ESSAYS IN BANKING AND PRODUCTION

A Dissertation in Economics

by

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Abstracts

Chapter 1
“Market Power and Cost Efficiencies in Banking”

A merger wave during the last 20 years has led to a decrease in the number of commercial banks from 12,343 in 1990 to 6,222 in 2012. For anti-trust and regulatory agencies, evaluating the relative importance of market power and cost efficiencies that result from a horizontal merger is important. To quantify these two effects, I develop an empirical model of banking which includes a demand model for differentiated products that allows market power effects to be calculated and a cost model that quantifies cost efficiencies from a merger. Since most of these banks operate in more than one market, incorporating the network structure of branches in the analysis is important. Cost parameters related to the network structure are estimated using moment inequality methods. Using the estimated parameters, I simulate mergers between banks of various sizes. I find that for a merger between 2 small banks (less than 500 branches), cost efficiencies play an important role in profitability. While for mergers involving a large bank (more than 500 branches) and a small bank or two large banks, the benefits accruing from market power are far more than the cost savings if there is substantial overlap in the networks of the merging banks. Although mergers involving large banks generate more market power, overall consumer welfare increases as the price effect of market power gets dominated by the consumer’s preference for a larger bank.

Chapter 2
“Market Structure and Growth of Banking in Rural Markets”

The passage of the Riegle-Neal act in 1994 enabled banks to expand their network of branches across the United States. Since rural markets are often seen as unattractive destinations for banks due to the lack of commercial activities, this could possibly lead to a lower branch density in rural markets relative to the larger metropolitan markets. Hence it is important to understand the underlying dynamics governing the market structure in these rural areas. In this paper, we study the incentive structure governing branching growth in rural banking markets in the United States. We develop and estimate a dynamic oligopoly model with a rich state space. We find that one-branch banks have a very different incentive structure than other banks in that they generate most of the revenue from non-interest income such as fund-management fees, loan-arrangement fees and by selling insurance. Banks with more than one branch generate revenue using the traditional method of collecting deposits and
investing in loans. There is a large adjustment cost involved in opening a second branch which results in few banks making that transition.

Chapter 3
“Unraveling Effects of Demand Shocks on Production Function Estimation and Firm Behavior”

The traditional productivity measures estimated using revenue-based firm-level data have both demand side and production side shocks embedded in them. In order to separate these two shocks, a small literature has exploited output price data but this data is typically not available in firm-level production data sets. In this paper, we use inventory data to disentangle and separately identify demand and productivity shocks without using any price data. Introducing a demand shock into the model also addresses the multi-collinearity bias pointed out by Ackerberg, Caves and Fraser (2006). Finally, we use our estimates to explain entry/exit dynamics and find that demand shocks are a more important driver of firm-turnover than productivity shocks.
## 2 Market Structure and Growth of Banking in Rural Markets

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Chapter 1

Market Power and Cost Efficiencies in Banking

Abstract

A merger wave during the last 20 years has led to a decrease in the number of commercial banks from 12,343 in 1990 to 6,222 in 2012. For anti-trust and regulatory agencies, evaluating the relative importance of market power and cost efficiencies that result from a horizontal merger is important. To quantify these two effects, I develop an empirical model of banking which includes a demand model for differentiated products that allows market power effects to be calculated and a cost model that quantifies cost efficiencies from a merger. Since most of these banks operate in more than one market, incorporating the network structure of branches in the analysis is important. Cost parameters related to the network structure are estimated using moment inequality methods. Using the estimated parameters, I simulate mergers between banks of various sizes. I find that for a merger between 2 small banks (less than 500 branches), cost efficiencies play an important role in profitability. While for mergers involving a large bank (more than 500 branches) and a small bank or two large banks, the benefits accruing from market power are far more than the cost savings if there is substantial overlap in the networks of the merging banks. Although mergers involving large banks generate more market power, overall consumer welfare increases as the price effect of market power gets dominated by the consumer’s preference for a larger bank.

1.1 Introduction

The removal of legal restrictions on intrastate and interstate banking was a gradual process that culminated with passage of the Riegle-Neal Act in 1994. Since then, the banking industry has undergone substantial restructuring. This gradual deregulation has led to a consolidation of banks over the last 30 years that is still ongoing. In 1990, there were 12,343 commercial banks and 2,815 savings FDIC insured banks in the United States.\textsuperscript{1} In 2012, these numbers had fallen to 6,222 commercial banks and 1,024 savings banks. This

\textsuperscript{1}Almost 98\% of the banks in the U.S. are FDIC insured.
consolidation in the banking industry has been driven primarily by mergers. As the number of banks has declined, the average size of banks, measured by deposits, has risen from 184 million dollars in 1990 to 978 million dollars in 2012. Since the banking industry is connected to all other industries and, as we have seen recently, widespread failures can lead to a financial crisis, it is important to understand the reasons behind the ongoing consolidation and its impact on the strength of competition and cost efficiencies. This paper will disentangle the driving forces behind the mergers and quantify its impact on consumer welfare.

Anti-trust and regulatory agencies always screen horizontal mergers for the role of market power and cost efficiencies as the possible driving forces behind the merger. For a merger between two conglomerates (firms present in more than one market), market power is often a geographically local phenomenon while cost efficiencies are realized at the firm level. In this paper I quantify and compare these two forces. Another aspect that is particular to banking industry mergers is the consumer’s preference for a large network of branches. As a result, just looking at the price effects to evaluate a merger could leave out an important effect of merger. This paper accounts for the role of price as well as the preference for large banks in the calculation of consumer welfare.

I develop a three stage empirical model of competition that captures the long-run effects of establishing a branch network and short-run effects due to price competition and capital structure. In the first stage, all banks choose their network of branches. The network decision comprises the number of branches to open and their location. In the second stage, banks choose equity capital. Equity capital is needed for three reasons: to satisfy government regulation constraints, signal safety to uninsured depositors, and acts as an alternative to deposits for funding loans. In the third stage, banks set deposit interest rates and compete in Bertrand competition to collect deposits. Consumers demand deposit services and choose banks based upon their characteristics. This choice of timing distinguishes long-run decisions about network structure from short-run decisions about capital choice and pricing of deposits.

Structural estimation of the model is done in three stages. First, demand parameters are estimated using supply-side and demand-side moments jointly. Second, the cost of raising equity capital is estimated by using moments formed by the first-order condition of equity capital. Finally, the remaining cost parameters are estimated using the moment inequality method proposed in Pakes, Porter, Ho and Ishii (2011), PPHI henceforth. To form inequalities, counterfactual policies are generated using addition and subtraction of branches in different markets. For inference, I use the PPHI method as well as the generalized moment selection approach proposed by Andrews and Soares (2011).

The presence of market power in the banking industry is well documented. Prager and Hannan (1998) find that a reduction in interest rates on local deposit accounts was associated with horizontal mergers that raised market concentration significantly. Berger, Demsetz, and Strahan (1999) use data for the 1990s and find a negative relationship between local market concentration and deposit rates. Simons and Stavins (1998) find that an increase in a local concentration measure (HHI) leads to a decrease in deposit interest rates.

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2The 2010 Horizontal Merger Guidelines adopted UPP(Upward Pricing Pressure) as one of the ways to evaluate a merger which is based on price effects alone.
On the cost side, there is a long debate about the presence of economies of scale in banking. Studies by Boyd and Graham (1998), Mester (1987), Berger, Hanweck and Humphrey (1987), and Boyd and Runkle (1993) did not find economies of scale beyond very small banks. These studies used data from the 1980s and didn’t incorporate risk aspects of banking into the banking technology. More recently, Hughes, Mester, and Moon (2001), Hughes, Lang, Mester, and Moon (1996), Hughes and Mester (1998) found significant economies of scale in most banks when capital structure and endogenous risk taking were explicitly considered in the analyses of production. My paper also contributes to this stream of literature. None of these papers controlled for market power at the local geographic level while calculating economies of scale at the national level. It is possible that the change in profits/costs with size could be different if we control for local market power. Hence, the conclusions about scale economies in the existing literature may be misleading as a result of ignoring the market power effect.

The estimation results show that consumers prefer banks who offer high deposit rates, have more branches locally and nationwide, and are more capitalized. The cost parameters estimated through moment inequalities are partially identified and I get set estimates for these parameters. I allow for the cost function to differ between small (less than 500 branches) and large banks (more than 500 branches). After controlling for market power, the evidence for cost efficiencies is weak at best for smaller banks. For larger banks, the cost function is less concave than smaller banks suggesting a decrease in cost efficiencies as banks get larger. The estimated interest rate to raise equity capital for small banks is 6.03% while for larger banks the interest rate is 5.24%. This result is reasonable given that large banks are more diversified and could be perceived as being too big to fail. From an investor’s point of view, this allows big banks to be considered as a safe investment.

Using the estimated parameters, I simulate mergers between different type of banks to compare the benefits that accrue from market power versus cost efficiencies. I simulate mergers in three categories: between two small banks, a small bank and a large bank and between two large banks. For mergers between two small banks cost efficiencies are found to play an important role. For a merger between a small and a large bank, the extra revenue generated by market power is much larger than the cost savings if there is substantial overlap in the networks of the merging banks. When two large banks merge the market power effect dominates the cost efficiencies effect. The reason behind these results is the decrease in the concavity of the cost function for larger banks. The mergers involving larger banks (small-large bank merger or large-large bank merger) increase consumer surplus if I account for both price effects as well as consumer’s preference for large networks. Hence, the market power effect of prices is dominated by a better quality product in mergers involving large banks.

The rest of the paper is organized as follows. Section 2.2 discusses data used for the analysis. Section 2.3 introduces the model. In Section 2.4, I outline the estimation strategy. Section 2.5 discusses the estimation results. Section 2.6 contains counterfactual experiments and section 2.7 concludes.
1.2 Data

1.2.1 Data Sources

The data used in this paper is a cross-section of commercial banks from 2006.

Data is taken from three sources. Information on bank ownerships, location of branches and deposits is taken from Summary of Deposits at the Federal Deposit Insurance Corporation (FDIC). The variables in the FDIC data can be divided into three categories: Bank Holding Company (BHC) variables, institution (bank level) variables, and branch variables. Bank holding companies (BHC) are at the top of hierarchy, with banks in the middle level and branches are at the bottom. A bank holding company (BHC) is a company that controls one or more banks. There are also banks that are not owned by any BHC. All BHCs in the U.S. are required to register with the Board of Governors of the Federal Reserve System whereas non-BHC banks can function under the supervision of the Comptroller of the Currency or the Federal Deposit Insurance Corporation. A BHC needs a separate charter for each bank.\(^3\) For example, Bank of America may have many bank charters and multiple branches across the country but it will have only one BHC. In this paper, the decision maker is a BHC. Some small banks are not registered as a BHC and for them the bank is the decision maker. For the rest of the paper, banks and bank holding companies (BHC) are used interchangeably.

I also use bank level data taken from the Call Reports available at Federal Reserve Bank of Chicago. Call reports contain information on interest expenses on deposits, interest revenues from loans, equity capital, total employees and wages. Using the hierarchy information in the FDIC data, the bank level data from the Call Reports is aggregated into BHC level data. The interest rate on deposits is calculated as a ratio of interest expenses to total deposits. Similarly, the interest rate on loans is calculated as a ratio of interest revenue to total loans. I use wages and employees per branch as instruments in the demand estimation. Data on demographic information such as population and income is taken from the Bureau of Economic Analysis (BEA). Total income in a market is used to calculate the outside good in the demand estimation where consumers choose banks for deposit services. I also use market level income as a measure of market size to construct the branch density variable used in demand estimation. Market level population is used to form weighting function used in the moment inequality estimation.

1.2.2 Market and Data Summary

A market is defined as a Metropolitan Statistical Area (MSA). Antitrust analysis has relied on the definition of a banking market at the MSA level. Using data from the Survey of Consumer Finances, Amel and Starr-McCluer (2001) find that households obtain 90% of

\(^3\)Becoming a bank holding company makes it easier for the firm to raise capital than as a traditional bank. The holding company can assume debt of shareholders on a tax free basis, borrow money, acquire other banks and non-bank entities more easily, and issue stock with greater regulatory ease. The downside includes responding to additional regulatory authorities.
the checking accounts, savings accounts and certificates of deposits within the local market. Kwast, Starr-McCluer and Wolken (1997) find that over 94% of small businesses use a local depository institution.

The sample covers 353 MSAs and 4,316 firms. Out of the 4,316 decision makers, 3,194 are BHCs and 1,122 are banks that are not part of a BHC. The average number of BHCs in a market is approximately 23. The smallest number of BHCs in a market (El Centro, CA) is 5, while the market with the most BHCs, Chicago-Joliet-Naperville, IL-IN-WI, has 227.

As banks get larger in size they set lower deposit interest rates. The correlation coefficient between the log of deposit interest rate and the log of the number of branches is -0.0493 (0.0012). This provides some preliminary evidence that bigger banks may exercise market power by setting lower deposit interest rates.

There are 8,252 market-bank observations in the data. The following table provides a size distribution,

<table>
<thead>
<tr>
<th>Size(# branches)</th>
<th>Total Banks</th>
<th>Average Assets(million $’s) per bank</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1,202</td>
<td>129</td>
</tr>
<tr>
<td>2 – 10</td>
<td>2,519</td>
<td>343</td>
</tr>
<tr>
<td>11 – 100</td>
<td>527</td>
<td>2,165</td>
</tr>
<tr>
<td>101 – 500</td>
<td>51</td>
<td>43,600</td>
</tr>
<tr>
<td>500+</td>
<td>17</td>
<td>295,000</td>
</tr>
<tr>
<td>Total</td>
<td>4,316</td>
<td>2,175</td>
</tr>
</tbody>
</table>

Table 1.1: Size Distribution

The size distribution is skewed towards smaller banks, where size is defined by the number of branches and there are very few large banks. This suggests that larger banks may have a different incentive structure than smaller banks. Cohen and Mazzeo (2007) treat single and multi-market banks separately to assess competition among retail depository institutions in rural markets. Ramiro (2009) finds that there are significant revenue and cost differences between single and multi-market banks. Motivated by this, I distinguish between small and large banks in the construction of the cost function. The cost function in this paper depends on the total size, measured as the number of branches in the network, and concavity of this function gives us a measure of the cost efficiencies.

The cut-off of small versus large banks is chosen at 500 branches ($log(500 + 1) \approx 6.23$) using the scatter-plot in figure 1.1. There are 17 banks above this cut-off. It is also important to separate the large banks from a policy standpoint. One of the objectives of the recent Dodd-Frank act was to immunize the economy from the failing of such large banks. Sometimes these large banks are also referred to as too-big-to-fail banks.\(^6\)

---

\(^4\)In total there are 366 MSAs. Small MSAs that do not have any commercial banks are not considered in the analysis.

\(^5\)P-values are reported inside the parenthesis.

\(^6\)The stated aim of the Dodd-Frank legislation is: To promote the financial stability of the United States
Overall there are two patterns worth noting in this section. First, the data provides some preliminary evidence of market power. I take that into account by developing a model where banks competitively collect deposits. Second, there maybe a need to distinguish between small and large banks in their technology. I address this issue by distinguishing between the small and large banks in the cost function. I incorporate these insights into the model.

1.3 Empirical Model of Consumer Demand and Firm Choice

I develop a model of consumer behavior and firm choice. Consumers choose banks for their deposits to maximize utility. Their utility depends upon the returns on deposits, security from bank failure and convenience of availing banking services. Banks choose the network of branches, equity capital and deposit interest rate in a three-stage game to maximize profits. The model will be used to quantify market power, cost efficiencies and consumer welfare in the simulated mergers. The model has local market competition as the source of market power while the cost efficiencies are at the firm-level.

by improving accountability and transparency in the financial system, to end “too big to fail”, to protect the American taxpayer by ending bailouts, to protect consumers from abusive financial services practices, and for other purposes.
1.3.1 Consumer Demand

Consumers either save money in a bank or spend it on the outside good. Consumers save money by choosing a bank for deposit services based upon the bank’s characteristics. Consumer $i$’s utility from deposit services of bank $j$ in market $m$ is:

$$U_{ijm} = \theta_1 P^d_{jm} + \theta_2 d_{jm} + \theta_3 ONE_j + \theta_4 \left(\frac{k_j}{n_j}\right) + \theta_5 \log(n_j + 1) + \theta_6 + \xi_{jm} + \epsilon_{ijm},$$

where $P^d_{jm}$ is the deposit interest rate and $d_{jm}$ is the branch density of bank $j$ in market $m$. Branch density ($d_{jm}$) is defined as the ratio of the number of branches in a market $m$ of bank $j$ to total income (a measure of market size) in the market $m$. The consumers have a preference for branch density because they incur a disutility from distance traveled for their deposit services, which was most recently shown by Ho and Ishii (2010). $ONE_j$ is the dummy variable for one-branch banks. Business model of one branch banks and multi-branch banks could be very different with the latter’s main focus on the expansion of their branch network. Therefore, I allow for them to have different effects on the consumer’s utility. ($\frac{k_j}{n_j}$) is the ratio of equity capital ($k_j$) to the total number of bank branches ($n_j$). The capital-asset ratio which banks use as a signal for safety to uninsured depositors (Hughes and Mester (1998)) is proxied by ($\frac{k_j}{n_j}$). I allow for the bank’s size ($n_j$) to enter the consumer utility function logarithmically since the size distribution is highly skewed. This term captures the importance of branches outside the depositors’ market as I already conditioned the utility on branch density inside the market. Consumers who travel a lot will care more about the total number of branches of a bank. Total branches of a bank also act as a signal of safety to the consumer as larger banks usually have a more diversified portfolio of loans and deposits. When simulating a merger, this preference for total branches owned by a bank will give positive utility to the consumer. Unobserved bank-market quality is denoted by $\xi_{jm}$ which includes characteristics like the number of service counters in a branch, quality of employees and time taken to serve a customer. Also, $\xi_{jm}$ will measure the firm-market fixed effects that are not captured by the observed variables. Measurement error is denoted by $\epsilon_{ijm}$ which is assumed to be type-1 extreme value distributed error.

Market share of a bank is calculated as the total deposits of a bank in a market divided by the total income in that market. Suppose there are $j = 1, 2, ..., J$ banks in a market $m$ and let the outside good be denoted by 0. Then the mean utility of a bank $j$ in market $m$, $\delta_{jm}$, can be defined as

---

7Using population as a measure of market size provides similar results.

8If I use capital-asset ratio instead of $\frac{k_j}{n_j}$, it would make the market share equation endogenous to solving an implicit integral equation, as in equilibrium: assets=deposits+capital. This makes the level of demand of deposits a function of deposits itself in the integral equation.

9Since I don’t have data on the number of ATM machines, total branches acts as a proxy for it. I am making the assumption that number of branches and number of ATMs are positively correlated.

10An alternative would be to define market shares in terms of bank accounts. The data on accounts is not available by market but is at the firm-level. Dick (2002) defines market shares in terms of accounts rather than deposits by allocating the total accounts of a bank to each market. She found that results are robust to this alternative definition.
\[ \delta_{jm} = \theta_1 P_{jm}^d + \theta_2 d_{jm} + \theta_3 O N E_j + \theta_4 \left( \frac{k_j}{n_j} \right) + \theta_5 \log(n_j + 1) + \theta_6 + \xi_{jm}. \]

Using the logit error assumption on \( \epsilon_{ijm} \), I can define the market share, \( s_{jm} \), as

\[ s_{jm} = \frac{\exp(\delta_{jm})}{1 + \sum_{k=1}^{J} \exp(\delta_{km})}, \]

where the utility of the outside good is normalized to zero.

### 1.3.2 Supply side

Banks generate revenues from loans and incur costs on interest expenses on deposits, equity capital, labor, and physical capital expenditures. A bank’s maximization problem is

\[
\begin{align*}
\max_{n_j, k_j, P_{jm}^d} & \quad \Pi_j \\
\text{s.t.} & \quad \Pi_j = L_j P_j^d - \sum_m D_m s_{jm}(\theta) P_{jm}^d - C(n_j, k_j) \\
& \quad L_j \leq \sum_m D_m s_{jm}(\theta) + k_j \\
& \quad G(k_j, L_j) \geq \Delta,
\end{align*}
\]

where \( L_j \) are the total assets of a bank, \( P_j^l \) is the average interest rate on assets, \( D_m \) denotes total deposits in market \( m \) and \( s_{jm}(\theta) \) is the market share of bank \( j \) in market \( m \). \( k_j \) is the equity capital of a bank i.e. bank’s own money at stake. The interest rate on assets, \( P_j^l \), is allowed to be correlated with \( \xi_{jm} \). This is important as a bank with high quality (or high brand effect) is likely to offer loans with higher interest rates. \( C(n_j, k_j) \) consists of two cost components: labor/physical capital cost and the cost of equity capital. The labor and physical cost incurred by a bank is for loan services, deposit services, advertising expenses and risk management. I assume this cost to be a function of the number of branches \( (n_j) \). Note that this cost is independent of the location of the \( n_j \) branches. It is intuitive to think that a branch in a bigger market should have higher costs compared to one in a smaller market. Although this is true to some extent, the objective of this paper is to find cost efficiencies which are realized at the firm level. These cost efficiencies are realized by a reduction in expenses at the firm level such as advertising expenditures which are common across many markets.

The first constraint captures feasibility i.e. total loans made by a bank can be funded either by deposits or by equity capital. The second constraint is a regulation constraint. As per the guidelines of the Board of Governors of Federal Reserve Bank, all chartered banks in the U.S. should have a capital-asset ratio above a threshold.\(^{11}\) In practice, all banks are well above the limit, hence this constraint never binds in the data.

\(^{11}\) As per the guidelines of Board of Governors of Federal Reserve Bank, all chartered banks in US have to satisfy three constraints: (1) Tier 1 capital / Risk-adjusted assets > 6% (2) Total capital / Risk-adjusted assets > 10% (3) Tier 1 capital / Average total consolidated assets > 5%. More than 99 % of the banks are well above the threshold limits.
Apart from the regulation constraint, there are two other roles for equity capital. First, it is a source of funding for loans as an alternative to deposits. Hence, labor cost and physical capital cost spent to collect deposits are affected by the level of equity capital. So failing to condition on equity capital can bias the cost parameters. Second, banks use equity capital as a signal of safety to uninsured depositors. This is included in the demand model. The role of equity capital in the cost function of a bank was first noted by Hughes and Mester (1998).

I assume a parametric form for the bank cost function,

\[ C(n_j, k_j) = \beta_1 n_j + \beta_2 n_j^2 + \beta_3 I(n_j > X)(n_j - X)^2 + [\beta_4^S I(n_j \leq X) + \beta_4^L I(n_j > X)]k_j + \gamma_j + \nu_{j,n_j}, \]

where \( \gamma_j \) is the bank level cost shock unobserved to the researcher but observed by the bank when it makes it decisions. The measurement error or specification error is denoted by \( \nu_{j,n_j} \). The parameter \( \beta_3 \) applies for large banks \( (n_j > X) \) only, where \( X \) is the chosen size cut-off between small and large banks. For small banks, the sign of \( \beta_2 \) will determine the presence or absence of cost efficiencies. For large banks, both \( \beta_2 \) and \( \beta_3 \) measure concavity of the cost function. The parameters \( \beta_4^S \) and \( \beta_4^L \) measure the interest rate paid on equity capital by small and large banks, respectively. As discussed in Section 1.2, small banks and large banks are distinguished in the cost function. The difference in production technologies between small and large banks will be captured in the parameter \( \beta_3 \). Also, any difference in the cost of external funding will be measured by \( \beta_4^S \) and \( \beta_4^L \). Note that although the bank will choose a network of branches, the cost function only depends on the total number of branches. The network effects are accounted for through the revenue side.

Using the demand and supply side of the model discussed above, I simulate and measure the market power and cost efficiency trade-off that will be relevant to evaluating a bank merger. Since market power is a geographically local phenomenon, it will be a function of the network of branches of the two merging banks. Market power will be measured as the difference in profits between the merged entity at new prices (deposit interest rate) and the two merging banks at pre-merger prices. The profit of the merged entity will include the joint effect of market power and consumer preferences for large networks. To understand the different forces, I need to isolate the effects to study them separately. Cost efficiencies are measured as the difference in cost expenditure between the merged entity and the two merging banks. Since cost efficiencies are realized at the firm-level the network structure is irrelevant here, only the total size of the network matters for the cost efficiency calculation. I also quantify the change in consumer welfare because of a merger.

In equilibrium, the profit function of a bank can be simplified by substituting the feasibility constraint at equality (assets=liabilities) and using the parametric cost function,

\[ \Pi_j = \sum_m D_{m s j m}(\theta)(P_j^d - P_j^{d m}) + P_j^l k_j - \beta_1 n_j - \beta_2 n_j^2 - \beta_3 I(n_j > X)(n_j - X)^2 - [\beta_4^S I(n_j \leq X) + \beta_4^L I(n_j > X)]k_j + \gamma_j + \nu_{j,n_j}. \]

\( ^{12} \)Data shows a negative relationship between size and capital-asset ratio. Hence, there is some evidence that larger banks need to signal less about their safety than smaller banks.

\( ^{13} \)This error term is similar to the non-structural error term in Pakes, Porter, Ho and Ishii (2011)
1.3.3 Timing of the Firm Choices

There are the three stages in the game between banks. In the first stage, banks choose the network of branches \((n_j)\) i.e. how many branches to open and where to locate them. This decision is made simultaneously by all banks. In the second stage, banks choose their equity capital \((k_j)\). Equity capital is chosen at the firm level. In the third stage, banks compete for deposits in a Bertrand competition within each geographic market and choose interest rates \((P_{jm}^d)\).

1.4 Estimation

The model is solved using backward induction. In the first stage, demand parameters are estimated. The second stage involves estimation of the cost parameter \((\beta^S_1 \text{ and } \beta^L_1)\) on equity capital. In the third stage, cost parameters related to the network structure are obtained using moment inequalities.

1.4.1 First Stage: Demand Estimation

Demand parameters are estimated using demand-side and supply-side moments jointly.

In the final stage of the game, bank’s compete for deposits and set their deposit interest rates (prices). I assume that the competition for deposits in each market is independent of the competition in other markets. Under this assumption, the first order condition w.r.t. \(P_{jm}^d\) is

\[
D_m \frac{\partial s_{jm}(\theta)}{\partial P_{jm}^d} (P_j^d - P_{jm}^d) - D_m s_{jm}(\theta) = 0 \quad \forall m.
\]

The first order condition above represents a trade-off: an increase in deposit interest rate will increase expenditure on all the existing deposits but increased deposit interest rate will also increase the market share of a bank for deposits and hence increase the revenue from loans. Using the fact that a consumer’s utility has a logit error term \((\epsilon_{ijm})\), I can write the slope of the market share function w.r.t. price as \(\frac{\partial s_{jm}(\theta)}{\partial P_{jm}^d} = \theta_1 s_{jm}(1 - s_{jm})\). Substituting this into the above equation I get,

\[
M_{jm}(\theta) \equiv \theta_1 (1 - s_{jm})(P_j^d - P_{jm}^d) - 1 = 0 \quad \forall m
\]  

(1.1)

This equation acts as the basis for the supply side moment. I denote this equation by \(M_{jm}(\theta)\).

To derive demand side moments, I need to calculate \(\xi_{jm}(\theta)\). Since a consumer’s utility has a logit error, the demand shock can be solved for explicitly as

\[
\xi_{jm}(\theta) = \ln(s_{jm}) - \ln(s_{0m})
\]
where \( s_{0m} \) is the market share of the outside option.

Demand side moments are derived by finding instruments \((Z_{jm})\) which are un-correlated with bank-market shocks \((\xi_{jm})\) to consumer utility. \(^{14}\) Specifically, I need instruments for prices \((P^d_{jm})\) and equity capital \((k_j)\). The correlation between prices and unobserved quality \((\xi_{jm})\) is obvious. In the second stage, banks choose \( k_j \) as a function of \( \xi_{jm} \) and other variables, hence they may be correlated. Intuitively, a bank with higher quality, may choose lower \( k_j \) as both are substitutes in the consumer’s utility. Instrumental variables used for prices are cost shifters (wages and employees per branch) and rival firm characteristics (number of rival banks in a market, number of rival branches in a market, size of rival banks). Instrumental variable used for \( k_j \) is wages since higher wages correspond to a higher cost of collecting deposits, which would lead firms to choose a higher level of equity capital. Overall, \( Z_{jm} \) includes wages, employees per branch, rival firm characteristics, \( d_{jm}, ONE_j \) and \( \log(n_j + 1) \). Hence, the estimating GMM equation is given by,

\[
E \left[ \frac{M_{jm}(\theta)}{Z_{jm} \xi_{jm}(\theta)} \right] = 0
\]

There are 11 moment conditions I use to estimate 6 parameters. Hence, the system is over-identified. I use two step GMM with an optimal weighting matrix to estimate the parameters.

1.4.2 Second Stage

In the second stage, banks choose equity capital \((k_j)\). Assuming risk-neutrality, a bank’s equity capital choice is modeled as

\[
\max_{k_j} \sum_m D_m s_{jm}(\theta)(P^l_j - P^d_{jm}) + P^l_j k_j - C(n_j, k_j)
\]

\[
s.t. \quad G(k_j, L_j) \geq \Delta \\
\theta_1(1 - s_{jm}(\theta))(P^l_j - P^d_{jm}) - 1 = 0.
\]

The last constraint is the FOC of Bertrand competition and appears as banks take into account the effect of equity capital choice on the deposit rates chosen in the last stage. The first constraint is the regulation constraint and almost all banks in the data easily satisfy it. Hence, I can assume an interior solution to the above maximization problem. On substituting the FOC of \( P^d_{jm} \) into profits yields,

\[
\Pi_j = \sum_m D_m \frac{s_{jm}(\theta)}{\theta_1(1 - s_{jm}(\theta))} + P^l_j k_j - C(n_j, k_j).
\]

\(^{14}\)This moment is developed in the spirit of Berry(1994), where the author finds that matching market shares to estimate demand parameters directly can lead to an endogeneity bias because price can be correlated to the unobserved quality term.
I can write the FOC of \( k_j \) i.e. \( \frac{\partial \Pi_j}{\partial k_j} = 0 \) as,

\[
\sum_m D_m \left[ \frac{\partial s_{jm}}{\theta_1} + \frac{s_{jm}}{(1 - s_{jm})^2} \right] + \frac{\partial s_{jm}}{\partial k_j} \left[ \frac{\partial C(n_j, k_j)}{\partial k_j} \right] = 0.
\]

On simplifying the FOC of \( k_j \) I get\(^{15}\)

\[
\sum_m D_m \left[ \frac{\theta_4 s_{jm}}{n_j (1 - s_{jm})} \right] + P_l = \beta_4^x,
\]

where \( x=\{S,L\} \) corresponds to small or large banks. The first term on the left corresponds to the marginal revenue from uninsured depositors and the second term on the left is the revenue per dollar of loans generated from loans that were funded by equity capital. Parameters \( \beta_4^S \) and \( \beta_4^L \) measure the marginal cost of equity capital to small and large banks respectively.

Assuming a mean zero measurement error in the above equation, parameters \( \beta_4^S \) and \( \beta_4^L \) can be estimated by taking expectation of both sides of the equation

\[
\beta_4^x = E\left[ \sum_m D_m \left[ \frac{\theta_4 s_{jm}}{n_j (1 - s_{jm})} \right] + P_l \right]
\]

In a more general setup, the marginal cost of equity capital could be measured as a function of observed variables such as size and geographic diversification. Geographic diversification measures the risk in the loan portfolio of bank as well as the risk in collecting deposits (Aguirregabiria, Clark and Wang (2011)), hence there is an incentive for investors to look at this aspect. The number of branches a bank has is an important decision criteria for investors as larger banks can be perceived as too big to fail. To understand the relationship between the cost of equity capital, the bank’s size and its diversification, I estimate these relationships using OLS regression. I measure geographic diversification by the number of markets a bank is present in.

### 1.4.3 Third Stage

The cost function parameters \( \beta_1, \beta_2 \) and \( \beta_3 \) are estimated in this stage. The estimates quantify how the network of branches affect the bank’s fixed cost and will enter the calculation of the cost efficiencies. To this end I employ the moment inequality estimator proposed by Pakes, Porter, Ho and Ishii (2011) (henceforth PPHI).

Let \( I_j \) be the information set of the bank when it chooses the network of branches \( (n_j) \). The information set \( I_j \) consists of \( \{\xi_{jm}\}_{j=1, m=1}^{J, M}, P_l, \) and \( \gamma_j \).\(^{16}\) The first component of \( I_j \), \( \{\xi_{jm}\}_{j=1, m=1}^{J, M} \), implies that banks know their fixed brand effect in each market and that of other banks when making the network choice. This means that a bank deciding to open

\(^{15}\) The details of the calculation can be found in the appendix 8.4.

\(^{16}\) The PPHI estimator allows for the possibility of the information set is unspecified. So, in principle there could be variables which are unobserved to the econometrician but are in \( I_j \).
a branch in a market knows how it will be perceived by the consumers conditional on the other observed variables in their utility function. The second component of $I_j$, $P_l^d$, means that banks know what kind of asset portfolio they will be investing in before deciding where to open branches and how many to open. For example, a lower $P_l^d$ means a bank is targeting a low risk-low return portfolio and knowing this it will open branches in markets with more predictable, low-return industrial activity. Another way to rationalize this assumption is to assume that banks are targeting a fixed level of returns on their assets before making any entry decisions. The third component of $I_j$, is the firm level cost shock, $γ_j$, and it corresponds to the management practices and organization structure that are specific to a particular bank. This implies that a bank making an entry decision knows about its specific management practices.\footnote{If $\{ξ_{jm}\}_{j=1,m=1}^{J,M}$ was not in the information set, to form moment inequalities I would have to simulate the expected levels of this variable from a distribution approximated from the demand estimation.}

A bank maximizes its expected profits,

$$\max_{n_j} E[Π_j | I_j]$$

where $Π_j$ is the firm-level profits previously specified in section 1.3.2. A choice of network consists of the number of branches to open and their locations across markets. A bank can choose to have 0, 1 or more branches in any market. The expectation arises because of the uncertainty in the bank’s observed profit at the time decisions are made. This uncertainty arises due the randomness in the decision of the rival banks, $n_{-j}$. The randomness could be due to the error term, $ν_{j,n_j}$, or due to the presence of mixed strategies.

The profit function of a bank $j$ is

$$Π_j = \sum_m D_mE[s_{jm}(θ)(P_l^d - P_{jm}^d) + P_l^d k_j - \beta_1 n_j - \beta_2 n_j^2 - \beta_3 I(n_j > X)(n_j - X)^2 - [\beta_4^S I(n_j \leq X) + \beta_4^L I(n_j > X)]k_j + γ_j + ν_{j,n_j}
$$ (1.3)

The location of branches affects the profits through the first term. For example, consider two banks with the same number of branches and similar in all aspects except for the location of these branches. These two banks collect different deposits in each market because the market share, $s_{jm}$, depends on the branch density ($d_{jm}$) in that particular market alongside other variables. This will lead to these two banks having different profits.

Note that the network choice parameters cannot be estimated directly using the maximum likelihood estimation. This is due to the fact that the possible network choices a bank has in the maximization problem are way too large compared to the number of choices observed in the data.\footnote{I observe 4,316 firm choices in data. The possible network choices for 4,316 firms in 353 markets with maximum allowed branches in a market as 500 are: $4316 \times 353^{500}$. Hence it is almost impossible to directly estimate the parameters with such sparse information.} Hence I employ the moment inequality method to partially identify the parameters.

A necessary condition for any Nash equilibria is that the expected profits from choices observed in the data are greater than any other feasible alternate choice. This forms the basis
of the moment inequality estimation method. I construct an expression for the difference in profits for the two policies and then take moments of this differenced profit expression to form the estimating inequalities. Using the profit function for the choice observed in the data \((n_j)\) and some other alternate policy \((n'_j)\), so that \((n_j - n'_j = t)\), I can difference the profits. The alternate policy, \(n'_j\), involves addition or subtraction of a fixed number of branches, \(t\), from the existing network. Following is the differenced profit equation,

\[
\Delta \Pi_j = \Delta Y_j(n_j, n'_j, n_{-j}) - \beta_1(n_j - n'_j) - \beta_2(n_j^2 - n'_j^2) - \beta_3[I(n_j > X)(n_j - X)^2 - I(n'_j > X)(n'_j - X)^2] + \nu_{j,n_j,n'_j},
\]

(1.4)

where \(\nu_{j,n_j,n'_j} = \nu_{j,n_j} - \nu_{j,n'_j}\) and \(\Delta Y_j(n_j, n'_j, n_{-j})\) is the part of the differenced profit function which does not contain any parameters to be estimated (because they have already been estimated in the first and second stage):

\[
\Delta Y_j(n_j, n'_j, n_{-j}) = \left[ \sum_m D_m s_{jm}(\theta)(P_j^l - P_j^d_{jm}) + P_j^d k_j - [\beta_4 s^I(n_j \leq X) + \beta_4^I I(n_j > X)]k_j \right]
\]

\[
- \left[ \sum_m D_m s'_{jm}(\theta)(P_j^l - P_j'^d_{jm}) + P_j'^d k'_j - [\beta_4'^s I(n'_j \leq X) + \beta_4'^I I(n'_j > X)]k'_j \right].
\]

To evaluate \((\Delta Y_j)\) all the endogenous variables need to be evaluated under the alternate policies: market shares \((s'_{jm})\), deposit interest rates \((p'^d_{jm})\) and equity capital \((k'_j)\). Market share and deposit rates are solved as a system of equations using the first order conditions for deposit rates (see equation (1)) with the alternative network structure. Equity capital is estimated non-parameterically from the first order condition for equity capital choice (see equation (2)) using a third degree polynomial function. In the above equation, the error term, \(\nu_{j,n_j,n'_j}\), is attributed to measurement error or specification error.

We can simplify the differenced profit function as,

\[
\Delta \Pi_j = \Delta R_j(n_j, n'_j, n_{-j}) + \nu_{j,n_j,n'_j},
\]

where \(\Delta R_j\) is defined as,

\[
\Delta R_j(n_j, n'_j, n_{-j}) = \Delta Y_j(n_j, n'_j, n_{-j}) - \beta_1(n_j - n'_j) - \beta_2(n_j^2 - n'_j^2) - \beta_3[I(n_j > X)(n_j - X)^2 - I(n'_j > X)(n'_j - X)^2].
\]

Using the above notation a moment function can be formulated as,

\[
S(\beta) = E[h(n'_j; n_j, I_j)\Delta R_j(n_j, n'_j, n_{-j})]
\]

where \(h(n'_j; n_j, I_j)\) is the weighting function defined below using instruments \(z_j\),

\[
h(n'_j; n_j, I_j) = \begin{cases} 
  g(z_j) & \text{if } n_j - n'_j = t \\
  0 & \text{otherwise}
\end{cases}
\]
where \( z_j \in I_j \) are demand shifters which are independent of cost shocks. Refer to the appendix 8.1 for the satisfaction of the sufficiency conditions for the PPHI estimator.

Essentially, I am looking for parameters that satisfy \( S(\beta) \geq 0 \). The dimension of the moment function is \( \text{dim}(h) \times \text{dim}(\Delta R_j) \) i.e. I have more moment restrictions if I have more weighting functions or have more alternate policies. Since banks are interacting agents in a particular market, I make use of this by forming the sample analog of the moment by averaging over banks in a market, followed by averaging over all markets:  

\[
s(\beta) = \frac{1}{M} \sum_m \frac{1}{J_m} \sum_{j_m} h(n_j'; n_j, I_j) \Delta R_j(n_j, n_j', n_{-j}). \tag{1.5}
\]

The following equation forms the basis for estimation

\[
\hat{\beta} = \{ \beta : \beta \in \arg \min_\beta ||(s(\beta))_-|| \}, \tag{1.6}
\]

where \((\cdot)_- = \min(\cdot, 0)\) and \(\hat{\beta}\) is the set of identified parameters. The norm used is \(L_1\). A usual concern with the set identification approach is that the identified set may potentially be so large that it is uninformative. In practice, this is taken care of by imposing a large number of moment restrictions. This is the case here.

In the objective function, there are two categories of moment conditions. The first set of moment conditions only apply to the small banks. The second set of moment conditions apply to all banks. This choice of moments is crucial for restricting the set size of \( \beta_3 \). The first set of moments provides identifying power only for \( \beta_1 \) and \( \beta_2 \). With \( \beta_1 \) and \( \beta_2 \) restricted by the first set of moments, the second set of moments identifies \( \beta_3 \). Also, this choice of moments is important as small banks may behave differently from the large banks.

I use three methods to do inference: PPHI inner and outer confidence interval methods and point-wise generalized moment selection method proposed by Andrews and Soares (2011). In the literature for inference of partially identified models, a distinction is made between constructing a confidence interval for the identified set versus a confidence interval for the true parameter. The first two methods from PPHI fall in the first category in which confidence intervals are for the extreme points of the identified set. Inference using generalized moment selections lies in the second category where I can do inference point-wise. Using generalized moment selection method, I can do inference for a point outside of the estimated set also. The algorithm used for the generalized moment selection inference can be found in appendix 8.2.

A growing industrial organization literature considers partially identified models using moment inequalities for estimation. Holmes (2011) studies diffusion of Walmart using the PPHI estimator. Ishii (2008) studies the effect of ATM surcharges on competition and welfare

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19 This idea was previously used by Ishii (2007).
20 Results with \(L_2\) norm are almost the same.
21 Note that this choice of moments could not be done another way i.e. one set of moments targeting large banks and second set of moments targeting all bank or small banks. This is because there are only 17 large banks and I wont have enough observations to average over.

1.4.4 Weighting functions and alternate policies

To decrease the size of the identified set, I use several moment restrictions. Hence, to increase the number of moment conditions in the objective function (equation (6)), I can either increase the number of weighting functions \( h(\cdot) \) or increase the number of alternate policies. For each combination of a weighting function and an alternate policy, I can form a moment inequality. The weighing functions used for estimation are:

1. Constant function
2. \( I[ \text{Mean population of the markets bank } j \text{ is present in } \geq \text{ population of market } m ] \)
3. \( I[ \text{Mean population of the markets bank } j \text{ is present in } \leq \text{ population of market } m ] \)

I use two weighting functions other than the constant function. The second weighting function in the above list, includes markets which are larger (in terms of population) than the average market the bank is present in while forming the moments. Using this weighting function includes more of the larger markets in the moment conditions. The third weighting function is just the opposite and includes markets which are smaller than the average market for a particular bank.

The alternate choice of network used to form moments deviates from the choice in the data only marginally so that the estimated bounds can be tighter. When the alternative policy used \( (n_j') \) only differs marginally from the actual policy \( (n_j) \), we are closer to the trade-off the banks may have faced when making the entry decision. For example, a bank with 100 branches in the data is more likely to have considered the possibility of opening 95 or 105 branches, rather than 50 or 200 branches. Also, since profits are calculated by summing over markets, I don’t add up the estimation error in demand parameters in the calculation of \( \Delta R(\cdot) \) in equation (5) if I change the policy in the data only marginally. Alternate choice of the network of branches has to involve either adding new branches or removing existing branches. Otherwise, if I just change the location of existing branches in the data to form an alternate policy without addition/subtraction of branches, the terms involving parameters to be estimated will vanish (see equation (4)). Policies that involve adding branches help to bound the marginal cost from below. Similarly, policies that involve subtracting branches bound the marginal cost from above. Hence, using these two kind of alternate policies jointly gives us tighter bounds for the cost parameters. In principle, any alternative policy will satisfy the inequalities since they correspond to the necessary condition of the Nash equilibrium.

I have to decide which markets to add/subtract branches, for construction of the alternate policies. For the moments involving all banks, I add/subtract branches only in the markets
where the banks have the largest presence. In the data, large urban areas see more growth in branching while in the smaller cities the number of branches has been almost stagnant.\textsuperscript{22} This fact suggests that banks are more interested in their choices regarding large markets. So, I create alternate policies that affect larger markets which usually are the markets where a bank has a large presence. For the moments involving small banks only, I add/subtract branches in markets where the banks have largest presence as well as in markets where the banks have least presence. This captures the fact that some of the small banks only target a small region and are in the growing phase. This is reasonable given the skewed size distribution in the data.

The alternate policies used in the moment conditions that involve all banks are,

1. Adding 1 branch in a market where the bank has its largest presence.
2. Subtracting 1 branch in a market where the bank has its largest presence.
3. Adding 1 branch each in the 5 markets where the bank has its largest presence.
4. Subtracting 1 branch each in the 5 markets where the bank has its largest presence.
5. Adding 1 branch each in the 10 markets where the bank has its largest presence.
6. Subtracting 1 branch each in the 10 markets where the bank has its largest presence.

The alternate policies used in the moment conditions that involve small banks only are,

1. Adding 1 branch in a market where the bank has its largest presence.
2. Subtracting 1 branch in a market where the bank has its largest presence.
3. Adding 1 branch each in the 2 markets where the bank has its largest presence.
4. Subtracting 1 branch each in the 2 markets where the bank has its largest presence.
5. Adding 1 branch each in the 2 markets where the bank has its least presence.
6. Subtracting 1 branch each in the 2 markets where the bank has its least presence.
7. Adding 1 branch each in the 10 markets where the bank has its largest presence.
8. Subtracting 1 branch each in the 10 markets where the bank has its largest presence.

Some small banks go out of business with alternate policies involving subtraction of branches. Profits of these banks are equated to zero under alternate policies.

\textsuperscript{22}Refer to FDIC 2006 FYI bulletin for details.
1.5 Results

This section is divided in two parts. The first part contains results from the demand estimation. These results show the presence of market power and consumer’s preference for a large network of branches. The second part contains results from estimation of the cost function. The parameter on equity capital will measure the cost of external funding. Remaining parameters in the cost function will measure the magnitude of cost efficiencies.

1.5.1 Demand Parameters

Demand parameters are estimated from 353 markets using demand and supply side moments jointly. The estimated parameters are reported in table 2. The parameter on the deposit rate, $\theta_1$, is 24.1617 suggesting that consumers prefer high deposit rates. The parameter on the branch density variable, $\theta_2$, is 22.2884 implying a preference for the distance traveled by depositors. It strengthens the finding of Ho and Ishii (2010) that consumers incur a disutility from distance traveled for their deposit services. The value of -0.5817 on $\theta_3$ indicates consumers aversion towards 1-branch banks for their deposit services. This supports the fact that the 1-branch banks are not after deposits and their business model may be different. This is inline with the finding in Dunne, Kumar and Roberts (2012), where the authors find that 1-branch bank’s main source of revenue is non-interest income. The parameter on the capital-size ratio, $\theta_4$, is estimated to be 2.3054 suggesting that consumers prefer banks which are more capitalized. Depositors have an incentive to look for signals about the safety of their deposits and the capital-size ratio acts as a proxy for capital-asset ratio. One possible reason for this parameter to be just significant could be that part of the population (insured depositors) don’t care too much about the safety of their deposits. The parameter on size, $\theta_5$, is 0.1561 and significant suggesting that consumers favor banks with more branches, although their branches may be outside of the market. Standard errors reported are heteroskedasticity robust standard errors.

Demand elasticities w.r.t. size are also calculated. For small banks, the average elasticity is 0.36 while for large banks, the average elasticity is 1.11. This large difference in elasticities shows consumer’s preference for large network of branches. However, the average interest rate elasticity is almost the same for small and large banks at 0.38 and 0.34 respectively. These numbers are close to the price elasticities estimated by Dick (2008) for all banks using MSA level data from 1993-1999 (0.30).

I perform three modifications to the base case as a robustness check. First, I estimate the model with both demand and supply moments jointly but without any instrumental variables for price and equity capital. Second, I estimate the demand parameters with demand-side moments only and with instrumental variables. Third, I estimate the demand parameters

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23 All the variables in demand estimation are scaled to be of the same order for numerical stability. Hence the magnitudes of the parameters doesn’t have any direct meaning.
I find that using instrumental variables changes the value of the parameter on the capital-size ratio variable to some extent, and using the supply side moments is crucial for identification of the parameter on price ($\theta_1$). This suggests that the correlation between unobserved quality and price is weak. Overall, using supply side moments and instrumental variables doesn’t provide any significant difference in the magnitudes of demand estimates.

Banks exercise market power by reducing their deposit interest rate. Since consumers have a preference for a large network of branches, banks with large size exercise more market power by lowering the deposit interest rate (hence reducing their interest expenses). Hence, market power increases with size.

### 1.5.2 Cost Function Parameters

There are two stages of the cost function estimation. First, the parameter on equity capital ($\beta_S^4$ and $\beta_L^4$) is estimated. Second, the parameters on the quadratic spline function of network size ($\beta_1$, $\beta_2$ and $\beta_3$) in the cost function are estimated using the moment inequality estimation.

Table 3 contains the estimates of $\beta_1$, $\beta_2$ and $\beta_3$. The negative sign on $\beta_2$ implies the presence of cost efficiencies for small banks (less than 500 branches). For larger banks (more than 500 branches), the parameter $\beta_3$ is added into the cost function. The positive sign on $\beta_3$ implies that cost efficiencies are smaller in magnitude for larger banks because concavity for larger banks is inferred by the sum: $\beta_2 + \beta_3$. As banks grow in size, cost efficiencies can come from a reduction in managerial expenses and advertising expenditures because these expenses don’t grow proportionally such as an expense for a advertisement on TV or newspaper doesn’t grow with size.

The estimates imply that the physical capital and labor cost of setting up the first branch is between 6.3780 million dollars and 6.6472 million dollars ($\beta_1 + \beta_2$). For the second branch this cost drops by 9.8 thousand dollars to 12.8 thousand dollars ($2\beta_2$). For each new branch, up to the size of 500 branches this cost declines by a factor proportional to $\beta_2$. The decline

---

24 Refer to the appendix 8.3 for the second and third case.
in the marginal cost due to concavity is not big for banks in the very lower tail of the size distribution, e.g. a bank with 10 branches will get a reduction of 2% in the marginal cost for the next branch it adds. The cost savings become significant with somewhat larger banks, e.g. a bank with 100 branches will get a reduction of 15% in the marginal cost for an extra branch. Once I cross the barrier of 500 branches, concavity in the cost function is reduced. At the lower end of $\beta_3$, with a value of 0.0012, the large banks still have concavity in their cost function. At the upper end of $\beta_3$, with a value of 0.0121 the cost function for large banks becomes convex with no cost efficiencies.

The inference results are also listed in table 3. The confidence intervals constructed using the PPHI outer method and the moment selection method are similar qualitatively, while the inner method of PPHI produces somewhat tighter confidence intervals. Although the estimated set suggests the presence of cost efficiencies, some of the confidence intervals for $\beta_2$ and $\beta_3$ contain zero implying that the evidence for cost efficiencies is not very strong in the data. The main qualitative difference between this paper and earlier studies on cost efficiencies in banking is that I control for market power. The existing literature on banking scale economies has conflicting findings. Stiroh (2000) used 1991-1997 data to find that the largest bank holding companies have stronger cost efficiencies than the smaller ones. Boyd and Graham (1998) examined the effects of mergers and found evidence of cost efficiency gains for only the smallest banks. The gains disappeared quickly with increases in size and were negative for larger banks. Hughes, Mester, and Moon (2001), Hughes, Lang, Mester, and Moon (1996), Hughes and Mester (1998) find strong cost efficiencies for all banks and the largest banks have slightly more cost efficiencies than rest of the banks. None of the above mentioned papers controlled for market power at the local geographic level while calculating cost efficiencies at the national level. These existing studies measure cost efficiencies as the percentage change in profits/costs with unit change in size (measured by assets). It is possible that the change in profits/costs with size could be due to the lowered interest expenses on deposits (market power). This could be the reason why some of the above studies find strong evidence of cost efficiencies. But once I control for market power, the evidence of cost efficiencies becomes weak at best. Hence, the existing findings in the literature may be misleading by ignoring the market power effect.

<table>
<thead>
<tr>
<th>Parameter Values</th>
<th>95 % Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower Bound</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>6.3844</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>-0.0064</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>0.0012</td>
</tr>
</tbody>
</table>

Table 1.3: Cost Function Estimation(in million dollars)

The parameters on the equity capital are in the Table 4. This parameter measures the interest rate on the funds generated from investors. Large banks pay an interest rate of
5.24% while the smaller banks have to pay a higher rate of 6.03%. These results support the fact that the larger banks are at an advantage when it comes to external funding. The attractiveness of large banks to investors could be attributed to the fact that either their portfolio is more diversified or they are too big to fail. A similar result was found by Shull and Hanweck (2001), where they find that the top 10 largest banks paid less for funds than smaller banks.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter</th>
<th>Value</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equity Capital (Small banks)</td>
<td>$\beta^4_S$</td>
<td>0.0603</td>
<td>0.0250</td>
</tr>
<tr>
<td>Equity Capital (Large banks)</td>
<td>$\beta^4_L$</td>
<td>0.0524</td>
<td>0.0082</td>
</tr>
</tbody>
</table>

Table 1.4: Cost Function Estimation: Equity Capital Parameters

Using the parameters, I do some preliminary analysis to distinguish between diversification and too big to fail motives behind the difference in the cost of equity capital. I measure diversification by the number of markets a bank is present in and I measure size by number of branches. I run OLS regressions with the log of size and log of the number of markets a bank is present in as independent variables. Table 5 contains all the results. The dependent variable is the log of the marginal cost in all three regressions which is calculated from equation (2). Specification (1) contains log of the size as the only independent variable. Specification (2) contains log of the number of markets a bank is present in as the independent variable. Specification (3) has both of them as the independent variable. The standard errors are not yet corrected for the error in the demand parameters. In specification 3, which is the most general one, increase in size decreases the interest rate on cost of funds. This shows some evidence of investors preferring to invest in larger banks over the diversification incentive.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter (Std. Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(Size)</td>
<td>-0.0375(0.0038)</td>
</tr>
<tr>
<td>log(# Markets)</td>
<td>-0.04022(0.0087)</td>
</tr>
</tbody>
</table>

Table 1.5: Cost Function Estimation: Parameters for variable marginal cost of equity capital.

Overall, the demand and cost estimates suggest that both market power at the geographic market level and a weak evidence of cost efficiencies at the firm level are present as banks

---

25 For calculating standard errors on these parameters, I have to account for the error in the first stage estimation of demand parameters. This will be available in the next version.

26 To answer this question, one has to incorporate risk into the bank’s profit function. By incorporating risk I mean that bank’s care about both mean profits and the variance of profits so that portfolio diversification can be endogenized. I leave this topic for future research.
increase in size. To assess the relative importance of these two effects I simulate mergers between two banks in the next section.

1.6 Industry Analysis and Counterfactual Experiments

1.6.1 Industry Analysis

The banking industry is one of the important industries in the U.S. with total assets of approximately $11.7 trillion in 2006. For decades, commercial banks had been geographically constrained by the McFadden Act of 1927 that prohibited them from operating across state lines. Additionally, state laws often restricted banks ability to branch across county lines and in many states prohibited branch banking entirely. The states deregulated their banking laws at different times. Some deregulated as early as 1970 whereas others were deregulated only when the Riegle-Neal Act was passed in 1994. The after effects of Riegle-Neal Act on market structure are significant. This gradual deregulation has led to a consolidation of banks over the last 30 years and is still ongoing. In 1990, there were 12,343 commercial banks and 2,815 savings banks that were FDIC insured. In 2006, the number of commercial banks was reduced to 7,402 while savings banks were reduced to 1,279. Since the financial crisis started in 2007, the drop in the number of banks is also due to bank failures and the forced mergers of failing institutions with healthy ones, as well as regular mergers between healthy banks.27 In 2012, these numbers were reduced to 6,222 commercial banks and 1,024 savings banks. Figure 2 shows the number of regular mergers (excluding corporate re-organization mergers and failing bank mergers) from 2000-2010.28

Before the financial crisis in 2007, there were more than 100 regular mergers per year. After 2007, the number of regular mergers drops but still there are more than 50 mergers per year. The presence of so many mergers, suggests the need to study them in depth and understand the driving forces behind these mergers and its effects on consumers.

1.6.2 Merger Simulations

I use the estimated parameters to simulate some actual mergers between banks that occurred in 2006 or later. For the set identified parameters, I use the mid-point of the set for the following merger simulations.29 The objective of this exercise is to quantify the effects of market power, cost efficiencies and equity capital on the profitability of a merger. I also

---

27 A regular merger is defined as a merger between two banks which are owned by separate bank holding companies and neither of the banks is a failing institution.

28 All bank mergers must be approved by one of the three federal bank regulators: Office of the Comptroller of the Currency (OCC), Federal Deposit Insurance Corporation (FDIC) or Board of Governors of the Federal Reserve System (FRB). Over the years OCC and FRB have published lesser details about the mergers making it difficult to distinguish between regular mergers and corporate re-organization mergers. The histogram is based on the numbers from FDIC alone.

29 I am currently working on robustness to this choice of mid-point of the parameter set. I plan to uniformly sample the parameter set and run the counterfactual experiments for each parameter.
calculate the change in consumer welfare due to the decrease in deposit rates and increase in network size because of the merger.

In the following experiments, revenues from loans are split in two categories: loans funded through deposits \( \sum_m D_m s_{jm}(\theta)(P^l_j - P^d_{jm}) \) and loans funded through equity capital \( P^l_{kj} \). Costs are also split in two categories: operating costs \( \beta_1 n_j + \beta_2 n_j^2 + \beta_3 I(n_j > X)(n_j - X)^2 \) and cost of raising equity capital \( \beta^S_{kj} \text{ or } \beta^L_{kj} \). The numbers in the tables below are the difference between the merged entity with joint profit maximization and consolidated numbers of the two banks with pre-merger values.

There are two demand-side effects due to a merger. First, consumers get a better quality product as they prefer larger network of branches (demand synergies). Second, consumers get a lower interest rate on deposits as firms re-optimize deposit rates. I attribute this second effect to market power. To isolate market power, I have to separate these two effects so that I can measure the effect of price alone. I explain my calculation of market power using a simple example. Say, bank 1 and bank 2 merge into a bank 12. Each bank’s network and deposit rate are denoted by \( n_i \) and \( p_i \) respectively, where \( i = 1, 2 \text{ or } 12 \). The merged bank’s network, \( n_{12} \), is the combined network of bank 1 and bank 2, while the deposit rate, \( p_{12} \), is obtained by re-optimizing prices with the combined network of branches. Let the loan revenues funded through deposits for bank \( i \) be denoted by \( r(p_i, n_i) \). I can measure the combined effect of demand synergies and market power by

\[
E_1 \equiv r(p_{12}, n_{12}) - r(p_1, n_1) - r(p_2, n_2).
\]

\[ \text{(1.7)} \]

\[ ^{30} \text{In the real calculation there are other variables also, but to simplify the exposition I omit them in this example.} \]
$E_1$ measures the combined effect because consumer’s utility depends on both prices and total size of the network. To measure the demand synergies component of the total effect, I assume a hypothetical scenario. I assume that both the merging banks, 1 and 2, are present in the economy with each bank having all characteristics of the merged bank except the deposit rate. In this setup, both the merging banks re-optimize prices.\(^{31}\) Let this price be denoted by $p$. This setup will measure the effect of the network on profits without any price effects coming from the reduction of competition. Note that in this hypothetical scenario there is no reduction in the number of players in a market. I quantify demand synergies by measuring

$$E_2 \equiv r(p, n_{12}) - r(p_1, n_1) - r(p_2, n_2),$$

(1.8)

where $r(p, n_{12})$ is the revenue of one of the merging banks with the combined network. Finally, to calculate the market power effect, I subtract the equation (8) from the equation (7) ($E_1 - E_2$). Using this approach, there is no market power effect in the markets where the merging banks do not overlap. This is inline with the fact that market power is a local geographic phenomenon. A similar calculation is done for consumer surplus to isolate the market power from the combined effect.

The cost efficiency in a merger between two banks with $n_1$ and $n_2$ branches is quantified by,

$$CE(n_1, n_2) \equiv [\beta_1(n_1 + n_2) + \beta_2(n_1 + n_2)^2 + \beta_3I((n_1 + n_2) > X)((n_1 + n_2) - X)^2] - [\beta_1n_1 + \beta_2n_1^2 + \beta_3I(n_1 > X)(n_1 - X)^2] - [\beta_1n_2 + \beta_2n_2^2 + \beta_3I(n_2 > X)(n_2 - X)^2].$$

(1.9)

The first term in $CE(n_1, n_2)$ is the operating cost of the merged entity, the second and third terms are operating costs of the two merging banks. The concavity in the quadratic function generates cost savings for the merged bank. Similarly, cost savings from equity capital (say for a merger between two large banks) are measured by,

$$E_3 \equiv \beta_4^Lk_{12} - \beta_4^Lk_1 - \beta_4^Lk_2,$$

(1.10)

where $k_{12}$ is the equity capital corresponding to the merged bank. Note that the choice of mid-point for the cost parameters will only affect the measurement of cost savings, the market power calculation is immune to this choice.

While simulating the mergers, I need to make a choice for the loan rate and the unobserved bank-market quality ($\xi_{jm}$) of the merged entity. I choose the maximum loan-rate and maximum $\xi_{jm}$ of the two banks for the merged entity.\(^{32}\) Using the maximum value for unobserved quality is roughly equivalent to using the unobserved quality of the larger bank. Since the larger bank is usually the acquiring bank, it is reasonable to assume that the brand-market fixed effects of the merged entity are that of the acquiring bank.

---

\(^{31}\)Note that both the merging banks will choose the same price.

\(^{32}\)Results are very stable even if I pick minimum loan rate.
I simulate two mergers in each of the following three categories: small bank and small bank, small bank and large bank, large bank and large bank. From 2006 onwards, there have been more than 50 regular mergers every year. In many of these mergers, the acquired bank had less than 5 branches. For simulating the mergers involving small banks (less than 500 branches), I chose the ones where the bank size was not too small (more than 30 branches) so that the change in magnitudes for important variables is significant. For simulating mergers between two large banks (more than 500 branches), I pick one regular merger (Regions Bank and Amsouth Bank) and one failing bank merger (Wells Fargo and Wachovia). When Wachovia bank was collapsing in the financial crisis, it was forced by FDIC to sell itself.

There are some common elements in each merger simulation. The network of branches of the two banks are merged exogenously and after that the merged entity chooses new equity capital and deposit interest rates. For the merged bank, the deposit rate in each market decreases and market share increases compared to the individual banks. This drives up the gains from revenue sources in a merger. Equity capital of the merged bank is strongly correlated with size, hence the merged bank has a higher equity capital than each of the merging banks.

1.6.3 Mergers between two small banks

The first merger simulation in this category is between Prosperity Bank, TX (75 branches in 6 markets) and State Bank, TX (37 branches in 5 markets) which occurred in 2007. The two banks overlap in 4 markets. Prosperity bank is headquartered in El Campto, TX and State Bank was headquartered in La Grange, TX. Due to the merger, total revenues increased by 30.1 million dollars, most of which is contributed by equity capital. The merged bank generates extra 8.8 million dollars in revenue from deposits, of which only 1.45 million is attributed to market power. This shows that there are strong demand synergies (preference for large networks) compared to the market power effect. There are significant cost efficiencies leading to a savings of 20.8 million dollars and most of it comes from reduction in operating expenses. Cost efficiencies seem to be playing a more important role in this merger compared to market power. Overall, consumer surplus decreases by a small amount indicating that that the utility from a better quality product (bigger size of the merged entity) is not offset by the decreased deposit rates due to market power. The loss in consumer surplus due to market power is -0.22 basis points. In this setup, consumer surplus is the utility, in interest rate terms, that the consumer receives.

The second merger in this category is between First Tennessee Bank (232 branches in 24 markets) and Sterling Bank (41 branches in 3 markets) that occurred in 2006. First Tennessee Bank is headquartered in Memphis, TN and Sterling Bank was headquartered in Houston, TX. There is only 1 overlapping market among the merging banks. The merged

\[^{33}\text{Note that other banks are not allowed to re-optimize their network choice in response to the merger. This is not feasible in the current setup as I have not solved for the bank’s policy function.}\]
entity is able to generate an extra 52.9 million dollars through offering a better quality product and charging lower deposit rates. Since there is only one overlapping market out of the total 26 markets the merged firm is present in, there is almost no market power effect here. There is extra revenue generated through equity capital as well (39.6 million dollars) but that is almost offset by the extra cost (36.3 million dollars) incurred to raise that much equity. Operating costs drop by 108 million dollars due to cost efficiencies resulting from the merger. In this simulation, cost efficiencies seem to be an important driver of the merger. Overall, consumers benefit from this merger as the depositors of the smaller bank get an big increase in the quality of the product because of the added network of a bigger bank. The loss in consumer surplus due to market power is -0.03 basis points. Note that this magnitude is much smaller than the first merger in this category. This happens because less overlap in markets reduces the market power effect.

Overall, in mergers between two small banks cost efficiencies play a more important role. The consumer welfare either drops or increases by a small amount. This happens because the banks in these mergers are small and consumers don’t benefit too much from the demand synergies. Note that since prices are chosen in the last stage of the game, cost savings are never passed on to the consumers.

### 1.6.4 Mergers between a small bank and a large bank

The first merger in this category is between PNC bank (837 branches in 23 markets) and Mercantile-Safe Deposit and Trust Company (195 branches in 7 markets) that occurred in 2007. PNC bank is headquartered in Pittsburgh, PA and Mercantile-Safe Deposit and Trust Company was headquartered in Baltimore, MD. These banks overlap in 3 markets. As a result of the merger, revenues from deposits increase by 54.8% which translates into 835
<table>
<thead>
<tr>
<th>Change in Revenues</th>
<th>$ Change(million dollars)</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>From deposits(Combined effect)</td>
<td>52.90</td>
<td>5.3%</td>
</tr>
<tr>
<td>From deposits(Market Power effect)</td>
<td>0.0022</td>
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</tr>
<tr>
<td>From Equity</td>
<td>39.60</td>
<td>8.3%</td>
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<tr>
<td>Change in Total Revenues</td>
<td>92.50</td>
<td>6.3%</td>
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</table>

<table>
<thead>
<tr>
<th>Change in Cost</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>From Operating Cost</td>
<td>-108</td>
<td>-7.4%</td>
</tr>
<tr>
<td>From Equity</td>
<td>36.30</td>
<td>7.2%</td>
</tr>
<tr>
<td>Change in Total Costs</td>
<td>-71.70</td>
<td>-3.7%</td>
</tr>
<tr>
<td>Change in Total Profits</td>
<td>164</td>
<td>32.7%</td>
</tr>
<tr>
<td>Change in Total Consumer Surplus</td>
<td>0.094</td>
<td>0.03%</td>
</tr>
<tr>
<td>CS loss due to Market Power</td>
<td>-0.03</td>
<td></td>
</tr>
</tbody>
</table>

Table 1.7: Merger Simulation: First Tennessee Bank (232 branches in 24 markets) and Sterling Bank (41 branches in 3 markets).

million dollars. Out of the 835 million dollars, only 27.4 million dollars can be attributed to market power. This implies presence of strong demand synergies. Revenue from equity comes around to be 500 million dollars which is largely offset by the cost of raising equity, 440 million dollars. Cost savings due to merger synergies are 22.6% which in dollar terms are 738 million dollars. Total revenues increase by 1.3 billion dollars (33.2%) whereas total costs decrease by 298 million dollars (5.1%) only. In this simulation, I can clearly see cost efficiencies dominating market power as a possible driving force for merger. This happens because there are very few overlapping markets. Consumer surplus increases by 6.67 basis points indicating that the effect of increased market power is dominated by a better quality product (larger bank). The loss in consumer surplus due to market power is -0.31 basis points. Note that the loss in consumer surplus here is larger than both the small-small mergers, but is still offset by demand synergies.

The second merger in this category is between Wells Fargo Bank (2,613 branches in 127 markets) and Greater Bay Bank (41 branches in 5 markets) that occurred in 2008. Wells Fargo Bank is headquartered in San Francisco, CA and Greater Bay Bank was headquartered in Palo Alto, CA. Before the merger, Wells Fargo was present in all the 5 markets where Greater Bay Bank was located. The revenue from loans funded by deposits increases by 1.01 billion dollars (11.6%). Out of these 1.01 billion dollars, 339 million dollars can be attributed to market power. The revenues from loans funded by equity is almost balanced by the cost incurred to raise that equity. Operating costs decline by 62 million dollars (-0.8%) which is really small as compared to the gains from market power. Overall the total revenues go up by 1.26 billion dollars while total costs also rise by 170.80 million dollars. Hence, the profitability of this merger is driven by market power more. The large market power effects are present due to a lot of overlapping markets between the two merging banks.
<table>
<thead>
<tr>
<th>Change in Revenues</th>
<th>$ Change(million dollars)</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>From deposits(Combined effect)</td>
<td>835</td>
<td>54.8%</td>
</tr>
<tr>
<td>From deposits(Market Power effect)</td>
<td>27.4</td>
<td>20.1%</td>
</tr>
<tr>
<td>From Equity</td>
<td>500</td>
<td>20.1%</td>
</tr>
<tr>
<td>Change in Total Revenues</td>
<td>1,335</td>
<td>33.2%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Change in Cost</th>
<th>$ Change(million dollars)</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>From Operating Cost</td>
<td>-738</td>
<td>-22.6%</td>
</tr>
<tr>
<td>From Equity</td>
<td>440</td>
<td>17.3%</td>
</tr>
<tr>
<td>Change in Total Costs</td>
<td>-298</td>
<td>-5.1%</td>
</tr>
<tr>
<td>Change in Total Profits</td>
<td>1,633</td>
<td>90.6%</td>
</tr>
<tr>
<td>Change in Consumer Surplus</td>
<td>6.67</td>
<td>1.92%</td>
</tr>
<tr>
<td>CS loss due to Market Power</td>
<td>-0.31</td>
<td></td>
</tr>
</tbody>
</table>

Table 1.8: Merger Simulation: PNC Bank (837 branches in 23 markets) and Mercantile-Safe Deposit and Trust Company (195 branches in 7 markets).

The total consumer surplus goes up suggesting that the effect of decreased interest rates is more than offset by a better quality product (larger bank). This happens because the utility of consumers of Greater Bay Bank increases a lot as the network size increases from 41 to 2,654 due to the merger. The loss in consumer surplus due to market power alone is -1.3 basis points. Note that this consumer surplus loss is larger than the loss in both small-small bank mergers.

Overall, the loss in consumer surplus due to market power is more compared to the small-small bank mergers. But the change in total consumer surplus is larger compared to the small-small bank mergers. Hence, I can conclude that although market power increases when large banks are merging, demand synergies increase at a greater rate. The cost efficiencies seems to be driving the mergers when there is not a lot of overlap between merging banks. When a large bank is involved in a merger, banks are practically breaking even in terms of equity capital. This happens because of two reasons. First, equity capital is costlier than deposits so banks with large network of branches don’t want to raise more equity to fund loans. Second, large banks have strong brand effects and don’t need to signal safety to depositors through capital reserves.

### 1.6.5 Mergers between two large banks

The first merger in this category is between Regions Bank (971 branches in 89 markets) and Amsouth Bank (561 branches in 44 markets) that occurred in 2006. They overlap in 36 markets. Both Regions Bank and Amsouth Bank are headquartered in Birmingham, AL. The revenue from loans funded by deposits increased by 3.8 billion dollars (158%) while operating costs decreased only by 648 million dollars (15%). Out of the 3.8 billion dollars increase in revenue, 1.26 billion dollars can be attributed to market power. This is largely
### Table 1.9: Merger Simulation: Wells Fargo Bank (2,613 branches in 127 markets) and Greater Bay Bank (41 branches in 5 markets).

Driven by a big overlap of markets. Like the previous merger simulations, the change in revenue and cost from equity capital roughly balance each other. Overall, total revenues increase by 5 billion dollars while total costs increase by 853 million dollars. At this point, the concavity in the cost function has been diminished by a significant amount. Clearly, the major driver behind this merger is market power. The total consumer surplus increases by 4.25 basis points suggesting that the effect of decreased interest rates is more than offset by a better quality product (larger bank). The loss in consumer surplus due to market power is -13.2 basis points which is larger compared to any of the mergers in last two categories.

<table>
<thead>
<tr>
<th>Change in Revenues</th>
<th>$ Change(million dollars)</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>From deposits (Combined effect)</td>
<td>1,010</td>
<td>11.6%</td>
</tr>
<tr>
<td>From deposits (Market Power effect)</td>
<td>339</td>
<td>1.9%</td>
</tr>
<tr>
<td>From Equity</td>
<td>247</td>
<td></td>
</tr>
<tr>
<td>Change in Total Revenues</td>
<td>1,257</td>
<td>5.8%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Change in Cost</th>
<th>$ Change(million dollars)</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>From Operating Cost</td>
<td>-62.20</td>
<td>-0.8%</td>
</tr>
<tr>
<td>From Equity</td>
<td>233</td>
<td>1.9%</td>
</tr>
<tr>
<td>Change in Total Costs</td>
<td>170.8</td>
<td>0.8%</td>
</tr>
</tbody>
</table>

| Change in Total Profits                                 | 1,086                     | 96.9%    |
| Change in Total Consumer Surplus                        | 16.13                     | 1.04%    |
| CS loss due to Market Power                             | -1.30                     |          |

### Table 1.10: Merger Simulation: Regions Bank (971 branches in 89 markets) and Amsouth Bank (561 branches in 44 markets).

<table>
<thead>
<tr>
<th>Change in Revenues</th>
<th>$ Change(million dollars)</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>From deposits (Combined effect)</td>
<td>3,794</td>
<td>158.0%</td>
</tr>
<tr>
<td>From deposits (Market Power effect)</td>
<td>1,260</td>
<td>44.7%</td>
</tr>
<tr>
<td>From Equity</td>
<td>1,451</td>
<td></td>
</tr>
<tr>
<td>Change in Total Revenues</td>
<td>5,054</td>
<td>92.8%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Change in Cost</th>
<th>$ Change(million dollars)</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>From Operating Cost</td>
<td>-648</td>
<td>-15.0%</td>
</tr>
<tr>
<td>From Equity</td>
<td>1,501</td>
<td>37.9%</td>
</tr>
<tr>
<td>Change in Total Costs</td>
<td>853</td>
<td>10.3%</td>
</tr>
</tbody>
</table>

| Change in Total Profits                                 | 4,201                     | 92.8%    |
| Change in Total Consumer Surplus                        | 4.25                      | 0.34%    |
| CS loss due to Market Power                             | -13.20                    |          |

29
Table 1.11: Merger Simulation : Wells Fargo Bank (2,613 branches) and Wachovia bank (2,795 branches).

The second merger in this category is between Wells Fargo Bank (2,613 branches in 127 markets) and Wachovia bank (2,795 branches 105 markets) which occurred in 2008. The merging banks overlap in only 8 markets. Wachovia bank was headquartered in Charlotte, North Carolina and Wells Fargo Bank is headquartered in San Francisco, CA. This merger took place during the financial crisis and it was a FDIC forced merger. The difference in total revenues from this merger is 10.9 billion dollars while an extra total cost of 19.2 billion dollars needs to be incurred. This shows that the merger was not profitable under normal scenarios. Total consumer surplus went up by 22.4 basis points. This particular simulation exercise also acts as a robustness check for our parameters.

The driving force behind merger between two large banks is mostly market power. Also, the reason why cost efficiencies are not large in this category of mergers is because the parameter $\beta_3$ is important and decreases the concavity in the cost function. Also, consumer welfare goes up in the merger between two large banks due to consumer’s preference for a larger network of branches.

### 1.7 Conclusion

This paper quantifies the degree of market power and cost efficiencies for U.S. banks. This paper develops a model of consumer behavior and firm choice where market power is a geographically local phenomenon whereas cost efficiencies are realized at the firm level. I develop a three-stage empirical model in which consumers choose banks for deposit services and banks choose the network of branches, equity capital and deposit rates. To estimate the cost parameters related to the network choice, I use moment inequality methods.

Demand estimates suggest that consumers prefer large, more capitalized banks and that market power increases with size. After controlling for market power, the evidence for cost efficiencies is weak for smaller banks (less than 500 branches), and they even decline as banks...
get larger (more than 500 branches). This is a contribution to the existing literature which
doesn’t control for market power when calculating cost efficiencies. I also find that smaller
banks are at an disadvantage when it comes to borrowing money from external sources
(raising equity capital).

Using the estimated parameters, I simulate mergers in three categories: between two small
banks, a small bank and a large bank and between two large banks. For mergers between
two small banks, cost efficiencies play an important role. For a merger between a small and a
large bank, the extra revenue generated by market power is larger than the cost savings when
there is a lot of overlap in the markets of merging banks. And for merger between two large
banks, market power effect dominates the cost efficiencies effect. Consumer surplus always
goes up in the mergers involving large banks. This happens because the market power effect
is dominated by the consumer’s preference for large network of branches. Hence, just looking
at the market power or cost efficiency is not sufficient for approving/declining a merger. The
fact that consumers have a better product at disposal should be taken into account.
Bibliography


Appendix A

Sufficiency conditions for PPHI estimator

To use the PPHI estimator, the weighting function and errors should satisfy two sufficiency conditions.

Condition 1: \( E \left[ \sum_j \sum_{n_j'} h(n_j'; n_j, I_j) \nu_{j,n_j,n_j'} \right] \geq 0 \)

Condition 2: \( E \left[ \sum_j \sum_{n_j'} h(n_j'; n_j, I_j) \Delta \gamma_{j,n_j,n_j'} \right] \leq 0 \)

Using the information that \( E[\nu_{j,n_j,n_j'} | I_j] = 0 \) and since \( I_j \) doesn’t contain any information about rivals condition 1 is trivially satisfied.

Condition 2 is also trivially satisfied as \( \Delta \gamma_{j,n_j,n_j'} \) equals zero. In my model, the structural error \( \gamma_j \) is fixed before the network choice.
Appendix B

Inference using Generalized Moment Selection

Following steps are used in sequence to calculate the confidence sets,

1. Form a 3-dimensional grid of points in \((\beta_1, \beta_2, \beta_3)\) space which extends well beyond the identified set.\(^1\)

2. At each grid point \(\beta_g\), evaluate the objective function: \(Q(\beta_g) = ||(D_M^{-1/2} s(\beta_g))||\), where \(D_M\) is a diagonal matrix with variance of moments on its diagonal.

3. At each grid point a critical value is calculated through simulation, \(c_a(\beta_g)\).

4. If \(Q(\beta_g) \leq c_a(\beta_g)\), then \(\beta_g\) is in confidence set.

The calculation of critical value is the most important step in the above method. To compute the critical value, an approximation to the distribution of objective function under the null is simulated. The distribution of the sample moments in the expression of objective function are simulated by a normal with mean zero and variance calculated using the data across markets. Next, of all the simulated moments under the null, only the nearly binding moments at each \(\beta_g\) enter the expression for simulating the objective function. A moment \(k\) is defined to be nearly binding if \(\sqrt{ME(s_k(\beta_g))}/\hat{\sigma}(s_k(\beta_g)) < \sqrt{2ln(\ln(M))}\), where the expectation operator is replaced by its sample analog and \(M\) is the total number of markets.

\(^1\)The grid is constructed so that the null hypothesis is rejected at the end points of the grid. In other words, the end points of the grid are such that they are not in the confidence interval.
Appendix C

Robustness for demand estimates

The demand estimates in the paper are calculated using both demand and supply side moments. The table below has estimates with only demand side moments. This acts as a robustness check for the baseline results used in the paper.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameter</th>
<th>Demand moments only (with IV)</th>
<th>Demand moments only (without IV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>$\theta_1$</td>
<td>42.2818</td>
<td>38.2860</td>
</tr>
<tr>
<td>Price</td>
<td></td>
<td>25.5104</td>
<td>5.2018</td>
</tr>
<tr>
<td>Branch Density</td>
<td>$\theta_2$</td>
<td>22.3717</td>
<td>22.2994</td>
</tr>
<tr>
<td>Branch Density</td>
<td></td>
<td>0.5920</td>
<td>0.5869</td>
</tr>
<tr>
<td>1-Branch Dummy</td>
<td>$\theta_3$</td>
<td>-0.5763</td>
<td>-0.5763</td>
</tr>
<tr>
<td>1-Branch Dummy</td>
<td></td>
<td>0.0521</td>
<td>0.0521</td>
</tr>
<tr>
<td>Capital-Size Ratio</td>
<td>$\theta_4$</td>
<td>1.5304</td>
<td>1.4429</td>
</tr>
<tr>
<td>Capital-Size Ratio</td>
<td></td>
<td>2.3211</td>
<td>1.0357</td>
</tr>
<tr>
<td># Branches</td>
<td>$\theta_5$</td>
<td>0.1605</td>
<td>0.1604</td>
</tr>
<tr>
<td># Branches</td>
<td></td>
<td>0.0106</td>
<td>0.0087</td>
</tr>
<tr>
<td>Constant</td>
<td>$\theta_6$</td>
<td>-6.9207</td>
<td>-6.8580</td>
</tr>
<tr>
<td>Constant</td>
<td></td>
<td>0.4182</td>
<td>0.0888</td>
</tr>
</tbody>
</table>

Table C.1: Logit Demand Estimation : With demand moments only
Appendix D

First order condition of equity capital

Here is the simplifying algebra of the first order condition of the equity capital ($k_j$). Assume that $j$ is a small bank.

$$\frac{\partial \Pi_j}{\partial k_j} = 0$$

$$\sum_m D_m \left[ \frac{\partial s_{jm}}{\partial k_j} + \frac{s_{jm}}{(1 - s_{jm})^2} \right] + P_j^l - \frac{\partial C(n_j, k_j)}{\partial k_j} = 0$$

$$\sum_m D_m \left[ \frac{\partial s_{jm}}{\partial k_j} + \frac{s_{jm}}{(1 - s_{jm})^2} \right] + P_j^l - \beta_4^s = 0$$

$$H_j + P_j^l - \beta_4^s = 0$$

where $H_j = \sum_m D_m \left[ \frac{\partial s_{jm}}{\partial k_j} + \frac{s_{jm}}{(1 - s_{jm})^2} \right] + P_j^l$.

Using the logit error assumption in the utility of the consumer I can simplify $\frac{\partial s_{jm}}{\partial k_j}$, 

$$\frac{\partial s_{jm}}{\partial k_j} = \frac{\partial s_{jm}}{\partial (k_j/n_j)} \frac{\partial (k_j/n_j)}{\partial k_j} = \frac{\theta_4 s_{jm}(1 - s_{jm})}{n_j}.$$ 

Note that $n_j$ is treated as constant in the above equation, because in the second stage when the banks are choosing $k_j$, bank size ($n_j$) has already been decided in the first stage. Hence I have,
Substituting the value of $H_j$ in the FOC I get,

$$
\sum_m D_m \left[ \frac{\theta_4 s_{jm}}{\theta_1 n_j (1 - s_{jm})} \right] + P^l_j = \beta_4^S.
$$

The above equation forms the basis for estimation of $\beta_4^S$. A similar calculation can be done for large banks as well.
Chapter 2

Market Structure and Growth of Banking in Rural Markets

Abstract

The passage of the Riegle-Neal act in 1994 enabled banks to expand their network of branches across the United States. Since rural markets are often seen as unattractive destinations for banks due to the lack of commercial activities, this could possibly lead to a lower branch density in rural markets relative to the larger metropolitan markets. Hence it is important to understand the underlying dynamics governing the market structure in these rural areas. In this paper, we study the incentive structure governing branching growth in rural banking markets in the United States. We develop and estimate a dynamic oligopoly model with a rich state space. We find that one-branch banks have a very different incentive structure than other banks in that they generate most of the revenue from non-interest income such as fund-management fees, loan-arrangement fees and by selling insurance. Banks with more than one branch generate revenue using the traditional method of collecting deposits and investing in loans. There is a large adjustment cost involved in opening a second branch which results in few banks making that transition.¹

2.1 Introduction

The removal of restrictions on geographic expansion in the banking industry ended in 1994 with the passage of Riegle-Neal Interstate Banking and Branching Efficiency Act. Different states deregulated their banking laws at different times, some states deregulated as early as 1970 whereas some were deregulated in 1994. The after effects of Riegle-Neal Act on market structure are significant. The banking industry in the US has been expanding at the branch level for many years now. We see a steady increase in the total number of bank branches in the US since 1980. With banks having more choices to expand their network of branches, we run into the possibility that rural market might be less served. This paper will study the

¹This chapter is joint work with Mark Roberts and Tim Dunne.
entry-exit patterns post-1994 in the rural markets and will analyze the profitability drivers of banks in these markets.

In this paper, we model a bank’s decision to exit and to adjust its size. Since the size of a bank today will have an impact on its future profitability, it is natural to model this in a dynamic framework. Also, there are adjustment costs associated with changes in size of banks and to model these costs a dynamic model is needed. A bank’s payoff is a function of its state variables: own size, size distribution of all the banks in a market and demographic variables that affect market demand. Modeling the choice of size by banks takes the form of a dynamic game since a bank’s decision about size affects the size distribution in the market which affects other bank’s payoffs.

Our measure of size is the number of branches owned by a bank in a particular geographical market. There are several economic determinants whose interplay governs a bank’s decision. Firstly, there is an adjustment cost associated with adding branches. This cost includes real estate expenditure as well as operational and managerial costs. Secondly, there are scrap values (sell-off values) which banks receive when they exit. These scrap values are a function of size and future profitability of the bank. Thirdly, returns on deposits might change with size. For example, a bank with five branches in a market might have different investment opportunities than that of a one branch bank. This difference in investment opportunities affects the returns on deposits and hence also affects the bank’s decision to choose its size. Fourthly, deposits collected by a bank depends upon the distribution of competitors size present in the market (oligopoly effect). Competitors with different sizes might affect a bank differently, we allow for this effect in our model. Finally, there are period fixed costs and non-interest revenues which affect a bank’s profitability. These non-interest revenues includes fund-management fees, loan-arrangement fees and revenues by selling third party financial products such as insurance. In our model, we will study the impact of all these factors on a bank’s size and will quantify their effects.

Solving dynamic games with a large state space can lead to a ‘curse’ of dimensionality. To deal with this, the usual approaches taken in the literature condense the state space by collapsing multiple variables into one summary variable, two stage methods and simulation based approaches. We combine the two stage CCP approach (Hotz and Miller 1993) and the simulation based stochastic algorithm in (Pakes and Mcguire 2001) to solve this game. The standard way of calculating continuation values is by integrating a firm’s value over all the future possible states, by using the insight of Pakes and Mcguire (2001) we bypass this and instead use simple averages of the returns from simulated past outcomes.

2.1.1 Relevant Literature

There has been a lot of work studying the effect of banking de-regulation on market structure. Most of this work is in reduced form except for a few recent papers.

Dick (2006) studies the effect of the Riegle-Neal Act and finds that concentration at MSA

\footnote{This particular combination of two approaches to solve a dynamic game is also used in a paper by Collard-Wexler (2010) where he studies demand fluctuations in a ready-mix concrete industry.}
level is virtually unaffected while at the regional level (several states combined) concentration increased. The author uses HHI index as a measure of concentration. Stiroh and Strahan (2003) study the competitive effects of banking deregulation on market structure. They find that deregulation leads to substantial re-allocation of market share towards better performing banks. Performance is measured by return on owners equity (ROE) and costs. Morgan, Rime and Strahan (2004) find that banking deregulation leads to smaller state business cycles and they are more alike. They argue this happens because the banks across states become more integrated via bank holding companies making the fluctuations in two states converge. Fluctuations in business cycles are captured by changes in gross state product, employment and personal income. Amel and Liang (1992) finds significant entry into local markets after intra-state branching restrictions are lifted happens via de novo branching. Jayaratne and Strahan (1996) find evidence that relaxation of the bank branching regulations was associated with increases in real per-capita growth in income and output. Levine, Levkov and Rubinstein (2009) find that banking deregulation reduces the racial wage gap by spurring the entry of non-financial firms.


The next section discusses some patterns in the industry. Section 2.3 discusses the data that I will use in my study. Section 2.4 contains the market definition and trends in data. Section 2.5 contains the theoretical model. Section 2.6 contains the algorithm used for the estimation. Section 2.7 discusses the empirical results. Section 2.8 concludes.

### 2.2 Industry Overview

The banking industry has undergone a substantial transition in the last two decades. Most notable events are the SNL crises in the beginning of 1990s, deregulation by Riegle-Neal Act and the big financial crises of 2008. Due to these events, market structure has been constantly reshaping itself.

#### 2.2.1 National Trends in the Banking Industry

Although the number of banks chartered have declined over the years, the number of branches and total deposits have increased steadily.

In the last two decades, trends in the banking industry have been interesting. The total number of banks in U.S. has dropped from 13,002 in 1994 to 7,821 in 2010. At the same time,
number of bank branches steadily grew from 81,297 in 1994 to 98,515 in 2010\(^2\). In figure 2.1 we can see this trend clearly. These numbers suggest a possible increase in concentration at the national level.

![Figure 2.1: Number of banks and number of branches in U.S.](image)

The increase in the number of branches can be attributed to the importance spatial location carries in the banking industry. Banks add branches so that they can locate close to their customers. Although there has been an increase in e-commerce activity and a surge in ATM networks in past few decades, the need for physical branches has not been reduced. Ho and Ishii(2010) show that distance traveled is an important source of disutility to a bank customer.

The decrease in the number of banks in the US is mostly due to mergers until 2007. As states slowly de-regulated their branching restrictions in the last two decades, larger banks started acquiring smaller banks in other markets increasing their geographic spread. One possible motive behind this can be that the banks are reducing their portfolio risk by holding assets in different markets. As different markets have somewhat separate business cycles, this can help the banks diversify their portfolios.

With the increase in number of bank branches, total deposits also go up. Table 2.1 shows that not only nominal deposits go up but also the real deposits (inflation adjusted) go up.

---

\(^2\)These numbers are based upon Summary of Deposits (SOD) data from FDIC.
The rate of growth in total deposits is higher than the growth in number of branches. Hence, we observe an increase in the average deposit per branch in the economy.

<table>
<thead>
<tr>
<th>Year</th>
<th>No. of branches</th>
<th>Nominal dollars</th>
<th>Deflated$^3$ by CPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1994</td>
<td>81,297</td>
<td>38,825</td>
<td>57,072</td>
</tr>
<tr>
<td>1995</td>
<td>80,999</td>
<td>39,688</td>
<td>56,754</td>
</tr>
<tr>
<td>1996</td>
<td>81,375</td>
<td>40,901</td>
<td>56,852</td>
</tr>
<tr>
<td>1997</td>
<td>82,109</td>
<td>42,587</td>
<td>57,918</td>
</tr>
<tr>
<td>1998</td>
<td>83,314</td>
<td>43,904</td>
<td>58,832</td>
</tr>
<tr>
<td>1999</td>
<td>84,312</td>
<td>44,876</td>
<td>58,787</td>
</tr>
<tr>
<td>2000</td>
<td>85,492</td>
<td>46,832</td>
<td>59,476</td>
</tr>
<tr>
<td>2001</td>
<td>86,069</td>
<td>50,264</td>
<td>61,825</td>
</tr>
<tr>
<td>2002</td>
<td>86,578</td>
<td>53,202</td>
<td>64,374</td>
</tr>
<tr>
<td>2003</td>
<td>87,790</td>
<td>58,459</td>
<td>69,566</td>
</tr>
<tr>
<td>2004</td>
<td>89,785</td>
<td>60,865</td>
<td>69,995</td>
</tr>
<tr>
<td>2005</td>
<td>92,046</td>
<td>64,465</td>
<td>72,201</td>
</tr>
<tr>
<td>2006</td>
<td>94,741</td>
<td>68,075</td>
<td>73,521</td>
</tr>
<tr>
<td>2007</td>
<td>97,274</td>
<td>68,899</td>
<td>72,344</td>
</tr>
<tr>
<td>2008</td>
<td>99,164</td>
<td>70,850</td>
<td>71,559</td>
</tr>
<tr>
<td>2009</td>
<td>99,550</td>
<td>75,938</td>
<td>76,318</td>
</tr>
<tr>
<td>2010</td>
<td>98,515</td>
<td>77,913</td>
<td>77,913</td>
</tr>
</tbody>
</table>

Table 2.1: Deposits per branch

This increase in the number of branches along with the increase in deposits per branch indicates that the industry is still growing. This expansion of industry alongside the decrease in number of total banks in the country makes this an interesting phenomenon to study.

The next section outlines in detail the sources of the data used and formation of panel data set.

### 2.3 Data sources

We take data from three sources. Yearly data from 1994-2010 on bank ownerships, location of branches and deposits is taken from the Federal Deposit Insurance Corporation (FDIC). The data on demographic information, population and per-capita income, is taken from the US Census Bureau and Bureau of Economic Analysis (BEA), respectively.

The variables in FDIC data can be divided in three main categories: Bank Holding Company (BHC) variables, institution (bank level) variables, and branch variables. Some of the key variables in FDIC data are: BHC id, bank id, branch id, total assets (institution $^3$Base year is 2010.
level), dollar deposits(branch level), street address( and zip code) of branches. The details about the creation of panel data can be found in the Appendices.

The next section defines a market and discusses some important trends in the data.

2.4 Markets and data trends

In this section, we define our markets and describe some important trends in them. Later on we will try to explain these trends using the model.

2.4.1 Market Definition

To study bank exit and growth decisions we focus on a set of 710 geographic markets. The 710 markets are taken from a list of cities defined as incorporated places by the US Census Bureau. These places are isolated medium-sized towns with mean population close to 13,000. Population in these markets range from 2,300 to 120,000. Per-capita income is less dispersed than population and ranges from $12,300 to $64,283.

In all these markets, the maximum number of branches owned by any bank in the whole panel is five. We will discuss the implications of this later on.

2.4.2 Size distribution of banks

In our dataset, roughly two-thirds of the banks in these 710 geographic markets are 1-branch banks. The size distribution is clearly skewed towards smaller banks suggesting large transition costs of getting bigger. Table 2.2 summarizes the size distribution of all banks in the markets across the panel(observatiob is at market-bank-year level). It shows that 37,368 of the total 55,837 market-firm-year observations are for 1-branch firms. In a given year, the same bank appearing in different markets are counted separately e.g. Bank of America in 2006 in market 1 and Bank of America in 2006 in market 2 are counted as two separate observations. A firm here is a bank in each of the geographic markets.

<table>
<thead>
<tr>
<th>Branches</th>
<th># Banks</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>37,368</td>
<td>66.92%</td>
</tr>
<tr>
<td>2</td>
<td>12,371</td>
<td>22.16%</td>
</tr>
<tr>
<td>3</td>
<td>4,303</td>
<td>7.71%</td>
</tr>
<tr>
<td>4</td>
<td>1,434</td>
<td>2.57%</td>
</tr>
<tr>
<td>5</td>
<td>361</td>
<td>0.65%</td>
</tr>
<tr>
<td>Total</td>
<td>55,837</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 2.2: Size distribution of banks

^2Isolated markets are helpful in studying the oligopolistic effects as there are no overlapping markets.
The time-series trend of the size distribution for all banks in the 710 markets is summarized in Table 2.3. We measure the size of a bank by the number of branches it owns. The number of small banks with 1, 2 or 3 branches grew substantially over time, while the number of bigger banks with 4 or 5 branches remained practically the same from 1994-2008. The number of banks with 1 branch grew by 24% (2,283 to 2,835) while 2 branch and 3 branch banks grew by 40% (686 to 957) and 24% (239 to 298), respectively. Whereas the number of banks with 4 or 5 branches practically remained the same or increased by a small fraction, 11% (96 to 107) for 4 branch banks and -7% (27 to 25) for 5 branch banks. This pattern is surprising since it suggests that the potential entrants and smaller incumbent banks are able to open 1 branch more frequently compared to addition on an extra branch by a bigger bank in these growing markets. We try to explain this pattern using a dynamic oligopoly game in next section.

In the 710 markets we study, the total number of all banks increased by 27% (3,331 to 4,222) over the panel. This increase in the number of banks is not inline with the overall trend in the industry where the total number of banks decline. Hence, this set of markets may be problematic when we explain the expansion of banks across geographical markets. But for this paper where we model the expansion of a bank inside a market, this set of markets may work fine because the number of branches in them still goes up from 4,891 in 1994 to 6,196 in 2008.

Our choice of geographic markets governs the entry and exit patterns, which we discuss
2.4.3 Entry and exit

Definition of entry and exit

The banking industry has a three-tier ownership structure with Bank Holding Companies (BHC) at the top and branches at the lowest level. Banks are at the middle level in this hierarchy and are the decision makers in our model. We study the entry and exit at the bank level in a geographic market. We made this modeling choice because in the data typically all branches of a bank exit simultaneously suggesting that decisions are made at the bank level. If a bank starts operations in a market with a new set of branches, we call it an entry. If all branches of an existing bank shut-down or are acquired by another bank in the same market, we call this an exit. If a bank $A$ is acquired by another bank $B$ existing in the same market, we consider this as an exit of bank $A$ without any entry. In this case, the number of players in a market gets reduced. If a bank $C$ is acquired by another bank $D$ who is currently not operating in the market, we consider this as an exit of bank $C$ and entry of bank $D$. The number of players in the market would remain the same in this case and there would be no change in market structure.

Entry patterns

Table 2.4 summarizes the pattern of entry in the 710 geographic markets. The entry rate in a given year is calculated as the ratio of total number of entrant banks with $n$ branches divided by the total number of incumbent banks with $n$ branches. Entry rates of 1-branch banks are much higher compared to the larger size banks. The last row of Table 2.4 shows that, mean entry rates of 1-branch banks are highest at 9.84% while lowest entry rate is of 5-branch banks at 3.60%. This is reasonable as the setup costs for 1-branch bank would be lowest. Intuitively, we would expect most of the banks to start with 1-branch and grow from there. We do see some entry with 2,3,4 and 5 branches, but most of them are entry by acquiring an existing bank.

Table 2.4 shows that entry rates in the geographic markets increases in the beginning years of the panel and drop gradually thereafter. The entry rates increase gradually from 9.48% in 1995 to 15.34% in 1998 and then drop after that. This can be attributed to Riegle-Neal Act as it was passed in 1994 and would have lead to an expansion by banks in new markets.

We explain the theoretical model in the next section.

---

7 We are working on the case where merger between an out-market bank and in-market bank is not counted as entry and exit since there is no change in the market structure by this merger.
### Table 2.4: Distribution of entrants

<table>
<thead>
<tr>
<th>Year</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
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#### 2.5 A theoretical model of bank size

We develop a dynamic oligopoly model with entry/exit and imperfect information. It is based on the framework developed by Ericson-Pakes (1995). We model the bank’s decision regarding size and exit in a geographic market given an exogenous entry process. Each period a bank receives a private profit shock and decides how big it wants to be tomorrow. A bank’s decision about size is based upon the rational expectation about its future profitability. A bank forms beliefs about its competitors action while making decisions, which are correct in equilibrium.

In the short-run, banks compete with each other and collect deposits. Collected deposits are a function of bank’s size, size distribution of all banks in the market and demographic factors. We measure a bank’s size by the number of branches owned by it in a particular geographic market.

In the sections below, we discuss the primitives of the model, the bank’s dynamic problem, timing and the equilibrium concept used.

#### 2.5.1 Environment and state variables

Banks compete with each other by choosing the number of branches. An incumbent bank can either choose to exit or to have 1, 2,...,N branches next time period. Each time period a bank \( i \) makes a decision to have discrete number of branches \( a_i^t \in \{0, 1, 2, \ldots, N\} \) tomorrow. The decision may involve opening up of new branches or closing down of existing ones.
Let $S_t^n$ denote the number of banks with $n$ branches at time $t$ in a particular market. A bank can have a maximum of $N$ branches. Let $z^t$ denote demographic variables at time $t$. This would include market level variables like population and per-capita income. Using these variables we can denote the aggregate state of a market at time $t$ as:

$$S^t = \{S^t_1, S^t_2, ..., S^t_N, z^t\}$$

Demographic variables, $z^t$, are assumed to evolve as an exogenous first-order markov process. Whereas, market structure state variables $\{S^t_n\}_{n=1}^N$ evolve endogenously from the decisions of all banks.

Apart from the market level state variables, there are two firm-level state variables as well. The first firm-level state variable is public information and measures the number of branches owned by bank $i$ at time $t$, $b^t_i$. Before making the decision, each bank $i$ receives a private profit shock $\epsilon^t_i$. This private shock is a vector containing a shock for each possible action. Hence, the complete state vector for a particular bank would be $\{b^t_i, S^t, \epsilon^t_i\}$.

### 2.5.2 Dynamic Problem

An incumbent bank $i$ receives a private shock $\epsilon_i$ every time period and can either choose to exit and collect a scrap value $\phi$ or can choose the number of branches tomorrow, $a_i$. The scrap value is a function of a bank’s own size and aggregate market state. The decision of a bank to stay in the market or to exit is denoted by $\chi \in \{0, 1\}$. Every period a bank receives a period payoff of $\pi(b^t_i, s, a^t_i)$. The payoff $\pi(b^t_i, s, a^t_i)$ is a function of its size today($b^t_i$), aggregate market state($s$) and size tomorrow($a^t_i$). Size today and aggregate market state govern the deposits accruing to a bank and hence determines the period interest income. Another component of the payoff are the non-interest fixed costs of a bank which are a function of its size. This is a reasonable assumption as most of the non-interest fixed cost accrued to a bank comes from operating expenditures which are determined by the number of branches owned by a bank. Size tomorrow will determine the effect of adjustments costs on the payoff. The dynamic problem of an incumbent bank associated with the above setup can be expressed as:

$$V(b^t_i, s, \epsilon^t_i) = \max_{\chi \in \{0, 1\}} \{\chi \phi(b^t_i, s), (1-\chi) \max_{a^t_i} E_{a^t_i} [\pi(b^t_i, s, a^t_i) + \epsilon^t_i a^t_i + \beta E_{\epsilon^t, s'} [V(b^t_j, s', \epsilon^t_i | a^t_i)]]\}$$

where $s \in S^t, b^t_i \in \{1, ..., N\}$ and $\epsilon^t_i$ is the action specific private shock vector. A bank’s decision is based upon rational expectations about future and beliefs about other player’s actions.

The ex-ante value function of the bank i.e. before it observes the private shock vector is:

$$V(b^t_i, s) = E_{\epsilon^t_i} (V(b^t_i, s, \epsilon^t_i))$$

---

8 We are omitting the market subscript in rest of this section for notational convenience.
9 Interest income = Interest revenue - Interest cost
Before a bank $i$ observes its private shock $\epsilon_i$, it will have an expected value for each of the possible choices. Let this \textit{ex-ante choice-specific} value function be denoted by $W(a_i, b_i, s)$. The \textit{ex-ante} value function $V(b_i, s)$ and the choice specific value function $W(a_i, b_i, s)$ are related as:

$$V(b_i, s) = E_{\epsilon_{a_i}}[\max_{a_i}(W(a_i, b_i, s) + \epsilon_{a_i})]$$

We make the following assumption on the private shock vector.

\textbf{Assumption 1.} $\epsilon^t_i$ is distributed as Type I extreme-value across $i$ and $t$.

Once we calculate $W(a_i, b_i, s)$, we can use the above assumption to form conditional choice probabilities for the number of branches chosen for tomorrow given today’s number of branches and aggregate market state:

$$Pr(a_i|b_i, s) = \frac{\exp(W(a_i, b_i, s))}{\sum_{a_j} \exp(W(a_j, b_i, s))}$$

These probabilities will form the basis of the empirical estimation. This assumption may seem extreme as the profitability of having different number of future branches should be interdependent. We make this assumption only because it makes the calculation easy during estimation.

\subsection*{2.5.3 Exogenous entry process}

A bank’s future profitability depends upon the market structure in the future. This future market structure is governed by the decisions of the incumbent banks and entrants. We assume one potential entrant each time period. Potential entrant banks can enter with $1, \ldots, N$ branches. We use a linear probability model to exogenously generate entrants every time period.

\subsection*{2.5.4 Timing}

The timing of the game is as follows:

1. Incumbents receive a private shock, $\epsilon_i$, and decide whether to exit or to have $a_i$ branches next period.
2. Entrants are generated by an exogenous process.
3. Incumbents compete for deposits and receive period payoffs $\pi(b_i, s, a_i)$.
4. Exiting banks collect scrap value $\phi(b_i, s)$. Entrants become incumbents and market evolves to a new state.
2.5.5 Equilibrium

The equilibrium concept is symmetric Markov perfect equilibrium (MPE). By symmetric we mean that strategies of a player don’t depend upon the identity of other players. There exists an equilibrium in pure strategies under some regularity conditions on private shocks $\epsilon_i$ (Doraszelski and Satterthwaite(2010)).

Let $A = \{ A_i(b_i, s, \epsilon_i) : \forall i \}$ be the set of all strategy profiles. The best response function of a player $i$ for a given strategy profile $A = \{ A_i, A_{-i} \} \in A$ is defined as:

$$R_i(b_i, s, \epsilon_i, A_{-i}) = \text{argmax}_a \{ W^A(a_i, b_i, s) + \epsilon a_i \}.$$ 

The best response function gives the optimal strategy for player $i$ if all other players don’t deviate from $A_{-i}$ today and in the future. Note that the choice specific value function $W(a_i, b_i, s)$ used above is implicitly conditional on the strategy profile $A$. To make this more clear, we can expand $W(a_i, b_i, s)$ as:

$$W(a_i, b_i, s) = E_{A_{-i}|A_i}[\pi(b_i, s, a_i) + \beta V(a_i, s')]$$

The above equation also shows us the relation between the choice specific value function $W(a_i, b_i, s)$ and the ex-ante value function $V(a_i, s')$. A Markov perfect equilibrium (MPE) in this game is a strategy profile $A^* = \{ A^*_i, A^*_{-i} \}$ such that for any player $i$ and for any $(b_i, s, \epsilon_i)$ we have

$$A^*_i(b_i, s, \epsilon_i) = R_i(b_i, s, \epsilon_i, A^*_{-i})$$

The empirical strategy relies on constructing the choice specific value function $W(a_i, b_i, s)$ as a function of parameters and using it to form an estimate of conditional choice probability (CCP). This conditional choice probability (CCP) based on the model is used to form a likelihood function which is maximized to estimate the structural parameters.

2.6 Computation algorithm and estimation strategy

Each bank has 8 state variables in its dynamic problem. A state space point, $x$, can be written as, $x = \{ b, s_1, s_2, s_3, s_4, s_5, z_1, z_2 \}$, where $b$ is the number of branches owned by the bank, $\{ s_1, ..., s_5 \}$ are market structure variables given the fact that the maximum number of branches a bank has is five, $z_1$ and $z_2$ are demographic variables. The state space is formed by taking a convex hull of the states observed in the data. This state space consists of approximately 9.5 million points. Solving this dynamic oligopoly game using

\[\text{If we include larger markets which have banks with more than five branches, it will have a direct as well as an indirect effect on the size of state space. The direct effect would come from the addition of extra market structure variables which will account for banks with more than five branches. Indirect effect will come from the increased range of the pre-existing market structure variables, since larger markets will have a higher number of smaller banks as well.}\]

\[\text{Since we are forming state space by making a convex hull, number of points in state space is just the multiplication of the range of all state variables: (6x14x9x6x7x3x10x10) = 9,525,600.}\]
standard fixed point iteration (Pakes-Mcguire ’94) will be very cumbersome and expensive because of the size of state space. Instead, in this paper we combine the conditional choice probability (CCP) approach (Hotz-Miller ’93) and the simulation based stochastic algorithm of (Pakes-Mcguire ’01) to circumvent the ‘curse’ of dimensionality.

Following is a step-by-step description of the algorithm:

1. Estimate the conditional choice probability (CCP) directly from the data:
   \[ \hat{P} = P_r(a_i|b_i, s) \]  

   The above equation denotes the probability of owning \( a_i \) branches tomorrow given today’s state vector is \( \{b_i, s\} \). We use a multinomial logit to estimate the CCPs. Estimates from this step are particularly crucial as the policy functions generated from this step are using extensively in our algorithm. Hence we try to be as general as possible in the choice of covariates.

2. Estimate the transition rule for demographic variables, \( z = \{z_1, z_2\} \), population and per-capita income. We assume that demographic variables are first-order markov and generate a transition rule using Tauchen’s method separately for each of the variables. Assuming \( z \) to be first order markov, we get \( z^{t+1} \sim G(.|z^t) \).

3. Calculate the choice specific value function \( W(a_i, b_i, s|\theta) \). This is an important step in the algorithm. We make the period payoff function \( \pi(b_i, s, a_i|\theta) \) linear in parameters\footnote{This linearity assumption allows us to calculate the value function just once. We will explain this later in the section.}.

   \[
   \pi(b_i, s, a_i|\theta) = \sum_{j=1}^{5} I(j = b_i)[\theta_{d,j} D_i + \theta_{f,j} a_i I(a_i = b_i) + \theta_{x,j} b_i I(a_i = 0) + \theta_{b,j} a_i I(a_i > b_i) + \theta_{s,j} a_i I(a_i < b_i)]
   \]

   Each time period a bank earns deposits \( D_i \). Banks compete in the short run for total deposits available in the market and earn their share as a function of market structure, demographics and their own size. Deposits are a liability for the bank, as it has to pay an interest to the depositors, but banks invest these deposits in loans and generate interest revenue. Hence, the parameters on deposits \( \theta_{d,j} \) can be interpreted as a measure of the interest spread (loan rate minus deposit rate). Except for the parameter on deposits all other parameters come into effect only when a particular choice is made. We assume that banks have to pay certain fixed costs each period such as operating costs and wages to employees. Banks also earn non-interest revenue each period such as fund-management fees, loan-arrangement fees and by selling third party financial products such as insurance. We cannot separate a bank’s non-interest
revenue from the fixed costs as we are measure this by a fixed effect as an intercept. This cumulative effect of non-interest revenue and fixed costs on bank profits is measured by $\theta_{f,j}$ when a bank doesn’t open or close any branches. When a bank opens new branches, $\theta_{b,j}$ measures the transition cost of getting bigger plus the period fixed cost and non-interest revenues. When a bank closes branches, $\theta_{s,j}$ measures the adjustment cost of getting smaller, period fixed cost and non-interest revenue. Sell-off values are measured by the parameters $\theta_{x,j}$. All the parameters are measured per branch basis except $\theta_{d,j}$.

The payoff function is linear in parameters $\theta_{d,j}, \theta_{x,j}, \theta_{f,j}, \theta_{b,j}$ and $\theta_{s,j}$ which allows us to write it as:

$$\sum_{j=1}^{5} I(j = b_i)\theta_{d,j}\theta_{x,j}\theta_{f,j}\theta_{b,j}\theta_{s,j} [D_i b_i I(a_i = 0) a_i I(a_i = b_i) a_i I(a_i > b_i) a_i I(a_i < b_i)]$$

$$= \sum_{j=1}^{5} I(j = b_i) \theta_{j,\rho}(b_i, s, a_i)$$

where $\rho(b_i, s, a_i)$ is a vector containing components of pay-off function without the parameters.

We can use this linearity of payoff function in parameters to simplify the choice specific value function as follows:

$$W(a_i, b_i, s|\theta) = E_{\hat{P}}[\sum_{t=0}^{\infty} \beta^t \pi(b_i, s, a_i|\theta)] = \theta . E_{\hat{P}}[\sum_{t=0}^{\infty} \beta^t \rho(b_i, s, a_i)] = \Gamma(a_i, b_i, s) (2.3)$$

The main advantage of the above specification is that we need to calculate $\Gamma(a_i, b_i, s)$ just once since it doesn’t depend on the structural parameters$^{13}$. Unlike the standard value function iteration where the fixed point of the value function needs to be calculated for each set of parameters, this approach requires the fixed point to be calculated only once. In the above equation $E_{\hat{P}}$ denotes that banks form symmetric beliefs about other player’s actions for all time periods. Implicit here is the assumption that the same MPE is played in each time period. We use the stochastic simulation-based algorithm based on the (Pakes-Mcguire 2001) to calculate $\Gamma(a_i, b_i, s)$. We will describe the calculation of $\Gamma$ function in next subsection.

4. Using $\Gamma(a_i, b_i, s)$ we can form the conditional choice probabilities, $\Psi(a_i|b_i, s; \theta)$, as a function of structural parameters $\theta$:

\footnote{Linearity of the pay-off function in parameters is also been exploited in Bajari, Benkard and Levin (2007).}
\[ \Psi(a_i|b_i, s; \theta) = \frac{\exp(W(a_i, b_i, s))}{\sum_{a_j} \exp(W(a_j, b_i, s))} = \frac{\exp(\theta \Gamma(a_i, b_i, s))}{\sum_{a_j} \exp(\theta \Gamma(a_j, b_i, s))} \]

This is the only place where we use the *Type-I Extreme Value* distributional assumption on the private shocks.

5. Once we have model based choice probabilities, we can proceed in many ways to estimate the model parameters e.g. MLE, GMM etc. We use the maximum likelihood estimator in this case. The log likelihood follows directly from the estimated CCP:

\[ \mathcal{L} = \sum_{i=1}^{T} \log(\Psi(a_{imt}|b_{imt}, s_{mt}; \theta)) \]

where \( i \) is the firm in market \( m \) at time \( t \) observed in the data.

An important step in the above procedure is to calculate the function \( \Gamma(a_i, b_i, s) \). In the next subsection we describe how we use a variant of the Pakes-Mcguire (2001) algorithm for the calculation of \( \Gamma(a_i, b_i, s) \) function \(^{14}\).

### 2.6.1 Algorithm for calculation of \( \Gamma \) function

In order to calculate the long run payoffs in the choice specific value function (equation 2.3), we need to calculate the \( \Gamma(a_i, b_i, s) \) function. In Pakes and Mcguire (2001), the continuation values are never calculated explicitly by integration. Instead, they are approximated by a simple average of the returns from the past outcomes. Also, the value function is calculated point-wise in the state space rather than once at all possible points. These two insights of Pakes and Mcguire (2001) break the link between the size of state space and ‘curse’ of dimensionality and ease the calculation of \( \Gamma \) function.

We need to define some notation before we proceed to the algorithm. We define a location space as \( \mathcal{L} = A \times X \) where \( A = \{0, 1, ..., 5\} \) is the action space and \( X \) is the 8 dimensional state space\(^{15}\).

To keep a count of times a state space point is visited we define a *hit counter* function, \( h(l) \), where \( l \in \mathcal{L} \). Before starting the algorithm we initialize the values of \( \Gamma(l) \) to some initial guess and set hit-counter \( h(l) = 0 \) for all \( l \in \mathcal{L} \). This *hit counter* function is used to take a weighted average over all past outcomes.

The algorithm we use to calculate \( \Gamma \) is as follows:

1. Pick any aggregate market-level state, \( s \in S \), where \( s = \{s_1, s_2, s_3, s_4, s_5, z_1, z_2\} \).

2. Using the markov transition rule, \( G(\cdot|z) \), draw values of the demographic variables, \( z_1' \) and \( z_2' \), for tomorrow.

\(^{14}\)Collard-Wexler (2010) uses a similar approach in his paper.

\(^{15}\)Each state space point \( x_i \in X \) has two components, \( x_i = (b_i, s) \) where \( b_i = \{0, 1, ..., 5\} \) corresponds to the number of branches owned by the bank and \( s \in S \), where \( S = S_1 \times S_2 \times S_3 \times S_4 \times S_5 \times Z_1 \times Z_2 \) is the aggregate market structure space. Entrants take the value \( b_i=0 \).
3. Draw actions for all the banks present in the market using the CCP estimated from
the data, \( a_i \sim \hat{P}(.|x_i) \) (equation 1.1). Combining both the state \( x_i \) and its action \( a_i \nolimits \)
into a tuple gives us a set of locations visited today\(^{16} \).

4. Using the decisions of incumbent banks from the last step and the potential entrant\(^{17} \) we
can calculate tomorrow’s aggregate market-level state variable, \( s' = \{s'_1, s'_2, s'_3, s'_4, z'_1, z'_2 \} \).

5. Increment hit-counter for all the locations visited today i.e. for all \( l_i = \{a_i, x_i \} \) pairs
visited today: Update \( h(l_i) = h(l_i) + 1 \).

6. For each \( l_i = \{a_i, x_i \} \) visited today, compute \( R_n \) corresponding to the \( n^{th} \) component
of the payoff function: \[
R_n(a_i, x_i) = \rho_n(a_i, x_i) + \beta \sum_{a_j} \Gamma_n(a_j, x'_i) \hat{P}(a_j|x'_i)
\]
In the above equation \( \rho_n \) is the \( n^{th} \) component of the payoff function, \( \pi() \). Do this for
all \( n \) components of the payoff function.

7. Update the \( \Gamma \) function for all locations \( l_i \) visited today, as below:
\[
\Gamma'_n(l_i) = (1 - \frac{1}{h(l_i)})\Gamma_n(l_i) + \frac{1}{h(l_i)} R_n
\]
If we expand the above updating rule, its just a simple average over all past outcomes
at location \( l_i \). By doing this we are circumventing the need to calculate transition
probabilities, \( Pr(x'_i|a_i, x_i) \) which saves us from the ‘curse’ of dimensionality.

8. Check for the stopping-criteria. If not satisfied, go back to step 1 and start the iteration
with \( s = s' \).

For the locations visited in the last 1 million iterations we test the stopping criteria. The
stopping criteria is based on a test by Fershtman and Pakes(2010). The stopping criteria is
based on the fact that the values of \( \Gamma \) in memory are close enough to \( \Gamma^* \) which is defined
using the following equation:
\[
\Gamma'_n(a_i, x_i) = \rho_n(a_i, x_i) + \beta \sum_{a_j} \Gamma_n(a_j, x'_i) \hat{P}(a_j|x'_i) Pr(x'_i|x_i, a)
\]
For each location \( l_i = \{a_i, x_i \} \), \( \Gamma^*(a_i, x_i) \) is calculated using the same algorithm we used
to calculate \( \Gamma \). We iterate one step forward using the values of \( \Gamma \) in memory and repeating
this process \( K \) times. The average of all these \( K \) values obtained from one step iteration
would be our candidate for \( \Gamma^*(a_i, x_i) \). One of the drawbacks of this procedure is that the
stopping criteria is very computationally expensive.

\(^{16}\) Set of all location visited today= \( \{ \{ a_i, x_i \} : \text{for all incumbents } i \} \).

\(^{17}\) We assume one potential entrant per time period. Using a linear probability model for entry we draw
the action for this potential entrant.
It takes typically 100-150 million iterations for the algorithm to converge. By convergence, we mean that the values of $\Gamma$ in memory satisfy the stopping criteria. As we iterate through the state space, the spread of locations visited decreases and certain locations are visited more often than others. The algorithm gives more accurate values for the locations which are visited frequently. The last 1 million locations visited form the recurrent class, $R$, and is used for the estimation\(^{18}\).

We make the assumption that the observed data comes from an economy which is in a steady state. Close to 85% of the state space points are in common between the recurrent class and the data. We assume that the remaining 15% data points won’t be observed if the real economy is stationary, hence we don’t use these points for estimation.

Calculation of expectation by simple averages of past outcomes won’t work very well if the initial guess for $\Gamma$ is incorrect. To correct for this, we reset the hit-counters after every 3 million iterations but keep the value of $\Gamma$ in memory. We do this 10 times before going for one long run. Doing this improves the guess for starting value of $\Gamma$ for the long run.

Once we have values for $\Gamma$, we use it to form the choice specific value function $W(a_i, b_i, s|\theta)$ (equation 2.3) as a function of parameters. This forms the basis of our estimation strategy.

### 2.7 Results

In this section we will discuss the numerical results of our model which consists of the parameters in the payoff function. We estimate the payoff parameters in two steps. In the first step, payoff parameters corresponding to the short-run competition among banks for collecting deposits are estimated. In the second step, the remaining payoff parameters are estimated using the maximum likelihood estimation.

#### 2.7.1 Parameters corresponding to the competition for deposits

Banks compete for deposits in the short-run. Deposits earned by a bank depend upon the market structure, demographics and size (number of branches) of a bank. We estimate the static parameters using a Bresnahan and Reiss(1991) type of reduced form competition model. We assume the following functional form for deposits:

$$D_{imt} = \sum_{j=1}^{5} \beta_j s_{jimt} + \sum_{k=1}^{5} \alpha_k br_{kmt} + \beta_{pop} pop_{mt} + \beta_{pci} pci_{mt}$$

$D_{imt}$ denotes the deposits accrued by the bank type $i$ in market $m$ at time $t$. $\{s_{1mt}, ..., s_{5mt}\}$ are the market structure variables which tells us the number of banks in each size class, $\{br_{1mt}, ..., br_{5mt}\}$ are dummy variables for bank types which distinguishes banks with different number of branches, population(pop) and per-capita income(pci) are the demographic variables at market-year level. In the above regression equation an observation is at the\(^{18}\)

---

\(^{18}\)Theoretically, whole state space is the ergodic set as any point in state space can be reached in finite number of iterations, but in practice only a small part of the state space is visited even with 500 million iterations.
market-bank-year level. There are a total of 55,837 observations at the market-bank-year level. Table 2.5 contains all the parameter values obtained by running the above regression equation.

The coefficients on $\beta_1 - \beta_5$ measure the effect of market structure on the deposits accrued by a bank. Market structure variables $s_{1mt} - s_{5mt}$ include all banks in a market i.e. competition as well as the bank itself. We observe a positive sign on $\beta_1$, which suggests the presence of complementarities between the 1-branch banks and the bigger banks. For complementarities to exist, incentive structure of 1-branch banks should be different from the bigger banks e.g. 1-branch banks may focus on the non-interest revenues as a major source of income whereas bigger banks may focus on the interest income. The presence of different incentive structures will be confirmed later on when we estimate the remaining parameters using the maximum likelihood. The negative sign on $\beta_2 - \beta_5$ captures the competitive-effect of other banks on the deposits accrued by a bank. The coefficients $\beta_2 - \beta_5$ measure the loss in dollar deposits due to the presence on an additional competitor bank(size $\geq$ 2 branches) in the market. From the coefficients on dummy bank category variables, $\alpha_1 - \alpha_5$, we can make the following observation: conditional on the market structure, deposits grow almost linearly with each additional branch. Each additional branch brings in approximately 50-60 million dollars.\(^{19}\)

Population and per-capita income variables are de-trended\(^ {20}\), hence the coefficients $\beta_{\text{pop}}$ and $\beta_{\text{pci}}$ represent the effect of variance in the demographics on deposits. In a market with population more than its mean in the time-series, a bank is likely to get more deposits. A negative coefficient on per-capita income suggests that people deposit more in times of economic downturn. This does not sound reasonable and intuitive\(^ {21}\).

We use the coefficients from the above reduced form regression to estimate deposits, $\hat{D}_{imt}$, for the state space points that are not observed in the data. This is needed for the calculation of the $\Gamma$ function because in our algorithm when we simulate tomorrow’s state it can lead to a state which is not observed in the data.

Using the estimated deposits, $\hat{D}_{imt}$ we calculate the $\Gamma$ function using the algorithm described in the last section. Using the $\Gamma$ function, we form the maximum likelihood function which forms the basis for the estimation of the remaining parameters in the payoff function.

### 2.7.2 Maximum likelihood estimation

First step in the estimation of remaining parameters is to estimate the conditional choice probabilities (CCPs) directly from the data. We use a multinomial logit model for estimating them\(^ {22}\). Using these CCPs we calculate the $\Gamma$ function and hence obtain the choice specific

\(^{19}\)A natural question comes here: Why doesn’t the banks grow past 5 branches in these markets? We will discuss this later in the section.

\(^{20}\)In the data, population and per-capita have an upward trend. So, to make the time series stationary we de-trend them by subtracting the mean at market level.

\(^{21}\)If we don’t de-trend population and per-capita income, coefficients on both the variables are positive and significant. It looks like we are losing a lot of information by de-trending.

\(^{22}\)It is intuitive to assume that that a bank’s choice of having $x$ branches versus $y$ branches next period will be correlated. Hence, multinomial probit would have been a better choice as it allows for a correlation
value function \( W(a_i, b_i, s|\theta) \) as a function of the parameters. Using the \( W(a_i, b_i, s|\theta) \) function we can form estimates of CCPs based upon the model which can be directly used in forming the likelihood function. Using maximum likelihood estimation (MLE) we estimate the remaining parameters of the payoff function. The functional form of the pay-off function was given in equation 2.2.

Table 2.6 contains all the remaining parameters. The parameter on deposits, \( \theta_d \), measures the interest spread rate offered by banks. It increases with the number of branches owned by a bank suggesting that smaller banks are more aggressive by either charging lower loan-rates or by offering higher deposit rates. For banks with 1 or 2 branches this parameter is negative implying that these banks rely on non-interest income to be profitable. This also suggests a different incentive structure for small size banks.

Parameter \( \theta_f \) measures the cumulative effect of period operating costs and non-interest income on the value of a bank when its size remains same the next period. For banks with more branches \( \theta_f \) drops, suggesting that operating costs increase faster with size as compared to non-interest income. There is a sharp decline in the parameter from $14.3 million for 1-branch banks to $3.5 million per branch for 2-branch banks. This suggests that 1-branch banks have disproportionately high non-interest income or low operating costs compared to other banks. This suggests that the main revenue source for 1-branch banks is the non-interest income which comes from activities such as fund-management or selling insurance products. For these activities a bank has a lesser incentive to open more branches than a bank whose revenue depend primarily on the deposits collected. Banks with 5 branches are faced by a large operating costs and this parameters takes a negative value of $1.46 million. These large operating costs may be the reason for non-existence of banks with more than 5 branches although the deposits grew almost linearly with each additional branch.

Parameter \( \theta_x \) measures the scrap value per branch. As banks get bigger, value of each additional branch is lower. There is a sharp decline in scrap values of 1-branch banks from $39.3 million to $14.1 million per branch for 2-branch banks supporting the presence of so many 1-branch banks in data. The decline in scrap values is not very big as the size grows past 2-branches.

Parameter \( \theta_b \) measures the one-time payment of a transition cost of getting bigger plus operating costs and non-interest income. As banks grow bigger, value of \( \theta_b \) drops suggesting its easier for bigger banks to add an extra branch. Cost of adding a branch is disproportionately higher for 1-branch banks at 33.3 million. We attribute this high cost to restructuring costs, operating costs and coordination costs. Once a bank owns 2 branches, cost of adding an extra branch is around the same ballpark which ranges from approximately $10 million to $15 million.

Parameter \( \theta_s \) measures the one-time payment of transition cost of getting smaller plus operating costs and non-interest income. There is no informative trend in this parameter except that the cost of becoming a 1-branch bank by closure of a branch by a 2-branch bank is highest suggesting some major re-structuring costs.

The likelihood function corresponding to the multinomial probit estimation was not globally concave and hence couldn’t be optimized.
Entry costs for potential entrants were measured as an overlay on the parameter $\theta_b$ which turned out to be insignificant. Hence the entry costs can be measured by the magnitude of the parameter $\theta_b$.

Standard errors are small except for the parameters on the deposits for the larger banks. Also, standard errors are large for the 5-branch banks because of the fewer number of observations.

Overall, parameters for 1-branch banks are so different from other banks that it suggests a different incentive structure for 1-branch banks.

\section*{2.8 Conclusion}

This paper makes an initial attempt to estimate a dynamic model of bank size and exit in a geographic market. We pick a set of rural markets in which the number of small banks (1, 2 or 3 branches) grew more over time while the number of banks with 4 or 5 branches grew very slowly or remained the same. We attribute this difference in growth to the increase in operating fixed costs and decrease in non-interest revenue with size. The increase in number of 1-branch banks is mostly due to the new entrants. As banks grow bigger their incentive structure changes. The small size banks (mostly 1-branch banks) rely on non-interest income as a major source of revenue while larger banks focus on interest income for revenues. We also find that the change from 1-branch bank to 2-branch bank requires a high re-structuring cost preventing banks from getting bigger. As banks grow bigger, sell-off value per branch gets smaller hinting at some evidence of decreasing returns to scale.
<table>
<thead>
<tr>
<th></th>
<th>Coef.</th>
<th>Std. Err.</th>
<th>t value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>825.67</td>
<td>167.57</td>
<td>4.93</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>-514.46</td>
<td>234.41</td>
<td>-2.19</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>-445.54</td>
<td>380.20</td>
<td>-1.17</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>-4417.96</td>
<td>657.36</td>
<td>-6.72</td>
</tr>
<tr>
<td>$\beta_5$</td>
<td>-6964.05</td>
<td>1416.21</td>
<td>-4.92</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>48,353</td>
<td>3820.45</td>
<td>-57.7</td>
</tr>
<tr>
<td>$\alpha_2$</td>
<td>97,645</td>
<td>3842.40</td>
<td>-44.54</td>
</tr>
<tr>
<td>$\alpha_3$</td>
<td>158,893</td>
<td>3926.00</td>
<td>-27.99</td>
</tr>
<tr>
<td>$\alpha_4$</td>
<td>205,100</td>
<td>4207.89</td>
<td>-15.13</td>
</tr>
<tr>
<td>$\alpha_5$</td>
<td>268,785</td>
<td>3870.84</td>
<td>69.44</td>
</tr>
<tr>
<td>$\beta_{pop}$</td>
<td>0.0310</td>
<td>0.2166</td>
<td>0.14</td>
</tr>
<tr>
<td>$\beta_{pci}$</td>
<td>-0.8226</td>
<td>0.1133</td>
<td>-7.26</td>
</tr>
</tbody>
</table>

Table 2.5: Short-run competition for deposits (in thousands of dollars)

<table>
<thead>
<tr>
<th>Bank type</th>
</tr>
</thead>
<tbody>
<tr>
<td>(# branches)</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
</tr>
</tbody>
</table>

Table 2.6: Parameters of the payoff function (1 unit = 10 million dollars)
Bibliography


Appendix E

Panel data creation

For the analysis, a panel data set is created by linking branches across years. The branch id variable in the FDIC data is not consistent over time and sometimes even missing (more than 10% of total obs). We create a new branch id variable in the FDIC data by matching the branches across years. We develop a matching algorithm for creating this new branch id variable. Table 2 contains the important variables used in the matching algorithm.

<table>
<thead>
<tr>
<th>FDIC Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>UNINUMBR</td>
<td>Branch id</td>
</tr>
<tr>
<td>CERT</td>
<td>Bank id</td>
</tr>
<tr>
<td>BKMO</td>
<td>Main office dummy</td>
</tr>
<tr>
<td>ADDRESBR</td>
<td>Street address of the branch</td>
</tr>
<tr>
<td>ZIPBR</td>
<td>Zip code of the branch</td>
</tr>
<tr>
<td>CITYBR</td>
<td>City name of the branch location</td>
</tr>
</tbody>
</table>

Table E.1: Important variables in the FDIC data

To assign a new branch id variable, PBRN (Permanent Branch Number), to each branch in our data set we use the following steps:

1. Combine data from two consecutive years.

2. Based upon some criteria (e.g. bank id and street address of branch) match branches which appear in both years.

3. Branches which are found to appear in both years are assigned a common id.

4. Remaining branches (i.e. which are not present in both years based on the above criteria) are matched on a different criteria.

5. Goto step 2 until there are no matches.
This algorithm works in levels - it matches branches on one criteria, if they don’t match they are passed on to the next level where they are matched on another criteria. As expected, the strictness of the criteria loosens as we proceed to the subsequent levels.

In the **first level**, branches are matched on a combination of FDIC branch id, UNINUMBR, and the first 3 digits of the zip code of the branch. All the branches which are found to have the same FDIC branch id across both years and same 3-digit zip code are assigned a common branch id(PBRN) and the value of the PBRN variable is carried over from the previous year for the matched branches. Here are the number of matches for the first level when the 1997-98 data was matched:

<table>
<thead>
<tr>
<th>Year</th>
<th>Total Branches</th>
<th>Matched on level 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>82,109</td>
<td>61,626</td>
</tr>
<tr>
<td>1998</td>
<td>83,314</td>
<td>61,626</td>
</tr>
</tbody>
</table>

The first level accounts for the maximum number of matches among all levels. All of these 61,626 matches are removed from both years and only the remaining observations are considered for the following levels.

The original data from the FDIC doesn’t assign UNINUMBR to the main office branches of banks. Assigning PBRN to these main offices is the purpose of the **second level**. Main offices can be identified by a dummy variable(bkmo=1/0). Main offices present across both years are identified by using bank id, CERT, and the main office dummy. We assign all the main office branches of the subsequent year(1998 in our example) a PBRN carried over from the previous year(1997). Here are the number of matches for second level on 1997-98 data:

<table>
<thead>
<tr>
<th>Year</th>
<th>Unmatched Branches</th>
<th>Matched on level 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>20,483</td>
<td>10,508</td>
</tr>
<tr>
<td>1998</td>
<td>21,688</td>
<td>10,508</td>
</tr>
</tbody>
</table>

All the 10,508 matched branches are removed from both years after assigning them PBRN values. Remaining observations are considered for level three.

**Level three** forms a matching criteria by combining three variables: bank id, street address and five digit zip code of the branch. Street address of a branch is converted into a numeric equivalent(using STATA’s `encode` function). Based upon this criteria, level three looks for matches across years in the observations which were not matched by level one and level two. All the matches are assigned a PBRN carried over from the previous year. Here are the number of matches for level three on 1997-98 data:

---

4 UNINUMBR alone is not consistent across years. In many cases, same UNINUMBR across years was assigned to branches which were at different locations.

5 We begin the matching process in the first year of our data set 1994. In this year a unique PBRN value is assigned sequentially to each branch.

6 From 2004 onwards most main offices are assigned UNINUMBR in FDIC data but before that they are completely missing.

---

65
<table>
<thead>
<tr>
<th>Year</th>
<th>Unmatched Branches</th>
<th>Matched on level 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>9,975</td>
<td>4,651</td>
</tr>
<tr>
<td>1998</td>
<td>11,180</td>
<td>4,651</td>
</tr>
</tbody>
</table>

If the physical location of a branch is unchanged across both years but if its ownership has changed, then our level three will not assign a PBRN to such a branch. In other words, branches matched in level three doesn’t account for changes in firm ownership. All the matched observations in level three are removed after assigning PBRNs to the subsequent year branches and remaining observations are considered for level four.

**Level four** forms a matching criteria by combining two variables: street address and five digit zip code of the branch. Using this criteria, level four looks for matches across both the years. All the matched branches of subsequent year are assigned a PBRN from the previous year(1997 in our example). Level four matches branches only on the base of physical location. So, even if firm ownership changes we will assign the same PBRN to a branch whose physical location didn’t change across both years. Alongside creating PBRN we also create dummy variables for each level which can inform us about the level on which a branch was matched. Following are the number of matches for level four on 1997-98 data:

<table>
<thead>
<tr>
<th>Year</th>
<th>Unmatched Branches</th>
<th>Matched on level 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>5,324</td>
<td>957</td>
</tr>
<tr>
<td>1998</td>
<td>6,529</td>
<td>957</td>
</tr>
</tbody>
</table>

All the matched observations are removed after assigning the PBRNs and remaining observations are considered for level five.

**Level five** relaxes the criterion of level four. It forms a matching criteria by combining three variables: street address of branch, city, 3 digit zip code of the branch. In the FDIC data, sometimes zip code changes in the last one or two digits although the street address and city remains same. To take into account such cases(which are very few), level five matches observations based on this criteria. All the matched branches of the subsequent year are assigned a PBRN from the previous year. Here are the number of matches for level 5 on 1997-98 data:

<table>
<thead>
<tr>
<th>Year</th>
<th>Unmatched Branches</th>
<th>Matched on level 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>4,367</td>
<td>52</td>
</tr>
<tr>
<td>1998</td>
<td>5,572</td>
<td>52</td>
</tr>
</tbody>
</table>

**Level six** matches observations across consecutive years using fuzzy address matching. Sometimes addresses reported refer to the same location but are coded differently e.g. “ave” for “avenue” , “6 st.” for “Sixth Street”. Usual string matching functions doesn’t work in such cases. Here we use STATA’s module for probabilistic matching of observations which is called *reclink*. Observations in two datasets are merged based upon some matching variables(address and zip code of the branch in our case) and a matching probability is
assigned to the matched observations. All the observations above a certain threshold of matching probability are checked manually. The critical value of matching probability is set fairly low which allows us to catch most of the matches. Matched observations are assigned a PBRN from the previous year. Here are the number of matches for level 6 on 1997-98 data:

<table>
<thead>
<tr>
<th>Year</th>
<th>Unmatched Branches</th>
<th>Matched on level 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>4,315</td>
<td>1,240</td>
</tr>
<tr>
<td>1998</td>
<td>5,520</td>
<td>1,240</td>
</tr>
</tbody>
</table>

After passing all observations through these 6 levels, each branch that appeared in both years (‘97 and ’98) will have been assigned a PBRN. To assign PBRNs to the remaining observations (i.e. new branches that first appeared in ’98), we increment the PBRN variable from the maximum PBRN assigned in 1997.

Although numbers are reported only for 1997-98, the results are consistent for other years. After the creation of the panel data set we move on to the analysis of markets.
Chapter 3

Unraveling Effects of Demand Shocks on Production Function Estimation and Firm Behavior

Abstract

The traditional productivity measures estimated using revenue-based firm-level data have both demand side and production side shocks embedded in them. In order to separate these two shocks, a small literature has exploited output price data but this data is typically not available in firm-level production data sets. In this paper, we use inventory data to disentangle and separately identify demand and productivity shocks without using any price data. Introducing a demand shock into the model also addresses the multi-collinearity bias pointed out by Ackerberg, Caves and Fraser (2006). Finally, we use our estimates to explain entry/exit dynamics and find that demand shocks are a more important driver of firm-turnover than productivity shocks.¹

3.1 Introduction

The estimated productivity using value data on inputs and outputs contains both the true productivity shock on the supply side as well as the demand side shock. It is known in the literature that using revenue based data can lead to a mis-measurement of productivity. Klette and Zvi Griliches (1996) and Jacques Mairesse and Jordi Jaumandreu (2005) consider how intra-industry price fluctuations can affect production function and productivity estimates. Melitz (2000), Jan De Loecker (2005) and Gorodnichenko (2005) have extended these analyses to accommodate multi-product producers and factor price variation. Katayama, Lu, and Tybout (2003) demonstrate that revenue-based output and expenditure-based input measures can lead to productivity mis-measurement. To rectify this problem, one solution is to use the price data to model the demand side explicitly leading to productivity estimates which are immune from the demand shock, as in Foster, Haltiwanger and Syverson

¹This chapter is joint work with Hongsong Zhang.
(2008) and Roberts, Xu, Fan and Zhang (2012). Since price data is mostly unavailable to the researchers, these approaches are sometimes not feasible.

In this paper, we extend the Olley and Pakes (1996) model to explicitly allow for the demand shocks to affect firms’ inputs decisions.\(^2\) Our model is based on the premise that variation in the inventory stock contains important information about the demand shock. Using this idea, we are able to recover the hidden demand shock without using any price information. Since inventory information is more readily available to researchers, our method has an advantage in terms of its usability.

We introduce the productivity shock as well as the demand shock explicitly into the model. It is a well-known fact that estimating production function directly is subject to the endogeneity bias. This happens because firms’ input choices depend on the unobservables such as productivity and demand shocks. We have two unobservables, demand shock and productivity, which can’t be solved for using the standard Olley and Pakes (1996) methodology unless we assume strong bijection conditions as proposed by Ackerberg, Caves, and Frazer (2006). We solve this problem by relating inventory stock and demand shocks in an intuitive way and explicitly backing out the demand shock.

We estimate our model using a plant-level data set from Colombia, which has detailed information on plant-specific inventory stocks. Estimation results for 14 industries show that ignoring demand shock tend to overestimate the labor coefficient and material coefficient, but underestimate the capital coefficient. The magnitude of the bias is significant, especially on the capital coefficient. Labor and material coefficients have a median(mean) bias of 3.07%(5.71%) and 1.97%(2.67%) respectively, while the capital coefficient has a median(mean) bias of 18.8%(26.29%) across all 14 industries. These empirical evidence further supports that the demand shock should not be ignored in production function estimation. We also find that demand shocks are more dispersed than the productivity shocks across firms and time. This suggests that firm heterogeneity is driven more by demand shock as compared to the productivity shock.

Using the estimates of productivity and demand shock we try to understand the dynamics of firm turnover. We look at the correlation between firm turnover rate and the estimated demand shock/productivity shock. It is well understood in the literature that the combined effect of both shocks in the revenue based productivity measure will cloud any firm behavior analysis. Our paper compares which aspect of firm heterogeneity, demand shock or productivity, is more important for firm behavior analysis. For the three industries analyzed in this paper (Clothing, Pharmaceuticals and Plastics), demand shocks are found to be more important driver of the firm turnover decision. This result is rather interesting as most of the applied research attributes firm turnover to the productivity shock. Our findings are consistent with Foster, Haltiwanger and Syverson (2008) and Roberts, Xu, Fan and Zhang (2012), which use price data to disentangle demand and productivity shocks to conduct firm behavior analysis.

\(^2\)The seminal work by Olley and Pakes (1996) provided an approach to estimate production functions via the famous two-stage approach based on firms dynamic decision of investment choice as a function of productivity. This paper led to subsequent studies in production analysis thereafter (Levinsohn and Petrin (2003), Ackerberg, Caves, and Frazer(2006), De Loecker and Jan (2009), Doraszelski and Jaumandreu (2009)).
This paper also suggests one way to address the multi-collinearity problem prevailing in the Olley and Pakes style models. As Ackerberg, Caves and Frazer (2006) and Bond and Soderbom (2005) pointed out, there is a multi-collinearity problem in the Olley and Pakes (1996) first stage estimation, because both the investment and labor choice are functions of the same variables: capital, productivity and age. To identify the labor coefficient in the first stage, we need some independent variation between the labor and investment. Demand shock and inventory stock turn out to be such variables which can provide this independent variation under certain timing assumptions.

The rest of the paper is organized as follows. Section 3.2 constructs a model. Section 3.3 details the estimation strategy. Section 3.4 discusses the data used for empirical analysis. Section 3.5 reports the empirical results of our model and compare it with Olley and Pakes (1996). Section 3.6 looks at some industry dynamics. Finally, we conclude in Section 3.7.

3.2 The Model

A dynamic model of firm production is developed. Our model is based upon the standard method of Olley and Pakes(1996), (OP henceforth). We extend their model by incorporating demand shocks and inventory stocks into the framework.

The production function is Cobb-Douglas, \( Y_{jt} = \exp(\omega_{jt})K_{jt}^{\alpha_k}L_{jt}^{\alpha_l}M_{jt}^{\alpha_m} \), where \( Y_{jt}, K_{jt}, L_{jt}, M_{jt} \) represent the output, capital stock, labor and material respectively. The parameters \( \alpha_k, \alpha_l \) and \( \alpha_m \) are the associated factor share parameters. \( \omega_{jt} \) is the firm’s productivity shock. The productivity is assumed to follow a first order Markov process, which is standard in literature. We denote the markov process for productivity as:

\[
\omega_{jt} = g(\omega_{jt-1}) + \eta_{jt}
\]

where \( \eta_{jt} \) is the innovation in the productivity at time \( t \). We assume that \( \eta_{jt} \) is an i.i.d. shock across firms and time.

Timing of the model is as follows:
1. In the beginning of a time period, \( \eta_{jt} \) is realized.
2. Firms choose their own labor \( (l_{jt}) \) and material \( (m_{jt}) \) based upon the state variables: capital stock \( (k_{jt}) \), productivity \( (w_{jt}) \), last period’s demand shock \( (z_{jt-1}) \) and last period inventory stock \( (inv_{jt-1}) \).
3. Production \( (y_{jt}) \) takes place.
4. Demand shock \( (z_{jt}) \) is realized. Inventory stock \( (inv_{jt}) \) and period profits \( (\pi_{jt}) \) are realized.
5. Firms choose their investment \( (i_{jt}) \) levels.
6. Economy evolves to tomorrow and all the capital stock \( (k_{jt}) \) is updated.

After the labor and material choices are made by the firm, production for the current time period is fixed. Production decision by a firm is based upon the expected level of demand. Demand shock is realized after the labor and material choices are made. Hence, the realized demand shock coupled with the production quantity determines the inventory stock. We will be precise about the determination of the inventory stock in the next subsection. Investment
decision is made after the realization of the demand shock and hence is based upon: demand shock \((z_{jt})\), inventory \((inv_{jt})\), capital \((k_{jt})\) and productivity \((w_{jt})\). This timing is inline with the fact that demand shocks affecting inventory levels is a short-term phenomenon while investment affecting the capital stock is a long-run choice.

The Bellman equation corresponding to the beginning of the time period is as below:

\[
V_1(k_{jt}, w_{jt}, z_{jt-1}, inv_{jt-1}) = \max_{l_{jt}, m_{jt}} E\left[ \pi_{jt} + V_2(k_{jt}, w_{jt}, z_{jt}, inv_{jt}) \right]
\]

where \(\pi_{jt}\) is the period profit earned by the firm. Note that the choice of labor and material in the above equation is dynamic since their choice affects the production quantity today which determines the inventory stock tomorrow which is a state variable. The Bellman equation corresponding to the investment choice is as follows:

\[
V_2(k_{jt}, w_{jt}, z_{jt}, inv_{jt}) = \max_{i_{jt}} E(w_{jt+1} + 1 \left[ \beta V_1(k_{jt+1}, w_{jt+1}, z_{jt}, inv_{jt}) \right]
\]

This gives us the policy function for investment: \(i_t(k_{jt}, w_{jt}, z_{jt}, inv_{jt})\). Note that while the decision of labor and material is based upon last period’s inventory stock and last period’s demand shock, investment decision is based upon the current period inventory stock and current period demand shock. This difference is crucial in breaking the multi-collinearity in the first stage of standard OP estimation method which authors in ACF argue about.

### 3.2.1 Evolution of Inventories and Demand shock

In each time period, we have the following accounting equation

\[
Y_{jt} + inv_{jt-1} = S_{jt} + inv_{jt}
\]

where \(Y_{jt}\) is production amount by firm \(j\), \(S_{jt}\) is the sales by firm \(j\), \(inv_{jt-1}\) and \(inv_{jt}\) are inventories at the beginning of period and at the end of period respectively. Now, demand shock \((z_{jt})\) is defined as the disturbance in expected sales of a firm as follows

\[
S_{jt} = E(S_{jt}|I_{jt}) + z_{jt}
\]

where \(I_{jt}\) is the information set of a firm \(j\) at time \(t\) which includes all the beginning of period state variables. Note that the demand shock \((z_{jt})\) is a mean zero variable. This mean zero assumption implies that the sales prediction by the firm will not be biased in a positive or negative direction. To proceed further, we need to make an assumption about firm’s inventory choice behavior. We assume that each firm is targeting a fixed stock of inventories, \(\lambda_j\), each time period. We make this simplifying assumption as modeling the production smoothing motive of a firm by allowing inventory stock as a choice variable is not the main objective of this paper\(^3\). Hence, production decision of a firm is governed by the following accounting equation

\[
Y_{jt} + inv_{jt-1} = E(S_{jt}|I_{jt}) + \lambda_j
\]

\(^3\)We can extend this to allow for production smoothing motive to endogenize the choice of \(\lambda_j\). This will not change the idea of this paper, but increases some technical difficulties. However, the optimal choice of inventory stock is another interesting research topic. We leave this for future research.
Using equation (2), we can simplify equation (3) as

\[
    z_{jt} = S_{jt} - Y_{jt} - inv_{jt-1} + \lambda_j
    \tag{3.4}
\]

\[
    z_{jt} = M_{jt} + \lambda_j
\]

where \( M_{jt} = (S_{jt} - Y_{jt} - inv_{jt-1}) = -inv_{jt} \). Note that \( M_{jt} \) is just data.

If we relax the fixed inventory target (\( \lambda_j \)) assumption and consider a more general model where firms target a time specific inventory level, say \( \lambda_{jt} \). In this case, firms inventories are affected not only by the demand shock but also by the productivity shock. Firms may want to produce more and save in the periods with high productivity shocks. In this general model, a firm can have a positive level of inventories even if the realized demand shock equals to the expected level. Our model is mostly applicable to industries where inventories are driven more by demand shocks than by production smoothing motive. In the results section, we do some basic empirical analysis to verify this for the analyzed industries.

### 3.3 Estimation

We estimate the parameters in a two-step procedure. In the first step, we recover demand shock \( (z_{jt}) \) explicitly using the inventory stock data. This is needed because the policy function for investment \( i_t(k_{jt}, w_{jt}, z_{jt}, inv_{jt}) \) has two unknowns, \( w_{jt} \) and \( z_{jt} \), hence can’t be used directly in the standard OP framework to solve for \( w_{jt} \). In the second step, we follow the standard two-stage estimation in the spirit of OP and estimate all the production parameters.

We assume that the targeted inventory is fixed for each firm and it is a function of observable firm characteristics \( X_j \), \( \lambda_j = f(X_j) \). We use average sales and average capital stock as observable firm-level characteristics. Using equation (4), the demand shock could be written as

\[
    z_{jt} = M_{jt} + f(X_j)
\]

Rearranging this equation yields an estimation equation

\[
    M_{jt} = -f(X_j) + z_{jt}
\]

We estimate the above equation by parameterizing \( f(X_j) \) and we treat \( z_{jt} \) as the structural error. After estimating this equation, the demand shock could be recovered as

\[
    \hat{z}_{jt} = M_{jt} + f(X_j)
\]

Once \( \hat{z}_{jt} \) is recovered, we have only one unobservable in the investment policy function. Our timing and state variables suggest the following form for the investment policy function:

\[
    i_{jt} = i_t(k_{jt}, w_{jt}, z_{jt}, inv_{jt})
\]
In the above equation, everything except \( w_{jt} \) is observed by us. Assuming monotonicity between productivity and investment in the above equation, it can be inverted and used in the standard OP framework. Using the OP method, stage 1 of the estimation involves the following production equation:

\[
y_{jt} = \beta_l l_{jt} + \beta_m m_{jt} + \beta_k k_{jt} + w_{jt} + \epsilon_{jt}
\]

where \( \epsilon_{jt} \) can be interpreted as a measurement error or the part of the productivity unobserved to the firm. It is well known in the literature that running this regression equation directly suffers from endogeneity issues. To deal with this, we use the insight of OP and back-out productivity, \( w_{jt} \), from the investment policy function:

\[
w_{jt} = w_t(i_{jt}, k_{jt}, inv_{jt}, \hat{z}_{jt})
\]

In this equation, our approach differs from OP in that we control for inventory stock and demand shock when recovering the unobserved productivity. The first stage estimation equation can be re-written as:

\[
y_{jt} = \beta_l l_{jt} + \beta_m m_{jt} + \phi(i_{jt}, k_{jt}, inv_{jt}, \hat{z}_{jt}) + \epsilon_{jt}
\]

If we assume labor and material to be static as is the case in OP, \( \beta_l \) and \( \beta_m \) can be estimated consistently in the first stage only. Even if labor and material are dynamic, we have independent variation between labor/material and \( \phi(i_{jt}, k_{jt}, inv_{jt}) \) provided by inventory stock (\( inv_{jt} \)) and demand shock (\( \hat{z}_{jt} \)) which gives us identification. To estimate the capital coefficient, \( \beta_k \), we use the markov assumption on productivity in the second stage of the estimation. From the first stage, we can get:

\[
\hat{\phi}_{jt} = \hat{y}_{jt} - \hat{\beta}_l l_{jt} - \hat{\beta}_m m_{jt}
\]

We also know that,

\[
\hat{\phi}_{jt} = \beta_k k_{jt} + g(\hat{\phi}_{jt-1} - \beta_k k_{jt-1}) + \eta_{jt}
\]

The last equation forms the basis of the second stage estimation and the capital coefficient, \( \beta_k \), is consistently estimated from it.

Ackerberg, Caves, and Frazer (2006) argue that the first stage of OP suffers from multi-collinearity problems since there is no independent variation between labor/material and investment.\(^4\) This collinearity problem becomes even more severe in Levinsohn and Petrin (2003), which uses intermediate inputs instead of investment to recover the unobserved productivity in the first stage. To identify the labor coefficient in the first stage, we need some independent variation between the labor and investment. Specifically, we need some

\(^4\)Ackerberg, Caves, and Frazer (2006) also noticed this problem, and they suggested to introduce some variables which affects the labor choice but not the investment choice. But it is very hard to find a good variable of this kind. They also suggested using a new timing to identify the model, or estimate the labor coefficient together with other coefficients in the second stage to avoid the collinearity problem.
variables which affect the labor choice but not the investment choice, or vice-versa. Demand shock and inventory stock turn out to be such variables which can provide this independent variation under certain timing assumptions. According to the timing in our model, labor and material depend upon last period’s inventory stock ($\text{inv}_{jt-1}$) and last period’s demand shock ($z_{jt-1}$) while investment decision depends upon current period inventory stock ($\text{inv}_{jt}$) and current period demand shock ($z_{jt}$). This independent variation lets us identify $\beta_l$ and $\beta_m$ in the first stage only. Also note that this variation holds whether labor/material are static or dynamic.

3.4 Data

The data used in this paper is from the Colombian manufacturing census from 1977 to 1991, which was collected by the Departamento Administrativo Nacional de Estadistica (DANE). The census covers all plants in the manufacturing sector for 1977-1982; after 1982, it covers only plants with ten or more employees. It contains detailed information about plants’ domestic and imported inputs usage, output, and many other plant characteristics. For a detailed introduction to the data, please refer to Roberts and Tybout (1996).

We use data from 14 Colombian industries. The industry choice reflects several considerations. First, all the 14 industries are important industries for the Colombian economy. Second, the number of observations in these industries is large enough for empirical investigation. Third, with the interest of looking at the effect of ignoring the demand shock on production function estimation, we choose a wide range of industries which are diverse in their production processes and demand patterns.

3.4.1 Summary Statistics

Table 1 consists of the 14 industries we used to estimate our parameters. Inventories reported are point sampled at the end of the year at the firm level. Inventory share is calculated as the ratio of value of inventory to the value of sales at the firm level. There are two things to note here. First, there is a lot of variation across industries in the inventory share (5% to 38%). Secondly, in a particular industry, the variance of inventory share across firms is significant. Mean to variance ratio of inventory share across industries has an average of 2.74 and a median of 1.73. This implies some variation in the demand shock across firms and time in an industry. This supports our assumption about the firm-time specific demand shock.

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5In the estimation we also drop observations for 1990 and 1991 because the industry code changed since 1990 and we do not have enough information to match the old and new industry codes.
3.5 Estimation Results

This section reports the three groups of parameters/variables which are important for our analyses: input shares, productivity and demand shock. The estimated input shares are compared with that from Olley and Pakes (1996), in which the demand shock was not considered. After that we use the estimated values of demand shock and productivity to understand drivers of firm turnover.

3.5.1 The Labor Share, Material Share and Capital Share

This subsection reports the estimated input shares of the production function. The estimation results of our model are compared with that of OP in which the demand shock was not considered. The results show that the labor and material shares are over-estimated and the capital share is significantly under-estimated if we ignore the demand shock. Table 2 contains the details of the estimation results.

The first finding in table 2 is that both labor and material coefficients are lower in our model, compared to the OP method. This indicates that ignoring the demand shock biases up the coefficients of first stage parameters. The demand shock affects the production decision, as a result the production function estimation, both directly and indirectly. We define the effect of demand shock ($z_{jt}$) on the labor and material coefficients as the direct effect. The effect of the exclusion of inventory stock on labor and material coefficients is called the indirect effect, because the variation in inventory is driven by demand shock itself. We discuss the details of the bias caused by ignoring demand shock in the appendix 1. As discussed in the appendix, the model predicts that the indirect effect of ignoring demand shock will bias labor and material coefficients up, and the direct effect of ignoring demand shock via inventory will bias labor and material coefficients down. As a result, the bias direction of labor and material coefficients is uncertain. If the indirect effect affects labor and material coefficients more than the direct effect, then both labor and material coefficients will be biased up, and vice versa. The estimation results implies that the indirect effect of demand shock (through inventory stock) dominates the direct effect.

The second finding in table 2 is that the capital coefficient is always lower in OP model compared with that in our model. This is natural given the result that labor and material coefficients are larger when the demand shock is ignored.

We also want to emphasize that the magnitude of the bias is large in all the industries examined. In the three industries examined in table 2, when the demand shock is not considered (in OP), the labor share is biased up by 4.64% - 17.08%, and the material share is also biased up by 1.87% - 6.91%. At the same time, capital share is biased down by 20.50% - 46.33%. This indicates that in order to generate a consistent estimator of the production function, besides productivity it is necessary to carefully deal with the unobserved demand shock. We estimate 11 more industries, and the results support the findings here. These results are reported in the appendices.
3.5.2 Productivity and Demand Shock

In this subsection, we discuss the estimates of productivity and demand shock. Estimated productivity is fairly persistent over time. While, demand shocks show higher dispersion than productivity across firms in our sample.

In the three industries examined in table 3, the productivity has a persistence above 0.75. This means that firms can carry a big part of their productivity to next period.

The demand shock has higher dispersion across firms, when compared with productivity. Table 4 reports the mean, variance, the 75th-to-25th quantile ratio, and the 90th-to-10th quantile ratio for each of the three industries. In each industry, the variance of demand shock is much higher than that of productivity. Also, the 75th-to-25th quantile ratio and the 90th-to-10th quantile ratio of demand shock are also much higher than that of productivity. This finding implies that the demand shock is an important source of firm heterogeneity, probably even more important than productivity. As a result, we need to give demand shock enough emphasis when understanding firms behavior.

This finding supports our assumption that firms are targeting a fixed level of inventories \( \lambda_j \) every time period for these three industries. Since the productivity has a lower variance than the demand shock, firms have higher chances to be hit by an extreme demand shock than by an extreme productivity shock. This provides some evidence that the production smoothing motive is weaker here as compared to the demand shock variation as shocks at the extreme end of the distribution are the drivers of inventories. Hence, the observed inventory levels are driven more by demand shocks than by the smoothing motive in these three industries.

3.6 Some Key Dynamics

The previous section finds that the demand shock is an important source of firm heterogeneity. In this section, we try to understand some of the underlying dynamics associated with the model. In particular, we discuss two things. First, we discuss the evolution of productivity. Second, we study how productivity and demand shock affects entry/exit decision of firms. The primary focus of our analysis is the connection between firm heterogeneity (productivity and demand shock) and firm behavior dynamics (entry/exit). The idea behind this exercise is to determine the relative importance of technology versus demand factors in driving the entry/exit decision of the firm. The analysis in this section also acts as a robustness check for the demand shock measure we constructed using inventories.

We also use the estimated productivity and demand shock measure to analyze firms’ export/import decision. The results are consistent with the findings here, and support that demand shock is an important determinant of firms’ export/import decision, more important than productivity in many industries. To save some space, these results are not

\[ \text{The persistence is defined as the persistence parameter in the first order markov process of productivity} \]

\[ \text{This is true even when the variance is normalized by the mean.} \]
reported in the paper. These results are available upon request and will be included in the online appendix.

3.6.1 Entry/Exit Rate

An important application of productivity research is to understand the firm turnover in operation. Table 5 shows the turnover rate in the three industries examined. The entry rate is defined as the share of new firms to the total incumbents in each year, and exit rate is defined as the share of firms that stopped operating to the total incumbents in each year. For example, in clothing industries on average 16.61% of firms are new each year and 13.79% firms exit at the end of each year. Firm turnover rate in clothing industry and plastic industry is almost double that in the pharmaceutical industry. In the next two subsections, we will look at the connection between firm heterogeneity (productivity and demand shocks) and entry/exit behavior.

3.6.2 Evolution of Productivity and Demand Shock

We start with some simple descriptive statistics on the differences in means between continuing and entrants/exiting firms. We compute these differences in means by regressing productivity and demand shocks on entry and exit dummies, while controlling for firm age and size. The coefficient on the entry(exit) dummy thus measures the average difference between the productivity/demand shock of entrants (exiters) and incumbent firms. The major finding here is that demand shock is a stronger driver than productivity of the entry/exit decision of the firms.

Table 6 includes the details of the regression. The first finding is that the entrants have either lower productivity or no difference in productivity as compared to incumbent firms. This indicates that the startup firms may not immediately reach the production frontier due to some sunk cost or needs some learning process to improve their productivity. The fact that the coefficient on age is positive also supports this idea. As firms grow older, they learn more and become more productive.

Our second finding is that the entering firms have worse demand shocks than incumbent firms. This finding has important implication on the customer base hypothesis and the market capital hypothesis. The fact that new entrants have lower demand shocks leads us to believe that probably firms need time to improve their market conditions by marketing or investing in advertisement. The fact that age have a positive and significant effect on demand shock also supports this idea.

The third finding is that the exiting firms have relatively lower productivity or no difference in productivity, compared to incumbent firms. In plastics industry, the exiting firms have relatively lower productivity, and in clothing and pharmaceuticals industries the exiting firms have no difference on productivity compared to incumbents.

8The coefficient on exit dummy is not significant in most general specification.
A natural response to this observation is: If the exiting firms do not differ in productivity compared to incumbent firms, why do they exit and the incumbents do not? The negative coefficient on exit dummy in the demand shock regression shows that exiting firms have worse demand shocks than incumbent firms. This suggests that exiting firms exit because they are hit by some bad demand shock. In the next sub-section we will argue that demand shock plays a more important role in determining firms’ turnover as compared to the productivity.

**Selection on Entry/exit**

We now turn to the primary focus of our analysis in this section: the determinants of firm turnover. We explore the role of demand shocks and productivity on firm survival both in isolation and jointly, testing if each has a significant impact on firms’ exit decisions. We also control for size effect in the regressions. This analysis potentially allows us to check whether the firm turnover studies in the literature based on productivity alone are misleading.

We report the detailed regression results in table 7. The dependent variable is an exit dummy. If a firm exits that year, then the dependent variable equals 1, and otherwise 0. Each column in table 7 represents a particular regression, with different regressors. The first two columns report the results from the isolated regressions. They show that higher productivity and/or higher demand shock both reduce the firms’ probability of exiting. When controlling for firm size, as shown in column three and four, good demand shock still significantly reduces the probability of exiting. The productivity has a mixed result. In plastics industry, a good productivity still reduces the probability of exiting. But in the clothing and pharmaceutical industries, the productivity does not significantly change the productivity of exiting. Column five and six regress the exit dummy on productivity and demand shocks, with or without firm size controlled. The results are consistent with that we got in column three and four: good demand shocks significantly reduce the probability of exiting, and the a good productivity shock either reduces or has no significant effect on the exiting probability.

Overall, the estimation results imply that the demand shocks play a more important role in determining firms’ exit decision, while productivity may or may not be as informative. It seems that demand shock is an important source of firm heterogeneity when forecasting firms exit decision, probably more important than productivity. This finding has important implication on analyzing the firms turnover behavior. It actually implies that the firm turnover analysis based on productivity alone (excluding demand shocks) conducted in the literature is actually misleading in some sense. To analyze firms turnover more reliably, we want to stress the need to consider another aspect of firm heterogeneity, demand shock, besides productivity.

**3.7 Conclusion**

We develop a model of production function estimation which explicitly accounts for demand shocks at the firm level. A standard approach in the literature is to use price data to build a
demand model and use that along with the production side to estimate the model. However in this paper, we adopt a different approach by using inventory data and claim that the variation in the inventory stock provides us with relevant information about the demand shock. We develop a structural model and are able to back out the demand shock estimates explicitly which are used in a Olley-Pakes style two-stage estimation procedure.

Another advantage of introducing demand shock and inventory stock as state variables is that it can help us solve the multi-collinearity problem (which is pervasive in Olley-Pakes style models) as argued by Ackerberg, Caves and Fraser(2006).

The model is estimated using a plant-level data set from Colombia, which has detailed information on plant-specific inventory stock. Our estimation results for 14 Colombian industries show that ignoring demand shock leads to a upward bias of labor and material coefficient, and a downward bias in capital coefficient. Labor and material coefficients have a median(mean) bias of 3.07%(5.71%) and 1.97%(2.67%) respectively, while the capital coefficient has a median(mean) bias of 18.8%(26.29%) across all 14 industries. The magnitude of the bias is significant (especially on the capital coefficient), further supporting that the demand shock should not be ignored in production function estimation.

We find that in the Colombian data, demand shocks are more dispersed than productivity for the clothing industry, plastic industry and pharamceutical industry. We find that the productivity levels are fairly persistent over time. Finally, we look at the correlation between firm turnover and the firm-specific shocks (productivity and demand shocks). We find that demand shocks play a more important role in determining firms’ exit decision, while productivity may or may not be as informative. This suggests a need to account for demand shocks while doing any firm behavior analysis.
Bibliography


Appendix F

Discussion of the Bias

In this section we show that, ignoring the demand shock can lead to a bias in the production function parameters. We only need to look at the first stage bias, because second stage bias is completely determined by first stage estimates.

In the first stage of the OP framework, while inverting the investment policy function to solve for productivity($w_{jt}$), the true model will have two extra variables compared to OP, which are inventory stock($inv_{jt}$) and demand shock($z_{jt}$). We claim that OP method suffers from an omitted variable bias. In the remaining part of this section, we try to get an expression to understand the magnitude and direction of this bias.

For the first stage of estimation, let the correct specification be,

\[ Y = \beta_1 X_1 + \beta_2 X_2 + \epsilon \text{ where } \epsilon \sim N(0,\sigma^2) \]

where $X_1$ is the set of variables included in the mis-specified model is so that $X_1 = \{l, m, k, i\}$ and $X_2$ is the set of excluded variables, so $X_2 = \{inv, z\}$. The mis-specified model will look like:

\[ Y = \beta_1 X_1 + \epsilon^* \text{ where } \epsilon^* = \beta_2 X_2 + \epsilon \]

In the mis-specified model, the estimated coefficient would be:

\[ E[\hat{\beta}_1] = \beta_1 + P_{1,2} \beta_2 \]

where $P_{1,2}$ is the matrix of regression coefficients from the regression of $X_2$ on $X_1$. Hence, we can say that

\[ P_{1,2} = (X'_1 X_1)^{-1} X'_1 X_2 \]

Hence omitted variable bias in the first stage regression would be $P_{1,2} \beta_2$. To quantify the bias, we have to consider the following regressions:

\[ inv_{jt} = \alpha_1 l_{jt} + \alpha_2 m_{jt} + \alpha_3 k_{jt} + \alpha_4 i_{jt} + \epsilon^1_{jt} \]

\[ z_{jt} = \gamma_1 l_{jt} + \gamma_2 m_{jt} + \gamma_3 k_{jt} + \gamma_4 i_{jt} + \epsilon^2_{jt} \]

Hence, $P_{1,2} = \begin{pmatrix} \alpha_1 & \alpha_2 & \alpha_3 & \alpha_4 \\ \gamma_1 & \gamma_2 & \gamma_3 & \gamma_4 \end{pmatrix}$ and $\beta_2 = \begin{pmatrix} \beta_{inv} \\ \beta_z \end{pmatrix}$

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So, the magnitude of bias in the labor coefficient is \((\alpha_1 \beta_{\text{inv}} + \gamma_1 \beta_z)\) and in the material coefficient is \((\alpha_2 \beta_{\text{inv}} + \gamma_2 \beta_z)\). The magnitude and direction of total bias depends on all the four correlation terms.

We want to intuitively explore the sign of the parameters \(\beta_{\text{inv}}\) and \(\beta_z\), which are the conditional correlation parameters in the first stage regression. Investment policy function, \(i_t(k_{jt}, w_{jt}, z_{jt}, \text{inv}_{jt})\), is inverted in the first stage to solve for productivity \(w_{jt}\). In the investment policy function a higher inventory stock \(\text{inv}_{jt}\) would result from a higher productivity shock \(w_{jt}\) keeping everything else same. Hence there would be a positive correlation between inventory stock \(\text{inv}_{jt}\) and production quantity. So, the parameter \(\beta_{\text{inv}}\) would be positive. A similar argument would show that \(\beta_z\) would carry a negative sign.

We expect \(\gamma_1\) and \(\gamma_2\) to be positive because labor and material policy functions depend upon \(z_{jt-1}\) and since demand shock being markov we expect a positive correlation between \(l_{jt}\) or \(m_{jt}\) and \(z_{jt}\). We find strong evidence for this in the data.

Signs on \(\alpha_1\) and \(\alpha_2\) are less deterministic. As a higher labor or material stock leads to increased production, which pushes towards a higher inventory stock. But a a higher labor or material stock also means that the firm is expecting a higher demand shock, hence a lower inventory stock. The net effect of these two forces will determine the final sign on \(\alpha_1\) and \(\alpha_2\). In the data also we observe a similar trend.

The demand shock affects production decision, as a result the production function estimation, both directly and indirectly. We define the effect of demand shock \((z_{jt})\) on the labor and material coefficients as the direct effect. The effect of the exclusion of inventory stock on labor and material coefficients is called indirect effect, because the variation in inventory is driven by demand shock itself. In the above analysis, the direct effect bias on labor is \(\gamma_1 \beta_z\), while the indirect effect bias is \(\alpha_1 \beta_{\text{inv}}\). The net bias in parameters is the combined effect of the direct and indirect effect. If the indirect effect dominates the direct effect and \(\alpha_1 > 0\) and \(\alpha_2 > 0\), \(\beta_l\) and \(\beta_m\) would be upward biased and hence \(\beta_k\) would be downward biased. The direction reverses if direct effect dominates the indirect effect. The domination of one effect on the other would depend on the data and the nature of the industry.
Appendix G

Tables

The tables in this appendix reports the estimation results for all 14 industries. This table compares the results from our model with the results from the conventional OP (without demand shock). The results show very similar pattern to that summarized in section 3.6.
## Table 1: Summary Statistics

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## Table 2: Labor Share, Material Share and Capital Share

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<td>labor share</td>
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<td>0.6294</td>
<td>0.7564</td>
</tr>
<tr>
<td>material share</td>
<td>0.2861</td>
<td>0.3040</td>
<td>0.7892</td>
</tr>
<tr>
<td>capital share</td>
<td>0.1203</td>
<td>0.0734</td>
<td>-39.0343</td>
</tr>
<tr>
<td>Scale</td>
<td>0.9932</td>
<td>1.0068</td>
<td></td>
</tr>
</tbody>
</table>

Notes: (1) Standard deviation is reported in parentheses. (2) diff.(%) is defined as the percentage of deviation of the estimates in OP from our model.

## Table 3: Persistence of Productivity

<table>
<thead>
<tr>
<th></th>
<th>Clothing (3220)</th>
<th>Pharmaceuticals (3522)</th>
<th>Plastics (3560)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Persistence</td>
<td>Std.</td>
<td>Persistence</td>
</tr>
<tr>
<td>Productivity</td>
<td>0.7564</td>
<td>(0.0075)</td>
<td>0.7892</td>
</tr>
</tbody>
</table>

Notes: standard deviation in parentheses.
Table 4: Dispersion of Productivity and Demand Shock

<table>
<thead>
<tr>
<th></th>
<th>Clothing (3220)</th>
<th>Pharmaceuticals (3522)</th>
<th>Plastics (3560)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Productivity</td>
<td>D.shock</td>
<td>Productivity</td>
</tr>
<tr>
<td>mean</td>
<td>3.9069</td>
<td>9.6690</td>
<td>2.3946</td>
</tr>
<tr>
<td>variance</td>
<td>0.5888</td>
<td>7.6075</td>
<td>0.0844</td>
</tr>
<tr>
<td>Q75/Q25</td>
<td>1.2317</td>
<td>1.6103</td>
<td>1.1994</td>
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<tr>
<td>Q90/Q10</td>
<td>1.6563</td>
<td>2.1099</td>
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</table>

Note: Q75 represents 75th quantile of the distribution. Others are similarly defined.

Table 5: Firm Turnover: Entry Rate and Exit Rate

<table>
<thead>
<tr>
<th></th>
<th>Clothing (3220)</th>
<th>Pharmaceuticals (3522)</th>
<th>Plastics (3560)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entry Rate</td>
<td>0.1661</td>
<td>0.0816</td>
<td>0.1830</td>
</tr>
<tr>
<td>Exit Rate</td>
<td>0.1379</td>
<td>0.0842</td>
<td>0.1352</td>
</tr>
</tbody>
</table>
Table 6: Evolution of Productivity and Demand Shock

<table>
<thead>
<tr>
<th></th>
<th>Productivity</th>
<th>Demand Shock</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4) (5)</td>
<td>(1) (2) (3) (4) (5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Clothing</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entry</td>
<td>-0.2263</td>
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<td>-0.0722</td>
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<tr>
<td></td>
<td>(0.0197)</td>
<td>(0.0214)</td>
<td>(0.0272)</td>
<td>(0.0183)</td>
</tr>
<tr>
<td>Exit</td>
<td>-0.2214</td>
<td>-0.0602</td>
<td>-0.0633</td>
<td>-0.1661</td>
</tr>
<tr>
<td></td>
<td>(0.0198)</td>
<td>(0.0203)</td>
<td>(0.0275)</td>
<td>(0.0185)</td>
</tr>
<tr>
<td>Age</td>
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<td>0.0019</td>
<td>0.0049</td>
</tr>
<tr>
<td></td>
<td>(0.0008)</td>
<td>(0.0007)</td>
<td>(0.0005)</td>
<td>(0.0008)</td>
</tr>
<tr>
<td>Size</td>
<td>0.1702</td>
<td>0.6136</td>
<td>0.0637</td>
<td>0.948</td>
</tr>
<tr>
<td></td>
<td>(0.0028)</td>
<td></td>
<td>(0.0022)</td>
<td>(0.0026)</td>
</tr>
<tr>
<td><strong>Pharmaceuticals</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entry</td>
<td>-0.2214</td>
<td>-0.0602</td>
<td>-0.0722</td>
<td>-0.1824</td>
</tr>
<tr>
<td></td>
<td>(0.0198)</td>
<td>(0.0203)</td>
<td>(0.0275)</td>
<td>(0.0185)</td>
</tr>
<tr>
<td>Exit</td>
<td>-0.1838</td>
<td>-0.0619</td>
<td>-0.0477</td>
<td>-0.1661</td>
</tr>
<tr>
<td></td>
<td>(0.0203)</td>
<td>(0.0176)</td>
<td>(0.0226)</td>
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<tr>
<td>Age</td>
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<td>0.0017</td>
<td>0.0019</td>
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<td>(0.0008)</td>
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<tr>
<td>Size</td>
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<td>0.6136</td>
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<td>0.948</td>
</tr>
<tr>
<td></td>
<td>(0.0022)</td>
<td></td>
<td>(0.0022)</td>
<td>(0.0026)</td>
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<tr>
<td><strong>Plastics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entry</td>
<td>-0.1452</td>
<td>-0.0584</td>
<td>-0.0840</td>
<td>-0.1408</td>
</tr>
<tr>
<td></td>
<td>(0.0176)</td>
<td>(0.0219)</td>
<td>(0.0161)</td>
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<tr>
<td>Exit</td>
<td>-1.7595</td>
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</tr>
<tr>
<td></td>
<td>(0.0658)</td>
<td>(0.2506)</td>
<td>(0.2513)</td>
<td>(0.0183)</td>
</tr>
<tr>
<td>Age</td>
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<td>0.0769</td>
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<td>0.0769</td>
</tr>
<tr>
<td></td>
<td>(0.0048)</td>
<td>(0.0048)</td>
<td>(0.0006)</td>
<td>(0.0008)</td>
</tr>
<tr>
<td>Size</td>
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<td>0.6926</td>
<td>0.6926</td>
<td>0.6926</td>
</tr>
<tr>
<td></td>
<td>(0.0156)</td>
<td></td>
<td>(0.0156)</td>
<td>(0.0156)</td>
</tr>
</tbody>
</table>

Notes: Column (1) to (5) represent five different regressions for productivity or demand. (1) regresses productivity (demand) on entry. (2) regresses productivity (demand) on exit. (3) regresses productivity (demand) on entry and exit, while controlling age. (4) regresses productivity (demand) on entry and exit, while controlling both age and firm size. Standard deviation in parentheses.
## Table 7: Demand Shock, Productivity and Firm Turnover (Exit)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Clothing</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>wjt</td>
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<td>-0.0034</td>
<td>-0.0021</td>
<td>0.0034</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0043)</td>
<td>(0.0050)</td>
<td>(0.0053)</td>
<td>(0.0055)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>zjt</td>
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<td>-0.0045</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0012)</td>
<td>(0.0014)</td>
<td>(0.0015)</td>
<td>(0.0016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td></td>
<td>-0.0087</td>
<td>-0.0057</td>
<td></td>
<td>-0.0068</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0017)</td>
<td>(0.0017)</td>
<td></td>
<td>(0.0016)</td>
<td></td>
</tr>
</tbody>
</table>

| **Pharmaceuticals** |                 |                 |                 |                 |                 |                 |
| wjt             | -0.0590         | 0.0039          | 0.0301          | 0.0416          |                 |                 |
|                | (0.0243)        | (0.0300)        | (0.0319)        | (0.0329)        |                 |                 |
| zjt            | -0.0120         | -0.0089         | -0.0140         | -0.0109         |                 |                 |
|                | (0.0025)        | (0.0035)        | (0.0033)        | (0.0039)        |                 |                 |
| Size           |                 | -0.0115         | -0.0046         |                 | -0.0057         |                 |
|                |                 | (0.0032)        | (0.0037)        |                 | (0.0038)        |                 |

| **Plastics**    |                 |                 |                 |                 |                 |                 |
| wjt            | -0.0898         | -0.0694         | -0.0493         | -0.0448         |                 |                 |
|                | (0.0137)        | (0.0164)        | (0.0184)        | (0.0189)        |                 |                 |
| zjt            | -0.0137         | -0.0112         | -0.0087         | -0.0075         |                 |                 |
|                | (0.0020)        | (0.0025)        | (0.0026)        | (0.0029)        |                 |                 |
| Size           |                 | -0.0067         | -0.0051         |                 | -0.0033         |                 |
|                |                 | (0.0029)        | (0.0031)        |                 | (0.0032)        |                 |

**Notes:** Column (1) to (5) represent five different regressions. (1) regresses exit dummy on productivity. (2) regresses exit dummy on demand shock. (3) regresses exit dummy on productivity, while controlling firm size. (4) regresses exit dummy on demand shock, while controlling firm size. (5) and (6) regresses exit dummy on both productivity and demand shock, without/with firm size controlled. Standard deviation in parentheses.
Table A1: Estimation Results for 14 Industries from Colombia

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Our Model</th>
<th>Olley Pakes</th>
<th>diff(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Std. Estimate</td>
<td>Std. Estimate</td>
</tr>
<tr>
<td><strong>Diary Products, inv/sales=5.01%</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>labor share</td>
<td>0.2704</td>
<td>0.0086</td>
<td>0.2742</td>
</tr>
<tr>
<td>material share</td>
<td>0.6786</td>
<td>0.0063</td>
<td>0.6856</td>
</tr>
<tr>
<td>capital share</td>
<td>0.0500</td>
<td>0.0006</td>
<td>0.0439</td>
</tr>
<tr>
<td>g1</td>
<td>0.5767</td>
<td>0.0253</td>
<td>0.2510</td>
</tr>
</tbody>
</table>

| **Plastics, inv/sales=24.67%** |           |             |         |           |             |             |
| labor share        | 0.8461    | 0.0153      | 0.8623   | 0.0134    | 1.92        |
| material share     | 0.0700    | 0.0058      | 0.0729   | 0.0058    | 4.08        |
| capital share      | 0.0984    | 0.0017      | 0.0815   | 0.0013    | -17.21      |
| g1                 | 0.6334    | 0.0253      | 0.4179   | 0.0279    | -34.03      |

| **Pharmaceuticals, inv/sales=21.70%** |           |             |         |           |             |             |
| labor share        | 0.4827    | 0.0146      | 0.5218   | 0.0140    | 8.11        |
| material share     | 0.3709    | 0.0116      | 0.3483   | 0.0111    | -6.11       |
| capital share      | 0.1017    | 0.0021      | 0.0870   | 0.0016    | -14.40      |
| g1                 | 0.6730    | 0.0228      | 0.4167   | 0.0283    | -38.08      |

| **Motor Vehicles, inv/sales=22.52** |           |             |         |           |             |             |
| labor share        | 0.3916    | 0.0110      | 0.3991   | 0.0107    | 1.92        |
| material share     | 0.5331    | 0.0084      | 0.5340   | 0.0083    | 0.18        |
| capital share      | 0.0720    | 0.0006      | 0.0645   | 0.0005    | -10.48      |
| g1                 | 0.3877    | 0.0232      | 0.2514   | 0.0237    | -35.15      |

| **Textile Finishing, inv/sales=19.23%** |           |             |         |           |             |             |
| labor share        | 0.4268    | 0.0095      | 0.4540   | 0.0089    | 6.37        |
| material share     | 0.4639    | 0.0071      | 0.4728   | 0.0067    | 1.92        |
| capital share      | 0.1102    | 0.0009      | 0.0756   | 0.0005    | -31.37      |
| g1                 | 0.6945    | 0.0190      | 0.4291   | 0.0239    | -38.21      |

| **Clothing, inv/sales=26.39%** |           |             |         |           |             |             |
| labor share        | 0.5868    | 0.0048      | 0.6294   | 0.0046    | 7.27        |
| material share     | 0.2861    | 0.0030      | 0.3040   | 0.0028    | 6.25        |
| capital share      | 0.1203    | 0.0006      | 0.0734   | 0.0002    | -39.03      |
| g1                 | 0.7564    | 0.0075      | 0.5746   | 0.0090    | -24.04      |

| **Furniture (Non-metal), inv/sales=35.41%** |           |             |         |           |             |             |
| labor share        | 0.4037    | 0.0084      | 0.4122   | 0.0079    | 2.11        |
| material share     | 0.5424    | 0.0070      | 0.5441   | 0.0069    | 0.30        |
| capital share      | 0.0507    | 0.0006      | 0.0425   | 0.0005    | -16.26      |
| g1                 | 0.7101    | 0.0165      | 0.7746   | 0.0158    | 9.09        |

| **Other Electronic Equipment, inv/sales=26.17%** |           |             |         |           |             |             |
| labor share        | 0.3848    | 0.0119      | 0.3984   | 0.0114    | 3.52        |
| material share     | 0.5600    | 0.0108      | 0.5922   | 0.0100    | 5.76        |
| capital share      | 0.0663    | 0.0009      | 0.0289   | 0.0004    | -56.42      |
| g1                 | 0.7574    | 0.0199      | 0.2076   | 0.0315    | -72.59      |

| **Pharmaceuticals, inv/sales=21.70%** |           |             |         |           |             |             |
| labor share        | 0.4177    | 0.0122      | 0.4891   | 0.0124    | 17.08       |
| material share     | 0.3900    | 0.0096      | 0.4169   | 0.0099    | 6.91        |
| capital share      | 0.1725    | 0.0017      | 0.0926   | 0.0004    | -46.33      |
| g1                 | 0.7892    | 0.0185      | 0.5064   | 0.0258    | -35.83      |

| **Motor Vehicles, inv/sales=22.52** |           |             |         |           |             |             |
| labor share        | 0.3974    | 0.0093      | 0.4034   | 0.0093    | 1.52        |
| material share     | 0.4978    | 0.0070      | 0.5079   | 0.0066    | 2.02        |
| capital share      | 0.1102    | 0.0008      | 0.0955   | 0.0005    | -13.34      |
| g1                 | 0.5678    | 0.0212      | 0.5572   | 0.0230    | -1.87       |

Notes: (1) Standard deviation is reported in parentheses. (2) diff(%) is defined as the percentage of deviation of the estimates in OP from our model. (3) g1 is the persistence of productivity, in either our model and the traditional Olley and Pakes model.
Vita
Pradeep Kumar

Education

**The Pennsylvania State University**, University Park, Pennsylvania, 2008-2013
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Final Defense passed in May 2013.

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Research Interests

Industrial Organization, Applied Econometrics