interdependent. To capture this important feature and examine how it affects consumer welfare following mergers, I propose an optimal transport network model by endogenizing firm pricing, routing, and investment decisions. The simulation results show there is a large degree of heterogeneity of welfare changes in different geographic markets following railroad mergers, and it depends on the ownership of networks and the location of each market within the network. Moreover, the decomposition of sources of cost efficiency shows that reduction of interchange cost on average accounts for 44% of cost reduction. The freedom to allocate resources on average accounts for 20% of cost reduction, and the consolidation of traffic and reoptimization of routing on average accounts for 36% of cost reduction. The structure model can be further used in conducting various counterfactual results such as policy simulations and evaluation of future mergers. The result of how cost efficiency and price incentives vary with respect to different topographic that a network has, may also help us understand the tradeoff between efficiency gain and market concentration in other network industries, such as telecommunications and electricity, airline, and railroad industries.

Certain limitations of this paper suggest areas for further exploration. First, the total amount of investment is fixed. One could look further at how the free capital market affects the predicted results by relaxing this assumption. Second, it is difficult to integrate two large networks into one. For example, when the Union Pacific railway acquires the Southern Pacific railway, integration of their networks is difficult and has a large negative impact on freight transportation in the short run. The trade-off between short-term chaos and long-term efficiency gain is not considered in my model. Moreover, when the number of firms decreases, firms may find it easier to collude. In the U.S. freight railroad industry there are more lawsuits alleging collusion by railroad companies after 2004, when the main mergers are finished. These features are not captured in my model but are worth exploring.

Chapter 3

A Structural Empirical Model of R&D, Firm Heterogeneity, and Industry Evolution

Joint with Daniel Yi Xu[1]

3.1 Introduction

A large empirical literature has documented substantial and persistent firm productivity heterogeneity even within narrowly-defined industries.[2] Theoretical models of industry dynamics by Jovanovic (1982), Hopenhayn (1992), and Ericson and Pakes (1995) have been developed to explain the patterns of individual firm size, success, and failure observed in longitudinal micro-level data. These existing theoretical models share a common feature: a stochastic process that changes a firm's productivity (or knowledge of its productivity) over time. This process of productivity evolution is a key component that drives the success and failure of individual firms and the overall evolution of industry structure.

In this paper, we study an important source of productivity evolution: the investment in R&D by individual firms. Specifically, using micro data for producers in the Korean electric motor industry for the period 1991 to 1996, we estimate how a firm's productivity is affected by its R&D investment and how the R&D investments are determined by industry competition. There exists strong empirical evidence that a firm's technological

[1]Duke University and NBER

[2]See Bartlesman and Doms (2000) for an excellent survey of the micro productivity literature.

position does not just evolve exogenously. Griliches (1998) provides an extensive survey of the empirical literature linking own firm R&D spending, R&D spill-overs and productivity growth. We extend these previous studies by investigating the R&D decision of firms within a dynamic industry equilibrium model.

We contribute to the existing literature in several dimensions. First, it is widely observed that a large fraction of firms reporting no R&D activity in even high tech industries. We reconcile this observation with Gibrat's law by allowing firms to survive by imitation. Furthermore, solving the firm's dynamic optimization problem enables me to identify how firm investment, output, and exit decisions interact with its productivity change, which relates firm R&D directly to firm heterogeneity. Second, the equilibrium industry structure provides a natural link from individual firm performance to aggregate industry productivity and output by two mechanisms: the "market selection" mechanism, which operates through resource re-allocation from low efficiency to high efficiency firms or through entry and exit, and the active "firm learning" mechanism, which operates through individual firm's productivity improvement over time. Finally, following estimation of the model parameters, we are able to evaluate how pro-competition policies affect firm R&D, physical investment, entry, exit, and industry aggregates quantitatively.

The idea of investigating firm R&D, inter-firm spill-overs, and the evolution of industry structure simultaneously dates back to Dasgupta and Stiglitz (1980). Under imperfect product market competition, firms maximize their value of continuation given expectations about the evolution of their own and competitors' states. This implies that a firm's learning effort and investment decision are endogenously shaped by the level of product market competition as well as by pressure from potential entrants.[3] Yet, few previous empirical studies have attempted to estimate such a dynamic equilibrium model.[4] My estimation

[3]Spence (1984) shows that imperfect competition induces a free-rider problem in R&D effort given the existence of a spill-over. More recently, Bloom, Schankerman and Van Reenen (2004) use a panel of U.S. firms to empirically identify technological spill-over and product market rivalry.

[4]Some exceptions include Benkard (2004), Ryan (2005) and Collard-Wexler (2006), who use empirical dynamic oligopoly models to analyze industry pricing, industry performance, and optimal

builds on the industry dynamics model pioneered by Ericson and Pakes (1995). We adapt it to an environment with both physical-capital and knowledge-capital investments. The firms make entry, exit, and investment decisions each period and improve their productivity as a result of their own investments in knowledge capital. Furthermore, we allow for a technological spill-over from more productive to less productive firms. Finally, firms experience technological setbacks due to idiosyncratic exogenous shocks.

Ericson and Pakes (1995) propose a Markov Perfect Equilibrium concept to characterize the evolution of an industry. To circumvent the well-known heavy computational burden of the Markov Perfect Equilibrium, we use the "oblivious equilibrium" concept proposed by Weintraub, Benkard, and Van Roy (2007) to solve the industry equilibrium of the theoretical model. When there are large number of firms within the industry, the "oblivious equilibrium", which assumes that firms ignore current information about competitors states and condition their choices on the knowledge of the long run average industry state, closely approximates a Markov Perfect Equilibrium.

The model is used to study the process of R&D and productivity growth for producers in the Korean electric motor industry. In the first step, we utilize the model specification for static market competition to estimate the demand elasticity, returns to scale in production, and the process of plant level productivity. We also recover the plant's entry decision and new entrant's initial productivity distribution. In the second step, we use a Simulated Method of Moments estimator to estimate the dynamic investment model to recover the cost of R&D, the magnitude of the spill-over, adjustment costs of investment, and the distribution of plant scrap values. We apply a recent approach by Chernozhukov and Hong (2005), which is based on the Markov Chain Monte Carlo (MCMC) method, to obtain point estimates and confidence intervals. By explicitly controlling for imperfect competition, productivity heterogeneity and both physical-capital and knowledge-capital investment, the model is rich enough to reproduce the observed market structure and in-

industry policy. Recently, Lentzand Mortensen (2005) estimate an equilibrium model of firm innovation developed by Klette and Kortum (2004) using a panel of Danish firms.

dustry turnover patterns.

Furthermore, the estimation results show that each element of the model is critical in explaining the observed pattern in the data. The empirical results show that: first, a firm's own R&D effort improves its future productivity while this process is subject to substantial idiosyncratic uncertainty. The within-industry R&D spill-over is significant and helps to explain the observed producer R&D spending and productivity evolution patterns. On average, one dollar of competitor's R&D expenditure can substitute for 1.6 cents of own R&D input. Taking into account that the total R&D spill-over pool is much larger relative to any producer's own spending and the R&D spill-over is a public good, spill-overs are quite important to the less productive producers. Second, each producer also incurs substantial adjustment costs for physical capital investment. Third, the mean random scrap value and entry cost equals four years and six years of average firm profit, respectively. The relatively narrow hysteresis band, defined as the difference between the entry cost and the mean scrap value, explains the high turnover rate observed in the industry data. Finally, there is a complementarity between a firm's physical capital investment and its innovation incentives. Not only does a firm's own R&D investment, but also its physical capital investment, responds to the spill-over.[5]

Using the point estimates of the parameters, we implement counter-factual experiments to study the effects of two different pro-competitive policies. In the first experiment, the competitive pressure comes from the more elastic substitution between products within the industry. We investigate the case where there is a 5% reduction in the price-cost margin. In the second experiment, the entry cost is reduced to introduce 50% more entrants. As the simulations show, the two policies have very different implications for firm R&D effort, firm turnover, and industry productivity. Increasing the elasticity of substitution between products increases a firm's innovation incentive but slows firm turnover. In the long run, a 5% drop in price-cost margin improves industry productivity by 2.8%. On the other hand, lower entry cost doesn't change the industry productivity. Although the market selection

[5]Bernstein and Nadiri (1989) report the same pattern using a dynamic duality approach.

is enforced by higher firm turnover, this is offset by a reduction in firm incentive to invest in R&D.

The paper is organized as follows. The following section highlights several interesting aspects of the data and motivates the modelling strategy. The related literature is also reviewed. The second section describes the economic environment and the industry equilibrium. The third section estimates and reports the model parameters. We implement counter-factual simulations of a set of policy changes and conclude in the final section.

3.1.1 Korean Electric Motor Industry

This paper will analyze a panel data set of Korean plants that manufacture electric motors (SIC31101 and SIC31102) from 1991 to 1996.[6] The data is from the Korean Annual Mining and Manufacturing Survey, which is collected by Korean Statistical Office for all the establishments with more than 5 workers on an annual basis. Environmental concerns have put energy efficiency on high priority for a lot of governments, including Korea. As an intermediate input sector, electric motor industry is important in this respect.

The majority of previous studies of R&D investment and knowledge spill-overs use data from Compustat or various kinds of R&D surveys, which usually include a limited number of firms competing in multiple industries.[7] Therefore, it is not a data set that meets the need of linking producer heterogeneity, industry structure and productivity dynamics. In our dataset, we observe a significant level of producer heterogeneity in size and capital intensity: the standard deviation of value-added shares in our sample is 4107.4, and the dispersion ratio of the 95 percentile over the 10 percentile is 39.88. Capital intensity (the ratio of capital over total value-added) has a standard deviation of 0.839, and the dispersion

[6] SIC31101 and SIC31102 is equivalent to NAICS 335312 (Motor and Generator Manufacturing) in U.S census. The establishments primarily engaged in manufacturing electric motors (except internal combustion engine starting motors), power generators (except battery charging alternators for internal combustion engines), motor generator sets (except turbine generator set units), and transformers.

[7] Griliches (1998) documents many studies using this data.

ratio of the 95 percentile over the 10 percentile is 36.78.

On the other hand, several features of the Korean electric motor industry data provide support for the estimation of our empirical model. First, each establishment reports detailed R&D expenditure on an annual basis, which provides us with a measure of its learning input. Second, electric motors is a manufacturing industry with a long history, mature technology and a large number of single-establishment firms.[8] Furthermore, the primary competition within this industry is based on producing motors with higher energy efficiency and lower cost. Firm R&D investment serves this purpose, and industry incumbents usually engage in in-lab process innovation. In our sample, 14.4% of firms have conducted active R&D investment, and among them the R&D intensity has a standard deviation of 0.387, and the dispersion ratio of 95 percentile over 10 percentile is 34.44.

Lastly, starting from 2000s, Korean Government is focusing on promoting knowledge-intensive industries such as Korean Electric Motor Industry. First, Korean Government is providing direct subsidy to R&D activities. For example, Korean Government is enacting tax deduction for facilities investments in research tests (Jung and Mah, 2013). Second, Korean Government is solidifying the foundation of R&D activities carried out by public research institutes, universities, and private companies, hence enhancing the communication between private and public institutes. Therefore, under such policy changes, it is important for us to learn how direct subsidy and R&D spillover will affect the aggregate R&D efforts and productivity in this industry.

The model we use in this paper is in part motivated by these observations. It intends to reconcile the observed producer heterogeneity in size, growth, decline, capital intensity and R&D intensity with the theory of optimizing agents. At the heart of the model is a stochastic process of individual producer's productivity, which is driven by past R&D investment and idiosyncratic shocks. Meanwhile each producer also invests in physical capital based on their expectations about the evolution of their own productivity and industry structure. Thus R&D expenditure, physical investment, exit and entry are the policy functions of

[8] On average 82% of the plants in the data are single-plant firms.

each producer's dynamic optimization problem. Given some initial industry state, some producers grow stronger and gain market share, while others become weaker and finally exit the industry. An equilibrium is defined when the industry evolution is consistent with individual producer's perception.

3.1.2 Related Literature

There are three separate but relevant lines of literature that are related to this paper. The first builds the link between market structure and productivity. There have been two mechanisms explored by recent work. A series of papers by Aghion et al (2001, 2005 and 2006) emphasize this link by considering firm innovation effort as the primary source of productivity improvement.[9] Either market competition or entry pressure affects industry productivity through the change in each firm's R&D decisions. Using micro-level panel data from the UK, Aghion et al (2006) show that an entry threat spurs innovation incentives in sectors close to the technological frontier while in lagging sectors it discourages innovation. A second mechanism that has been emphasized in the literature is the impact of market competition on the process of resource reallocation among firms. Hopenhayn (1992) and Melitz (2003) are two examples. They abstract from the endogenous innovation considerations by taking firm productivity as exogenous. The primary mechanism they emphasize is the role of more intense market competition on resource allocation from less to more productive firms or the selection of more productive firms to stay in operation. On the empirical side, Foster, Haltiwanger, Krizan (2000) tests this mechanism using U.S. census data. Aw, Chung and Roberts (2004) use various two-digit industries from Korea and Taiwan and find that impediments to exit or entry can explain the difference in productivity and turnover patterns between the same industry in those two countries. Tybout (2000) reviews evidences from previous studies on developing countries. In summary, both mechanisms, "active learning" and "market selection" are confirmed to play a role. In our empirical model, both these mechanisms are present as a result of individual firm's opti-

[9]Earlier works start with Dasgupta and Stiglitz (1980) and Aghion and Howitt (1992).

mization decisions.

The second line of literature explains and substantiates firm innovation efforts, especially the production experience and ideas the firms can obtain from each other freely *within* one specific industry. There have been quite a few game theoretical papers that analyze firm technology innovation decisions when knowledge spill-overs are present. Specifically, Spence (1984) proposes a model of firms with Cournot competition in a homogeneous good. Each firm's cost depends on their accumulated industry knowledge. In a symmetric market equilibrium, he shows that with a positive spill-over, industry R&D is lower than the optimal level. However, as Jennifer Reinganum (1989) summarizes in her review article, "since it is largely restricted to special cases (e.g. deterministic innovations, drastic innovations, two firms, symmetric firms), this line of work has not yet had a significant impact on the applied literature in industrial organization; its usefulness for policy purposes should also be considered limited". In contrast, the empirical studies have found enormous heterogeneity across firms in their R&D decisions. Cohen and Klepper (1992), for instance, show that the distribution of firm R&D intensities within industries tends to be uni-modal, positively skewed, with a long tail to the right and to include a large number of non-performers. To match the empirical observations, it will be crucial to have a model which can accommodate firm-level heterogeneity in the investment decision. In terms of empirical studies, both Jaffe (1988) and Bloom, Schankerman and Van Reenen (2004) use Compustat and U.S. patent data to derive the significance of these effects from a set of reduced form regressions using patent output, R&D or Tobin'q as dependent variables.[10] They find a significant "strategic effect" from product market competition and a "spill-over effect" from firms in close technological space. However, these previous studies don't look at the firm's R&D decisions using a dynamic industry equilibrium framework. Thus they are not able to provide predictions on the effect of firm's innovation effort on industry productivity and evolution.

Finally, the empirical model of this paper draws heavily from the fully-dynamic work-

[10]Jaffe (1988) used PICA database as additional source because product market information is provided by Compustat from 1993 onwards.

horse industry evolution models by Hopenhayn (1992) and Ericson and Pakes (1995). In particular, I adopt a recent simplification of the computational algorithm by Weintraub, Benkard, and Van Roy (2007). Weintraub, Benkard and Van Roy (2007) develop an algorithm for computing an "oblivious equilibrium", in which each firm is assumed to make decisions based on its own state and knowledge of the long run average industry state. They further prove that, if the industry is not highly concentrated, as the market becomes large the oblivious equilibrium closely approximates the Markov Perfect Equilibrium defined in Ericson and Pakes (1995).

3.2 A Dynamic Model of R&D Investment

3.2.1 Sequence of Actions

In this section we extend the model of dynamic competition by Weintraub, Benkard and Van Roy (2007) to incorporate a knowledge spill-over and physical capital accumulation. Time is discrete and indexed by $t = 1, 2, 3, ..., \infty$. The firms within an industry are indexed by $i = 1, 2, 3, ...$ For each period t, each firm's state $\omega \in \Omega$ can be described by a pair of knowledge x and physical capital k, where x takes discrete values from the set $\mathbb{X} = \{x^1 < x^2 < x^3 <, ...\}$ and k takes discrete values from the set $\mathbb{K} = \{k^1 < k^2 < k^3 <, ...\}$. Accordingly $\Omega \in \mathbb{X} \times \mathbb{K}$ takes all the possible combinations of knowledge capital and physical capital, which is also a set of discrete values. The industry state at each period t is denoted s_t. Each of its element $s_t(\omega)$ is the total number of firms at state ω. The set of possible industry states is denoted by $\mathbb{S}$.

At the beginning of period t, all the incumbent firms engage in competition in the product market and simultaneously set their prices for each period t. A firm with state (x_t, k_t) earns profit $\pi(x_t, k_t; s_t)$. Then, incumbent firms and potential entrants make their exit and entry decisions simultaneously. Each incumbent firm observes an idiosyncratic scrap value ϕ_t, which is *i.i.d.* across different firms and time and has a well defined density function with support $\mathbb{R}_+$. Given the industry state s_t and its own state (x_t, k_t), the firm decides

whether to exit. If it decides to exit, it can get the period profit plus the scrap value. The exit strategy $\chi_t = 1$ if a firm decides to exit and $\chi_t = 0$ otherwise. If it instead decides to remain in the industry, it can choose to invest in either knowledge capital or physical capital or both to improve its own state.

Meanwhile, there is also a pool of ex-ante identical potential entrants. To enter the industry, an entrant needs to pay a fixed amount of entry cost κ. Upon entry, the new entrants can draw their initial states from a distribution Φ^e. Each potential entrant compares its expected entry value with the entry cost to decide whether to become an incumbent next period. If it decides to enter, $\epsilon_t = 1$, otherwise $\epsilon_t = 0$. The number of firms entering at industry state s_t is a Poisson random variable, with mean $M(s_t)$.

In summary, the timing of events in each period is as follows:

1. Incumbent firms simultaneously set their prices to receive static period profit $\pi(x_t, k_t; s_t)$
2. Incumbent firms privately observe an idiosyncratic scrap value ϕ_t. If they exit, they get that value. If not, they make R&D and physical capital investment decisions.
3. Potential entrants decide whether to enter next period based on current industry state s_t. Each entrant pays a fixed entry cost κ.
4. Firms exit and receive their scrap values.
5. The investment outcome of each firm is realized, the new entrants enter and take their initial draws of x and k from a fixed distribution Φ_e.

3.2.2 Static Competition

We will first look at how firms interact with each other in the product market each period. We assume each firm within an industry has a standard Cobb-Douglas production function with returns to scale parameters γ.

$$q_t = exp(x_t)(l_t^{\alpha}(k_t)^{1-\alpha})^{\gamma}, \tag{3.1}$$

where q_t is the output of the individual firm. x_t captures how much a firm's knowledge lies behind the current frontier, so it has a maximum value of zero. k_t is physical capital input and l_t is labor input.

Each firm produces a differentiated product and each one of them faces a demand function such that

$$q_t = Q_t(p_t/P_t)^\eta = \frac{I_t}{P_t}(\frac{p_t}{P_t})^\eta \tag{3.2}$$

where p_t is the price set by the firm, while Q_t and P_t are the industry-level output and price index. Accordingly, I_t is defined as the industry market size at time t. This demand function is from the widely-used monopolistic competition model by Dixit and Stiglitz (1977). The parameter η captures the elasticity of substitution between different products. Notice that since there is a limited number of firms within one single industry, we follow Yang and Heijdra (1993) and assume that each firm's output decision influences the aggregate industry price index.[11]

Thus each period, a firm takes quasi-fixed factors (k_t, x_t), exogenous variable factor prices w_t, aggregate market price P_t as given and chooses variable inputs l_t to maximize its profit

$$\pi_t = p_t(I_t, P_t, q_t)q_t - w_t l_t. \tag{3.3}$$

We could rewrite this problem as

$$max_{l_t} P_t^{1+\frac{1}{\eta}} I^{-\frac{1}{\eta}} (exp(x_t) k_t^{(1-\alpha)\gamma})^{1+\frac{1}{\eta}} (l_t^{\alpha\gamma})^{1+\frac{1}{\eta}} - w_t l_t. \tag{3.4}$$

and the optimal labor decision is derived as

$$l_t^* = [\frac{w_t I^{\frac{1}{\eta}}}{(exp(x_t) k_t^{(1-\alpha)\gamma})^{1/\eta+1} P_t^{1+\frac{1}{\eta}} (1+1/\eta)\alpha\gamma}]^{\frac{1}{(1+1/\eta)\alpha\gamma-1}}. \tag{3.5}$$

[11] In the empirical application, we assume $I_t \equiv I$ is taken as exogenous to the model and time invariant. There have been recent interest in the interaction between aggregate uncertainty and firm responses (i.e., Bloom (2006)), which is out of the scope the current model.

In equilibrium, the normalized industry price index P_t is determined by the industry state s_t. Let $\varphi_t = exp(x_t)k_t^{(1-\alpha)\gamma}$ and $s_t(\varphi)$ be the number of firms whose $\varphi_t = \varphi$, then

$$P_t = I^{1-\alpha\gamma}(\frac{w}{(1+1/\eta)\alpha\gamma})^{\alpha\gamma}(\sum_{\varphi} s_t(\varphi)\varphi^{\sigma})^{-\frac{1}{\sigma}}. \tag{3.6}$$

where $\sigma = \frac{1+\eta}{\eta-(1+\eta)\alpha\gamma}$. Finally, the equilibrium maximized profit for firm with individual state $\varphi_t = exp(x_t)k_t^{(1-\alpha)\gamma}$ is

$$\pi(\varphi_t, s_t) = I(1-(1+\frac{1}{\eta})\alpha\gamma)\frac{\varphi_t^{\sigma}}{\sum_{\varphi} s_t(\varphi)\varphi^{\sigma}}. \tag{3.7}$$

In summary, the profit of each firm only depends on their relative magnitude of knowledge capital x_t and physical capital k_t. Under competition the implied cost reductions show up in a decline of the aggregate price index.

3.2.3 Transition of States: Knowledge Production and Physical Investment

Each period, a firm can choose to invest in either knowledge capital or physical capital or both to improve its own state. There are major differences between the two types of investment. Consider a firm with state (x_t, k_t). The investment in physical capital has a deterministic outcome. It also involves an adjustment cost $c(k_t, k_{t+1})$. So a firm could directly choose the level of physical capital k_{t+1} for next period. In contrast, the improvement of knowledge capital involves uncertainty and depends on the firm's own R&D, competitor's R&D, and its current knowledge capital level.

For each period t, firms exert learning effort to keep up with or to close their gap with the current frontier technology. The input of knowledge production consists of two components. One part is the firm's own research and development $d_t = d(x_t, k_t; s_t)$, and the cost of knowledge production is $c_d \cdot d_t \cdot k_t^{d_k}$, where the per-unit cost is larger for larger firms, if d_k is larger than 0. The other part is the R&D spillover from other establishments competing in the same industry d_{-t}. So the transition of knowledge capital from x_t to x_{t+1} is determined jointly by d_t and d_{-t}, and also subject to uncertainty. We assume that

within a narrowly defined industry, "technology space" and "product space" are reasonably well overlapping. Thus, the rival establishments' technological positions will affect a firm's knowledge production directly. In our model, the spillover effect for a firm with individual state (x_t, k_t) is defined as

$$\sum_{x>x_t} \sum_{k} \theta \frac{s_t(x,k)}{N_t}$$

Recall that s_t is the industry state at time t, and N_t is defined as the total number of incumbents at time t. This specification assumes that a firm gets the spillover only from the firms which have higher knowledge capital than it has. This brings a backward advantage for the incumbents who are far from the technological frontier.[12] The composite term entering the knowledge production takes the following form:

$$D_t = d(x_t, k_t; s_t) + \sum_{x>x_t} \sum_{k} \theta \frac{s_t(x,k)}{N_t}$$

This specification is related to Jovanovic and MacDonald (1994) in the sense that learning depends on the firm's state and actions, and on the state of the industry, including the distribution of know-how in use. [13] However, unlike Jovanovic and MacDonald (1994), in our model the decision to invest in R&D doesn't preclude the opportunity to get the knowledge externality. The effectiveness of R&D in improving the next period productivity also depends on how big the firm builds itself into. This is also consistent with the empirical observations that while total R&D investment increases with the size of the firm, the R&D intensity is independent of firm size. [14]

Furthermore, like Weintraub, Benkard and Van Roy (2007), there is an idiosyncratic

[12] Using UK plant-level data, Grifflith, Redding, and Simpson (2005) shows that technology transfer plays an important role in productivity improvement of non-frontier establishment.

[13] Jovanovic and MacDonald (1994) show that in a competitive industry, imitation by the firms that lag behind the frontier force some convergence of technology among establishments as the industry matures.

[14] See Klette and Kortum (2004) for a nice summary of the patterns of R&D investment and their relationship with productivity.

exogenous depreciation shock each firm will suffer with probability δ each period. In reality, it could capture two risks faced by individual firms. The first one is the firm level "organizational forgetting" documented by Benkard (2004), which causes the production process less efficient. The second one is the possibility that an individual firm has difficulty keeping up with the improvement in the industry frontier such that its relative position deteriorates. With all the pieces we described so far, we can now introduce the knowledge production function. Specifically, for $x_t = x^j \in \mathbb{X}$

$$x_{t+1} = \begin{cases} x^{j+1}, & \text{with probability } \frac{(1-\delta)D_t}{1+D_t}; \\ \\ x^{j-1}, & \text{with probability } \frac{\delta}{1+D_t}; \\ \\ x^{j}, & \text{with probability } \frac{1-\delta+\delta D_t}{1+D_t} \end{cases} \tag{3.8}$$

The firm needs to pay an extra investment cost $c(k_t, k_{t+1})$ for adjusting physical capital level from k_t to k_{t+1}. By normalizing the purchase price of capital $c_k = 1$, we specify the adjustment cost of each establishment as:

$$c(k_t, k_{t+1}) = c_a(i_t/k_t)^2 k_t, \tag{3.9}$$

where $i_t = k_{t+1} - (1 - \delta_c)k_t$ is the investment (divestment), c_a is the parameter for the component of convex cost of adjustment.[15]

3.2.4 Incumbent's Maximization Problem

Given the knowledge production technology described in the last section, for an establishment with (x_t, k_t) the value of continuation $V_c(x_t, k_t; s_t)$ is given by

$$\begin{aligned} V_c(x_t, k_t; s_t, \phi_t) = max_{d_t, k_{t+1}} (1-\xi) \cdot \{ & -c_d d_t k_t^{d_k} - c_k(1 - \mathbb{1}_{\{i_t<0\}} \cdot \wp) \cdot i_t \\ & -c(k_t, k_{t+1}) + \beta E_{s_{t+1}}[V(x_{t+1}, k_{t+1}; s_{t+1}) | x_t, d_t, d_{-t}, s_t]\} + \xi \cdot \phi_t, \end{aligned} \tag{3.10}$$

[15]The presence of irreversibility is emphasized by Abel and Eberly (1996). We also estimated the model using a slightly different version that incorporated a parameter for resale cost. All our results are robust with this change.

where $d_t(x_t, k_t; s_t)$ and $k_t(x_t, k_t; s_t)$ are associated policy functions. c_d is the cost of per unit of R&D input, and d_k is the parameter of r&d cost w.r.t. capital size. One caveat is that there is an asymmetry of divestment (by the degree of $\wp$).

Let $V(x_t, k_t; s_t)$ be the establishment's value at the beginning of the current period. Each period, each incumbent establishment decides whether to stay or exit, so

$$V(x_t, k_t; s_t) = \pi^*(x_t, k_t; s_t) + E_{\phi_t}[max\{V_c(x_t, k_t; s_t, \phi_t), \phi_t\}], \tag{3.11}$$

where ϕ_t is the scrap value, which is assumed to be a random variable with distribution $U[0, u_b]$, and ξ is an exogenous exit rate. The incumbent's decision rule $\chi(x_t, k_t; \phi_t, s_t) = 1$ if it decides to exit, $\chi(x_t, k_t; \phi_t, s_t) = 0$ otherwise.

3.2.5 Entrant's Problem

The potential entrants are ex-ante identical. Upon entry, they draw their initial endowment of x and k. It is assumed that each period's exogenous technological progress is embodied in the new generations of potential entrants to the industry. So their *relative* technological positions are drawn from a time invariant distribution Φ^e. Each potential entrant incurs entry cost κ. Potential entrants' decision $\epsilon = 1$ if

$$V_e(s_t) \equiv \beta E_{s_{t+1}}[\int V(x_e, k_e, s_{t+1}|a, \epsilon) d\Phi^e|s_t] \geq \kappa. \tag{3.12}$$

The mass of entrants for time t is a poisson random variable with mean $M(s_t)$.[16] The new entrants give additional competitive pressure to the incumbents' improvement. Any incumbent who can not keep up with the technological frontier's movement is going to be finally driven out of the business by superior "new generations".

[16]The poisson random variable is justified by the following entry model: there are N potential entrants, $v_N(i)$ is the expected present value for each entering firm if i firms enter simultaneously. Each potential entrant employs the same strategy, the condition for a mixed strategy Nash Equilibrium is: $\sum_{i=0}^{N-1} C_{N-1}^i p_N^i (1-p_N)^{N-1-i} v_N(i+1) = \kappa$. The equation has a unique solution $p_N^* \in (0,1)$, the number of firms entering is a binomial random variable Y_N with parameters (N, p_N^*). As $N \to \infty$, $Y_N \Rightarrow Z$, which is a poisson random variable with mean M.

3.2.6 Equilibrium

Following Ericson and Pakes (1995) and Weintraub, Benkard and Van Roy (2007), we define symmetric markov perfect strategies to be an action denoted by $a \in \mathbb{A}$ and entry decision $\epsilon \in \Lambda$. Specifically in our case, $a = \{d, k, \chi\}$, where $d : \Omega \times \mathbb{S} \times \mathbb{R}_+ \to R_+$ is each firm's R&D investment strategy, $k : \Omega \times \mathbb{S} \times \mathbb{R}_+ \to \mathbb{K}$ is its physical investment strategy and $\chi : \Omega \times \mathbb{S} \times \mathbb{R}_+ \to \mathbb{R}_+$ is its exit strategy. Similarly, define the entry strategy for potential entrants as: $\epsilon \in \Lambda : \mathbb{S} \to \mathbb{R}_+$. Define the value function $V(x, k, s|a', a, \epsilon)$ as the expected discounted payoffs for a firm at individual state (x, k) and industry state s playing strategy $a' \in \mathbb{A}$ while all rival firms follow strategy $a \in \mathbb{A}$ and potential entrants follow strategy ϵ. Then Markov Perfect Equilibrium strategies a and ϵ satisfy that:

1. For an incumbent $V(x, k, s|a, a, \epsilon) \geq V(x, k, s|a', a, \epsilon)$, $\forall a' \in \mathbb{A}$

2. Entrants satisfy the zero profit condition such that $\beta E_{s'}[\int V(x, k, s'|a, \epsilon) d\Phi^e|s] \leq \kappa$, with equality if the mass of entrants $M(s) > 0$

3.2.7 Oblivious Equilibrium and Computation

In this section, we define an "Oblivious Equilibrium". This equilibrium concept is based on Weintraub, Benkard and Van Roy (2007) who establish that when the number of establishments is large, oblivious strategies, which ignore current information about competitors' states and are conditioned only on the knowledge of long run average industry state, can closely approximate a Markov Perfect Equilibrium. Let $\tilde{\mathbb{A}} \in \mathbb{A}$ and $\tilde{\Lambda} \in \Lambda$ be the set of oblivious strategies. Then for oblivious strategies $a = (d, k, \chi) \in \tilde{\mathbb{A}}$ and $\epsilon \in \tilde{\Lambda}$, the associated expected state of the industry in the long run is $S_{a,\epsilon}$. Define $\tilde{V}(x, k|a', a, \epsilon)$ as the expected payoff of an incumbent under the assumption that its competitors' state will be equal to $S_{a,\epsilon}$ in all future periods. Then oblivious equilibrium strategies a and ϵ satisfy, given self-generated $S_{a,\epsilon}$:

1. For an incumbent $\tilde{V}(x, k|a, a, \epsilon) \geq \tilde{V}(x, k|a', a, \epsilon)$, $\forall a' \in \mathbb{A}$

2. Entrants satisfy the zero profit condition such that $\beta \int \tilde{V}(x, k|a, \epsilon) d\Phi^e \leq \kappa$, with equality if the mass of entrants $M > 0$

Weintraub, Benkard, and Van Roy (2007) proves that when incumbent's strategies and the entry rate function are oblivious, the industry state s_t is an irreducible, aperiodic and positive recurrent Markov Chain. Their key insight is that when there are a large number of firms and the market tends not to be concentrated, each individual firm can not benefit by unilaterally deviating to an optimal (non-oblivious) strategy by keeping track of the true industry state, *averaged over the invariant distribution of industry states.* In other words, in any industry state that has significant probability of occurrence, the oblivious strategy approximates the Markov Pefect Strategy.

The Oblivious Equilibrium provides an attractive alternative for our estimation and computation purpose. The Korean electric motor industry, which is already a detailed level 5-digit industry, still has on average 180 firms each year during our sample period. It's infeasible, and possibly unreasonable, to assume that each firm keeps track of industry state every single period and solves their optimization problem and computes the industry equilibrium. On the other hand, the model structure still allows for strategic interactions between heterogeneous firms and can accommodate important industry aspects such as an imperfectly competitive product market and the R&D spill-overs across different producers.

Our procedure for calculating the equilibrium will follow the above definition closely. Given a set of parameters, the steps to compute the equilibrium are:

1. Initial guess of the mean number of entrants M

2. Initial guess of the average long run industry structure s_0

3. Solve the monopolistic competition equilibrium aggregate price P given s_0.

4. Solve the incumbent's maximization problem and recover their optimal investment policy and exit policy: $a = (d, k, \chi)$ given s_0.

5. Construct the transition matrix $T_{x,k,\chi}$ using the optimal policies. The long run average industry structure is calculated as $s_1 = M(I - T_{x,k,\chi})^{-1}\Phi^e$.

6. If $|s_0 - s_1|$ is not close enough, go back to step (2).

7. Check the free-entry condition of potential entrants. If it doesn't hold, go back to step (1).

3.3 Estimation of Model Preliminaries

3.3.1 Korean Electric Motor Industry Data

The Korean Annual Manufacturing Survey reports detailed information on each producer's physical investment, R&D investment, number of workers and value-added. In this section I will briefly review some key data patterns for the electric motor industry.

First, by tracking each firm over the years, we assign them into three groups: those who survive until the end of 1996 and increase their total value-added shares compared with the beginning of sample, those who survive until the end of 1996 but decrease their total value-added shares, and those who exit the sample before the end of 1996. Table 1 summarizes the productivity change and investment patterns for each of three groups. Plant productivity is systematically correlated with plant expansion, decline and exit. Notice that the change in plant productivity, measured by differences in log TFP from 1991 to 1996 for expanding plants, is 0.029. The change is significantly higher than that of the other two groups. The plants that expand also invest much more. After controlling for the scale of plants,the improving plants' investment to value-added ratio is on average 0.133, 50% more than those who exit and 300% more than those who deteriorate. We also report the average R&D investment and R&D intensity of each plant over the sample period.[17] There is a strong positive relationship between average R&D intensity and the change in productivity over the years. The R&D intensity of expanding plants is four times more than that of the other two groups.

[17]For plants that exited, until the year of their exit.

Table 3.1: Success and Failure of 1991 Establishments

Different Life Path	Survive and Expand Output	Survive and Reduce Output	Exit by 96
LnTFP(end)-LnTFP91	0.029	0.021	−0.025
	(0.291)	(0.054)	(0.134)
Investment in Capital	668.790	48.954	80.459
	(1546.40)	(84.569)	(211.951)
Investment Intensity (I/Vadd)	0.133	0.031	0.085
	(0.152)	(0.027)	(0.171)
R&D	150.148	13.444	9.773
	(615.976)	(40.333)	(33.911)
R&D Intensity (R&D/Vadd)	0.027	0.006	0.006
	(0.093)	(0.017)	(0.02)

R&D and investment in millions of won. Standard Deviations in Parentheses.

Second, a considerable fraction of producers report zero R&D expenditure.[18] The R&D performers account for only 15% of the total observations during the sample years. The average R&D expenditure is 39.27 million won per year.[19] The major components of it are the wages for R&D workers and materials for R&D. As in Figure 1 and consistent with many previous empirical findings, the distribution of R&D intensity is positively skewed.[20] Among R&D performers, R&D intensity is negatively correlated with size, measured using either labor or capital.

[18]Doraszelski and Jaumandreu (2006) reports similar patterns of R&D expenditure using Spanish Manufacturing Survey data.

[19]The average exchange rate between won and U.S. dollar during the sample period is 786:1.

[20]For instance, Cohen and Klepper (1992) reports the R&D intensity in FTC Line of Business Data to be positively skewed, with a long tail extending to the right.

Table 3.2: Summary Statistics

variable	mean	std.	1%	median	99%	N
R&D expenditure	24.02	203.15	0	0	598	2767
R&D expenditure/Value-added	0.01	0.13	0	0	0.25	2767
Physical capital	637.83	2871.55	0	78.96	15194.3	2767
Physical investment	113.49	636.86	−39	2.83	2209	2767
Value-added	1052.515	4107.37	29.19	247	19026	2767
Wage bills	429.37	1616.64	17.8	113.36	6503.98	2767

units of variables: millions of won

Units of variables: millions of won

Third, we observe significant resource reallocation during the sample period. Physical investment at the establishment level, which includes net capital expenditures (purchase minus sales) on buildings, machinery/equipment, and transport vehicles, averages 173.45 million won per year. There is huge heterogeneity in plant investment decisions, ranging from −40 (1 percentile) to 6439 (99 percentile). The electric motor industry also features high turnover. The average annual entry rate of new establishments on average is .34 and the exit rate of incumbents is .28 over the sample years.

Finally, the data does not provide information on physical units of output. Establishments show large dispersion in their value-added and labor size. On the cost side, we also have the information on total material expenditure and total wage expenditure for each establishment per year. The ratio of total revenue and total cost is stable at approximately 1.22 over the years.

3.3.2 Estimating Production Function and Demand Elasticity

The first stage of estimation focuses on the static part of the model, the production function and the demand curve faced by the industry. The key parameters to be recovered from this stage are the demand elasticity η and the returns to scale γ. Furthermore, given consistent estimates of the production function, establishment level productivity for each time period can be constructed.

To be consistent with the theoretical model, we assume that labor is short-run variable input, while capital is quasi-fixed. The empirical production function for each establishment i at time t is assumed to take the following form

$$Q_{it} = L_{it}^{\alpha_{lit}} K_{it}^{\alpha_{kit}} exp(\alpha_0 + x_{it} + u_{it}) \tag{3.13}$$

where $\alpha_0 + x_{it}$ is the productivity and u_{it} is an i.i.d. idiosyncratic shock. Notice that α_{lt} and α_{kt} are not restricted to be constant over time. Equation (14) can be rewritten in logarithm terms as

$$q_{it} = \alpha_0 + \alpha_{lit} l_{it} + \alpha_{kit} k_{it} + x_{it} + u_{it} \tag{3.14}$$

Then we follow ACF(2015) in estimating the production function. Assume that a firm's material input demand at t is obtained from a non-parametric and invertible function $f_t(\cdot)$ where

$$m_{it} = f_t(x_{it}, k_{it}, l_{it})$$

Substitute this back into equation (15), we will get

$$q_{it} = \alpha_0 + \alpha_{lit} l_{it} + \alpha_{kit} k_{it} + f_t^{-1}(m_{it}, k_{it}, l_{it}) + u_{it}. \tag{3.15}$$

However, since real output is not observed, we will use the information from the demand structure to rewrite this equation in terms of deflated value-added.[21] The plant-level

[21] I will need a quite restrictive demand structure (Dixit-Stiglitz). Considering the large number of firms in the industry, it is a reasonable approximation. Katayama, Lu and Tybout (2005) provide an alternative based on a nested-logit demand model.

demand

$$Q_{it} = (Q_{It})(P_{it}/P_t)^{\eta}$$

can be written in logarithm terms as:

$$p_{it} - p_{It} = \frac{1}{\eta}(q_{it} - q_{It})$$

Combined with the fact that log total revenue is

$$r_{it} = p_{it} + q_{it}$$

we have the p_{It} deflated revenue $\tilde{r}_{it}$ as:

$$\tilde{r}_{it} = (1 + \frac{1}{\eta})q_{it} - \frac{1}{\eta}q_{It} \tag{3.16}$$

Finally, substituting the production function for q_{it} we defined in equation (16), we get an equation linking deflated plant revenue and the production function, demand parameters and plant productivity:

$$\tilde{r}_{it} = \tilde{\alpha}_0 + \tilde{\alpha}_{lit}l_{it} + \tilde{\alpha}_{kit}k_{it} + \tilde{f}_t^{-1}(m_{it}, k_{it}, l_{it}) + \tilde{u}_{it}. \tag{3.17}$$

Then in the second stage, we assume the productivity evolves according to a Markov Process, where

$$\begin{aligned} x_{it} &= g(x_{it-1}, d_{it-1}) + \xi_{it} \\ &= m_0 + m_1 x_{it-1} + m_2 \log(\frac{D_{it-1}}{K_{it-1}}) + \xi_{it} \end{aligned} \tag{3.18}$$

Then we rely on following moment conditions to estimate the model:

$$E\left[\xi_{it}\begin{pmatrix} l_{it-1} \\ k_{it-1} \\ l_{it-1} \cdot k_{it-1} \end{pmatrix}\right] = 0 \tag{3.19}$$

The estimation results are reported in table 3. The estimated mark-up is approximately 1.0138.

Table 3.3: Production Function Parameters

	ACF
$\tilde{\alpha}_l$	0.6403*
	(0.008)
$\tilde{\alpha}_k$	0.3735*
	(0.003)
m_0	0.4287*
	(0.002)
m_1	0.7947*
	(0.003)
m_2	0.0046*
	(0.000)

Significant at the 1% level. Standard Errors in Parentheses.

3.4 Estimation of Dynamic Parameters

Given the first stage estimates of production function coefficients $\tilde{\alpha}_0$, $\tilde{\alpha}_k$ and the demand elasticity η, we estimate the set of dynamic parameters $\Theta_0 = [d_k, c_d, c_a, u_b, \delta, \theta, \wp]$ in the second stage. The first parameter d_k is the cost parameter of r&d with respect to capital size, which captures the effect of capital size on r&d cost. c_d is the effectiveness of R&D inputs to improve plant knowledge capital. c_a is the physical capital adjustment cost. u_b is the parameter of plant's scrap value distribution. δ represents the idiosyncratic uncertainty of the change in plant-level knowledge capital. θ controls the size of R&D spillover effect, and $\wp$ captures the asymmetry of divestment of physical capital. Since the estimation involves solving a complicated dynamic industry equilibrium with no closed form solutions, we use the method of simulated moments approach, which minimizes a distance criterion between key moments from the actual data and the simulated data.

Recent empirical techniques have been proposed to estimate the dynamic industry equilibrium model without solving the equilibrium. Especially related to this study is the estimation procedure proposed by Bajari, Benkard and Levin (2006), which handles both continuous and discrete control variables. Their approach breaks the estimation into two stages. In the first stage, firm policy functions are recovered by regressing observed actions on the observed state variables. The probability distribution which defines the evolution of the state of the industry is also recovered at this stage. In the second stage, the structural parameters which make these observed policies optimal are estimated. The major breakthrough of their approach is to avoid the computational burden of Markov Perfect Equilibrium, with trade-off of the precise calculation of agent's value function and policy function.

We only have the plant-level data for one single industry over a six year period, while the possible state space is very large. It makes the sampling error of estimating the policy functions a major concern if we were to adopt the strategy of Bajari, Benkard and Levin (2006). On the other hand, the large number of firms and low industry concentration make the weaker notion of equilibrium-Oblivious Equilibrium especially attractive, since it is proved to be a good approximation of MPE in this case.

However, there is also a cost of using Simulated Method of Moments at this stage compared with Bejari, Benkard, Levin (2006). The industry evolution model we use is not proved to have a unique equilibrium in general. Although the profit function, production technology, and the entrant's initial distribution are estimated without computing the model, there is a risk that the computational algorithm might select a different equilibria than that observed in the data. On the other hand, since we are only focusing on one single industry, this problem is alleviated by matching a full set of moments on policies and transition of states from observed and simulated data, which allow the data to confirm the correct equilibrium. Nevertheless, the uniqueness of the computed equilibrium is a strong assumption.

3.4.1 Moments

In this section, we describe the set of data moments utilized and how they are relevant for the identification of key parameters. The sample we use to estimate the dynamic parameters is an unbalanced panel of plants in the electric motor industry at year 1991 and their subsequent annual observations through 1996. All the entrants in subsequent years are only used to construct a frequency estimate of the initial state distribution Ψ^e and are excluded from the construction of moments.

Table 5 report the moments we use in our estimation. The first set of moments captures the key features of optimal plant R&D investment behavior in equilibrium. The R&D investment cost c_d affects plant's R&D investment intensity. It is also the driving force behind the productivity improvement of R&D performers. On the other hand, the idiosyncratic shock δ is shaped by the proportion of positive r&d investors. Given its own technological position and expectation on industry productivity evolution, a plant makes an optimal decision on whether to stick with the "corner solution" of investing zero R&D. Thus, the fraction of R&D performers is affected by δ. Notice here that all moments of the change of firm productivity overtime are constructed conditional on survival. So they are also affected by the industry competition and turnovers.

The second set of moments described in Table 5 relate to the plant's physical investment behavior. Following Cooper and Haltiwanger (2005), the cost parameters c_a helps to capture the nonlinear relationship between plant-level investment and profitability. The level of the investment ratio and the fraction of plant's positve investment depend critically on its magnitude. Fraction of divestment identifies parameter $\wp$, which controls the asymmetry of divestment, and the covariance between adjusted investment and productivity level helps identify d_k, which determines the effect of capital on R&D expenditure. On the other hand, since we model firm's investment behavior within an industry equilibrium, the investment moments also help to pin down other key model parameters such as intensity of competition, technological spill-over and R&D costs. Recent empirical investment literature also emphasized the role of partial irreversibility in describing micro-level plant investment

behavior, i.e. if the plant has to incur a significant loss by selling its existing asset, then it takes more caution to invest during periods of high productivity shocks. On the other hand, when there is a negative shock plants tend to hold on to capital. We estimated a slightly more complicated model of incorporating this feature and the estimation results on all other parameters turn out to be robust to this extension.

Thirdly, the long run exit pattern helps to identify the scrap value distribution parameter.[22]

Finally, we use the autocorrelation between productivity to identify parameter θ, which controls the R&D spillover effect: we simulate a sequence of $\{x_{it}\}$ from our structural model, and calculate the autocorrelation based on the simulated sequence of productivity. More specifically, we run the second-stage estimation of the production function on the simulated sequence of productivity, where

$$\begin{aligned} \hat{x}_{it} &= g(\hat{x}_{it-1}, \hat{d}_{it-1}) + \xi_{it} \\ &= \tilde{m}_0 + \tilde{m}_1 x_{it-1} + \tilde{m}_2 \log(\frac{\hat{D}_{it-1}}{\hat{K}_{it-1}}) + \xi_{it} \end{aligned} \tag{3.20}$$

Then we match the estimated coefficients $\tilde{m}$'s with the coefficients m's estimated from the data, by changing the spillover parameter θ.

[22]Obviously, the other moments are also affected by the exit pattern of incumbent firms in an industry equilibrium setting.

Table 3.4: Key Data Moments

	Identification	Data
R&D Investment and Productivity Improvement		
fraction of R&D performers	pin down δ	11%
R&D intensity of performers (R&D/Value-added)	pin down c_d	0.06
std relative productivity level	pin down δ/c_d	0.30
Physical Capital Investmet		
mean investment ratio ($\frac{i}{k}_{it}$)	pin down c_a	.19
fraction of positive investment	pin down c_a	49.5%
fraction of divestment	pin down $\wp$	5%
Cov(i/K, X)	pin down d_k	0.08
Firm Turnover		
mean exit rate	pin down u_b	15%
Estimated Evolution Path of Productivity		
m_1 (coefficient of lagged productivity)	pin down θ	0.7879*
		(0.003)
m_2 (coefficient of $\frac{D_{it}}{K_{it}}$)	pin down d_k	0.0046*
		(0.000)

3.4.2 Empirical Implementation and Computation Details

The estimation of the dynamic parameters Θ_0 is implemented according to the following procedures. First, denote the set of data moments in table 5 as Γ^d, which is a 10 by 1 vector. Second, for a given set of parameters Θ, the industry equilibrium is solved and optimal policy functions for R&D expenditure, physical investment and survival (d^*, k^*, χ^*) are generated. Third, initialized by the observed data in 1991, we use the optimal policy functions to simulate the path for each plant. Notice that for a single simulation, each plant's behavior and subsequently their investment outcomes need to be updated simulta-

neously for each time period. We are able to calculate $\Gamma^s(\Theta)$ for simulation s. Finally, the simulated moments are defined as:

$$\Gamma^S(\Theta) = \frac{1}{S}\sum_{s=1}^{S}\Gamma^s(\Theta)$$

The MSM estimate $\hat{\Theta}$ minimizes the weighted distance between data and simulated moments:

$$L(\Theta) = min_{\Theta}[\Gamma^d - \Gamma^S(\Theta)]'W[\Gamma^d - \Gamma^S(\Theta)]$$

where W is a positive definite matrix.

In our numerical analysis, $\hat{W}$ is calculated from a bootstrap procedure: we randomly re-sample the data, and calculate the interested moments for each sample, then we obtain a variance-covariance matrix based on these bootstrap samples.

The discretized space of productivity $\mathbb{X} \equiv [x_{\min}, x_{\max}]$, and the range of $\mathbb{X}$ is determined by standard deviation of productivity in the data. The number of grid M_x in $\mathbb{X}$ affects R&D incentives, because R&D investment is instantaneous and non-accumulative in our model. For example, move from some value x_0 to $x_0 + \Delta x$ needs more steps hence more R&D investment, if M_x is larger. Therefore, R&D expenditure will be higher if M_x is larger, given $x_{\min}$ and $x_{\max}$ are fixed. In our numerical analysis, M_x is chosen to balance the R&D incentive and computation burden. The discretized space of capital $\mathbb{K} \equiv [k_{\min}, k_{\max}]$. $k_{\min}$ and $k_{\max}$ are chosen to match $x_{\min}$ and $x_{\max}$ based on firm's static profit maximization strategy, where $k_{\min} = \frac{\log(\frac{\sigma(1-\alpha)\gamma}{c_k+\delta_k})+\sigma x_{\min}}{1-\gamma\sigma(1-\alpha)}$ and $k_{\max} \approx \frac{\log(\frac{\sigma(1-\alpha)\gamma}{(1-\beta)(c_k+\delta_k)})+\sigma x_{\max}}{1-\gamma\sigma(1-\alpha)}$. The number of grid M_k in $\mathbb{K}$ is chosen in a way that $\forall k \in \mathbb{K}, \delta K \in \mathbb{K}$. Otherwise, the discretized $\mathbb{K}$ will generate "unwilling" investment or divestment.

The objective function $L(\Theta)$ is from a complicated dynamic problem, thus is non-smooth and with many local optima. To handle this, we apply a recent approach proposed by Chernozhukov and Hong (2005), which develops a class of Laplace Type Estimators (LTE) to circumvent this problem in the computation of the classical extremum estimators. Their estimation procedure focuses on LTE, which are functions of integral transformations of the criterion function $L(\Theta)$ and can be computed using Markov Chain Monte Carlo. In addition,

we use their inference procedures to calculate confidence intervals from the quartiles of the Quasi-posterior distribution.

3.4.3 Estimation Results

Several of the model parameters are directly calculated from the data. The mass of entrants M is normalized to be 100, and we follow Cooper and Haltiwanger (2005) to set annual discounting rate β at 0.95 and annual rate of depreciation δ_c at 0.06. Finally, labor's share parameter is calculated as the average of sample observation's labor expenditure share α_{lit}. It has a value of 0.65. (M is 100, investment cost c_k is normalized to be 1, depreciation rate of capital δ_c is 0.15, discount rate β is 0.925, η is -5, exogenous exit rate ξ is 0.02, which is calculated as the exit rate of firms with both productivity and capital above the 90 percentile of the industry in the data).

The following table reports the point estimates and their $5\% - 95\%$ confidence interval. The point estimates are the mean of random draws from the posterior distribution using Markov Chain Monte Carlo. We use the M-H algorithm in Chernozhukov and Hong (2005) to derive the confidence interval for the point estimates.

Table 3.5: Dynamic Parameter Estimates

	Point Estimate	90% confidence interval
δ	0.72	$[0.43, 0.96]$
c_d	0.45	$[0.24, 0.67]$
θ	1.60	$[1.20, 1.97]$
d_k	0.30	$[0.07, 0.52]$
c_a	0.19	$[0.02, 0.34]$
$\wp$	0.47	$[0.06, 0.91]$
u_b	2.74	$[1.78, 3.79]$

By solving the industry equilibrium using the reported point estimates Θ, we can also

infer the fixed entry cost κ using the model's free entry condition, equation (13). To further evaluate the overall fit of the estimation, we also report the simulated moments at the point estimates in Table 3.6.

Table 3.6: Model Fit

	Data	Simulation
R&D Investment and Productivity Improvement		
fraction of R&D performers	11%	9%
R&D intensity of performers (R&D/Value-added)	0.06	0.06
std relative productivity level	0.30	0.24
Physical Capital Investmet		
mean investment ratio ($\frac{i}{k}_{it}$)	.19	.20
fraction of positive investment	49.5%	53%
fraction of divestment	5%	5%
Cov(i/K, X)	0.08	0.07
Firm Turnover		
mean exit rate	15%	14%
Estimated Evolution Path of Productivity		
m_1 (coefficient of lagged productivity)	0.7879*	0.7569*
	(0.003)	(0.000)
	0.0046*	0.0049*
	(0.000)	(0.000)

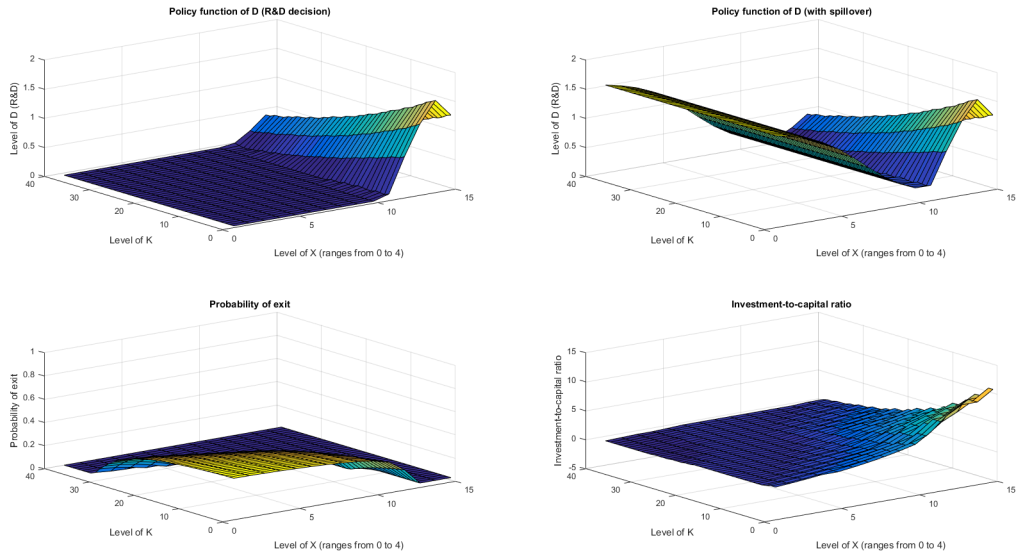
Simulation is conducted $100,000$ rounds with burn-outs.

The simulated data does a good job of repeating the pattern of R&D investment and the productivity evolution, which is the core piece of this model.

3.4.4 Evaluation of Results

The policy function derived from our simulation (with the estimated set of parameters) is shown as

Figure 3.1: Evaluation of Results

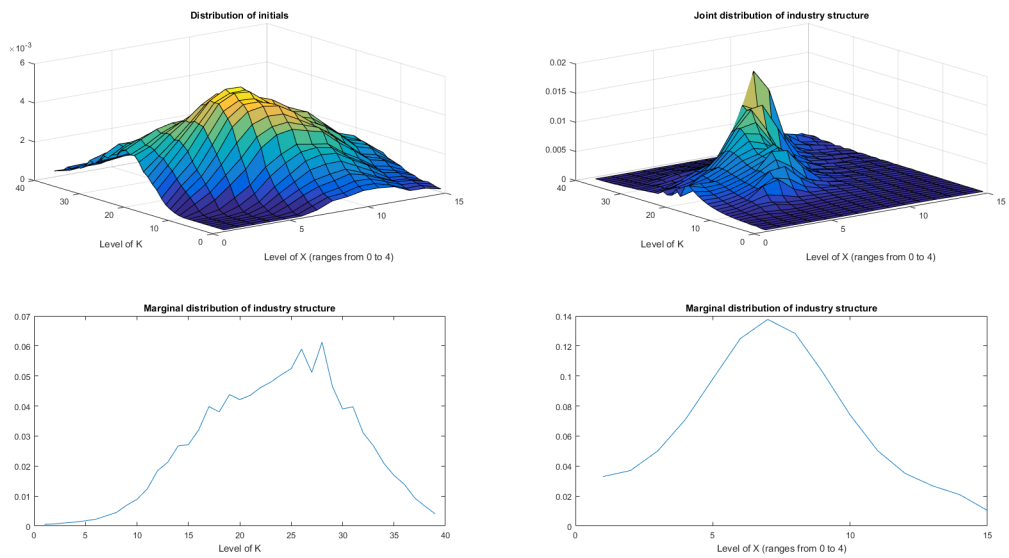


The top-left panel shows that firms with higher productivity are more willing to make R&D investment, but higher capital level lowers R&D incentive because it brings higher R&D investment cost. The kink in the top-left panel is driven by the limit of maximum productivity a firm can achieve in the model. The top-right panel shows the summation of individual R&D activity and R&D spillover. From the top-right panel we can see that backward firms enjoy a significant amount of R&D spillover. which helps them move upward in the spectrum of productivity. The bottom-left panel shows the probability of exit of firms in the (productivity, capital) space: firms with both low productivity and low capital have the highest probability of exit, which is around 0.34. The probability of exit decreases when either productivity or capital increases. After reaching certain threshold in the (productivity, capital) space, firms will only suffer from possibility of exogenous exit, which is 0.02 in our model. The bottom-right panel shows investment-to-capital ratio. Firms with high productivity and low capital have the highest incentive to make investment, which have an investment-to-capital ratio near 8.9.

Figure below shows distribution of industry structure. The top-left panel shows the distribution of entrant in our model, which has the highest density in the middle, but

smoothly distributed through the entire (productivity, capital) space. The top-right panel shows the distribution of industry structure in the equilibrium, from which we can observe that the industry is much more concentrated to states with middle-to-high level of capital, and middle level of productivity. The bottom-left and bottom-right panel shows the marginal distribution of capital and productivity in the equilibrium respectively.

Figure 3.2: Distribution Plots



How do the magnitude of the point estimates compare with previous studies? First, examine the R&D spill-over parameter θ, which has a value of 1.60. If we normalize the average R&D expenditure to 1 dollar, then a firm locating in the median of the spectrum of productivity will enjoy a 2.32 dollar R&D spillover from other firms. For a firm with lowest productivity in this industry, it will enjoy a 4.64 dollar R&D spillover from other firms. This may seem like a tiny amount at first glance, however, the total R&D spill-over pool is much larger relative to any producer's own spending. Taking into account that the R&D spill-over is a public good and affects the knowledge capital improvement of every producer, including those who do not perform R&D by themselves, spill-overs are important even though the magnitude of θ is small. Bloom, Schankerman and Van Reenen (2005) report that the private value of 1 dollar of spill-over is worth about 3 cents of own R&D in terms of the effect on market-value. Jaffe (1986) gets a similar number considering the

effect on firm patents. Both of these studies use patent information to construct the "true" relevant R&D for each firm. Thus it is not surprising that their estimate of θ is about 2 times larger than what I find for the Korean electric motor industry. But without further information to link my data with Korean patent data, it's infeasible for me to narrow the range of firms in the pool like they do. Second, the idiosyncratic depreciation probability δ equals 0.72. It captures the two forces that erode the plant-specific knowledge, both because of the improvement of the industry frontier and because the loss of its own knowledge. The estimated R&D expenditure parameter of capital d_k is 0.3, which implies that higher capital results in higher unit-cost of R&D investment. Because d_k is less than one, it also indicates that incremental of R&D unit-cost is concave with respect to incremental of total capital.

In terms of quadratic adjustment cost, Cooper and Haltiwager (2005) reports a value of 0.225 while not controlling for fixed cost and 0.025 while controlling for fixed cost. Bloom (2006) reports a quadratic adjustment coefficient of 4.743 on a monthly basis, which implies a yearly value of 0.39. Our estimate of c_a, which equals 0.19, is slightly lower. It indicates that it is less costly to acquire or sell physical capital in the Korean electric motor industry. Our estimate of divestment parameter $\wp$ is 0.47, which implies that divestment will have a price discount of capital around 50%.

The estimated upper bound of scrap value distribution ub implies an unconditional mean of ? mil won, which is around four times of the industry average profit. On the other hand, the entry cost implied from free-entry condition is ? mil won. These values results in a quite narrow hysteresis band, which is driven by the high turnover rate observed in the data.

3.5 Policy Simulation: Competition, Innovation and Productivity

Korea's S&T policy is geared to acquiring core competences in strategic technology areas and developing an innovation system that will enable the nation to make a successful

transition toward a knowledge–based economy. To achieve this policy goal, the Special Law for S&T Innovation was enacted in 1997. In accordance with the law, the Five–year Plan for S&T Innovation was launched in 1997. The plan contains specific plans for action to achieve the policy goal:

1. Corporate tax deduction of 50% of the increase in R&D and HRD investments over the annual average investments of thepast four year or 5% if the current expenditures for the same purposes (15% for SMEs).

2. Corporate tax deduction of 5% of the total investment in equipment and facilities for R&D and/or HRD. Direct R&D subsidy for SMEs within KWR 100 million or 75% of the total investment.

In brief, the goal of this government policy is to increase R&D intensity in the Korean electric motor industry. However, because of the existence of R&D spillover, there is a trade-off between increasing aggregate R&D efforts and increasing aggregate productivity. More specifically, because of R&D spillover, firms with low productivity will have low incentive to invest in R&D activities because of their relative position in the spectrum of industry-wide productivity. Therefore, the impact of R&D subsidy will be different, depending on the different level of R&D spillover in this industry.

The goal of our policy simulation is to study how aggregate productivity and aggregate R&D efforts will respond to R&D subsidiary plans, given different level of R&D spillover effect. We will provide a menu of responses based on different policy simulations.

Using the structural estimates from previous section, we are able to simulate the industrial response from this policy change. Moreover, the oblivious equilibrium concept provides a nice way to summarize the average long run industry state, which is based on the equilibrium strategies of the plants. Statistics can be constructed from this long-run industry state to reflect the policy effect over a relatively long period. In addition, the industry evolution patterns before and after the policy change can also be simulated. Theses will highlight the short run transitory dynamic effects.

The first exercise is to examine by how much R&D spillover affects aggregate R&D

efforts and hence dispersion of productivity among firms. With higher spillover effect θ, firms will have lower incentive to invest in R&D because now it is harder to differentiate from other firms by performing R&D. However, as a result dispersion of productivity will be smaller if the spillover effect θ is higher. To disentangle the effect of θ on dispersion of productivity and R&D incentives, we compare the benchmark case with another two cases: first, θ is increased by 50%, and R&D policy of firms is allowed to change endogenously. Second, θ is increased by 50%, but R&D policy is exogenously fixed to be the same as in the benchmark case. Table 10 summarizes the aggregate R&D efforts and dispersion of productivity.

Table 3.7: Effect of θ on R&D efforts and dispersion of productivity

	Aggregate productivity	Aggregate R&D efforts	Variance of productivity	productivity p90/p10 ratio
Benchmark	0.3492	24.8061	0.0725	5.4478
Case 1: High Theta	0.3519	21.4876	0.0636	5.246
Case 2: High Theta, exogenous R&D policy	0.3557	25.4621	0.0668	5.2502

From Case 1, we can see that a 50% increase of spillover effect θ result in a 0.8% increase of aggregate productivity, but also result in a 13.38% decrease of aggregate R&D efforts. By comparing Case 2 with Case 1, we can see that if the R&D policy is fixed unchanged when the spillover effect increases, the aggregate R&D efforts will actually increase, with an even further increase of aggregate productivity as in Case 1. However, the dispersion of productivity will also be larger in Case 2, as compared in Case 1.

Our counterfactuals target at reducing per-unit R&D expenditure c_d by 10%, 20%, 30%, 40%, and 50%, with government providing direct subsidy to R&D expenditure. Table 10 summarizes how aggregate R&D efforts and aggregate productivity will respond, under different scenarios when the R&D spillover in this market is either high or low.

Table 3.8: Solution menu of policy simulations, low θ

Counterfactual 1: low θ							
Cd		Aggregate productivity		Aggregate R&D efforts		Variance of productivity	productivity p90/p10 ratio
0.45	0	0.3492	0.00%	24.81	0%	0.073	5.40
0.405	10%	0.3531	1.12%	30.35	22%	0.077	5.43
0.324	20%	0.357	2.23%	38.31	54%	0.080	5.45
0.2268	30%	0.363	3.95%	47.20	90%	0.084	5.56
0.13608	40%	0.3699	5.94%	59.98	142%	0.090	5.79
0.06804	50%	0.3783	8.33%	79.35	220%	0.095	5.81

Table 3.9: Solution menu of policy simulations, high θ

Counterfactual 2 high θ,(a 50% increase of θ as,compared in counterfactual 1)							
Cd		Aggregate productivity		Aggregate R&D efforts		Variance of productivity	productivity p90/p10 ratio
0.45	0	0.3519	0.00%	21.49	0%	0.064	5.20
0.405	10%	0.3558	1.10%	26.17	22%	0.066	5.24
0.324	20%	0.3597	2.23%	33.23	55%	0.070	5.41
0.2268	30%	0.3647	3.64%	42.56	98%	0.074	5.44
0.13608	40%	0.3721	5.73%	53.50	149%	0.081	5.44
0.06804	50%	0.3796	7.88%	72.12	236%	0.086	5.58

Comparing Table 10.1 with Table 10.2, we can see that with the same amount of per-unit R&D subsidiary, the level of aggregate productivity will be higher and dispersion of productivity will be lower if θ is higher. However, the level of aggregate R&D efforts will be lower if θ is higher. Therefore, depending on different objective of government R&D policies, the role played by R&D spillover varies, and our counterfactual results provide a

menu of how the market will react to the R&D subsidiary plan under different scenarios.

3.6 Conclusion

This paper develops and estimates a structural model of R&D investment and productivity evolution by manufacturing plants in the Korean electric motor industry from 1991 to 1996. Plant-level decisions on R&D investment, physical capital investment, entry, and exit are developed using an equilibrium industry evolution model. Plant productivity is affected by its own R&D and by spill-overs from the R&D of its competitors. The model provides a detailed set of pathways connecting R&D investment, plant productivity, plant physical investment and industry turnover patterns observed in the data.

The structural parameter estimates show that a plant's own R&D expenditure has a positive effect on its future productivity. There is also a small spill-over effect with one dollar of competitor's R&D expenditure substituting for 1.6 cents of own R&D input. The public externality of R&D is important given the large number of firms within the same industry. A narrow difference between the entry cost and the mean scrap value explains the high turnover rate in this industry. Finally, the industry equilibrium model provides a natural link from individual plant R&D decisions to aggregate industry productivity and output. This feature of the model provides us with a powerful tool to evaluate various industry or innovation policies. As our example experiments show: increasing the elasticity of substitution between products increases plant innovation incentives but slows plant turnover. In the long run, a 5% drop in price-cost margin improves industry productivity by 2.8%. On the other hand, a lower entry cost, which increases total entry by 50%, does not change industry productivity.

There are quite a few possible extensions to the current framework. An interesting one will be to look at the interaction of firm's decision to export, R&D, and the overall industry evolution. Given the fact that trade and innovation policy are considered to be among the most important institutional settings of emerging economies such as Korea, it will be important to provide a general framework to evalute how they interact and affect long run

industry performance.

Chapter 4

Collateral Damage: The Impact of Shale Gas on Mortgage Lending

Joint work with James Roberts[1], Christopher Timmins[2], and Ashley Vissing[3]

4.1 Introduction

The Energy Information Administration reports that between 2007 and 2014, annual natural gas withdrawals from shale deposits in the U.S. rose from 1.99 to 13.8 million cubic feet,[4] growth that led to lower natural gas prices, higher natural gas demand, and substitution from other forms of fossil fuel consumption like coal. The recent rise of shale gas has been spurred by technological development that combines large-scale hydraulic fracturing and horizontal drilling techniques with other advances in three-dimensional surveying techniques. In addition to allowing for more efficient extraction from broad, tight-shale layers, the horizontal drilling technology increases access to large areas of shale from relatively confined surface areas, which allows firms to extract oil and natural gas stored in tight-shale formations located beneath densely populated neighborhoods.[5] Unlike traditional oil and

[1]Duke University and NBER

[2]Duke University and NBER

[3]Cornerstone Research

[4]Energy Information Administration, `https://www.eia.gov/dnav/ng/hist/ngm_epg0_fgs_nus_mmcfa.htm`

[5]In particular, many horizontal laterals can be drilled in different directions from a single wellpad, which may comprise less than an acre of land. Horizontal laterals can extend in mile-long segments

natural gas reservoirs, settlement patterns throughout the U.S. have evolved for decades with indifference to the location of shale. Consequently, we now often find residential properties located on top of those resources, bringing shale gas activity into homeowners' backyards, and beginning in 2014, more than 15 million Americans live within one mile of an active oil or gas shale well.[6] Our paper explores how the extraction technology changes have altered mortgage markets by evaluating how lenders internalize the increased risks born by leveraged houses located near to shale oil and natural gas development.

What are the chief risks born by proximity to these large-scale, hydraulically fractured wells? Current literature is evolving to identify and measure the health, economic, and geologic consequences of proximity to these industrial activities, especially in light of increased household exposure.[7] Among the identified risks is air pollution from well production and transmission activities, which leads to increased methane emissions.[8] Waste water disposal from fractured wells is linked to surface water contamination caused by radioactive salts and metals or by the chemicals used to the treat the fractured wells.[9] Geologically, there is a growing literature linking the employment of large-scale fracturing technology and increased incidence of tremors.[10] The hedonic literature identifies community-wide costs and benefits of proximity to shale, whereby the costs are greatest for households access-

beneath suburban and urban regions.

[6] Gold and McGinty (10/25/13). "Energy Boom Puts Wells in America's Backyards." *Wall Street Journal.*

[7] [Coase, 1960] noted that externalities are reciprocal in nature, and that the external costs of a production process will be low if no one is around to be affected by it. In contrast, the evolved shale gas extraction technology allows for many impacts on nearby landowners.

[8] The literature measures the impact of increased methane emissions during the drilling, fracturing and production phases of well development, in particular, including [Caulton et al., 2014], [Brandt et al., 2014], and the increases in other particulate matter, including [Colborn et al., 2011] and [Roy et al., 2014], and volatile organic compounds, as in [Gilman et al., 2013].

[9] [Olmstead et al., 2013], [Warner et al., 2013], [Fontenot et al., 2013], and [Hill and Ma, 2017]

[10] [Koster and van Ommeren, 2015] and [Cheung et al., 2016]

ing groundwater,[11] and more broadly, communities experience degradation of amenities through increased noise, road damage, and traffic accidents.[12] Conversely, the literature also identifies and measures economic benefits to having an active extraction industry, which includes higher wages, income, and municipal revenue.[13] Added to the economic benefits are royalties and bonus payments earned by households that own (and lease) the rights to their sub-surface minerals. We contribute to this literature by identifying and measuring an additional cost of these technologies that is internalized by the mortgage lending industry and passed on to homeowners through higher lending rates.

The fact that shale development has the potential to impact property values means that it also has the potential to interact in a variety of ways with mortgage lending practices. First and foremost, a mortgage loan is commonly secured for both surface and subsurface rights. Mortgages do not generally allow homeowners to sell or lease parts of their property without prior approval from the lender; however, mortgage experts generally report that requests for approval are rare ([NYT, 2011] and [Law, 2011]).[14] The situation is further complicated by the fact that most mortgages are not held in the portfolio of the primary lender, but are instead sold on the secondary mortgage market. Lenders participating in the

[11] Among other hedonic analyses, recent research has shown that shale development can negatively impact nearby housing prices ([Throupe et al., 2013], [Gopalakrishnan and Klaiber, 2014], [James and James, 2014], and [Muehlenbachs et al., 2015]), but other research has reached differing conclusions, as in [Delgado et al., 2014] and [Boslett et al., 2016].

[12] [Muehlenbachs and Krupnick, 2013] and [Graham et al., 2015] link increased incidence of traffic accidents to drilling activity.

[13] [Mason et al., 2015] and [Bartik et al., 2016] measure some of the economic benefits, and [Cesur et al., 2017] documents the benefits to infant mortality that are attributable to energy generation from natural gas as opposed to coal.

[14] Nationwide, Bank of America reports receiving approximately 100 such requests per month, fewer than a dozen are sent to Fannie Mae and Freddie Mac each year. ([NYT, 2011]) Chesapeake Energy, one of the largest drilling companies, only seeks permission from lenders before a property is drilled, not before it is leased; this violates mortgage rules, which require approval to sign a lease. ([NYT, 2011])

secondary mortgage market, in effect, sell their loans to government sponsored enterprises (GSE's)[15] or investment banks that bundle the loans (securitize) and sell the resulting securitized assets (mortgage-backed securities) to individual investors. Participation in the secondary market increases lenders' liquidity; however, GSE's are prohibited from purchasing mortgages on properties engaged in industrial activities including transport or storage of toxic substances (chemicals, oil and gas products, or radioactive materials) ([Law, 2011]), and shale gas extraction involves a number of activities that have the potential to violate these rules, which would leave the borrower (without prior approval) in technical default.[16,17] Because the primary lender is responsible if the borrower defaults due to shale extraction activities, lenders have strong incentives to precisely evaluate the risks incurred by lending to homeowners in regions with high levels of shale development.

We use the mortgage market to learn about additional external costs associated with

[15]Government sponsored enterprises (GSE's) include Fannie Mae (Federal National Mortgage Association) and Freddie Mac (Federal Home Loan Mortgage Corporation).

[16]Further, there may be other discrepancies between the terms specified in an oil or natural gas lease agreement and those specified in a mortgage. For example, some states void title insurance if a property is used for any commercial venture ([Law, 2011]) and, without title insurance, participation in the secondary market is limited. Homeowner insurance policies will also be violated if industrial activities are present, leading to default ([May, 2011]).

[17]Borrowers may even find themselves in violation of their mortgage agreement through no fault of their own, but rather simply because they happen to be located in close proximity to another property that engaged in shale development. For example, news reports described a couple in Washington County, PA who were denied a new mortgage for their property by Quicken Loans because of shale development on a neighboring plot. Quicken responded by saying – "While Quicken Loans makes every effort to help its clients reach their homeownership goals, like every lender we are ultimately bound by very specific underwriting guidelines. In some cases conditions exist, such as gas wells and other structures in nearby lots, that can significantly degrade a property's value. In these cases, we are unable to extend financing due to the unknown future marketability of the property. (`http://www.wtae.com/investigations/Couple-denied-mortgage-because-of-gas-drilling/12865512#.T6mu842bM44.facebook`)".

the "fracking boom" by quantifying the relationship between shale drilling risks and the frequency of subprime (higher priced) lending. In particular, we use loans issued to buy homes in Tarrant County, Texas, to test whether lenders mitigate shale development risks by issuing more subprime loans to households that are susceptible to drilling externalities. We measure the extent to which lenders' preferences (distaste) for shale gas risk have shifted relative to other forms of risk since 2010 (i.e., during a period when the industry reconsidered its lending practices and shale gas activities rapidly expanded). In particular, the rise in shale extraction was coupled with the collapse of the housing market and, with it, an increased scrutiny of GSE activities leading lenders to worry they may have to assume control of the shale-exposed mortgages as a consequence of technical default. We find that it is important to estimate differential preferences for shale risk (relative to income risk) before and after this period in which technical default and lost property values become more significant concerns among lenders. Moreover, we consider how those preferences vary with water source, which is an important component of house value and may be particularly vulnerable to shale risk. In particular, we ask whether lenders treat properties that are already exposed to nearby drilling differently from those that have signed a lease to extract their minerals and are likely to be exposed hydraulic fracturing operations, compared to those that do not yet have a lease.

We use a combination of housing, lending, and drilling data to capture variation in subprime lending practices across households that are more or less susceptible to the negative externalities of nearby drilling behavior. Our data spans the growth of shale gas activity and the periods before and after the financial crisis, and we are able to estimate how lenders' preferences differed across these two periods along several dimensions. In the data, we observe that lenders weight shale risk more heavily in their subprime decisions after the financial crisis. We then use a non-parametric estimator, first introduced by [Frölich, 2006], that captures firms' preference heterogeneity for income and shale risks and allows us to estimate the trade-offs across our two types of risk without imposing functional form assumptions. Focusing on the comparisons across water sources, we estimate a distribution

of lenders' preferences for the two sources of risk and show how it differs by groundwater versus piped water. In particular, we find that after the financial crisis, lenders are willing to bear significantly more income risk to reduce their exposure to shale risk among houses accessing groundwater.

Our paper differs from the existing shale gas literature by focusing on lenders' decisions who, we argue, are more likely to internalize risks especially in light of greater scrutiny in lending practices post-financial crisis, which evolved throughout 2008 and 2009.[18] Lenders face trade-offs between different types of lending risk on a daily basis, allowing them for develop an expertise in weighing the risks of any particular loan. Conversely, households may only buy a few houses over the course of their lives, which tasks households with a large information burden when deciding how to internalize perceived shale risks. Using measures that capture shale and income risks, along with other household characteristics, we non-parametrically estimate lenders' preferences to issue high risk loans, as indicated by a subprime mortgages. Following [Bajari and Benkard, 2005] and [Frölich, 2006], we characterize lenders' heterogeneous preferences and trade-offs between two types of risks: income and shale.

The remainder of the paper proceeds as follows. We begin by fitting the analysis into additional literature that is relevant to our questions in Section 4.2. We then describe the secondary market for mortgages in Section 4.3 and our data set in Section 4.4, which combines information from the Home Mortgage Disclosure Act with data on property appraisals and well locations. Section 4.5 describes the theory used to describe lenders' relative prefer-

[18] Our study is a complement to literature exploring whether there is an observed difference in mortgage default behavior for households living in active shale regions compared to non-shale. [Upton and McCollum, 2016] studies the probability of default in the presence of shale gas development, examining the default behavior of landowners in a period when national default rates were rising. He finds that landowners living in shale gas regions are less likely to default on their mortgage loans, lending credence to the positive economic impacts of shale gas development. [Shen et al., 2015] conduct a similar study with data describing default behavior of households in Pennsylvania located over the Marcellus Shale.

ences for shale and income risk and Section 4.6 describes the empirical framework. Section 4.7 reports estimates and Section 4.9 concludes with a discussion of policy relevance.

4.2 Other Relevant Literature

In addition to the already cited environmental economics literature identifying and measuring the costs and benefits of the growing shale extraction industry,[19] this paper contributes to literature concerned with the effects of the financial crisis on lending practices, subprime lending practices, more generally, and the relationship between shale development and foreclosure incidence.

In addition to estimating preference heterogeneity for shale and income risk, we capture differences in lending practices before and after the financial crisis, which is a period of increased foreclosures and significant changes to industry behavior that emphasizes greater scrutiny for each considered mortgage. We add to the literatures linking increased foreclosure rates with subprime lending[20] and impacts on property values and neighborhoods. [Gerardi et al., 2007] study the relationship between subprime lending and the increased incidence of observed foreclosures in the context of the Massachusetts housing market. Focusing their analysis on years encompassing the U.S. financial crisis, the authors find that, along with house price depreciation, subprime lending is positively correlated with the incidence of foreclosure citing that subprime borrowers are 20% more likely to face foreclose than prime borrowers. [McCarthy et al., 2002] cite the longer-term effects of foreclosures on households' access to stable and decent housing, and [Simons et al., 2009] and [Lin et al., 2009] capture the spillover effects of foreclosed properties on the surrounding blocks. Further, [Immergluck and Smith, 2006] find a positive correlation between foreclosures and violent crime levels at the neighborhood level.

In our analysis, we control for households' race and ethnicity in order to capture

[19] Our review of this literature is by no means complete, as it is a growing literature.

[20] Some of these studies also include those by [Newman and Wyly, 2004], [Immergluck and Smith, 2005], and [Quercia et al., 2007].

the oft cited relationship between subprime lending and sociodemographic characteristics. [Munnell et al., 1996] is the among the papers that use data assembled in compliance with the Home Mortgage Disclosure Act to study potential discriminatory lending practices toward minority households.[21] [Gerardi and Willen, 2009] study Massachusetts property-level data and find that subprime lending leads to more turnover in minority neighborhoods.

The model we present captures the risk taking behavior of local and national lenders when assessing mortgages for properties that are potentially impacted by shale gas development. This is a complement to a new literature documenting the relationships between shale gas activity and capital allocation and between shale gas activity and foreclosures. It also draws upon the literature analyzing other observable factors that lead to foreclosures, or more risky loans from the perspective of banks. A nascent literature explores the relationship between unconventional energy development and the local banking sectors. [Plosser, 2014] studies the deposit shock resulting from landowners profiting from nearby shale gas development and the banks' resulting capital allocation decisions. [Gilje, 2012] uses shale discoveries as a natural experiment to study credit supply and its implication for economic outcomes especially in areas dominated by smaller banks. [Gilje et al., 2016] explores whether banks export liquidity because they are exposed to positive shale gas shocks. The authors find that banks with branches located in non-shale areas increase lending in those branches, and the positive effect is more pronounced for 'difficult-to-securitize' loans. Finally, there is an older literature that employs models to capture the default probabilities for mortgages as a function of factors like loan-to-value ratios and house-price depreciation.[22] [Gerardi et al., 2009] is a more recent paper exploring the effects of house price

[21] The authors build on the literature analyzing discriminatory lending practices in mortgage markets that include [Black et al., 1978], [King, 1981], [Schafer and Ladd, 1981] and [Ladd, 1998], among many others with additional literature summarized in [Yinger, 1996] and [LaCour-Little, 1999]. A more descriptive analysis of the HMDA data and sociodemographic heterogeneity can be found in [Avery et al., 2006].

[22] Refer to [Quercia and Stegman, 1992] and [Kau et al., 1994] for other contributions to this literature.

depreciation on foreclosure rates versus relaxed underwriting standards. They find that the two mechanisms are interrelated, but, without house-price depreciation, there would not have likely been such a dramatic increases in the foreclosure rate.

4.3 Secondary Markets for Mortgages

Lenders interested in selling their mortgages to government sponsored enterprises (GSE's), like Fannie Mae (Federal National Mortgage Association) and Freddie Mac (Federal Home Loan Mortgage Corporation), in the secondary market must meet certain criteria that may be violated by proximity to shale development. These details are noted in the following section along with a short history of GSE's and potential risks of shale gas development.

Among the largest actors in the secondary mortgage markets are the GSE's. The government established these enterprises to introduce additional liquidity into the mortgage market and promote home ownership. In the U.S., 90% of all houses are purchased with mortgage financing. Lending institutions typically do not rely on their own capital to support most of the loans that they write over the long-term. Instead, loans are bundled (securitized) and sold to investors as mortgage-backed securities. The federal government, primarily through its GSE's, is the largest of these investors, purchasing over 90% of mortgages in the US today.[23] Fannie Mae and Freddie Mac assume the credit risk for all mortgages that are re-sold as mortgage-backed securities. In exchange for bearing this risk, the GSE's keep the guaranty fees associated with the loans. As recently as 2008, Fannie Mae and Freddie Mac had owned or guaranteed about half of the U.S.'s $12 trillion mortgage market. This, along with the low rates at which the GSE's are typically able to borrow, make them highly profitable enterprises. After the housing market crash of 2008, lenders began to evaluate the standards under which home mortgage loans were approved and credit was subsequently tightened. Both GSE's underwent significant scrutiny, were restructured, and fell under the conservatorship of the Federal Housing Finance Agency.

[23] https://smartasset.com/mortgage/everything-you-need-to-know-about-the-secondary-mortgage-market

Since that time, both the House Financial Services and Senate Banking Committees passed reforms that would have reduced the government's footprint in housing finance (although neither was passed into law),[24] and a similar plan was proposed by the Obama administration.[25] With this as a backdrop, the continued growth of shale gas in the U.S. led to congressional hearings beginning in 2009, continuing in 2010,[26] and culminating in a flurry of activity in the fall of 2011 both inside and outside Washington.[27]

4.3.1 The GSE's and Shale Gas

The GSE's specify a set of criteria to which lenders must adhere if they want to be able to sell mortgages on the secondary market, and there are many areas where these criteria may conflict with standard practice in shale gas or oil development. For example, Freddie Mac guidelines 39.4(i) specify that a mortgage can only be issued on a leased property if "exercise of the rights will not result in damage to the mortgaged premises or impair the use or marketability for residential purposes." Furthermore, the guidelines prohibit "right of surface or subsurface entry within 200 feet of a residential structure," and require "comprehensive endorsement to the title insurance company that affirmatively ensures the lender against damage or loss from exercise of such rights." Practically, this requires "no structure erected on premises exceeding three stories or 35 feet," that the premises "shall not be used for storage of any material machinery, equipment, or supplies," and that the property will "not be used for commercial purposes." Furthermore, the Freddie Mac guidelines 39.4(m) require that lenders must warrant that activities on the property:

[24] `https://www.nafcu.org/HousingFinanceReform/`

[25] `https://www.treasury.gov/initiatives/Pages/housing.aspx`

[26] Bateman, C. (June 2010).“ A Colossal Fracking Mess.” Vanity Fair. `http://www.vanityfair.com/news/2010/06/fracking-in-pennsylvania-201006`.

[27] Urbina, I. (November 24, 2011). "Officials Push for Clarity on Oil and Gas Leases." New York Times.
`http://www.nytimes.com/2011/11/25/us/officials-push-for-clarity-on-oil-and-gas-leases.html?_r=0`

1. must not interfere with the use and enjoyment of any present or proposed improvements on the mortgaged premises or with the use and enjoyment of the balance of the mortgaged premises not occupied by improvements,
2. must not affect the marketability of the mortgaged premises,
3. must have no or minimal effect on the value of the mortgaged premises,
4. must be commonly acceptable to private institutional mortgage investors in the area.

Fannie Mae and Freddie Mac have a fiduciary duty to establish rules that reduce the risk of lost house value or default. As noted in the introduction, the extraction of shale gas involves a number of activities that have the potential to violate these rules, which would leave the borrower (without prior approval) in technical default. Toxic chemicals are pumped, along with million gallons of water and sand, directly under mortgaged homes. "Produced" water, which is forced back out of the well, contains brine, fracking chemicals, and even radioactive substances. It is often stored on-site, sometimes in open holding ponds. Permanent easements for truck and pipeline transport, production platforms, and storage facilities (that can spill) are common on properties with or near drilling activity. Risks to home values can be a particular problem for homes where the water supply is threatened. Finally, without title insurance (see above), secondary lenders may not be able to hold mortgages.

The primary lender is responsible if the secondary lender does not know about the lease and the house goes into technical default as a result. Fannie Mae and Freddie Mac can demand that the originating lender buy back any loans that do not meet secondary market requirements ([Carpenter, 2011]). There is not a good measure of how many mortgages may currently be in violation of secondary mortgage market rules.

In light of these growing concerns, a primary lender who believes that a property may soon be approached for shale development may worry that the property could default, would have to be foreclosed upon, or that shale development might hamper its ability to sell the mortgage on the secondary market. A related concern might be that noncompliant mortgages already sold to the secondary market would have to be bought back. As such,

that lender may charge a premium to lend when there is concern over impending shale development. Alternatively, to the extent that they are able, lenders may simply exit markets where shale gas is prevalent.[28]

In the remainder of this paper, we quantify changes in lenders' preferences by estimating the changes in trade-offs between income and shale risk before and after the financial crisis and concurrent increased interest in shale gas at the federal level. This provides us with a new perspective on the costs of the risks associated with shale gas development for nearby homeowners, specifically measured via the decisions made by housing *professionals* (i.e., mortgage lenders).

4.4 Data

The following subsections describe our data location and sources and our variable construction methods. Our data is comprised of housing, drilling, and lending data that allows us to construct a household-level portrait of house transactions, household characteristics, and income and shale risk factors related to our dependent variables of interest, namely high-interest loans and foreclosures.

4.4.1 Tarrant Co., Texas

Our analysis will focus on shale gas development and its impact on property markets in Tarrant County, Texas. Tarrant Co., located in north-central Texas, is the home to approximately 1.8 million residents. It is comprised of 41 incorporated areas, including Fort Worth, which is the county seat. The population of Tarrant is approximately 27% Hispanic

[28] [NYT, 2011] reports that, in 2011, at least eight local or national banks did not typically issue mortgages on properties exposed to shale gas development. In other instances, lenders began requiring drilling companies to indemnify property owners against any future losses to home value, or requiring home owners to expressly agree not to sign a lease as long as they hold the mortgage.

or Latino (of any race).[29] Tarrant Co. and the underlying Barnett shale are typically considered to be the birthplace of modern hydraulic fracturing because of innovations made there by Mitchell Energy.

We also report summary statistics and present model specifications that include Denton Co., located north of Tarrant, where there is also active drilling but in a more rural setting. Finally, we estimate counter-factual relationships using Dallas Co. data where firms are restricted to drill wells located at least 1,500 feet away from residential and commercial buildings, effectively a drilling moratorium.[30] Dallas is located directly east of Tarrant County, and since there is no drilling, our counter-factuals assume lenders need only evaluate income risk (as compared to income and shale risk).

4.4.2 HMDA

HMDA was established to determine whether lenders serve communities' financial needs and facilitate enforcement of fair lending laws. When buying a house, one typically fills out a form at closing that transmits information about the race, sex and income of the buyer along with the loan amount and terms. As of 2006, there were 8,850 lenders covered by the disclosure rules (approximately 80% of home lending nationwide). In 1989, the HMDA law was amended to require disclosure of loan-level information, and in 2004, it was further amended to require disclosure of information about loan pricing. Specifically, the lender is required to report the spread between the annual percentage rate and the applicable Treasury yield if it is greater than or equal to 3 percentage points for a first-lien loan. After 2009, the rule for first-lien loans was changed to require reporting if the difference between the annual percentage rate and the applicable average prime offer rate is greater than or equal to 1.5 percentage points (i.e., both the baseline and the cutoff rule changed, see [Fed, 2009]. As such, HMDA does not specifically identify subprime loans,

[29] `www.tarrantcounty.com/en/county/about-tarrant.html`

[30] These setback rules are quite stringent compared to Fort Worth where setbacks are 600 feet. `https://www.texastribune.org/2013/12/11/dallas-city-council-tightens-gas-drilling-ordinanc/`

but rather "higher priced" loans; we use their reporting requirement in each period as the determinant of higher priced. We also follow the common practice in the literature and use these terms higher priced and subprime interchangeably. In 2004, the first year when pricing information was provided, fewer than 20% of households had higher priced loans, and higher priced loans were more common amongst black and Hispanic borrowers.

The number of loans reported as higher priced depends upon many factors, some of which have nothing to do with the borrower's riskiness. In particular, a narrowing of the difference between short and long-term interest rates can increase the the number of loans overall exceeding the higher priced threshold; we account for this in our empirical model below.

We employ the loan-to-income ratio as our measure of *income risk*. *Ceteris paribus*, given two borrowers with the same income, the borrower with the larger total loan amount will be more at risk of shocks that will prevent repayment of the loan, leading to default. HMDA reports both the size of the loan and the borrower's (self-reported) income. Further, HMDA describes whether or not the loan was securitized by a government agency or a commercial lender and whether the loan was issued by the Federal Housing or Veterans Administrations, which are important control variables included in the empirical specifications and are described in Section 4.7.1.

4.4.3 Dataquick & Corelogic

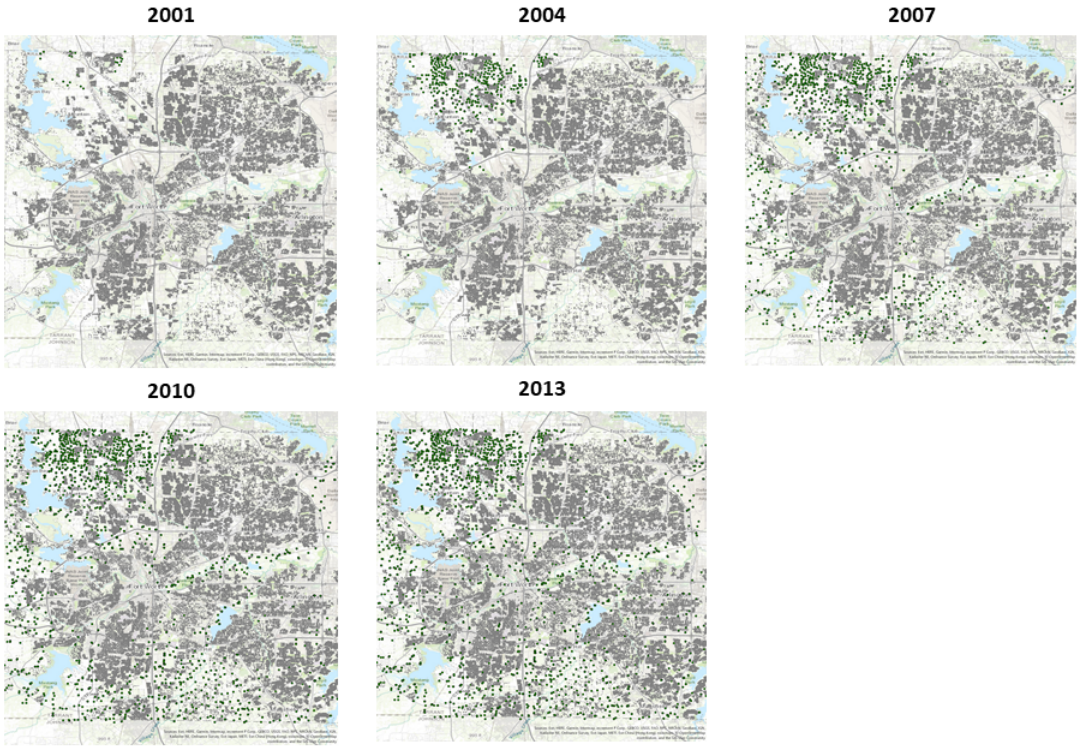
Data from the real estate data services companies, like Dataquick and Corelogic that are accessed through an a licensing agreement with the Duke University Department of Economics, are used in conjunction with information from the Tarrant Co. Assessor's Office, to measure the sale and assessed values of homes located in Tarrant, Denton, and Dallas counties of Texas, sale dates, and other house attributes like the counts of bedrooms, bathrooms, and living and land square footages. Further, these companies provide information describing the lenders and loan characteristics like loan amount, whether or not the loan was issued by the Federal Housing or Veterans Administrations, etc... Corelogic

uniquely identifies whether the home is eventually foreclosed, which is a second dependent variable explored for the purposes of our "back-of-the-envelope" calculations. We connect the HMDA data to our housing data by merging with the following data fields: lender name, lender amount, zip codes, and sale dates.

4.4.4 Exposure to Shale Development

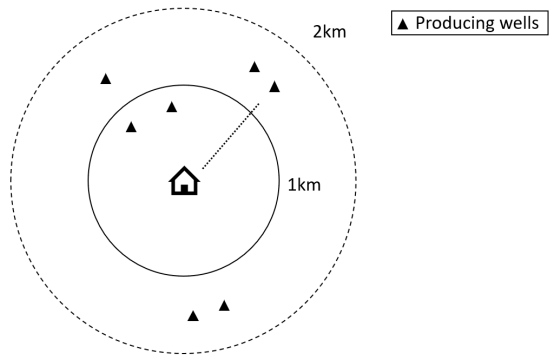
To estimate the relationship between shale risk and high-interest lending practices, we propose both a simple and complicated measure of shale risk. First, we consider two simple specifications: we count the number of producing wells located within 2-kilometers of the sold house as of the sale date, and we calculate the distance between the sold house and the nearest producing well. The logit estimates using these definitions are reported in the Appendix. However, by only looking at the number of producing wells or distance to the nearest producing well fail to accurately measure the shale risk. Figure 4.1 illustrates where producing wells emerge in Tarrant county in different time periods. From Figure 4.1, we observe that first the producing wells do not emerge in a uniform direction. From 2001-2004, the wells mostly locate on the north west region of Tarrant County, but after 2004 wells emerge from south as well. Moreover, the speed of emergence is different for different neighborhoods. Once wells start to emerge near a neighborhood, the drilling activites are become much more active in that neighborhood than other neighborhoods where no producing well exists. Therefore, any specification that only considers one characteristic (distance or number of wells within a certain distance) and specification that assumes linear relation on the characteristics will mis-measure the shale risk.

Figure 4.1: Patterns of Producing Activities



To better estimate shale risk, we use counts of wells and distance to the nearest producing well to estimate a duration model. In particular, shale risk is measured by the cumulative hazard function, which measures the total amount of risk that has been accumulated up to time t. In our duration model, exposure starts when a drilling well appears within the 3-km radius of the sold house and a failure occurs when a drilling well appears within the 1-km radius. For houses where a failure has not yet occurred, we consider the following attributes in calculating the cumulative hazard function: number of producing wells within 2-km radius, and distance to the nearest producing well. Figure 4.2 illustrates how the attributes are obtained.

Figure 4.2: Measure of Shale Risk



In particular, we use the proportional hazard (PH) model to calculate shale risk. Let τ be a non-negative random variable denoting the time to a failure event, and denote $S(t)$ as τ's survivor function and $h(t)$ as its hazard function. Then we have

$$
\begin{aligned}
S(t) &= 1 - F(t) = Pr(\tau > t) \\
f(t) &= \frac{dF(t)}{dt} = \frac{d}{dt}[1 - S(t)] = -S'(t) \\
h(t) &= \lim_{\Delta t \to 0} \frac{Pr(t + \Delta t > \tau > t | \tau > t)}{\Delta t} = \frac{f(t)}{S(t)}
\end{aligned}
$$

In our PH model, we assume that the hazard function $h(t)$ has a Weibull distribution, with time-varying covariates:

$$
\begin{aligned}
h(t) &= h_0(t) \exp(\beta_0 + \mathbf{x}(\mathbf{t})'\beta) \\
&= pt^{p-1} \exp(\beta_0 + \mathbf{x}(\mathbf{t})'\beta)
\end{aligned}
$$

The time-varying covariates $\mathbf{x_{it}}$ include: {number of producing wells within 2-km radius, distance to the nearest producing well}. Start of exposure is defined as when the first producing well emerges within 3-km radius. Length of exposure t is measured by total number of months since start of exposure, which is defined as:

$$t = \text{current date} - \text{start of exposure}$$

We estimate the parameters of this model through maximum likelihood estimation. The

likelihood function is:

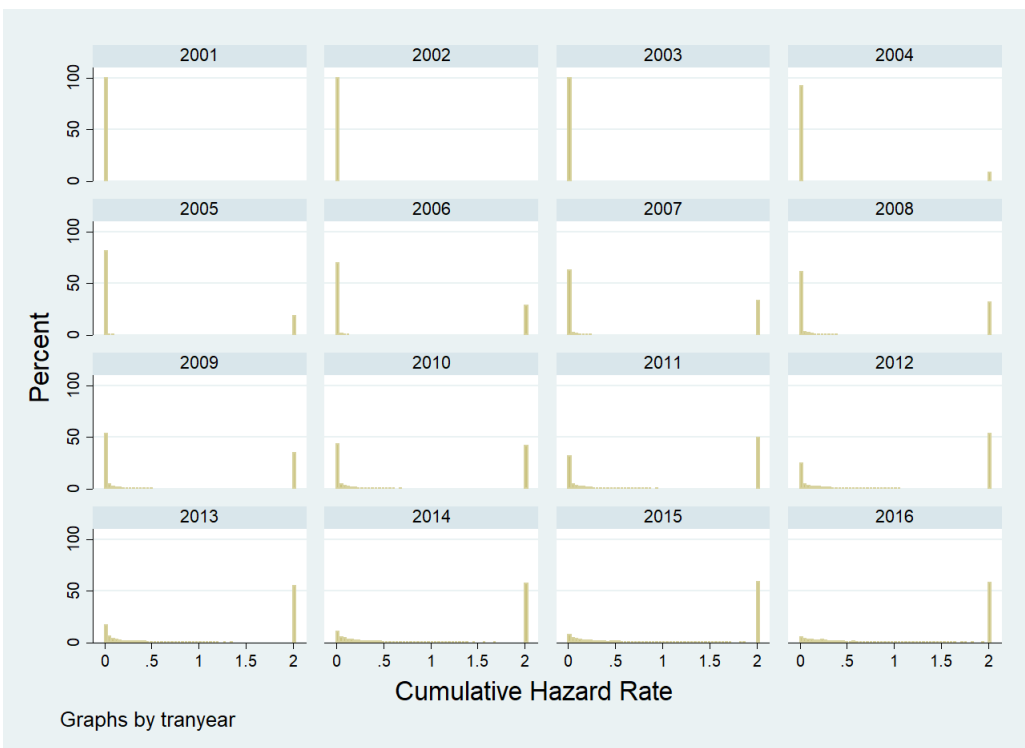
$$\mathcal{L}(\beta|t,\mathbf{x},T) = \prod_{i=1}^{k_1} f(t_i|\mathbf{x_i}(\cdot),\beta) \prod_{j=1}^{k_2} Pr(t_j > T|\mathbf{x_j}(\cdot),\beta)$$
$$= \prod_{i=1}^{k_1} S(t_i|\mathbf{x_i}(\cdot),\beta) \cdot h(t_i|\mathbf{x_i}(t_i),\beta) \prod_{j=1}^{k_2} S(t_j|\mathbf{x_j}(\cdot),\beta)$$

where T is the termination period in our sample, k_1 is the set of houses that are exposed to shale risk during the sample period, and k_2 is the set of houses that are not yet exposed to shale risk by the end of our sample period. The cumulative hazard function is then given by:

$$H(t) = \int_0^t h(u)du$$

Figure 4.3 depicts the distributions of cumulative hazard rates across years. The mass point at 0 indicates number of houses that have not yet been exposed to any shale risk. The mass point at 2 indicates houses that have had a failure (a producing well appears within 1-km radius).

Figure 4.3: Distribution of Cumulative Hazard Rate



The results of the PH model estimation are reported in Table 4.1:

Table 4.1: Estimation Results of PH Model

	PH Coefficient
Number of producing wells within 2000m	-0.0239***
	(-68.56)
Distance to the nearest producing well	-0.00216***
	(-134.21)
_cons	-6.204***
	(-170.32)
logP	0.615***
	(146.66)
N	82,400

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.4.5 Summary Statistics

We conclude this section by describing the dependent and independent variables, the characteristics of households with and without subprime mortgage rates, and motivating the inclusion of important control variables. Particularly, it is important to control for household characteristics, including race and ethnicity, loan characteristics, whether the loans are securitized and by whom, and whether the loan is to purchase an owner-occupied house.

Table 4.2 summarizes the house, household, sale, and loan characteristics of all transaction occurring from 1999 to 2016 in Dallas, Tarrant, and Denton counties. Denton county is comprised of fewer minorities while Dallas is comprised of more, and, on average, Denton sells larger homes measured by both the parcel (land) size and the living space. Tarrant and Denton counties both have drilling activity, though average well exposure is greater in Tarrant County, whereby shale exposure is measured by the count of producing wells located within 1,000 meters of the house at the sale date. Sales, loan, and income values are highest in Denton followed by Dallas. The frequency of foreclosures and the average mortgage interest rates (among those reported) in Tarrant fall between Denton, reporting the lowest, and Dallas, reporting the highest. Tarrant, on the other hand, has the highest levels of FHA and VA supported mortgages (consistent with lower income and sales values.

Table 4.2: Summary Statistics by County

	Tarrant		Denton		Dallas	
	Mean	(Std. Dev.)	Mean	(Std. Dev.)	Mean	(Std. Dev.)
House Characteristics						
Beds	3.354	(0.642)	3.466	(0.652)	3.287	(0.686)
Baths	2.104	(0.583)	2.494	(0.828)	2.367	(0.914)
Living (sqft)	2121.508	(811.609)	2360.904	(853.044)	2025.629	(855.58)
Land (sqft)	10257.93	(8269.194)	10644.38	(9941.089)	9595.025	(5274.123)
GW	0.645	(0.478)				
Age	18.733	(20.044)	11.647	(11.925)	29.072	(21.915)
Shale Exp. (wells)	0.575	(1.728)	0.269	(1.173)		
Household Characteristics						
White	0.81	(0.392)	0.844	(0.363)	0.684	(0.465)
Hispanic	0.193	(0.394)	0.117	(0.321)	0.282	(0.45)
Black	0.088	(0.284)	0.052	(0.222)	0.163	(0.369)
Asian	0.05	(0.218)	0.074	(0.262)	0.061	(0.239)
Income	81531.65	(54400.54)	95641.52	(57043.27)	90929.45	(80411.15)
Transaction & Loan Characteristics						
High Interest Loan	0.104	(0.306)	0.077	(0.267)	0.135	(0.342)
Loan-to-Income	2.094	(0.779)	2.245	(0.811)	2.193	(0.819)
Sale Amount	140566.4	(75242.53)	174225.6	(83716.19)	164406.1	(114878.6)
Loan Value	150060.6	(89365.52)	189920.7	(101263.2)	171042	(135882.9)
Annualized L2I	0.166	(0.058)	0.172	(0.061)	0.181	(0.064)
Foreclosure	0.077	(0.266)	0.064	(0.245)	0.086	(0.281)
Fixed Loan	0.897	(0.303)	0.884	(0.32)	0.845	(0.362)
FHA Loan	0.294	(0.456)	0.216	(0.412)	0.266	(0.442)
Gov't Sec.	0.341	(0.474)	0.349	(0.477)	0.296	(0.457)
Comm. Sec.	0.509	(0.5)	0.523	(0.499)	0.525	(0.499)
Owner Occ.	0.925	(0.264)	0.925	(0.263)	0.922	(0.268)
Obs.	202,286		78,792		178,222	

[a] Summarizes the primary variables used to describe the house, household, sales, and loan characteristics. The first and second columns compare mean and standard deviations across the Dallas and Tarrant counties used in the analysis.

Race & Ethnicity. It is important to control for the racial and ethnic composition of borrowers when performing empirical analyses that assess mortgage lending practices. As

noted in the literature and data sections, HMDA was established, in part, to ensure lending practices were non-discriminatory. Consequently, it is important to control for both income, debt, race, and ethnicity when empirically testing lending behavior. In Table 4.3 we see that a subprime mortgage is more often associated with minority status (black or Hispanic, in particular) and with lower income. Further, minority households are more likely to be issued loans insured by the Federal Housing Administration, described next in the text, and the loans are less likely to be secured by a government entities like Freddie or Farmer Mac and Fannie or Ginnie Mae.

Table 4.3: Summary Statistics by Race & Ethnicity

	Black		Asian		White		Hispanic	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Transaction & Loan Characteristics								
High Interest Loan	0.243	(0.429)	0.057	(0.232)	0.105	(0.307)	0.205	(0.404)
Loan-to-Income	2.309	(0.788)	2.194	(0.911)	2.138	(0.801)	2.312	(0.789)
Income	69,513	(45,973)	92,619	(66,026)	91,589	(68,454)	56,037	(41,639)
Sale Amount	135,651	(73,152)	166,959	(91,133)	159,936	(97,796)	108,744	(60,177)
Loan Value	143,716	(80,294)	173,240	(108,902)	171,252	(116,492)	114,305	(67,467)
Annualized L2I	0.188	(0.063)	0.169	(0.067)	0.167	(0.06)	0.189	(0.06)
Foreclosure	0.117	(0.321)	0.106	(0.308)	0.074	(0.262)	0.112	(0.315)
Fixed Loan	0.806	(0.395)	0.887	(0.316)	0.883	(0.322)	0.885	(0.319)
FHA Loan	0.401	(0.490)	0.122	(0.327)	0.255	(0.436)	0.406	(0.491)
Gov't Sec.	0.257	(0.437)	0.418	(0.493)	0.314	(0.464)	0.290	(0.454)
Comm. Sec.	0.603	(0.489)	0.435	(0.496)	0.531	(0.499)	0.486	(0.500)
Owner Occ.	0.93	(0.255)	0.849	(0.358)	0.927	(0.26)	0.954	(0.209)
Obs.	55,760		29,243		385,188		31,206	

[a] Summarizes the financial and loan characteristics of all transactions by race and ethnicity. Black and Hispanic households have higher rates of high interest and FHA loans and lower incomes and sales values.

FHA Loans. The models also control for whether the loan is insured by the Federal

Housing Administration or Veterans Administration. The FHA is a government agency that helps borrowers obtain mortgage loans by lowering the down payment requirements to as low as 3.5 percent down for qualified borrowers, whereas traditional lenders require up to twenty percent down, and in fact, the FHA insured more loans after the subprime crisis as demonstrated in Figure 4.4.[31,32] Borrowers that take advantage of FHA loans pay a mortgage insurance premium that varies with the financed amount. By around 2003, subprime lending supplanted much of the FHA loans by relaxing lending requirements further (some requiring zero down payments) and expediting the application process. After the subprime lending market crashed in 2007, FHA increased the number of approved loans, which reached 43.8% of all mortgages originated in November of 2009, and after the recession, FHA lending decreased to roughly 11%.[33] Mirroring the description of active players in the lending market, Figure 4.4 plots the share of loans insured by FHA or VA or are subprime. The dashed line plots those shares for regions with drilling activity while the solid lines are regions without drilling activity. The share of subprime loans is slightly greater in drilled regions of Texas post-2010, and for the whole duration, FHA insured a greater share of the loans originating in drilled regions.

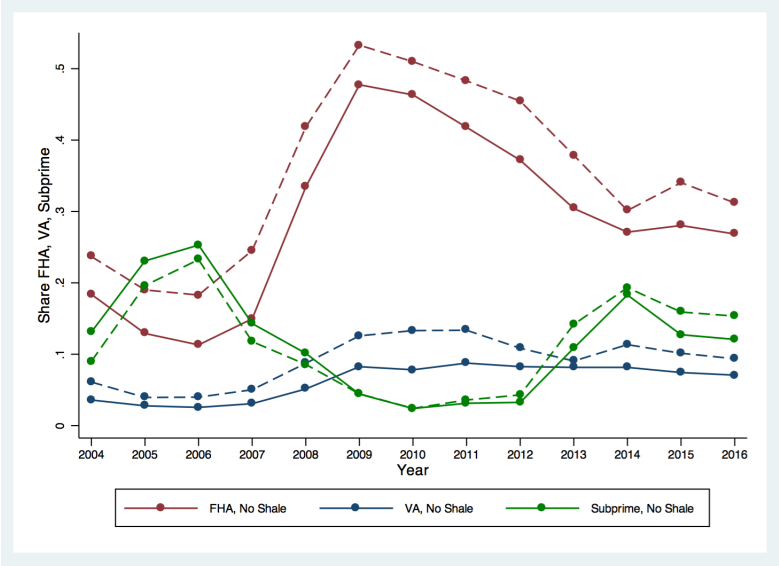
[31] The administration was establish as part of the National Housing Act of 1934, and in 1965, it became part of the Department of Housing and Urban Development.

[32] FHA interest rates do not vary with the borrowers' credit scores as they do with conventional loans that typically spike if the credit score is less than 620. `https://en.wikipedia.org/wiki/Federal_Housing_Administration`

[33] `https://www.clevelandfed.org/newsroom-and-events/publications/economic-trends/2015-economic-trends/et-20150414-fha-lending-rebounds-in-wake-of-subprime-crisis.aspx`.

This analysis explores whether FHA standards increased after the subprime lending market crashed by lending to more creditworthy borrowers. The authors find that FHA loans were extended to fewer deep subprime borrowers by the end of 2007 and to none by 2010.

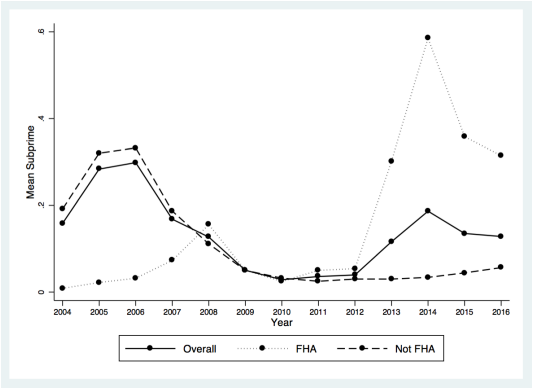
Figure 4.4: Frequency Originated Loan is FHA, VA, Subprime (by Shale Exposure)



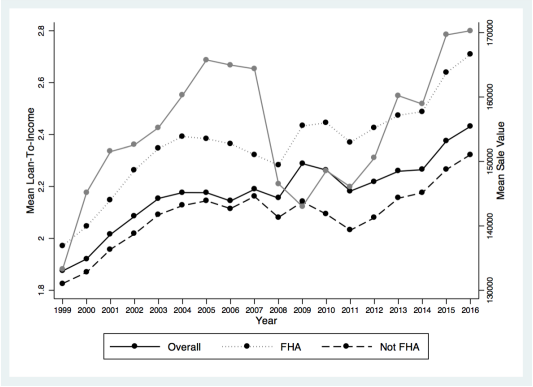
[a] Plots the share of loans issued by the FHA and VA or that are likely subprime across the state of Texas. The dashed lines indicate the share among counties with no drilling activity, and the solid lines indicate the shares among counties with drilling activity.

Figures 4.5a and 4.5b utilize the Texas-wide HMDA data to describe the frequency of high interest rate loans and mean loan-to-income values across years, stratified by whether the loan was insured by the Federal Housing Administration or not. With a decrease in FHA loans more generally, we find that FHA loans are less likely issued with high interest rates before 2007 as demonstrated in Figure 4.5a. After 2012, the frequency of FHA, high interest loans soars, commiserate with an overall increased dependency on FHA. Figure 4.5b demonstrates that FHA loans consistently insure loans issued to higher loan-to-income borrowers. The gray line demonstrates the mean sale value of homes across the same period (second y-axis), and one can visually see the fall in home prices in 2008 and 2009.

Securitized Loans. Loans may never be securitized, securitized by a government entity like Freddie or Farmer Mac and Fannie or Ginnie Mae, or they may be securitized by a commercial entity. Since primary lenders are held responsible for default, it may matter to whom they sell the originated loans. Figure 4.6a describes the mean frequency with



(a) Mean Frequency of Subprime Interest Rates (by FHA)



(b) Mean Loan-to-Income (by FHA)

Figure 4.5: FHA Summary

[a] 4.5a tracts the mean likelihood an FHA loan is issued with a high interest rate. We find that there are significantly higher interest rates among FHA loans after the subprime crisis. 4.5b tracts the mean loan-to-income values among all borrowers and stratified by whether the purchased home is insured by FHA. The gray line describes the mean sales values using the second y-axis.

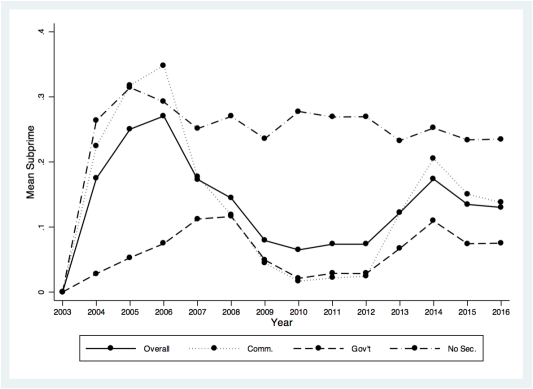
which a loan is issued with high interest rate across securitized and non-securitized loans. Loans originated between 2009 and 2012 tend to have lower interest rates, and those with the highest interest rates are often not securitized. Figure 4.6b describes the mean loan-to-income values across securitized and non-securitized loans, and on average, the loan-to-income values are lowest among non-securitized loans. The Appendix reports summaries of the data by whether the loans are not secured, commercially secured, or government secured.

Owner Occupied Status. Research by [Albanesi et al., 2017] documents that mortgage defaults were most prevalent in the middle of the credit score distribution and linked to real estate investors. Figures 4.7a and 4.7b use the Freddie Mac Single Family loan-level dataset to generate the mean credit scores and debt-to-income values among all non-FHA borrowers with loans originating between 1999 and 2016 in an effort to explore whether this is an issue for our analysis.

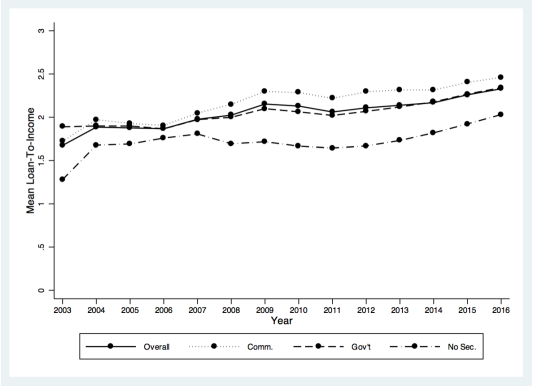
The mean credit scores among investors is larger than that of loans granted to purchase owner occupied units and their debt-to-income values are lower, both factors indicate greater credit-worthiness. In general, we see that non-FHA loans require higher credits scores post subprime crash. However, as noted before, after the crash, FHA loans comprised a greater share of all originated loans (most utilized by households with low credit scores). Among the non-FHA loans, investors' debt-to-incomes peaked near the financial crisis and then returned to the sub-owner occupied status thereafter. In general, the non-FHA loans were issued to individuals with smaller debt-to-incomes after the financial crisis, and a new upward trend begins thereafter.

Turning back to the HMDA Texas data, we find that investors are slightly more likely to have greater interest rates before the subprime crisis and lower, thereafter, as demonstrated in Figure 4.8a, and the average loan-to-income values are, on average, lower for investors as indicated in Figure 4.8b. The Texas data mirrors what is found in the Freddie Mac Single Family loan-level dataset.

National Lenders. In Table 4.4, we compare the number of different types of loans issued



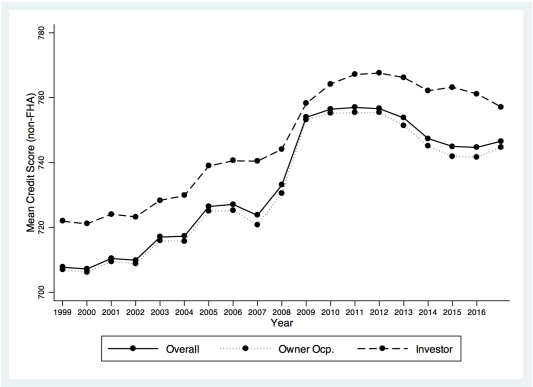
(a) Mean Frequency of Subprime Interest Rates (by Securitized)



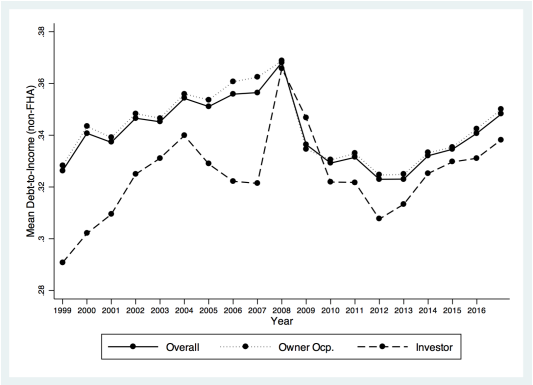
(b) Mean Loan-to-Income (by Securitized)

Figure 4.6: Securitized Summary

[a] 4.6a tracts the mean likelihood a securitized loan is issued with a high interest rate. Not securitized loans have the most consistently high interest rates, whereas the commercial loans are more likely to have higher interest rates before and after the subprime crisis. 4.6b tracts the mean loan-to-income values among all borrowers and stratified by whether the loan is securitized.



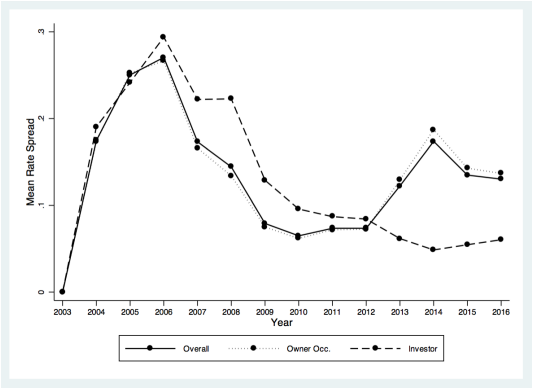
(a) Mean Credit Score



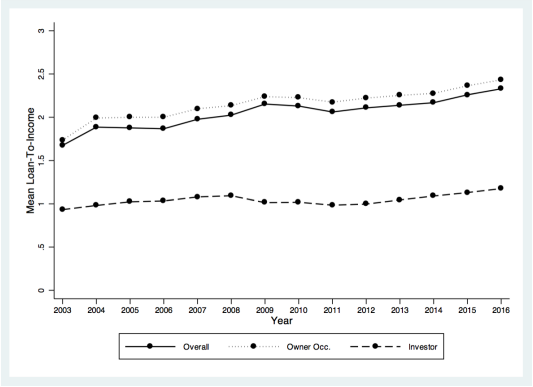
(b) Mean Debt-to-Income

Figure 4.7: Owner Occupied, Non-FHA Loan Summary

[a] 4.7b tracts the mean credit scores among all borrowers and stratified by whether the purchased home is owner occupied or not for all non-FHA loans using the Freddie Mac Single Family loan-level dataset. 4.7a tracts the mean debt-to-income values among all borrowers and stratified by whether the purchased home is owner occupied or not for all non-FHA loans.



(a) Mean Frequency of Subprime Interest Rates (by Occ.)



(b) Mean Loan-to-Income (by Occ.)

Figure 4.8: Owner Occupied Summary

[a] 4.8a tracts the mean likelihood a loan for an owner-occupied house is issued with a high interest rate. Investor loans are much less likely to have higher interest rates after 2009. 4.8b tracts the mean debt-to-income values among all borrowers and stratified by whether the loan originated for an owner-occupied house. Investors, on average, have much lower loan-to-income values.

by different types of lenders. In particular, it has been suggested that "national" lenders may have simply pulled out of shale dependent areas as shale risk became an issue.[34] We report significantly more loans in the non-shale areas because the sample includes Dallas; however, the fraction of local lenders offering lower interest rate loans is similar across shale and non-shale regions and across transaction years. High interest loans issued by local lenders is slightly higher in shale regions across most years except in 2006 and 2009 when non-shale regions experienced 5% more subprime, local lending.

[34] We include the following lenders as "national": Bank of America, Wells Fargo, Starkey Mortgage, Countrywide, America's Wholesale, DHI Mortgage, CTX Mortgage, J.P. Morgan, Chase Manhatten, Chase Bank, Merrill Lynch, Credit Suisse, Fidelity, Citi Group, Citi Mortgage, Citi Bank, Citizens Bank, Coldwell, National City, Century 21, PHI Mortgage, Wachovia, Washington Mutual, Fairway Independent, H. & R. Block, Prime Lending.

Table 4.4: Types of Loans Issued by Different Lenders

	Shale Risk				No Shale Risk			
Tran.	Subprime		Non-Subprime		Subprime		Non-Subprime	
Year	Local	National	Local	National	Local	National	Local	National
2004	109	14	598	451	3847	644	16496	12157
	(89%)		(57%)		(86%)		(58%)	
2005	474	89	1088	807	8987	1545	17070	13220
	(84%)		(57%)		(85%)		(56%)	
2006	1060	314	1908	1931	9705	2043	16027	15179
	(77%)		(50%)		(83%)		(51%)	
2007	419	189	2163	2338	2539	1420	11324	13999
	(69%)		(48%)		(64%)		(45%)	
2008	218	151	2105	2011	1067	803	8719	8641
	(59%)		(51%)		(57%)		(50%)	
2009	113	60	2246	1589	490	215	9722	5839
	(65%)		(59%)		(70%)		(62%)	
2010	105	10	2757	1620	328	28	8996	4977
	(91%)		(63%)		(92%)		(64%)	
2011	178	23	3360	1483	370	51	8296	3867
	(89%)		(69%)		(88%)		(68%)	
2012	231	23	4135	1426	349	33	8404	3016
	(91%)		(74%)		(91%)		(74%)	
2013	477	35	2305	711	715	88	4797	1564
	(93%)		(76%)		(89%)		(75%)	
2014	729	68	2459	786	1228	122	4445	1474
	(91%)		(76%)		(91%)		(75%)	
2015	691	67	3089	757	887	102	5091	1415
	(91%)		(80%)		(90%)		(78%)	
2016	354	29	1696	389	407	64	2680	719
	(92%)		(81%)		(86%)		(79%)	

[a] Summarizes the rate of subprime loans issued by local and national lenders across shale and non-shale risk regions and transaction years.

In fact, we find that this was not the case. Figure 4.9 compares the difference in the percentage of all shale loans written by local and national lenders in Tarrant Co. each year to the same difference for non-shale loans, we find an almost identical time path. We do

see that local lenders issued a much smaller percentage of *all* loans in the depths of the financial crisis, but that this reduction was proportional across shale and non-shale loans.

Figure 4.9: % Loans Local Lenders - % Loans National Lenders (Shale v. Non-Shale)

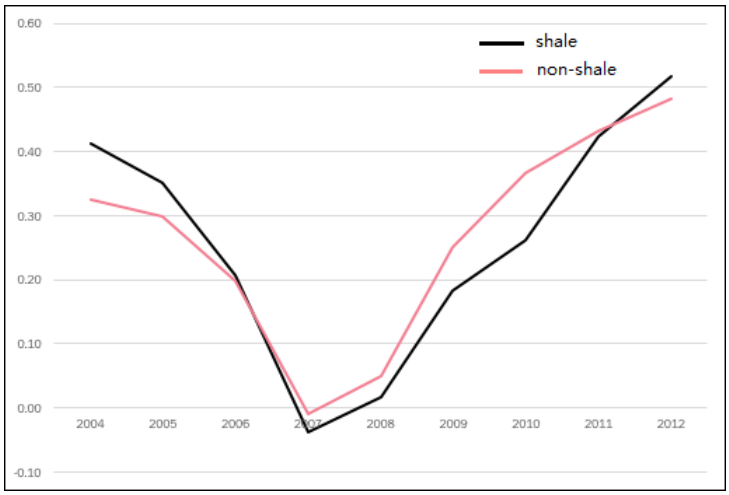
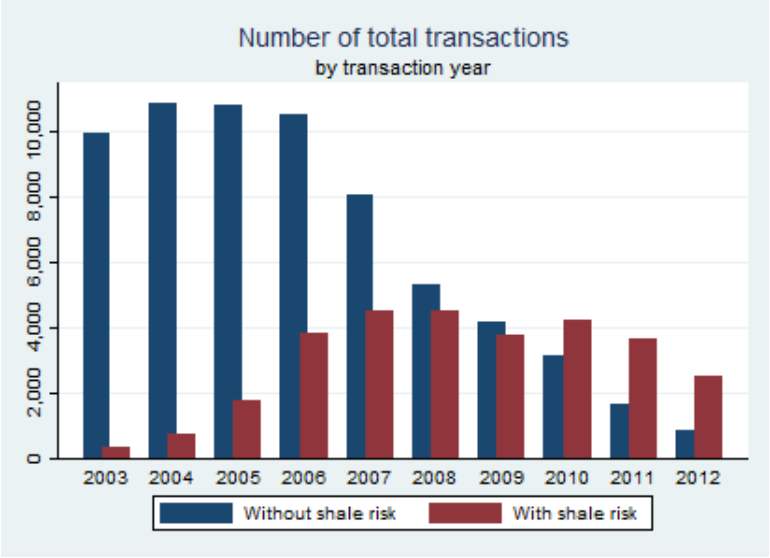


Figure 4.10 shows that, as shale development became more pervasive in Tarrant Co., loans with shale risk (unsurprisingly) outpaced those without.

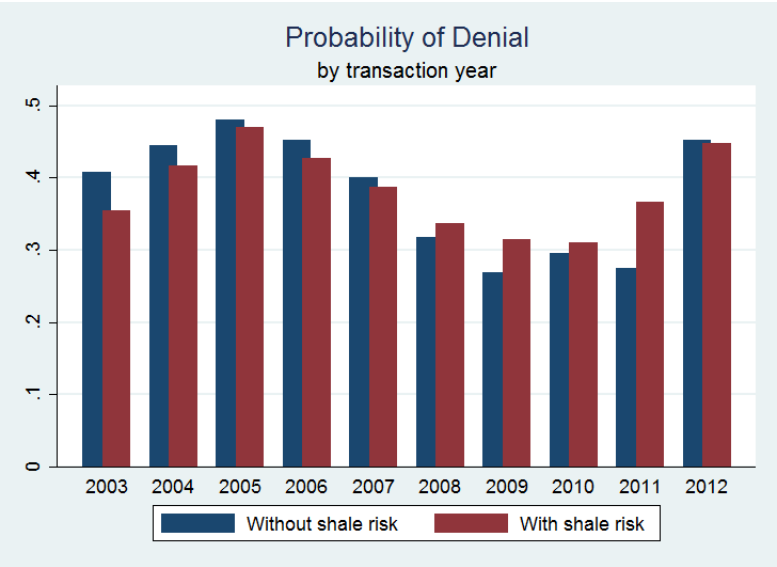
Figure 4.10: Number of Total Transactions



For the remainder of the paper, we focus on loan pricing, but it is worthwhile to look briefly at whether shale gas exposure led to loan applications being rejected altogether. Figure 4.11 looks at the probability of loan *denials*. We see that, early in the period, a greater likelihood of denial was associated with a non-shale risk loan, while later in the

period, the opposite is true. We are not, however, able to disentangle whether this is the result of lenders becoming more wary of shale gas or simply that there were more homes with shale gas exposure in the pool of mortgage applications. We therefore focus our attention on loan pricing, where we are able to differentiate between these two effects.

Figure 4.11: Probability of Denials



Water Source & Shale Exposure. Finally, many of our conclusions will focus on the house's water source (i.e., piped v. private groundwater well). We demonstrate in Table 4.5 that groundwater dependent houses are larger, newer, on bigger plots, and are occupied by higher-income individuals on average. Minority households tend to be located in more urban areas accessing district water. Loans issued to purchase houses located in the non-district water regions and with shale exposure tend to more often be securitized, and comparing whether a house is exposed to shale, those loans are often insured through the Federal Housing Administration.

Table 4.5: Summary Statistics by Water Source

	District Water		Non-district Water	
	Mean	Std. Dev.	Mean	Std. Dev.
House Characteristics				
Beds	3.209	(0.608)	3.433	(0.643)
Baths	1.952	(0.533)	2.185	(0.59)
Living (sqft)	1930.08	(724.53)	2221.65	(834.68)
Land (sqft)	8411.27	(5617.60)	11313.29	(9196.77)
Age	23.61	(25.26)	16.52	(16.02)
Shale Exp. (wells)	0.571	(1.488)	0.583	(1.857)
Household Characteristics				
White	0.790	(0.407)	0.823	(0.382)
Hispanic	0.248	(0.432)	0.164	(0.37)
Black	0.101	(0.301)	0.08	(0.271)
Asian	0.041	(0.199)	0.054	(0.226)
Income	74263.01	(52726.08)	84748.03	(54584.59)
Transaction & Loan Characteristics				
High Interest Loan	0.119	(0.324)	0.095	(0.294)
Loan-to-Income	2.062	(0.787)	2.108	(0.771)
Sale Amount	122284.7	(64883.77)	150010.1	(78770.94)
Loan Value	130745.5	(78082.72)	158923.7	(92549.31)
Annualized L2I	0.165	(0.057)	0.167	(0.058)
Foreclosure	0.085	(0.279)	0.074	(0.262)
Fixed Loan	0.906	(0.292)	0.891	(0.311)
FHA Loan	0.328	(0.469)	0.277	(0.448)
Gov't Sec.	0.319	(0.466)	0.351	(0.477)
Comm. Sec.	0.512	(0.5)	0.509	(0.500)
Obs.	69,937		124,361	

[a] Summarizes the primary variables used to describe the house, household, sales, and loan characteristics. The first and second columns compare the mean and standard deviations across properties likely to access district water and those likely accessing groundwater.

Table 4.6 summarizes the data across shale and non-shale exposed regions. The houses are slightly larger in areas with slightly greater levels of shale exposure. They are also more expensive when not located near shale, yet the loan values are lower.

Table 4.6: Summary Statistics by Shale Exposure

	No Shale Wells		Shale Wells	
	Mean	Std. Dev.	Mean	Std. Dev.
House Characteristics				
Beds	3.345	(0.643)	3.406	(0.619)
Baths	2.094	(0.593)	2.161	(0.488)
Living (sqft)	2098.952	(812.97)	2262.779	(776.325)
Land (sqft)	10136.71	(7612.469)	11129.84	(11610.4)
GW	0.657	(0.475)	0.552	(0.497)
Age	20.329	(20.393)	12.063	(16.666)
Shale Exp. (wells)			3.53	(2.811)
Household Characteristics				
White	0.805	(0.396)	0.84	(0.367)
Hispanic	0.199	(0.399)	0.174	(0.379)
Black	0.085	(0.278)	0.10	(0.299)
Asian	0.049	(0.216)	0.05	(0.218)
Income	80831.17	(54728.11)	82839.85	(52207.8)
Transaction & Loan Characteristics				
High Interest Loan	0.095	(0.293)	0.108	(0.31)
Loan-to-Income	2.067	(0.767)	2.203	(0.815)
Sale Amount	141524.7	(77181.46)	133294.7	(65010.93)
Loan Value	147380.7	(91162.74)	156983.1	(76204.43)
Annualized L2I	0.166	(0.058)	0.165	(0.057)
Foreclosure	0.072	(0.259)	0.109	(0.311)
Fixed Loan	0.893	(0.31)	0.936	(0.246)
FHA Loan	0.275	(0.447)	0.389	(0.487)
Gov't Sec.	0.34	(0.474)	0.337	(0.473)
Comm. Sec.	0.502	(0.5)	0.547	(0.498)
Obs.	161,030		36786	

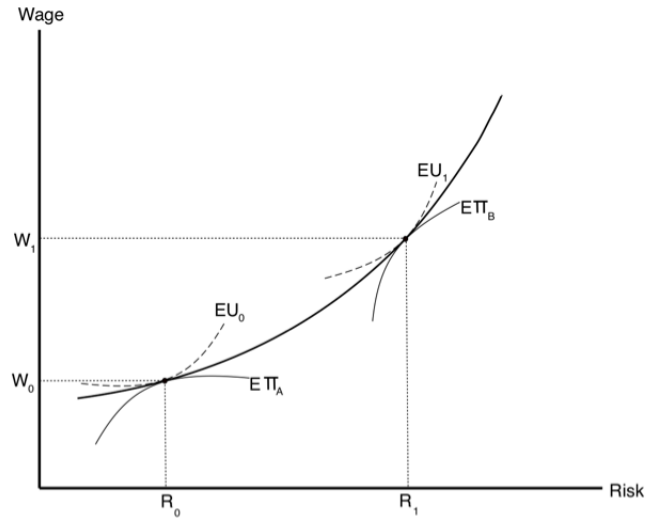
[a] Summarizes the primary variables used to describe the house, household, sales, and loan characteristics. The first and second columns compare the mean and standard deviations across households with and without shale exposure.

4.5 Theory

The theory for analyzing the decisions made by lenders with respect to various risks and lending rates is similar to that used to describe the trade-offs made by workers choosing amongst risky jobs. This is the idea behind *wage hedonics*, where the compensating differentials associated with different job attributes are used to measure their values ([Viscusi, 1993]). The idea even appears in Adam Smith's seminal work ([Smith, 2015]), where risky or unpleasant jobs are noted as commanding a premium. The problem has a simple graphical interpretation, which is described in the following figure. Firms are described by a series of iso-profit curves, denoted by π_A and π_B. Along each curve, a lower risk must be accompanied by a lower wage in order for a constant level of profit to be maintained. Firm A is better at providing a low risk environment and is able to pay a higher wage when risks are low compared with firm B.

Workers face similar trade-offs, which are described by iso-expected utility curves EU_0 and EU_1. In particular, each worker is willing to accept a higher risk in exchange for a higher wage payment, with their willingness to do so, or marginal rate of substitution between risk and compensation, being summarized by the slope of the iso-expected utility curve.

Figure 4.12: Iso-expected Utility Curves



As in other hedonic applications, the allocation of workers to jobs involves a sorting process whereby workers match with firms that yield them the highest expected utility, given firms' wage offers described by their iso-profit curves. In particular, the best that worker #0 (who requires relatively little in terms of compensation in exchange for taking on more risk) can do is to match with firm A, which requires relatively small increases in wages in exchange for more risk in order to hold profits constant. Worker #0 ends up netting (R_0, W_0) in hedonic equilibrium. Worker #1 requires more compensation in exchange for taking on additional risk (i.e., a steeper indifference curve) and ends up choosing to match with firm B, yielding (R_1, W_1). With continuously distributed workers and firms, the hedonic wage function describes the set of tangency points between the iso-profit functions of firms and iso-expected utility functions of workers.

We use $U(W)$ to represent the utility from wage W if a worker is in the healthy state and $V(W)$ to represent the utility from the same wage in an injured state; p represents the probability of that injury. EU represents expected utility:

$$EU = (1-p)U(W) + pV(W)$$

Taking the total differential of expected utility yields:

$$(1-p)U'(W)dW + pV'(W)dW - U(W)dp + V(W)dp = 0$$

With some re-arranging, we derive an expression for the slope of an iso-expected utility curve:

$$dW[(1-p)U'(W) + pV'(W)] + dp[V(W) - U(W)] = 0$$

$$\left.\frac{\mathrm{d}W}{\mathrm{d}p}\right|_{dEU=0} = -\frac{EU_p}{EU_W} = \frac{U(W)-V(W)}{(1-p)U'(W)+pV'(W)}$$

EU will be positively sloped if $U(W) - V(W) > 0$ (i.e., utility from a given wage is greater in the non-injured state) and if $U'(W), V'(W) > 0$ (i.e., utility is increasing in wages regardless of the injury state). 2nd order conditions require that curves have convexity as illustrated. Wage hedonic techniques use the slope of estimated relationship between risk and wage to recover $\frac{dW}{dp}|_{dEU=0}$.

In the case of banks issuing mortgages, there are two forms of risk that we consider: (i) shale (p_1) and (ii) income (p_2). Shale risk refers to the list of reasons that shale development might put a house into technical default according to the standard mortgage guidelines described in the introduction. Foremost is the risk of any outcome that might detract from the house's value as a residential structure. Income risk refers to the standard risk that liquidity constrained individuals will suffer income shocks that make it impossible for them to make timely mortgage payments.

Shale risk and income risk combine to create default risk, which is ultimately what concerns the lender. Perceived default risk faced by lender i is $D_i = D_i(p_1, p_2)$, where $0 \leq D_i \leq 1 \; \forall \, i$ and $\frac{\partial D_i}{\partial p_j} \geq 0 \; \forall \, i$ and for $j = 1, 2$. Assume that $D_i(p_1, p_2)$ is quasi-convex.

Firm i's expected profit from making a loan with risks p_1 and p_2 is given by:

$$E\Pi_i = (1 - D_i(p_1, p_2))\pi_i^G(\sigma) + D_i(p_1, p_2)\pi_i^B$$

where $\pi_i^G(\sigma)$ measures the profit associated with the 'good' state (i.e., in which there is no foreclosure) when the mortgage rate is σ (i.e., the actual rate or an indicator for subprime or not). $\pi_i^B(\sigma)$ measures expected profits in the bad state in which a foreclosure takes place and the lender takes control of the property, selling it for a loss. Taking the total derivative of expected profit with respect to the two forms of risk and rearranging, we can find the change in p_2 associated with a small change in p_1 that would hold $E\Pi_i$ fixed.

$$\left.\frac{\mathrm{d}\sigma}{\mathrm{d}p_j}\right|_{dE\Pi_i=0} = \frac{\frac{\partial E\Pi_i}{\partial p_j}}{\frac{\partial E\Pi_i}{\partial \sigma}} = \frac{\frac{\partial D_i}{\partial p_j}[\pi_i^G(\sigma) - \pi_i^B(\sigma)]}{(1 - D_i(p_1,p_2))\pi_j^{G\prime}(\sigma) + D_i(p_1,p_2))\pi_j^{B\prime}(\sigma)} \quad j = 1, 2$$

$$\left.\frac{\frac{\mathrm{d}\sigma}{\mathrm{d}p_1}}{\frac{\mathrm{d}\sigma}{\mathrm{d}p_2}}\right|_{dE\Pi_i=0} = \frac{\frac{\frac{\partial E\Pi_i}{\partial p_1}}{\frac{\partial E\Pi_i}{\partial \sigma}}}{\frac{\frac{\partial E\Pi_i}{\partial p_2}}{\frac{\partial E\Pi_i}{\partial \sigma}}} = \frac{\frac{\partial E\Pi_i}{\partial p_1}}{\frac{\partial E\Pi_i}{\partial p_2}}$$

This final term represents the negative of the slope of the iso-expected profit curve. As such, we can recover firm i's willingness to take on additional income risk in exchange for a one-unit reduction in shale risk by taking the ratio of the two hedonic gradients. Under our assumptions, this will be invariant to how we define the lending rate, and we can simply use a probability of subprime rather than an exact rate, which is useful because we do not see the exact rate unless it is a subprime.[35] We therefore learn about the lender's willingness to trade-off one type of risk for another holding the overall perceived default risk constant.

[35] Since 2004, the Federal Reserve Board required lenders to collect and report the spread between the annual percentage rate (APR) on a loan and the yield on Treasury securities of comparable maturity if the spread is equal to or greater than 3.0 percentage points for a first-lien loan. In December 2008, the Board published an amendment to this rule which requires the lenders to report the spread if it is equal to or greater than 1.5 percentage points for a first-lien loan. In order to make our estimates consistent across years, we define the threshold to be 3.0 percentage points across all our sample periods.

4.6 Empirical Model

4.6.1 Probability of Subprime — Local Logit Regression

Using a binary indicator variable for a high-priced mortgage as our proxy for subprime, we would like to measure the way in which the likelihood of a subprime mortgage varies with different risk variables without imposing a great deal of structure. Following on the model of [Bajari and Benkard, 2005], we allow the data to speak to the shape of this equilibrium hedonic function (in two different dimensions of risk) and recover a flexible representation of lender preferences that characterizes the distribution of heterogeneity. We then explore how these preferences vary over time and with water source.

Parametric regression models (such as the probit and logit) are commonly used to study binary dependent variables, but these models impose restrictive functional form assumptions. Semi-parametric binary choice estimators (single-index models) relax these restrictions but they effectively reduce the heterogeneity in the X characteristics to a single dimension. This restrics the interaction between covariates – specifically, the ratio of two marginal effects does not depend on X in the single-index model. Because we are interested in heterogeneity in the tradeoffs between two types of risk (income risk and shale risk), we instead follow [Frölich, 2006] to perform non-parametric regression for binary dependent variables (local likelihood logit estimation).

The local likelihood logit estimator is:

$$\hat{E}[Y \mid X = x] = \frac{1}{1 + e^{-x'\hat{\theta}_x}}$$

where

$$\hat{\theta}_x = \arg\max_{\theta_x} \sum_{i=1}^{n} \left(Y_i \ln\left(\frac{1}{1 + e^{-X_i'\theta_x}}\right) + (1 - Y_i) \ln\left(\frac{1}{1 + e^{X_i'\theta_x}}\right)\right) K_H(X_i - x)$$

The regressors include shale risk (defined as cumulative hazard rate), income risk (defined as the debt-to-income ratio), housing characteristics (lot size, house size, number of bathroom, number of bedroom and year built of a property), loan attributes (yield of 30-year treasury bond, and whether the rate is fixed or not), and year dummies.

The kernel weight $K_H(X_i - x)$ is computed as:

$$K_{h,\delta,\lambda}(X_i - x) = \prod_{q=1}^{q_1} \kappa\Big(\frac{X_{q,i} - x_q}{h}\Big) \prod_{q=q_1+1}^{q_2} \delta^{|X_{q,i} - x_q|} \prod_{q=q_2+1}^{Q} \lambda^{\mathbb{1}(X_{q,i} \neq x_q)}$$

The kernel function measures the distance between X_i and x for each variable through one of three components, depending upon the particular type of variable: continuous regressors (the first term), ordered discrete regressors (the second term) and unordered discrete regressors (the third term). In our application, continuous regressors include cumulative hazard rate, debt-to-income ratio, lot size, house size, and yield of 30-year treasury bond; ordered regressors include number of bathrooms, number of bedrooms, and the age of each property; non-ordered regressors include year dummies, and whether the rate is fixed or not.

Values for the bandwidth and hyper-parameters (h, δ, λ) in the kernel function are obtained from cross-validation, and the cross-validation criterion is based on maximizing the leave-one-out fitted likelihood function:

$$CROSSVAL(h, \lambda, \delta) = \sum_{i=1}^{n} Y_i \ln g(X_i, \hat{\theta}_{-X_i|h,\delta,\lambda}) + (1 - Y_i) \ln(1 - g(X_i, \hat{\theta}_{-X_i|h,\delta,\lambda}))$$

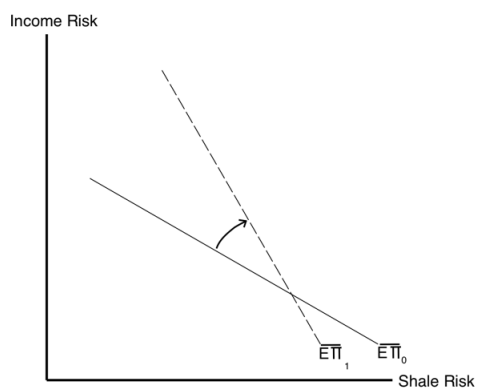
where $g(\cdot)$ is our local likelihood logit estimator.

We are interested in recovering banks' willingness to trade income risk for shale risk, which is revealed in the ratio of the two hedonic gradients, where

$$\rho(x) = \frac{\frac{\partial \hat{E}[Y|X=x]}{\partial x_1}}{\frac{\partial \hat{E}[Y|X=x]}{\partial x_2}} = \frac{\hat{\theta}_1(x)}{\hat{\theta}_2(x)}$$

Unlike the single index models, this ratio is a flexible function of the regressors, x. The negative of this ratio defines the negative of the slope of the expected iso-profit curve drawn in (shale risk, income risk)-space. Figure 4.13 illustrates a simple case with linear iso-profit curves.

Figure 4.13: Iso-profit Curves



A higher value suggests that iso-curve has become steeper, implying that lenders require a larger reduction in income risk in order to accept another unit of shale risk, holding expected profits constant.

4.7 Results

4.7.1 Simple Logit Analysis

We begin with a simple logit specification to explore the determinants of subprime status. In particular, we model the likelihood of subprime as a function of housing attributes, loan attributes (fixed or variable rate, and yield curve of 30-yr treasure bond), year dummies, the debt-to-income ratio (i.e., income risk), and the cumulative hazard rate (shale risk).

We estimate this model separately for two time periods – preceding and following the financial crisis (2003-2008 and 2010-2012). We expect that relative concerns of lenders over various sources of default risk might have changed after the financial crisis; in particular, the discussion in Section 4.3 suggests that policy makers placed increasing attention on shale risk beginning in 2010. While estimates based on the simple logit are generally insignificant, point estimates do behave as expected. Focusing on columns (1) and (2) of Table 4.7, the parameters on both forms of risk both increase in magnitude following the financial crisis, with that on shale risk becoming statistically significant. The lender's average willingness to trade-off income risk for shale risk (i.e., the ratio of the shale risk to income risk parameters) rises substantially.

We next differentiate additionally by water source (i.e., groundwater v. piped water). [Muehlenbachs et al., 2015] demonstrated that housing markets are particularly prone to capitalize the risks of nearby shale gas development when houses are dependent upon groundwater. We may therefore expect lenders to be particularly aware of shale risk when houses are groundwater dependent, and that this concern may have grown after the financial crisis. We find that this is indeed the case – we recover a large and statistically significant increase in the parameter on shale risk for groundwater dependent properties following the financial crisis, suggesting a large increase in lenders' willingnesses to take on additional income risk to avoid shale risk on these properties. The same is not true of houses that rely on piped water, where the ratio of income risk to shale risk actually goes down (although all piped water house risk parameters are statistically insignificant).

Table 4.7: Simple Logit Regression Results

	Logit Model period 1: 2001-2007	Logit Model period 2: 2010-2016	Tobit Model 2001-2007	Tobit Model 2010-2016
Cumulative hazard rate	0.0766***	0.107***	0.0413***	0.0817***
	(6.02)	(4.71)	(5.07)	(4.96)
Debt-to-income	0.196***	0.0611**	0.123***	0.0517**
	(17.20)	(2.72)	(16.78)	(3.15)
FHA loans	-3.242***	1.860***	-1.939***	1.254***
	(-49.22)	(42.05)	(-59.03)	(37.04)
VA loans	-5.341***	-3.041***	-2.896***	-1.810***
	(-11.92)	(-8.54)	(-17.58)	(-10.99)
Securitized loans	1.156***	-0.158***	0.745***	-0.222***
	(58.38)	(-4.28)	(58.03)	(-8.11)
Yield of 30 year treasury bond	-0.258***	0.0922	-0.191***	0.00940
	(-6.02)	(1.64)	(-7.04)	(0.24)
Number of bedrooms	0.343***	0.186***	0.208***	0.144***
	(17.74)	(4.61)	(17.01)	(4.96)
Number of bathrooms	-0.294***	-0.0664	-0.181***	-0.0360
	(-11.83)	(-1.27)	(-11.65)	(-0.97)
Living size	-0.000474***	-0.000616***	-0.000294***	-0.000440***
	(-24.56)	(-14.30)	(-24.50)	(-14.53)
Land size	-0.0134***	-0.00174	-0.00827***	-0.000414
	(-9.06)	(-0.55)	(-9.15)	(-0.19)
Age of property	0.00816***	0.00650***	0.00527***	0.00559***
	(15.06)	(6.44)	(15.14)	(7.56)
_cons	-6.367***	-5.140***	-3.162***	-3.581***
	(-13.04)	(-7.73)	(-14.37)	(-8.28)
sigma				
_cons			1.203***	1.482***
			(161.03)	(74.03)
N	131,489	51,198	131,548	51,264
Year FE	Y	Y	Y	Y
City FE	Y	Y	Y	Y

t statistics in parentheses

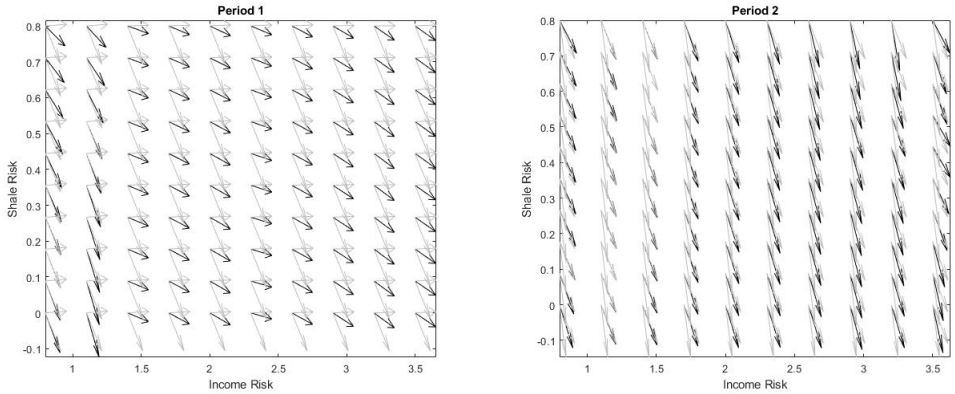
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

While the simple logit results suggest that lenders may have become increasingly concerned about shale risk following the financial crisis, and that this was particularly true for groundwater dependent houses, the strong functional form restrictions placed on the model by the simple logit may constrain our ability to learn about these relationships. In the following subsection, we relax these constraints by employing a flexible local logit specification.

4.7.2 Local Logit Estimation

We estimate the flexible local logit specification paying particular attention to the role of water source. In particular, we use estimated preference ratios $\rho(x)$ to illustrate lenders' indifference curves in (shale risk, income risk) space. We begin by taking the distribution of the ratios of debt-to-income (i.e., income risk) and shale risk, as it was defined earlier in the paper. These ratios represent the slopes of lenders' "indifference curves", drawn in the space of the two types of risks. We then calculate the kernal weighted averages of all estimated preference ratios at each point in risk space, where the smoothing parameter is set using Silverman's rule. The subsequent mapping describes the indifference curve map at every point in risk space. In Figure 4.14 Black arrows are used to describe mean estimates, while the gray arrows describe the 5% and 95% confidence bands calculated from 10 bootstrap iterations.

Figure 4.14: Indifference Curve Map



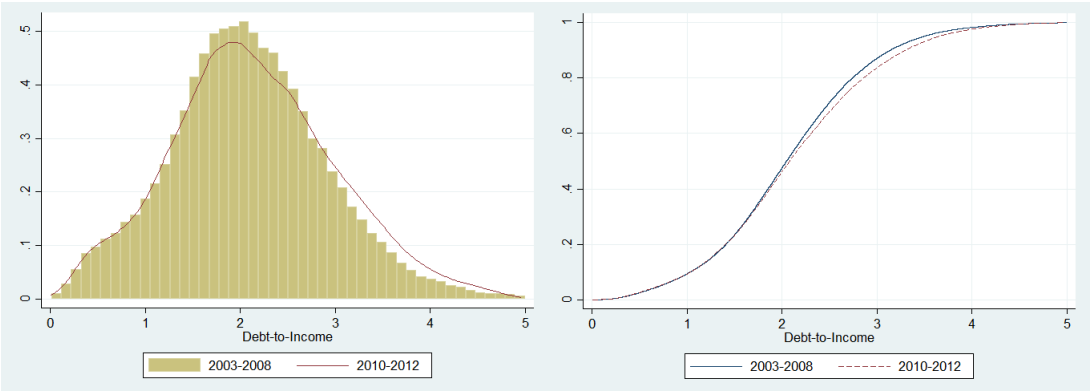
A number of interesting features appear immediately. First, in the period before the financial crisis, the slope of the indifference curves are indistinguishable from zero. Assuming income risk is always considered by lenders to be a "bad," this would imply that shale risk was not taken into consideration by banks in the earlier period. The right panel of figure 4.14 shows lenders' indifferene curves are now negatively sloped for those houses, and those slopes are statistically significant. The results shows that lenders are willing to take on significantly more income risk to avoid additional shale gas risk in the post-crisis period.

4.7.3 Robustness Check

Here we address some concerns that may generate alternative interpretations of our results.

One alternative story is that home buyers are likely to overstate their incomes in the period prior to the financial crisis, leading to an under-reporting of debt-to-income ratios , so the debt-to-income ratio in the first period is downward biased in our data set. To address this concern, below is a comparison between the distribution of debt-to-income ratio between the first and second period. Although the distribution in the pre-crisis period does

Figure 4.15: Distribution of Debt-to-Income Ratio



have a bit more mass at the lower values of the debt-to-income ratio, the differences are not large.

4.8 Valuing Shale Risk

To value the willingness to pay to avoid shale risk, through taking on additional income risk by lending to individuals with higher debt-to-income ratios, we use transaction and foreclosure information from Dallas County. Dallas neighbors Tarrant County and has comparable land and population sizes and population density, yet Dallas does not have active oil and natural gas drilling.[36] Figure 4.16 describes the rate of foreclosure by county across time, and Figure 4.17 describes foreclosure rates for homes with well exposure and not for Tarrant and Denton counties. Perhaps interestingly, shale exposed areas of Tarrant county experience the peak foreclosure period in 2011 rather than 2008 like the non-exposed regions including Dallas county. The year 2011 is during a period of volatile natural gas price, which likely affected the streams of royalty incomes for individuals with active oil and natural gas leases.

Our "back-of-the-envelope" calculation combines the estimated relationships between the debt-to-income ratio and rate of foreclosure, as described in the upper panel of Table 4.8,[37] and between the foreclosure rate and transaction value, as described in the lower panel of Table 4.8. In particular, we observe that a standard deviation increase in the debt-to-income ratio increases the likelihood that a home is foreclosed in the future by 0.129 in Dallas, and a foreclosed home sells for 25% percent less in Dallas (using the -0.28 coefficient in the lower panel of Table 4.8), controlling for other house observable characteristics and city and year fixed effects. Using the logarithm of the mean sales value for single family, residential homes located in Dallas County, we calculate the willingness to pay to avoid

[36] In particular, Dallas county is comprised of 909 square miles, 2.5 million people, and a population density of 2,950 individuals per square mile. Tarrant county, on the other hand, is comprised of 902 square miles, 1.8 million people, and a population density of 2,095 individuals per square mile.

[37] Table 4.8 also includes estimates using data from Tarrant County to demonstrate similarity across counties. However, note that debt-to-income has a smaller effect on the likelihood of foreclosure and foreclosed homes sell for more, on average, than those located in Dallas.

shale risk using the following formula:

$$WTP = \frac{\partial V_0}{\partial foreclosure} P(foreclosure|X)$$
$$= exp(11.12) - exp(11.12 - 0.129 * 0.28) = 2,394.9$$

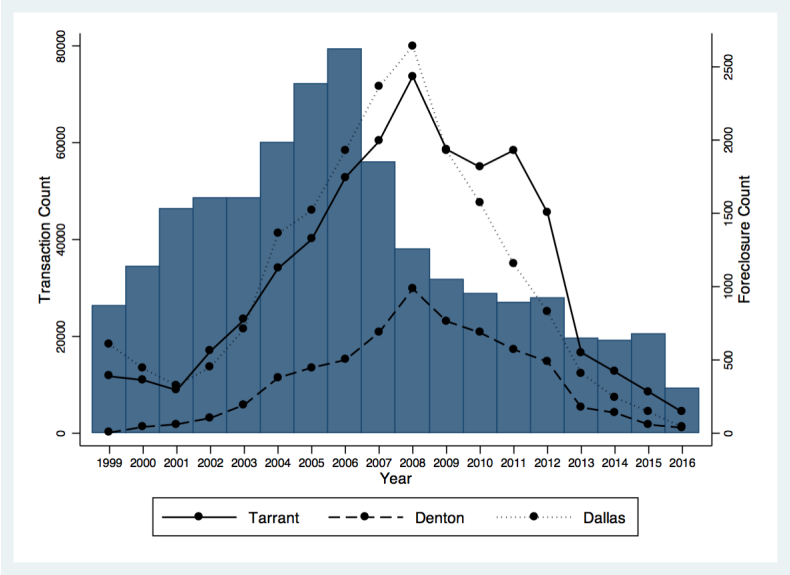
where V_0 is the mean value of a property sold in Dallas County within the sample period. The estimates from Dallas County suggest that an additional unit of shale risk is valued at $2,394.9, which is roughly 1.4% of the mean sales value among all homes sold in Dallas County during the sample period spanning 2003 to 2012.

In order to scale the willingness to pay, we compare that value to mean value earned on an average mortgage issued in Dallas. We approximate that the average mortgage interest rate is roughly 6.7% and the average loan amount is $151,476. Further, most of the loans in Dallas have 30 year term lengths and lenders earn around $190,513 on the average loan in Dallas. Our willingness to pay comprises roughly 1.2% of the profit earned on an average Dallas mortgage.

Table 4.8: Simple Foreclosure Logit & Hedonic

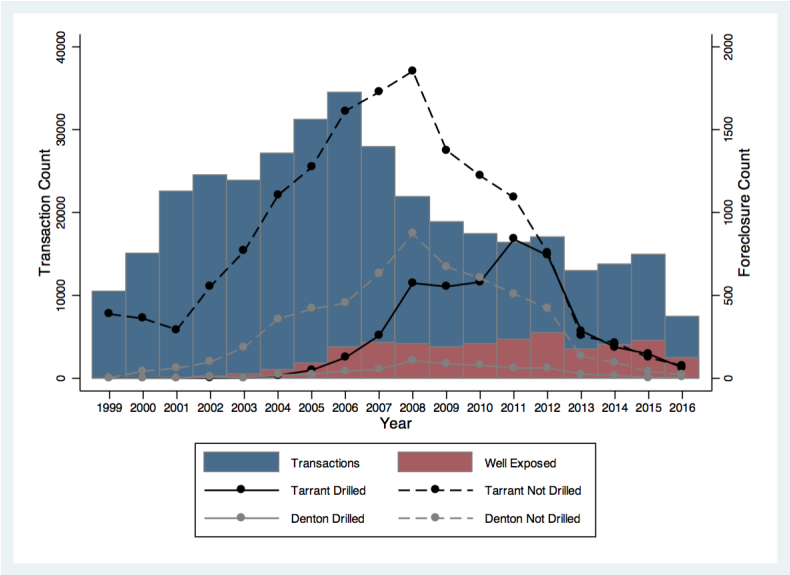
	Tarrant			Dallas	
Dependent Variable: Loan Foreclosed Dummy					
Loan-to-Income	0.23083***	0.19467***	0.19624***	0.12853***	0.11322***
	(0.01035)	(0.01134)	(0.01139)	(0.01002)	(0.01094)
Shale Exposure			-0.00823		
			(0.00767)		
Yield Curve	0.06523**	0.08393***	0.07781***	0.02829	0.05517*
	(0.02841)	(0.02860)	(0.02872)	(0.02909)	(0.02930)
FHA Loan		0.75802***	0.76085***		0.83941***
		(0.01913)	(0.01917)		(0.01924)
VA Loan		0.45506***	0.45263***		0.50779***
		(0.03615)	(0.03635)		(0.04954)
Gov't Secured		-	-		-
		0.27002***	0.26930***		0.28448***
		(0.02658)	(0.02668)		(0.02607)
Comm. Secured		-0.02607	-0.02551		-0.01978
		(0.02447)	(0.02457)		(0.02324)
Owner Occupied		-	-		-
		0.31868***	0.30640***		0.47901***
		(0.03641)	(0.03688)		(0.03349)
Constant	-	-	-	-	-
	2.65700***	2.75097***	2.75264***	5.32625***	5.06499***
	(0.18941)	(0.19248)	(0.19351)	(0.41727)	(0.41918)
Observations	216,819	216,819	213,986	192,206	191,599
Year FE	x	x	x	x	
City	x	x	x	x	

Figure 4.16: Foreclosures by County



[a] Count of foreclosed sales by year and county (right y-axis) layered on the count of total transactions (left y-axis).

Figure 4.17: Foreclosures by Shale Exposure



[a] Count of foreclosed sales by year and whether the property is exposed to drilling activity in Tarrant county (right y-axis) and layered on the count of total transactions (blue) and shale exposed transactions (red) each year (right y-axis).

4.9 Conclusion

This paper explores the housing market impacts of shale gas development. Previous work has done so using data on the capitalization of shale gas activities into housing prices and hedonic theory to give those estimates a welfare interpretation. In this paper, we come at the question from a different perspective, focusing instead on the pricing decisions of mortgage lenders. Mortgage lenders bear the risk that borrowers will default – a fact highlighted by a housing market bust and financial collapse less than a decade ago. These swings in the housing market coincided with the U.S. shale boom. By 2010, lenders and policy-makers had become much more mindful of these risks and began to recognize the role that shale gas development might play in default.

We estimate lenders relative preferences for two different types of risk – shale and income. We find strong evidence that lenders became more concerned with shale risk by the period following the financial crisis, and that this is particularly true when we differentiate by the source of houses' water supply. We might suspect that shale development would place the residential value of a groundwater-dependent property at greater risk. This indeed appears to be the case, with lenders showing a relative distaste for shale risk on loans to these properties.

These results confirm the conclusions of previous research with respect to the expected house price impacts of shale gas development for groundwater homes ([Muehlenbachs et al., 2015]). Importantly, they do so based on the decisions of agents (i.e., lenders) who make hundreds (possibly thousands) of lending decisions each year. One might worry that homebuyers in hedonic models might lack expertise – the typical individual may only buy a couple of houses over the course of her lifetime, and the cost of information acquisition is high. The same is not true for professional lenders.

Chapter 5

Conclusion

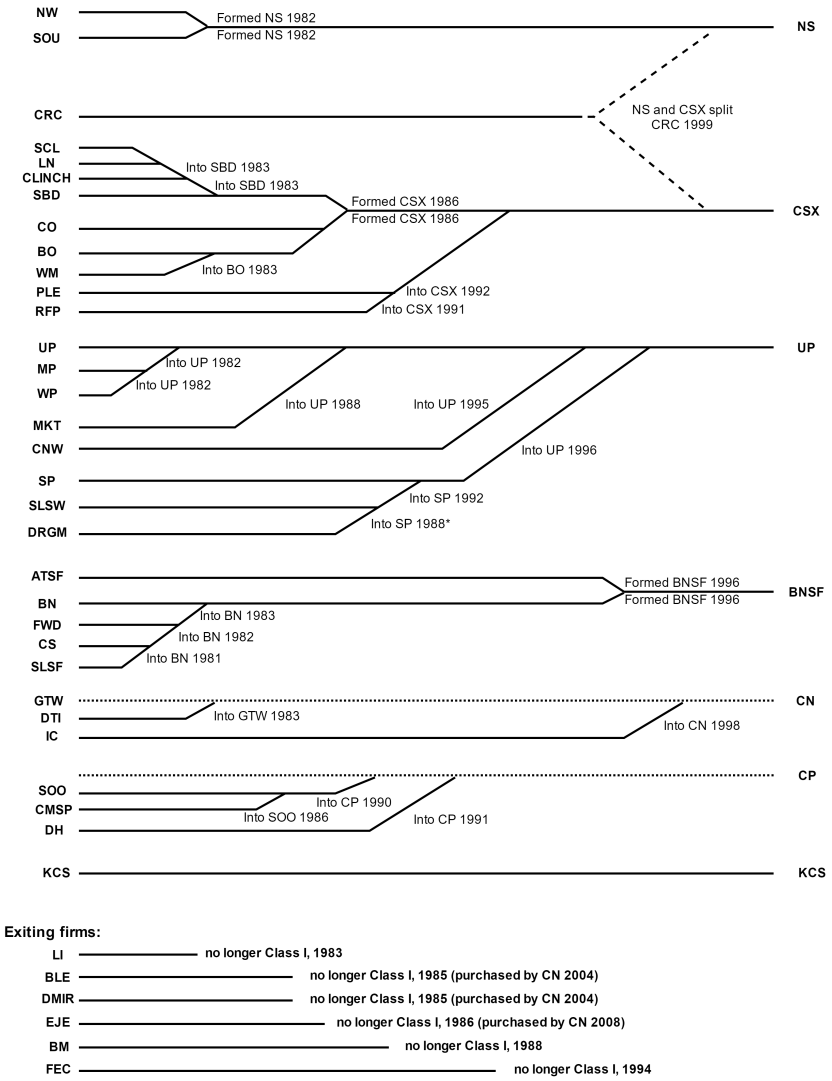
In this dissertation, I study the relationship between network and spatial analysis between firm behaviors and market outcomes. In chapter 2, I study the mechanism of cost efficiency following mergers of U.S. freight railroads and uncovers the sources. First, reduced-form result shows that following mergers, average shipment price significantly decreases, and the price effect of the merger is greater where railcars must be switched between two companies. However, given that markets are interdependent in railroad networks because of routing and investment decisions, merger efficiency cannot be measured simply by comparing individual markets. I address this with a structural model of firm pricing, routing, and investment decisions. Model estimates allow simulations that reveal sources of cost efficiency to include elimination of interchange costs, routing and consolidation of traffic, and re-optimization of investment. Welfare impacts show a great deal of geographic heterogeneity across markets. In addition to this work, Chapter 3 develops and estimates a dynamic industry equilibrium model of R&D, R&D spill-overs, and productivity evolution of manufacturing plants in the Korean electric motor industry from 1991 to 1996, and Chapter 4 analyzes mortgage lenders' behavior with respect to shale gas risk during the period of the U.S. shale gas boom, which coincided with the U.S. housing market rise, collapse and subsequent increase in lending industry scrutiny.

Appendix A

Appendix to Chapter 2

A.1 Merger History

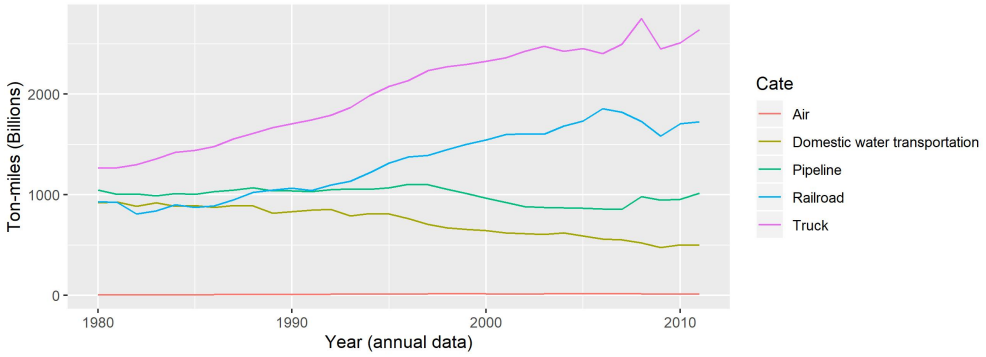
Figure A.1: Merger History of Railroads



A.2 Details of U.S. Railroad Industry

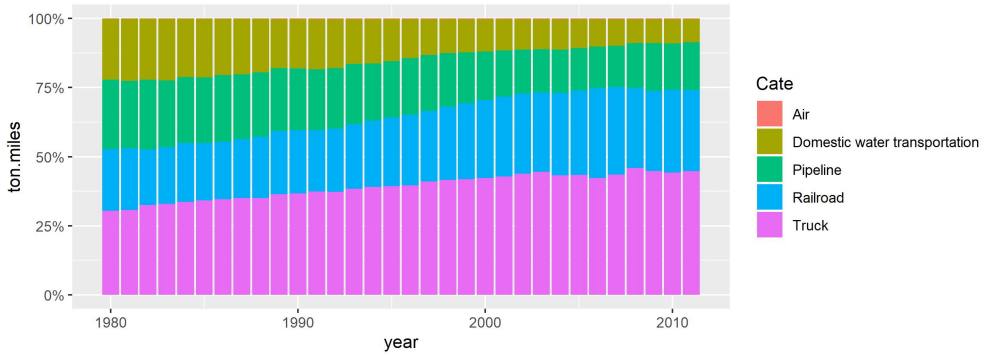
Figure A.2 and A.3 plots the total ton-miles of freight carried by mode, from 1980 to 2011 Importance of railroad industry among all the transportation mode. We can see that the U.S. railroad industry only accounts fo a small proportion of total ton-miles of freight (around 20%), and even accounts for a smaller proportion than pipelines at the start of 1980s. But it keeps increasing after the deregulation of 1980 and reaches 33% before the financial crisis. According to American Association of Railroads, if we only look at the intercity ton-miles, the railroad industry accounts for about 40 percent of the total shipping, more than any other transportation mode.

Figure A.2: U.S. total ton-miles of freight by mode



Source: U.S. Department of Transportation, Bureau of Transportation Statistics

Figure A.3: U.S. total ton-miles of freight by mode (percentage)



Source: U.S. Department of Transportation, Bureau of Transportation Statistics

A majority of the freight revenues in the U.S. freight railroad industry is generated by Class I railroads (see figure A.4, Class I railroads generate around 95% of the total freight revenues).

Figure A.4: U.S. Freight Railroad Industry 2012

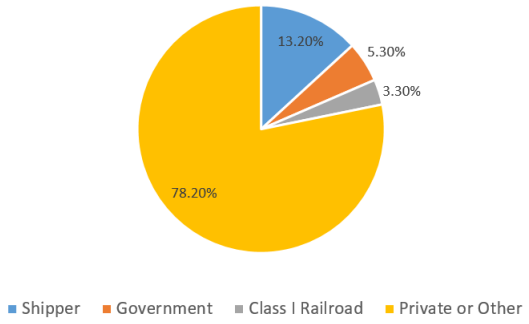
U.S. Freight Railroad Industry 2012

Railroad	Number	Miles	Employees	Revenue ($ bil)
Class I	7	95,264	163,464	$67.6
Regional	21	10,355	5,507	1.4
Local	546	32,858	12,293	2.6
Total U.S.	574	138,477	181,264	$71.6
Canadian	1	47		
Grand Total	575	138,524		

Source: Association of American Railroads, Analysis of Class I Railroads Annual Issues and Railroad Ten-Year Trends

Generally, the regional and local rails serve following purposes: first, shipping commodities from the main rails to end-users: for example, shipping coals from main rails to power plants; Second, serve as parking lot of railcars. A large proportion of regional and short lines are owned by leasing companies (Figure A.4) and serve this purpose; Third, used as interchanging places for different railroad companies to interchange the shippings.

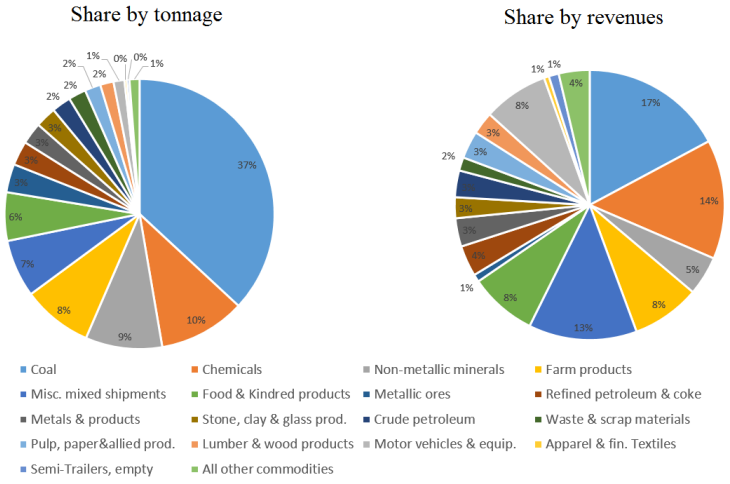
Figure A.5: Ownership of Regional and Short Lines



Source: American Short Line and Regional Railroad Association

The U.S. railroad industry ships various types of commodities, but the majority of carloads are generated by coal, chemical, and farm products. Although, the revenues generated by shipping coal are decreasing and the carloads of intermodal shippings (Misc. mixed shipments) are increasing nowadays.

Figure A.6: Carloads originated by commodity



Source: Association of American Railroads, Analysis of Class I Railroads Annual Issues and Railroad Ten-Year Trends

A.3 Regulation Changes in the U.S. Railroad Industry

History: 1887 - 1980

- 1887, the Interstate Commerce Act: create ICC value of service pricing (VOS pricing)
- 1973, The Regional Rail Reorganization Act ("3R" act): Establishment of US Railway Association, abandoning designated portions of the Northeast system
- 1976, Railroad Revitalization and Regulatory Reform Act ("4R" act): Creation of Conrail, permitting a railroad to adjust its rates up or down within a "zone of reasonableness", which is initially within 8 percent of the existing ICC tariff and widened over time. Accelerate the legal procedure dealing with abandoning unprofitable lines and expedite processing of merger
- 1980, The Staggers Act: The most important change is the removal of inefficient commodity rate regulation Enhanced the ability of abandoning lines and merge with others

Most recent: 1980 - current

- After the deregulation of 1980, ICC/STB no longer sets fixed prices for the railroad industry. Instead, it implements a constrained market pricing strategy, in which railroads are not allowed to set rates that are "too high". The STB does not have jurisdiction over the reasonableness of a rate for rail transportation unless the rail carrier providing the service has "market dominance". By statue, a necessary but not sufficient condition for a railroad to be considered to have market dominance is that the revenue produced by the rate is greater than 180% of its variable cost of providing the service as determined under the STB's Uniform Rail Costing System. When the rate goes beyond this 180% threshold, shippers are able to request STB to evaluate whether the service has "market dominance". There are three methods that

STB allow shippers to use to evaluate market dominance of rail carriers: Stand-alone cost constraint (the most frequently used tools in law suits, invented in 1985), the three-benchmark procedure (invented in 1996), and the simplified-SAC (invented in 2007).

- 1985, ICC's Coal Rate Guidelines: ICC implements the requirement of constrained market pricing, in which the rate set by rail carriers needs to satisfy three constraints:
  - Revenue adequacy constraint: intended to ensure that railroads earn enough revenue to make normal profits, but not more (3 rate law cases invoked this principle since 1980 but all settled between shipper and railroad company)
  - Management efficiency constraint: prevent the shippers from paying avoidable costs that result from the inefficiency of the railroad (0 cases invoked this principle since 1980)
  - Stand-alone cost constraint (SAC): Simulate the competitive rate that would exist in a contestable market by assuming a new highly efficient competitor railroad. The shipper must demonstrate that the "new" competitor would fully cover its costs, including a reasonable return on investment (full-SAC) (the most frequently used principle in rate cases. 50 rate cases invoked this principle after 1996, according to STB data base)
- 1995, ICC Termination Act
- 1996, The Three-benchmark procedure (only applies to cases where the total revenue of service is under $1 million over five years)
  - Revenue shortfall allocation method, the uniform mark-up above variable cost that would be needed from every shipper in the captive group ($R/VC > 180$) to cover the URCS fixed cost
  - R/VC for comparative traffic

- $R/VC_{>180}$ average captive price: calculate the average price of all the "captive" shippers

Only 3 rate cases use three-benchmark from 1996 - 2007, while 25 rate cases use full-SAC in the same period.

- 2007, Simplified SAC (only applies to cases where the total revenue of service is under \$5 million over five years): this allows shippers to use the existing infrastructure that serves the traffic, instead of coming up with a hypothetical stand-alone railroad to prove the market dominance of current service provider. Only 2 rate cases use simplified-SAC from 2007, while 20 cases use full-SAC in the same period

- 2013, Rate Regulations Reforms: remove limit of simplified-SAC, raise limit of three-benchmark to \$4 million (we see 6 rate cases after 2016, but all are using full-SAC method)

A.4 Robustness Check of Reduced-form Analysis

Study effect of merger on ratio of switching hours to road service hours case-by-case:

Table A.1: Effect of Merger on Ratio of Switching Hours to Road Service Hours

	(1) Ratio of Switching Hrs to Road Service Hrs	(2) (case-by-case)
Indicator of Merger	-0.115**	
	(-2.26)	
BNSF merger		-0.103
		(-1.12)
IC merger		-0.401
		(-1.60)
DRGW merger		0.171
		(1.65)
SP merger		-0.348
		(-1.70)
CNW merger		-0.570***
		(-7.81)
MKT merger		-0.316**
		(-2.79)
CRNS merger		-0.484***
		(-3.41)
CRCSX merger		-0.516***
		(-3.64)
_cons	0.782***	0.495***
	(13.34)	(4.71)
N	208	208
Firm FE	Y	Y
Year FE	Y	Y

t statistics in parentheses

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

Study effect of merger on average length of haulage case-by-case:

Table A.2: Effect of Merger on Average Length of Haulage

	(1) Log average length of hauling	(2) (case-by-case)
Indicator of Merger	0.0525**	
	(2.24)	
BNSF merger		-0.0574
		(-0.56)
IC merger		0.0784
		(1.70)
DRGW merger		-0.0238
		(-0.85)
SP merger		0.261
		(1.49)
CNW merger		0.589***
		(6.15)
MKT merger		0.628***
		(6.81)
CRNS merger		0.468***
		(5.16)
CRCSX merger		0.578***
		(6.37)
_cons	6.075***	6.404***
	(102.28)	(62.36)
N	208	208
Firm FE	Y	Y
Year FE	Y	Y

t statistics in parentheses

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

A complete summary statistics of commodities shipped by rail from waybill data:

Table A.3: Descriptive Statistics of Commodity Types and Car Ownership Category

	Number of Waybills	Percentage
Commodities		
Field Crops	466,584	3.85%
Forest Products	5,361	0.04%
Marine Products	2,138	0.02%
Metallic Ores	93,371	0.77%
Coal	1,002,580	8.28%
Crude Petroleum	2,855	0.02%
Nonmetallic Minerals	371,109	3.06%
Ordnance or Accessories	1,838	0.02%
Food or Kindred Products	882,352	7.28%
Tobacco Products	1,222	0.01%
Textile Mill Products	9,533	0.08%
Apparel or Other Textile Products	46,414	0.38%
Lumber or Wood Products	487,386	4.02%
Furniture or Fixtures	34,101	0.28%
Pulp, Paper or Allied Products	483,980	4.00%
Newspapers and Books	15,933	0.13%
Chemicals	635,119	5.24%
Petroleum or Coal Products	158,794	1.31%
Rubber or Miscellaneous Plastics Products	62,202	0.51%
Leather Products	2,484	0.02%
Clay, Concrete, Glass or Stone Products	323,923	2.67%
Primary Metal Products	354,360	2.93%
Fabricated Metal Exc.	24,387	0.20%
Machinery Exc.	23,351	0.19%
Electrical Machinery	70,893	0.59%
Transportation Equipment	1,098,439	9.07%
Instruments, Optical Goods	3,192	0.03%
Miscellaneous Products	21,965	0.18%
Waste or Scrap Materials	342,374	2.83%
Miscellaneous Freight Shipments	60,474	0.50%
Containers	660,513	5.45%
Mail	43,970	0.36%
Freight Forwarder	3,689	0.03%
Shipper Association	48,529	0.40%
Miscellaneous Mixed Shipments	3,434,269	28.35%
Small Packaged Freight Shipments	62,495	0.52%
Waste Hazardous	7,329	0.06%
Other	762,855	6.30%
Car Ownership Category		
Privately Owned	5,349,791	44%
Railroad Owned	3,621,221	30%
Trailer Train	2,202,838	18%
Non-Categorized	939,731	8%
Waybills (Carrier-Origin-Destination-Date)	12,113,581	

Source: STB, Carload Waybill Sample

Study effect of merger on price changes case-by-case. Table A.4 shows the estimation result of shipment price changes. The result suggests that on average a railroad merger reduces the shipment price by 9.4%. If we look at the merger effect case by case, we find that most of the large mergers result in a price reduction of more than 10%, such as the merger of the Burlington Northern and Santa Fe, the merger of the Southern Pacific and Union Pacific, and the merger of the Chicago and North Western Railway (CNW) and Union Pacific. The only exception is the merger of the Seaboard System Railroad (SBD), Chesapeake and Ohio Railway (CO), and Baltimore and Ohio Railroad (BO) which occurred in 1986. Mergers involving smaller railroad firms have an insignificant impact on shipment price, likely because these mergers affect only a small fraction of routes.

Table A.4: Effect of Merger on Price Change

	(1)	(2)
	Log Price	Log Price
Indicator of Merger	-0.094***	
	(0.014)	
SBD		0.106***
		(0.021)
BNSF		-0.114***
		(0.023)
LA		-0.043
		(0.058)
MSRC		0.052
		(0.059)
IC		-0.025
		(0.041)
CNW		-0.162***
		(0.039)
MKT		0.009
		(0.044)
DRGW		0.018
		(0.043)
SP		-0.119***
		(0.021)
SSW		-0.227***
		(0.040)
WC		0.006
		(0.058)
Log Weight	-0.259***	-0.260***
	(0.015)	(0.015)
Private Railcars	-0.112***	-0.110***
	(0.009)	(0.009)
Trailer Train Railcars	-0.052***	-0.053***
	(0.009)	(0.009)
Observations	12,110,107	12,110,107
Number of marketID	22,510	22,510
Adjusted R-squared	0.361	0.363
Year FE	Y	Y
Firm FE	Y	Y
Commodity FE	Y	Y
O-D Route FE	Y	Y

Standard errors in parentheses, clustered at O-D route level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Surface Transportation Board, Carload Waybill Sample

As a robustness check, I run the price regression for each type of commodity (defined in STCC):

Table A.5: Effect of Merger on Price Change (by Commodities)

	(1) Field Crops	(2) Metallic Ores	(3) Coal	(4) Nonmetallic Minerals	(5) Food or Kindred Products	(6) Apparel or Textile Products	(7) Lumber or Wood Products	(8) Furniture or Fixtures	(9) Pulp, Paper	(10) Newspapers
Indicator of Merger	-0.009	0.048	-0.179***	-0.036	-0.052***	0.049	0.016	-0.023	-0.013	-0.057
	(0.014)	(0.062)	(0.028)	(0.029)	(0.014)	(0.047)	(0.013)	(0.036)	(0.015)	(0.042)
Observations	466,222	93,316	1,002,552	371,035	882,066	46,409	487,275	34,095	483,952	15,933
Number of marketID	6,982	1,086	1,360	3,697	10,766	1,210	8,145	1,694	8,441	780
Adjusted R-squared	0.178	0.144	0.251	0.234	0.266	0.767	0.274	0.829	0.299	0.667
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
O-D Route FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

	(11) Chemicals	(12) Petroleum	(13) Plastics Products	(14) Clay, Concrete, Stone Products	(15) Primary Metal Products	(16) Fabricated Metal Exc.	(17) Machinery	(18) Electrical Machinery	(19) Transportation Equipment	(20) Miscellaneous Products
Indicator of Merger	-0.114***	-0.115***	-0.056**	-0.045***	-0.112***	-0.104***	-0.035	-0.146***	-0.022	0.022
	(0.031)	(0.024)	(0.028)	(0.015)	(0.027)	(0.035)	(0.037)	(0.038)	(0.035)	(0.035)
Observations	634,684	158,774	62,197	323,910	354,322	24,385	23,343	70,889	1,097,641	21,963
Number of marketID	10,462	4,175	2,087	6,670	6,639	2,009	2,072	1,996	7,177	1,163
Adjusted R-squared	0.157	0.210	0.730	0.262	0.163	0.558	0.413	0.569	0.321	0.765
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
O-D Route FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

	(21) Waste or Scrap Materials	(22) Miscellaneous Freight Shipment	(23) Containers	(24) Mail	(25) Shipper Association	(26) Miscellaneous Mixed	(27) Small Packaged	(28) 49
Indicator of Merger	-0.000	-0.103*	0.049	0.036*	-0.179***	-0.170***	0.019	-0.072***
	(0.022)	(0.055)	(0.052)	(0.019)	(0.035)	(0.034)	(0.041)	(0.018)
Observations	341,973	60,443	660,061	43,965	48,523	3,434,108	62,487	762,745
Number of marketID	7,843	2,775	2,747	903	1,245	5,821	633	9,562
Adjusted R-squared	0.195	0.412	0.426	0.611	0.468	0.569	0.670	0.224
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
O-D Route FE	Y	Y	Y	Y	Y	Y	Y	Y
O-D Route Cluter	Y	Y	Y	Y	Y	Y	Y	Y

Appendix B

Appendix to Chapter 3

B.1 Profit from Static Competition

The static competition model of heterogenous firms is built on Melitz (2003). We assume that firm i within an industry has a standard Cobb-Douglas production function with returns to scale parameters γ. We will describe individual firm's problem by abstracting from the notation i for convenience.

$$q_t = exp(\bar{X}_t + x_t)(l_t^{\alpha}(k_t)^{1-\alpha})^{\gamma}, \tag{B.1}$$

where q_t is the output for firm i. Firm's efficiency is defined by its distance from the industry technological frontier $exp(\bar{X}_t)$. x_t captures how much a firm's knowledge lies behind current frontier, so it has a maximum value of zero. k_t is physical capital input and l_t is labor input. Furthermore, we assume $\bar{X}_t$ follows a deterministic exogenous process, which is determined by the world technological frontier.

Each firm produces a differentiated product and each one of them faces a demand function such that

$$q_t = Q_t(p_t/P_t)^{\eta} = \frac{I_t}{P_t}(\frac{p_t}{P_t})^{\eta} \tag{B.2}$$

where p_t is the price set by firm i, while Q_t and P_t are industry level output and price index. Accordingly, I_t is defined as the industry market size at time t. This demand function is from the widely-used monopolistic competition model by Dixit and Stiglitz (1977). The parameter η captures the elasticity of substitution between different products.

Thus each period, a firm takes quasi-fixed factors (k_t, x_t), exogenous variable factor prices w_t, aggregate market price P_t, and current frontier technology $exp(\bar{X}_t)$ as given and

chooses variable inputs l_t to maximize its profit

$$\pi_t = p_t(I_t, P_t, q_t)q_t - w_t l_t \tag{B.3}$$

We could rewrite this problem as:

$$max_{l_t} P_t^{1+\frac{1}{\eta}} I^{-\frac{1}{\eta}} (exp(\bar{X}_t + x_t) k_t^{(1-\alpha)\gamma})^{1+\frac{1}{\eta}} (l_t^{\alpha\gamma})^{1+\frac{1}{\eta}} - w_t l_t. \tag{B.4}$$

Let's redefine industry price index as

$$\hat{P}_t = P_t exp(\bar{X}_t),$$

which allows us to write the optimal labor decision as

$$l_t^* = [\frac{w_t I^{\frac{1}{\eta}}}{(exp(x_t) k_t^{(1-\alpha)\gamma})^{1/\eta+1} \hat{P}_t^{1+\frac{1}{\eta}} (1+1/\eta)\alpha\gamma}]^{\frac{1}{(1+1/\eta)\alpha\gamma-1}}. \tag{B.5}$$

Let $\varphi_t = exp(x_t) k_t^{(1-\alpha)\gamma}$, $\sigma = \frac{1+\eta}{\eta-(1+\eta)\alpha\gamma}$, then $\frac{1}{(1+1/\eta)\alpha\gamma-1} = \frac{-\eta\sigma}{1+\eta}$. Substitute the optimal labor decision into the individual price equation $p(\hat{P}_t, q_t)$

$$\hat{p}(\hat{P}_t, \varphi_t) = p(\hat{P}_t, \varphi_t) exp(\bar{X}_t) = [\hat{P}_t^{(1+\frac{1}{\eta})(\alpha\gamma-1)} I^{\frac{1}{\eta}(1-\alpha\gamma)} (\frac{w}{(1+1/\eta)\alpha\gamma})^{\frac{1}{\eta}\alpha\gamma} \varphi_t^{-\frac{1}{\eta}}]^{\frac{-\eta\sigma}{1+\eta}}. \tag{B.6}$$

Furthermore $s_t(\varphi)$ is defined as the number of firms whose $\varphi_t = \varphi$. In equilibrium, normalized industry price index $\hat{P}_t$ is determined by the industry state s_t

$$\hat{P}_t = [\sum_{\varphi} s_t(\varphi) \hat{p}(\hat{P}_t, \varphi)^{1+\eta}]^{\frac{1}{1+\eta}}. \tag{B.7}$$

Substitute individual price equation $\hat{p}(\hat{P}_t, \varphi)$ into equilibrium industry price index

$$\hat{P}_t = I^{1-\alpha\gamma} (\frac{w}{(1+1/\eta)\alpha\gamma})^{\alpha\gamma} (\sum_{\varphi} s_t(\varphi)\varphi^{\sigma})^{-\frac{1}{\sigma}}. \tag{B.8}$$

Finally, we have the equilibrium maximized profit for firm with individual state $\varphi_t = exp(x_t) k_t^{(1-\alpha)\gamma}$ as

$$\pi(\varphi_t, s_t) = I(1 - (1 + \frac{1}{\eta})\alpha\gamma) \frac{\varphi_t^{\sigma}}{\sum_{\varphi} s_t(\varphi)\varphi^{\sigma}}. \tag{B.9}$$

Appendix C

Appendix to Chapter 4

C.1 Additional Empirical Analyses

C.1.1 Year-Specific Effects by Securitization

Table C.1 summarizes the sale and loan characteristics across loans that are not securitized (in the data) and commercially and government securitized. Loans securitized by a government entity like Freddie or Farmer Mac and Fannie or Ginnie Mae, are associated with lower income buyers, value homes, and loan-to-income ratios.

Table C.1: Summary Statistics by Securitization

	Not Secured		Gov't Secured		Commercially Secured	
	Mean	(Std. Dev.)	Mean	(Std. Dev.)	Mean	(Std. Dev.)
High Interest Loan	0.155	(0.362)	0.043	(0.202)	0.142	(0.349)
Income	101354.7	(92370.11)	84116	(55294.88)	85715.52	(62805.21)
Loan-to-Income	2.115	(0.838)	2.101	(0.787)	2.206	(0.799)
Sale Amount	165756.4	(123645.1)	151275.3	(80178.49)	155358	(93593.59)
Loan Value	181121.9	(164265.4)	154592.1	(83170.38)	166751.1	(108633.4)
Annualized L2I	0.173	(0.069)	0.167	(0.057)	0.175	(0.061)
Foreclosure	0.089	(0.285)	0.074	(0.262)	0.077	(0.267)
Fixed Loan	0.785	(0.411)	0.951	(0.215)	0.855	(0.352)
FHA Loan	0.101	(0.301)	0.281	(0.45)	0.314	(0.464)
Owner Occ.	0.875	(0.331)	0.931	(0.253)	0.934	(0.249)
Obs.	91,311		188,701		300,550	

[a] Summarizes the primary variables used to describe the loan characteristics across loans that are and are not securitized.

C.1.2 Tarrant County Logit Models - Simple Exposure

In Tarrant county, the relationship between loan-to-income is positive when estimating the logit using all years of data as demonstrated in the first column of Table C.2. Breaking the data in periods before 2008 and after 2009, the relationship between loan-to-income is positive in early periods and negative in later periods. After 2009, FHA loans are more likely to have greater interest rates (2.092***), whereas before 2008, the relationship is negative (-3.26***). A similar shift occurs for loans originated for owner-occupied houses. Conversely, a loan that is commercially securitized is less likely to have a high interest rate after 2009 (compared to before 2008), and government securitized are even less likely to be originated with high interest rates post 2009. Figure C.1 plot the year-estimates for the relationship between loan-to-income and the interactions with whether the loan is an FHA or Securitizes, and Figure C.2 adds the effect of shale risk. Before 2009, the high loan-to-income values among securitized loans were more likely to have high interest rates, and after 2009, the high loan-to-income values among FHA loans were more likely originated with high interest rates.

Stratifying the data by water access, the observed patterns for loan types across periods persist for both district and ground water regions, though the magnitudes are a little different. The primary different is that the relationship between shale risk and a high interest rate is a little significant among groundwater houses, though the magnitude is less after 2009. Figure C.2 suggests that shale risk has a positive and significant relationship with high interest rates in 2010 and 2013.

Table C.3 captures how the model estimates change with the addition of racial and ethnicity household characteristics and loan characteristics. Moving from column (1) to (2) reveals the importance of controlling for the racial and ethnic composition of borrowers. In Column (3) we control for whether the loan is insured by the Federal Housing Administration or the Veterans Administration. Column (4) controls for securitization, and in particular, we control for whether the loan is securitized by a government or commercial entity. Column (5) controls for whether the loan is originated for an owner-occupied house

(in lieu of an investor or secondary home buyer). The last two columns include interactions between loan-to-income values and whether the loan is securitized by a government entity or commercial entity, the house is owner occupied, and finally, whether the house is exposed to shale. Including interactions soaks up the observed effect of loan-to-income independently whereby both forms of securitization are likely to have high interest rates associated with high loan-to-income ratios. Interactions with shale soak up the effect of shale exposure independently, as well.

Table C.2: Subprime Logit - Tarrant County

Dependent Variable:	Subprime Loan						
				District Water		Groundwater	
	Full	Before 2009	After 2009	Before 2009	After 2009	Before 2009	After 2009
Shale Risk	0.00890	0.00797	0.01035	-0.02029	0.01446	0.02613*	0.01532*
	(0.00547)	(0.01161)	(0.00728)	(0.02228)	(0.01409)	(0.01495)	(0.00896)
V2I	0.03516***	0.07248***	-	-0.03465	-	0.14338***	0.01075
			0.08415***		0.19105***		
	(0.01262)	(0.01679)	(0.02579)	(0.02685)	(0.04058)	(0.02200)	(0.03410)
FHA Loan	-	-	2.09160***	-	2.02102***	-	2.09284***
	0.55000***	3.26782***		3.41661***		3.16380***	
	(0.02406)	(0.07391)	(0.05357)	(0.11581)	(0.08449)	(0.09683)	(0.07066)
VA Loan	-	-	-	-	-	-	-
	3.92082***	5.17340***	2.76600***	4.51112***	2.91574***	6.23394***	2.70941***
	(0.19058)	(0.44887)	(0.35848)	(0.50372)	(0.58809)	(1.00125)	(0.45309)
Gov't Sec.	-	-	-	-	-	-	-
	1.04558***	1.29909***	2.01126***	1.12973***	2.17845***	1.44928***	1.89200***
	(0.03097)	(0.04541)	(0.06409)	(0.06945)	(0.09884)	(0.06126)	(0.08644)
Comm.	0.10268***	0.55416***	-	0.64951***	-	0.46236***	-
Sec.			1.74178***		1.87563***		1.63638***
	(0.02484)	(0.03094)	(0.06122)	(0.04819)	(0.09332)	(0.04116)	(0.08320)
Owner	-	-	1.14094***	-	1.38999***	-	0.98351***
Occ.	0.24551***	0.29383***		0.17505***		0.36508***	
	(0.03351)	(0.03985)	(0.14986)	(0.06004)	(0.23868)	(0.05460)	(0.19943)
Hispanic	0.84592***	0.79341***	0.80235***	0.76699***	0.98185***	0.81981***	0.61738***
	(0.02321)	(0.03172)	(0.04591)	(0.04864)	(0.07007)	(0.04314)	(0.06272)
Black	1.30950***	1.58969***	0.66769***	1.66176***	0.82186***	1.54720***	0.54313***
	(0.02739)	(0.03636)	(0.06528)	(0.05739)	(0.10288)	(0.04842)	(0.08692)
Asian	-	-	-0.22017*	-0.17814*	-0.19348	-	-0.21228
	0.28462***	0.28114***				0.31539***	
	(0.04949)	(0.06182)	(0.11615)	(0.10053)	(0.20123)	(0.07924)	(0.14445)
Yield	-	-	0.21941***	-	0.12054	-	0.29365***
Curve	0.28462***	0.21739***		0.26760***		0.16283**	
	(0.03362)	(0.05717)	(0.06270)	(0.09051)	(0.09645)	(0.07522)	(0.08392)
Beds	0.25665***	0.27333***	0.17159***	0.27001***	0.18358***	0.25612***	0.13478**
	(0.02000)	(0.02593)	(0.04435)	(0.04160)	(0.06986)	(0.03399)	(0.05897)
Baths	-	-	-0.02763	-	0.00916	-	-0.04606
	0.17966***	0.22636***		0.29738***		0.19777***	
	(0.02550)	(0.03301)	(0.05629)	(0.05327)	(0.08731)	(0.04314)	(0.07551)
Living Size	-	-	-	-	-	-	-
	0.00041***	0.00037***	0.00057***	0.00038***	0.00067***	0.00029***	0.00042***
	(0.00002)	(0.00003)	(0.00005)	(0.00004)	(0.00007)	(0.00003)	(0.00006)
Land Size	-	-	-0.00303	-0.00373	0.00795	-	-
	0.00429***	0.00593***				0.00917***	0.01125**
	(0.00162)	(0.00206)	(0.00371)	(0.00433)	(0.00685)	(0.00254)	(0.00475)
Age	0.00671***	0.00844***	0.00522***	0.00399***	0.00001	0.01752***	0.01630***
	(0.00051)	(0.00069)	(0.00110)	(0.00092)	(0.00149)	(0.00128)	(0.00209)
Constant	0.19631	-0.30055	-	1.18883	-13.24518	-0.23164	-13.39840
			2.28994***				
	(0.22847)	(0.33985)	(0.77425)	(0.86276)	(674.47492)	(0.82153)	(487.88197)
Observations	121,476	56,750	44,386	21,148	16,282	34,577	27,385
Year FE	x	x	x	x	x	x	x
City FE	x	x	x	x	x	x	x

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] Each column reports estimates from a logit model of subprime loans. Each specification controls for year and city fixed effect along with house, household, and loan characteristics. The first column includes all transactions occurring between 2003 and 2016 in Tarrant County Texas, and the next two columns estimate the models separately for sales occurring before and after 2009, the rough timing of the financial crisis. The last four columns estimate the models separately for houses that are likely and not likely accessing groundwater. The shale risk increases the likelihood the loan is subprime among groundwater houses.

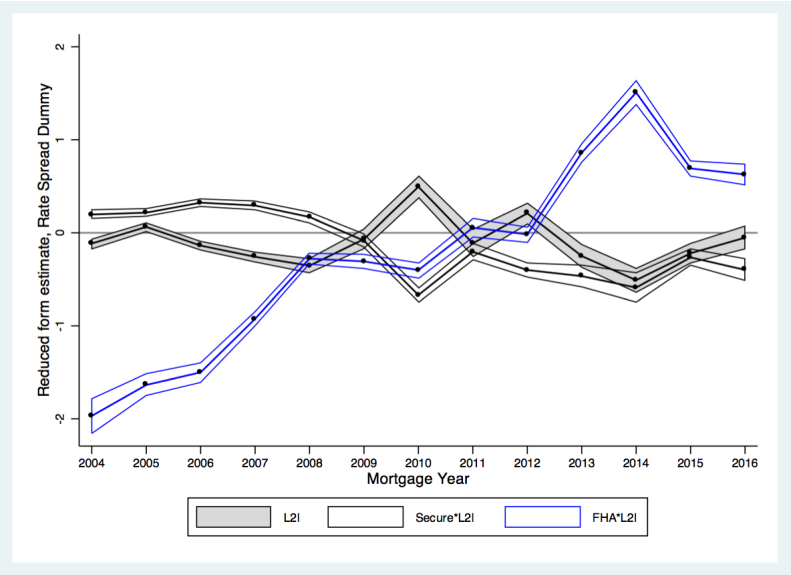


Figure C.1: County year-specific effects

[a] Each point is a coefficient estimating the year specific relationship between loan-to-income, L2I*Securitized Loan, and L2I*FHA Loan and the likelihood the loan is subprime. The model is estimated using a logit specification comprised of data from Tarrant, Dallas, and Denton counties, and the model controls for year and city fixed effects along with house, household, and loan characteristics.

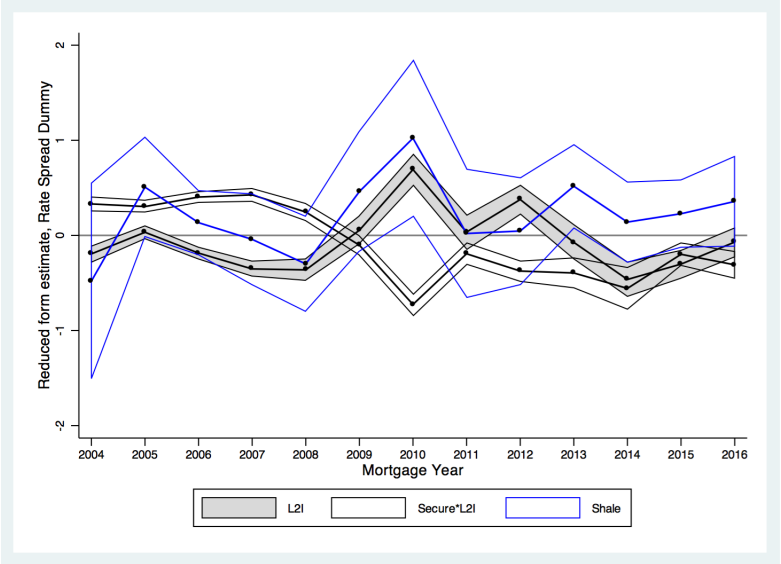


Figure C.2: Tarrant county year-specific effects

[a] Each point is a coefficient estimating the year specific relationship between loan-to-income, L2I*Securitized Loan, and shale exposure and the likelihood the loan is subprime. The model is estimated using a logit specification that controls for year and city fixed effects along with house, household, and loan characteristics. The year-specific effects of L2I*FHA Loan are estimated, as well, but not plotted.

Table C.3: Subprime Logit Variable Selection - Tarrant County

Dependent Variable:	Subprime Loan Indicator						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Shale Risk	0.00868*	0.00981**	0.01541***	0.01181**	0.01081**	0.01107**	-0.00430
	(0.00463)	(0.00498)	(0.00501)	(0.00509)	(0.00510)	(0.00510)	(0.00663)
L2I	0.05583***	-	0.01456	-0.01175	0.03252***	-0.05764	-0.06509
		0.04985***					
	(0.00997)	(0.01110)	(0.01119)	(0.01138)	(0.01224)	(0.04565)	(0.04570)
FHA Loan			-	-	-	-	-
			0.54120***	0.57576***	0.54553***	0.55454***	0.55889***
			(0.02284)	(0.02365)	(0.02392)	(0.02397)	(0.02400)
VA Loan			-	-	-	-	-
			3.87966***	3.91442***	3.88795***	3.89959***	3.90457***
			(0.19030)	(0.19044)	(0.19046)	(0.19047)	(0.19048)
Gov't Sec.				-	-	-	-
				1.06335***	1.06335***	1.73737***	1.72708***
				(0.03044)	(0.03047)	(0.08062)	(0.08067)
Comm.				0.10050***	0.09915***	-	-
Sec.						0.33682***	0.33179***
				(0.02383)	(0.02385)	(0.06183)	(0.06186)
Owner					-	-	-
Occ.					0.31956***	0.18222***	0.17808***
					(0.03249)	(0.06256)	(0.06258)
L2I*Gov't						0.32409***	0.31909***
						(0.03574)	(0.03577)
L2I*Comm.						0.21008***	0.20756***
						(0.02766)	(0.02767)
L2I*Occ.						-	-
						0.10399**	0.10531**
						(0.04276)	(0.04277)
L2I*Shale							0.05005***
							(0.01327)
Yield	-	-	-	-	-	-	-
Curve	0.30845***	0.30733***	0.32267***	0.29357***	0.28916***	0.28746***	0.28551***
	(0.02971)	(0.03206)	(0.03247)	(0.03274)	(0.03279)	(0.03281)	(0.03282)
Hispanic		0.85134***	0.85624***	0.85769***	0.86334***	0.87042***	0.86961***
		(0.02160)	(0.02187)	(0.02250)	(0.02251)	(0.02254)	(0.02254)
Black		1.25195***	1.36792***	1.34377***	1.33797***	1.34023***	1.33904***
		(0.02504)	(0.02584)	(0.02632)	(0.02636)	(0.02637)	(0.02637)
Asian		-	-	-	-	-	-
		0.17815***	0.30929***	0.22970***	0.26570***	0.26346***	0.26193***
		(0.04695)	(0.04705)	(0.04762)	(0.04786)	(0.04789)	(0.04789)
Beds	0.31120***	0.23141***	0.24977***	0.26334***	0.26038***	0.26045***	0.26066***
	(0.01731)	(0.01893)	(0.01911)	(0.01937)	(0.01938)	(0.01940)	(0.01940)
Baths	-	-	-	-	-	-	-
	0.25433***	0.16931***	0.20209***	0.20318***	0.20280***	0.20024***	0.19665***
	(0.02209)	(0.02387)	(0.02404)	(0.02440)	(0.02441)	(0.02442)	(0.02444)
Living Size	-	-	-	-	-	-	-
	0.00048***	0.00040***	0.00045***	0.00045***	0.00043***	0.00044***	0.00044***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Land Size	-	-0.00236*	-	-	-0.00272*	-	-
	0.00722***		0.00414***	0.00316**		0.00284**	0.00288**
	(0.00129)	(0.00137)	(0.00138)	(0.00139)	(0.00139)	(0.00139)	(0.00139)
Age	0.00750***	0.00754***	0.00587***	0.00594***	0.00602***	0.00599***	0.00624***
	(0.00043)	(0.00047)	(0.00048)	(0.00048)	(0.00048)	(0.00049)	(0.00049)
Constant	-0.04147	-0.19294	0.02789	0.03843	0.18609	0.44844**	0.43819**
	(0.16136)	(0.17496)	(0.17705)	(0.17875)	(0.17939)	(0.18897)	(0.18899)
Obs.	141,451	123,507	123,507	123,507	123,392	123,392	123,392
Year FE	x	x	x	x	x	x	x

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] Each column reports estimates from a logit model of subprime loans. Each specification controls for year and city fixed effect, and each column adds additional control variables. The second column adds controls for the race and ethnicity of the primary loan signatory and the coefficient for debt-to-income becomes negative, and the coefficient flips sign with the addition of a control for Black households. Controlling for loan type and lien status flips the sign of the estimate again.

C.1.3 Dallas County Logit Models - Simple Exposure

Table C.4 reports estimates for the subprime logit models using data from Dallas county where there is no drilling activity. The relationships between loan-to-income and high interest rates are counter-intuitively negative, and including interactions with loan types only matters before 2009.

Table C.4: Subprime Logit - Dallas County

Dependent Variable:	Subprime Loan Indicator					
	Full	Before 2009	After 2009	Full	Before 2009	After 2009
Loan-to-	-	0.00429	-	-0.05722	-0.02731	-0.14463
Income	0.02556**		0.12614***			
	(0.01135)	(0.01442)	(0.02692)	(0.04463)	(0.05401)	(0.17423)
FHA Loan	-	-	1.88704***	-	-	1.88684***
	0.96574***	2.91282***		0.97385***	2.92643***	
	(0.02410)	(0.05091)	(0.06004)	(0.02418)	(0.05098)	(0.06028)
Loan VA	-	-	-	-	-	-
	3.78806***	5.62431***	2.28080***	3.79365***	5.63156***	2.28001***
	(0.19925)	(0.58002)	(0.41438)	(0.19926)	(0.58004)	(0.41439)
Owner Occ.	-	-	-0.03500	-	-	-0.00991
	0.38281***	0.34331***		0.30852***	0.17595**	
	(0.03211)	(0.03844)	(0.12368)	(0.06114)	(0.07484)	(0.23020)
Gov't Sec.	-	-	-	-	-	-
	1.03366***	1.29715***	1.82906***	1.32020***	2.09264***	1.71799***
	(0.02919)	(0.03958)	(0.06946)	(0.07868)	(0.10959)	(0.18221)
Comm. Sec.	0.16820***	0.38738***	-	-0.06629	-0.01066	-
			1.37379***			1.50290***
	(0.02201)	(0.02638)	(0.06322)	(0.05968)	(0.07219)	(0.16465)
L2I*Occ.				-0.05733	-	0.00092
					0.13296**	
				(0.04287)	(0.05192)	(0.17495)
L2I*Gov't				0.12792***	0.35468***	-0.04646
				(0.03286)	(0.04523)	(0.07261)
L2I*Comm.				0.10378***	0.17551***	0.05191
				(0.02466)	(0.02998)	(0.06395)
Hispanic	1.41659***	1.49141***	1.07708***	1.41979***	1.49887***	1.07630***
	(0.02164)	(0.02715)	(0.05135)	(0.02166)	(0.02720)	(0.05136)
Black	1.75553***	1.99280***	0.83774***	1.75618***	1.99570***	0.83733***
	(0.02391)	(0.02936)	(0.06651)	(0.02392)	(0.02940)	(0.06651)
Asian	-	-	-	-	-	-
	0.24810***	0.25599***	0.27417**	0.25001***	0.25935***	0.27608**
	(0.04631)	(0.05755)	(0.11936)	(0.04633)	(0.05761)	(0.11938)
Yield Curve	-	-	0.15878**	-	-	0.15807**
	0.37817***	0.27580***		0.37667***	0.27303***	
	(0.03116)	(0.05016)	(0.06486)	(0.03117)	(0.05020)	(0.06487)
Beds	0.23941***	0.27054***	0.12035***	0.24017***	0.27235***	0.12075***
	(0.01799)	(0.02258)	(0.04518)	(0.01800)	(0.02260)	(0.04519)
Baths	-	-	-0.04370	-	-	-0.04406
	0.09646***	0.12032***		0.09627***	0.11994***	
	(0.01892)	(0.02352)	(0.04848)	(0.01892)	(0.02355)	(0.04849)
Living Size	-	-	-	-	-	-
	0.00059***	0.00061***	0.00054***	0.00060***	0.00061***	0.00054***
	(0.00002)	(0.00003)	(0.00006)	(0.00002)	(0.00003)	(0.00006)
Land Size	0.01327***	0.01210***	0.01337***	0.01319***	0.01209***	0.01340***
	(0.00188)	(0.00232)	(0.00488)	(0.00188)	(0.00233)	(0.00488)
Age	-	-0.00008	-	-	-0.00022	-
	0.00111**		0.00319***	0.00118**		0.00319***
	(0.00047)	(0.00059)	(0.00118)	(0.00047)	(0.00059)	(0.00118)
Constant	0.84746***	0.15080	-	0.97472***	0.35392	-
			0.95984***			0.94135***
	(0.17032)	(0.26502)	(0.27034)	(0.17985)	(0.27471)	(0.32901)
Observations	113,908	59,936	34,998	113,908	59,936	34,998
Year FE	x	x	x	x	x	x
City FE	x	x	x	x	x	x

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] Each column reports estimates from a logit model of subprime loans. Each specification controls for year and city fixed effect along with house, household, and loan characteristics. The first column includes all transactions occurring between 2003 and 2016 in Dallas County Texas, and the last two columns estimate the models separately for houses sold before and after 2009, roughly the time of the financial crisis.

C.1.4 Texas-wide HMDA

The final analysis uses the full set of HMDA loans in Texas to estimate a relationship between the loan-to-incomes and the probability the borrower is given a high interest rate, mimicking the logit models using the house transaction data in Dallas, Denton, and Tarrant. For all scenarios, the estimated relationships are negative, and they estimates increase in magnitude when estimating the model for all data after 2009. However, interacting loan-to-income with loan types, we see that after 2009, both FHA and securitized loans are more likely to have higher interest rates as the loan-to-income values increase rendering the combined estimate a little positive.

Shale exposure is measured as the cumulative count of wells in a particular county in a particular year since we only know what year the loan was originated in the HMDA data. After 2009, the relationship between additional drilling and subprime interest rates is more positive, which is consistent with the larger story.

Table C.5: Texas-wide Lending

Dependent Variable:	Subprime Interest Rate Indicator				
	Full	Before 2009	After 2009	Before 2009	After 2009
Loan-to-Income	-0.14074***	-0.07967***	-0.20221***	-0.09512***	-0.41774***
	(0.00126)	(0.00197)	(0.00201)	(0.00278)	(0.00302)
Drilling	0.01467***	0.00393**	0.03202***	0.00399**	0.03155***
	(0.00083)	(0.00155)	(0.00253)	(0.00155)	(0.00254)
FHA Loan	0.17207***	-1.28805***	1.07695***	-0.80766***	0.47613***
	(0.00241)	(0.00659)	(0.00385)	(0.02087)	(0.01012)
VA Loan	-1.66194***	-2.26956***	-1.30414***	-2.27979***	-1.23998***
	(0.01172)	(0.02599)	(0.01814)	(0.02599)	(0.01821)
Gov't Secured	-0.80109***	-0.79976***	-1.18910***	-0.79780***	-1.13538***
	(0.00279)	(0.00457)	(0.00448)	(0.00458)	(0.00453)
Comm. Secured	-0.29059***	0.16134***	-1.02929***	0.08027***	-1.41374***
	(0.00241)	(0.00351)	(0.00430)	(0.00723)	(0.00988)
Owner Occupied	0.13514***	0.02419***	0.47208***	0.01638***	0.65138***
	(0.00328)	(0.00452)	(0.00654)	(0.00453)	(0.00687)
L2I*FHA				-0.22860***	0.27338***
				(0.00956)	(0.00428)
L2I*Secured				0.04505***	0.19130***
				(0.00355)	(0.00409)
Hispanic	0.50070***	0.59024***	0.41186***	0.59149***	0.39830***
	(0.00236)	(0.00358)	(0.00384)	(0.00359)	(0.00386)
Black	0.66204***	0.86604***	0.37880***	0.86893***	0.35894***
	(0.00329)	(0.00478)	(0.00585)	(0.00479)	(0.00589)
Asian	-0.26815***	-0.26015***	-0.28585***	-0.26101***	-0.28063***
	(0.00493)	(0.00725)	(0.00869)	(0.00725)	(0.00876)
Constant	-0.38082***	-0.70890***	-0.93008***	-0.68690***	-0.74402***
	(0.02346)	(0.04020)	(0.03532)	(0.04025)	(0.03574)
Observations	3,221,677	1,196,852	1,608,589	1,196,852	1,608,589
Year FE	x	x	x	x	x
County FE	x	x	x	x	x

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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Biography

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