Returns to Scale and Regulations

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Abstract

Government regulators, after the passage of Dodd-Frank, are more interested than ever in the size of banks and the stress these banks are put under. In order to understand whether imposing limits on the size of banks causes a real economic cost, we analyze cost efficiency and returns to scale in the US. We analyze the returns to scale using the translog cost function as well as the Fourier flexible form, and study the affects of changes in size using Panel and Bayesian Panel VARs. Our results are in-line with the literature, finding that banks of all but the largest sizes exhibit increasing returns to scale. We also find a non-monotonic relationship between cost efficiency and bank size.

JEL Classification: C11, C14, G21, L11

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1 Introduction

In 1994, BankAmerica Corp expanded their securities division by purchasing Continental Illinois. While this acquisition was prohibited by the Glass-Steagall Act (which required that a bank not be maintaining both securities and commercial deposits businesses), in the years prior to 1994 the Federal Reserve had begun to loosen their interpretation of the regulation. In the period surrounding the 1999 repeal of Glass-Steagall BankAmerica Corp purchased a number of other firms (Robertson Stevens in 1997 and Fleet Boston in 2004). A similar trend appeared in after the most recent recessionary period. During the regulatory period following the Great Recession, Bank of America (the new name of BankAmerica Corp) purchased Merrill Lynch. The purchase, which closed in January 2009 (a year and a half before the Dodd-Frank Act was passed), created Bank of America Merrill Lynch, currently the second largest banking institution in America. This is relevant because we are interested in explicitly considering the effects that regulations have on a bank's total cost function; one way these effects may appear is via growth through mergers and acquisitions. It is evident that the last 25 years were characterized by heavy regulation and significant increases in bank size. Wheelock and Wilson (2012) suggest that bank holding companies tend to exhibit increasing returns to scale; in other words, as banks increase their output, their inputs tend to increase at a smaller rate. This essentially means that larger bank holding companies are able to obtain lower costs per unit of output than their smaller peers, which might explain the motivation of bank holding companies to become larger. The literature on returns to scale, however, does not come to a consensus about what returns to scale different bank sizes obtain. While Wheelock and Wilson (2012) find that returns to scale increase for larger bank holding companies, earlier studies (for instance, Clark (1984) and Clark (1988)) determine that these banks actually exhibit constant or decreasing returns to scale. This paper contributes empirically to the debate on returns to scale by examining the impact of size on returns to scale through Panel vector autoregressive (VAR) models.

The regulatory environment of the past 25 years is unique, and each period has potentially different impacts on returns to scale. For example, banking regulations which gave more freedom to bank holding companies (such as Gramm-Leach-Bliley) likely resulted in cost synergies through an increase in merger activity. Contrast this with Dodd-Frank, which was more restrictive and may have actually imposed costs on banks instead. To more effectively address whether bank size alters the cost of banking, we use recent cost decomposition data from the largest commercial bank holding companies and account for each pertinent regulatory period. Through the translog cost function and Fourier flexible form models we find that only the largest seven banks in America exhibit decreasing returns to scale, and all other banks exhibit increasing returns to scale. One of our main contributions is the use of Panel VAR and Bayesian Panel VAR to assess the relationship between an increase in firm size and returns to scale and cost efficiency. We find that an increase in total assets leads to an increase in cost efficiency, but a decrease in returns to scale.

2 Literature Review

As early as the 1960s, economists have been analyzing returns to scale in banks. Schweitzer (1972), as one of the earliest studies, uses data based on banks with under 100 million USD in assets in the year 1964. He finds increasing returns to scale for banks with under 3.5 million USD in assets, but decreasing returns to scale for banks with over 25 million. Furthermore, he finds that holding company affiliation with banks typically caused those with under 3.5 million in assets to exhibit more prominent scale economics. Christenson et al.'s (1973) first publish the transcendental logarithmic production function, which is extrapolated to become the translog cost function. Christenson et al. (1973) find that their new transcendental logarithmic production function is superior to preexisting models.

In the late 1980s a number of influential papers were published that found evidence supporting Schweitzer's (1972) conclusions. Clark (1984) used Box-Cox estimation techniques to estimate the cost function of banks from 1972-1977 with less than 425 million USD in assets. He concludes that it is highly unlikely that any banks generated increases in returns to scale. Lawrence (1989), however, critiques the Box-Cox method used by Clark (1984), as well as other earlier functional forms of measuring cost functions. Specifically, Lawrence (1989) rejects both a cost function resembling the Cobb-Douglas production function used in papers such as Bell and Murphy's (1968) as well as the Box-Cox estimation technique. He ultimately finds that the Box-Cox and Cobb-Douglas form are flawed models of bank costs and verifies that the translog cost function is the most appropriate method.

Clark (1988) emphasizes the disagreement in the early literature, most studies find large banks ($>$ 100 million in assets) did not exhibit increasing returns to scale. In fact, of the 13 studies considered, Clark (1988) only finds two studies that observe increasing returns to scale for banks with more than 100 million in assets (see Goldstein et al. (1987) and Benston et al. (1982)).

More recent literature, however, finds increasing returns to scale for banks with progressively larger asset bases. For instance, Noulas et al.'s (1990) and Hunter et al.'s (1990) findings are distinctly different than the previous literature: they measure increasing returns to scale up to 2 billion in assets, and decreasing returns to scale only after banks grow to an asset base of over 10 billion. McAllister and McManus (1993) analyze returns to scale using kernel regression techniques to create a nonparametric model. They determine that increasing returns to scale occur up to about 500 million in assets and then are somewhat constant at larger asset bases.

Mitchell and Onvural (1996) propose that the cost equations of bank holding companies should be represented as Fourier series or, more specifically, by the Fourier flexible functional form. Solving an exact solution represented by a Fourier series would require an infinite number of degrees of freedom, therefore the cost function can only be approximated by a finite number of trigonometric functions. Despite the limitations associated with Fourier series approximations, Mitchell and Onvural (1996) find that large banks are more cost efficient than smaller banks using one of the most broad datasets (banks with between .5 billion and 100 billion in assets). They also reject the accuracy of the translog cost model. They find that (despite a local approximation of only the largest banks) the translog function was inaccurate relative to the Fourier series approximations.

Wheelock and Wilson (2001) follow a similar structure to Mitchell and Onvural (1996) using the translog cost function, Fourier flexible form, and kernel regression methods to calculate returns to scale. Their data consists of banks with asset sizes between 1.8 billion and 21.6 billion USD in 1985, 1989, and 1994. Like Mitchell and Onvural (1996), their broad sample size represents a departure from earlier studies which typically either focused on smaller sized banks (Clark (1984)) or larger banks (Noulas et al. (1990)). Wheelock and Wilson (2001) conclude that returns to scale increase for banks up to about 500 million in assets; thereafter, larger banks generally exhibit constant returns to scale.

Recently, Wheelock and Wilson (2012) and Kovner et al. (2014) have found increasing returns to scale at substantially larger asset bases than previous studies. Wheelock and Wilson (2012) follow the same general structure of their earlier work and use non-parametric kernel regression estimators. Analyzing the 1984-2006 period, Wheelock and Wilson (2012) find that significant economies of scale exist for banks with as low as around $50 million in assets to those with nearly $2 trillion. Similar to this paper, Kovner et al. (2014) use a decomposition of 15 noninterest expenses to analyze the cost efficiency of banks. The authors find that every 10 percent increase in assets is associated with 0.3-0.6 percent decrease in noninterest expenses. We contribute to their findings by analyzing the relationship between asset size and cost efficiency through a Panel and Bayesian Panel VAR. Using 2012 and 2006 data, Wheelock and Wilson (2015) find that all banks generated increasing returns to scale, however, for the largest banks this conclusion was sensitive to their specification. This result suggests there may be uncertainty in the most recent findings of returns to scale, especially regarding the largest banks in the economy.

3 Bank Regulations and Their Effects on Costs and Returns to Scale

The literature on the effects of regulations on bank costs is extensive, but many papers focus either on a country's general policies at a given point in time (such as Barth et al. (2004)) or focus on older regulatory periods (such as Demirgüç-Kunt and Enrica Detragiache (2002)). These discussions help reinforce the connect between returns to scale and regulation; however, they provide little in helping to formulate expectations for how returns to scale and costs respond specifically to more recent regulatory periods in the US. By focusing on three banking regulations over the past 25 years, we can pinpoint the precise regulatory environment that impacts returns to scale and bank costs. The following sections give the details on these specific regulations and provide evidence on how they could affect bank costs, and therefore scale economies.

3.1 Riegle-Neal Interstate Banking and Branching Efficiency Act

The Riegle-Neal Act was originally passed in 1994 and is still in effect today. Following the Douglas Amendment to the McFadden Act in 1956, bank holding companies were prohibited from acquiring banks in other states, unless the bank to be acquired was located in a state which explicitly allowed interstate acquisitions. In September 1994, Congress enacted the Riegle-Neal Act allowing bank holding companies to acquire banks across state lines regardless of individual state laws (this provision became active on September 30, 1995). In addition, on June 1, 1997 the bill permitted interstate mergers of pre-existing banks. As Mulloy (1995) describes: "A bank in State A could merge with a bank in State B and the bank in State B could be operated as a branch of the bank in State A".

Cornett et al. (2006) analyze the effects of Riegle-Neal on banking profits. They measure a number of variables related to costs and revenues both before and after bank mergers completed during the period from 1990 to 2000. Firstly, the authors find that a majority of mergers occurred after the passage of Riegle-Neal. This conclusion echoes the findings of Chronopoulus et al. (2015) that bank sizes grew substantially after Riegle-Neal. Cornett et al. (2006), on the other hand, measure how the costs and revenues of banks changed after mergers following the Riegle-Neal Act. The authors ultimately conclude that increases in short-term profitability were higher in mergers which occurred in the period after Riegle-Neal was enacted due to cost synergies from consolidating operations.[1] Since some of the largest consolidations occurred after the passage of Riegle-Neal (for instance, the merger of First Chicago and BancOne in 1998 and Firstar and U.S. Bancorp in 2000) the resulting cost synergies were likely to significantly reduce the costs relative to a bank's output. Based on the findings of Cornett et al. (2006), the

[1] Examples of cost synergies post-merger include the elimination of redundant positions and the closing of overlapping branches.

period following Riegle-Neal was likely characterized by increasing bank returns to scale.

3.2 Gramm-Leach-Bliley Act

The Gramm-Leach-Bliley Act was enacted on November 12, 1999 with the intention of repealing the Glass-Steagall Act. The Glass-Steagall Act was passed during the Great Depression and aimed to reduce bank risk-taking by separating investment banking and commercial banking divisions. The Gramm-Leach-Bliley Act, on the other hand, allowed banks to maintain both investment and commercial banking divisions. Prior to the Gramm-Leach-Bliley Act being enacted, however, there had already been efforts by the Federal Reserve Board to interpret Glass-Steagall legislation more liberally. In fact, Macey (2000) argues that the Gramm-Leach-Bliley Act was merely the formal end to Glass-Steagall; structural shifts in the banking industry had already been occurring throughout the 20 years prior.[2] Since Glass-Steagall was interpreted loosely leading up to its repeal, one must consider whether costs and returns to scale would actually change post-enactment for commercial banks.

Chronopoulous et al. (2015) discuss the effect that the Gramm-Leach-Bliley Act had on bank profit persistence. Unlike the Riegle-Neal Act, the authors find that the Gramm-Leach-Bliley Act actually reduced competition by spurring consolidations that had previously been not allowed. This reduction in competition led to profit persistence increasing post-passage of the act. They, however, do not take bank cost decompositions or general cost measurements into account. Chronopoulous et al. (2015), further find that the merger activity following the Act caused an increase in bank size.

Barth et al. (2000) and Barth et al. (2004) discuss the potential impacts that

[2]For example, the regulator's interpretation of Glass-Steagall allowed commercial banks to acquire investment banks, but banned investment banks from acquiring commercial banks.

the Gramm-Leach-Bliley Act would have on bank costs. They argue that bank costs would be reduced, primarily from the cost synergies associated with combining investment and commercial banking facilities. For example, a commercial bank could leverage its current telecommunications and data processing divisions to include the sales of insurance and securities for low additional costs. The potential risks to profitability that the authors discuss are associated with the fact that investment banking is presumably more risky than commercial lending, thus a commercial bank acquiring an investment banking division may have a higher risk of insolvency. The authors, however, downplay this risk and develop plausible counter-arguments for why a combination of commercial lending and investment banking operations could lead to diversification and less risk.

3.3 Dodd-Frank Wall Street Reform and Consumer Protection Act

The Dodd-Frank Act was signed into law on July 21, 2010 and is still in effect today. In the several years prior to President Obama signing this law, the U.S. endured the worst recessionary period in the recent history. This recession was spurred, in part, by loose regulations governing financial institutions' securitization businesses. Over 2,000 pages long, Dodd-Frank reform aims to limit the risks that banks take and helps to minimize the severe results from bank failures. Although the Dodd-Frank legislation is far more detailed the primary focuses of the regulators are discussed in the following sections.

3.3.1 Mitigating Damage from Bank Failure

The Dodd-Frank Act seeks to prevent The damage to the economy caused by the bankruptcy of Lehman Brothers, Bear Stearns, and AIG. In order to similar control situations to those in the Great Recession, Dodd-Frank contains a number of clauses giving the FDIC power in cases of perceived insolvency. More specifically, if regulators determine that a bank's imminent default could have severe economic implications, regulators may submit an appeal requesting control over the bank in question. This effectively gives the FDIC the ability to navigate the troubled bank through the default and liquidation process. The FDIC, being more concerned with controlling economic shocks than returning equity to shareholders, will presumably cause fewer shocks in the economy than if the banking heads were to remain in control of their company. However with the FDIC presumably putting the interests of shareholders second, the bank could have a more difficult time raising capital. Thus, this clause could actually destabilize the banking industry due to reduced liquidity from limited access to capital markets.

3.3.2 Reducing Risk and Impact on Returns to Scale

Dodd-Frank aims to reduce risk by placing regulations on institutions and on the instruments that can be traded. Derviatives are by far the most risky instrument moving across the balance sheets of financial institutions. Dodd-Frank helps reduce this risk by requiring derivatives to be cleared and traded on exchanges. In order to generate revenue, these clearinghouses and exchanges necessarily charge fees, increasing the operating costs associated with trading a derivative. In order to reduce institutional risk, Dodd-Frank focuses primarily on the bank holding companies that are more likely to cause significant economic shocks (those banks with over 50 billion USD in assets). The regulation imposed a number of controls on the size and quality of reserves that these large institutions would be required to hold. The increase in held capital would create a significant buffer, preventing liquidity shocks that had previously damaged bank holding companies.

Dodd-Frank regulation also prohibits a single bank holding company controlling more than 10 percent of the total liabilities of all financial institutions. This effectively imposes a limit on the size of banks and restricts banking mergers and acquisitions. Wheelock and Wilson (2012) and Kovner et al. (2014) demonstrate that limiting size of banks causes significant increases in bank costs, primarily because banks exhibit increasing returns to scale. Berger and Hannan (1998), however, contradict this point with a discussion of the "quiet life" hypothesis. Under this hypothesis, banks in highly concentrated markets will collude and have little incentive to compete and cut costs. This means that if the size of market concentration is restricted, bank costs are likely to be reduced. Berger and Hannan (1998) test this hypothesis and find that reducing market concentration decreased bank operating costs by 8 percent to 32 percent. Based on these interpretations we can conclude that the effects of Dodd-Frank on bank costs and returns to scale are not binary. Despite the lack of a conclusion, a dichotomy between Dodd-Frank and the other acts is obvious here: while the Gramm-Leach-Bliley and Riegle-Neal Acts gave bank's more freedom, Dodd-Frank added more restrictions.

4 Data

Our dataset consists of 15 operating expenses for 198 commercial bank holding companies from 1992:3 to 2014:2. This data capture the largest publicly traded bank holding companies with assets valued at over 300 million ranked by the December 2007 Federal Reserve Board Report. Individual bank income statements and balance sheets are obtained from the Mergent Online database and are compiled by the authors. In order to assess costs more efficiently, these operating expenses can be broken into three general categories. Fixed costs (those expenses independent of output) include occupancy, supplies and printing, software and equipment. Quasi-fixed costs (those expenses that vary slightly in response to output changes) include personnel (including employee benefits). Variable costs (those expenses that change proportionally with output) include marketing, foreclosed property, telecommunications, litigation, data processing, loan processing, professional fees, postal and courier, and other noninterest expenses. In addition to these categories, we also use the total noninterest expenses reported by banks. These specific costs are chosen based on two criteria: that a large sample of banks reported a given expense and that the expense represented a significant portion of a general bank's operating costs. These variables are converted to 2009 dollars using the GDP deflator (following Wheelock and Wilson's (2012) approach).

Following Jaremski and Sapci (2014) we control real GDP and industrial production, representing the overall health of the economy. We also control for the inflation rate and M2 money supply for the effects of monetary policy. Lastly, we include the DOW Jones Industrial Average to control for the health of the financial markets.

Many of the bank holding companies in our dataset contain several quarters where data is unavailable for certain expenses. Often times missing data would be a result of a company switching accounting procedures. For example, consider a bank holding company that historically combines their occupancy and equipment expenses into a single account. In 2010, however, that bank holding company decided to separate their equipment and occupancy expenses into individual accounts. Prior to 2010 it would appear that this specific bank holding company has missing data, when in reality they had never reported individual accounts prior to this point. In these situations, we sum the bank holding company's accounts that were reported differently over time and present a single account. If a missing quarter occurs between quarters containing data, the missing entry is replaced with an average of the quarters before and after the entry as long as the missing entries do not exceed three for the entire sample. These procedures give more uniformity to the dataset and allow an approximation of the missing values.

Since banks do not provide individual financial statements for their fourth quarter, we obtained fourth quarter noninterest expenses by summing the three available quarters and subtracting the total from the similar cost presented in the annual reports. We paid special attention to matching the quarterly financial statements with annual statements for every bank and each year. When we fail to do so we obtained missing fourth quarter values by averaging the preceding third quarter and following first quarter values. If this adjustment is made for more than three years, however, we remove the bank from our dataset.

While the SEC regulates the reporting of general income statement information, the cost decomposition data used here is far more detailed and covered by the regulations mentioned in Section 4.1. Thus, oftentimes, bank holding companies had slightly different methods of reporting their more detailed financial information. Two such categories that required the most careful analysis were the personnel and occupancy expenses. For personnel, some banks report only salaries paid (breaking employee benefits into a separate account) whereas other holding companies would report only one general category. Similarly, some companies choose to group their occupancy costs with their equipment costs. Because the personnel and occupancy data were the largest cost categories, we combined the equipment and occupancy into one category and personnel and employee benefits costs into another for each bank holding company in our dataset.

4.1 General Cost Definitions

Mergent Online obtains their data from FR Y-9C filings, which must be filled out quarterly by bank holding companies with over 500 million USD in assets (more information on these requirements can be found in the Bank Holding Company Act, Regulation Y, and the Homeowners Loan Act). The FR Y-9C filing is a form which requires bank holding companies to provide a detailed view of their consolidated financial statements. In FR Y-9C filings, Schedule HI, item 7 contains a list of possible noninterest expenses a bank holding company could incur: salaries and employee benefits, expenses of premises and fixed assets, goodwill impairment, amortization expenses, other noninterest expenses, and total noninterest expenses. In addition, Schedule HI, memoranda item 7 contains several more possible expenses: data processing, advertising and marketing, director's fees, printing and supplies, postage, legal fees and expenses, FDIC deposit insurance assessments, accounting and auditing expenses, consulting and advisory expenses, interchange fees, and telecommunications expenses. Under this memoranda item, bank holding companies are also able to create additional accounts. Bank holding companies are not required to fill out every account, which leads to many different reporting standards among banks, making data collection more difficult.

The Federal Reserve Microdata Reference Manual lays out the definition of costs reported in FR Y-9C filings. Some of the largest operating costs definitions that we use in this paper are laid out below:

Table 1: Cost Decomposition and Descriptions

Variable	**Description**
Personnel	Personnel expenses include salaries and benefits for all officers and employees of the bank and its consolidated subsidiaries. This includes all guards and contracted guards, temporary office help, dining room and cafeteria employees, and building department officers and employees (including maintenance personnel).
Occupancy	All noninterest expenses related to the use of premises, equipment, furniture, and fixtures are included within occupancy. Premises and fixed assets are defined net of rental income. Rental income includes all rentals charged for the use of buildings not incident to their use by the reporting bank and its consolidated subsidiaries, including rentals by regular tenants of the bank's buildings, income received from short-term rentals of other bank facilities, and income from subleases (all of which are deduced from this expense). In addition to rental deductions, income from assets that indirectly represent premises, equipment, furniture, or fixtures included in "Premises and Fixed Assets" are also deducted.
Advertising and Marketing	Within this category are several items pertaining specifically to advertising and marketing: advertising, production, agency fees, direct mail, marketing research, public relations, seminars, and customer magazines.
Professional Fees	Described in the Federal Reserve's definition are several costs specific to professional services: sales training by consultants, public accountants' fees, management services, consulting fees for economic surveys, and other special advisory services. It is important to note that the following should not be included: legal fees, and data processing fees, as this paper classifies them separately.
Other Noninterest Expenses	Other noninterest expenses is a category intended to include items not required to be reported individually in Schedule HI, item 7. The Federal Reserve Microdata Reference Manual lists 31 unique costs that should be included in other noninterest expenses. Some of these costs include: civil penalties and fines, telephone expenses, office supplies, printing, costs of gifts given to depositors, research and development costs, and advertising. Generally, bank holding companies report many of these costs (such as advertising) separately in Schedule HI, memoranda item 7. Because they opt to break-out individual costs, bank holding companies often list two values for other noninterest expenses (we used the smaller of the two reported values). We also try to separate the categories into other noninterest expense as much as possible.
Total Noninterest Expenses	Total noninterest expense is given as the sum of all other expenses documented here.
Smaller Expenses	For many other items which are less material than occupancy and personnel, bank holding companies are asked to: "disclose in this item the component of Schedule HI, item 7(d), "Other noninterest expense," and the dollar amount of such component, that exceeds 1 percent of the sum of "Total interest income"." Thus, for an expense such as data processing, one must typically look through a bank's annual reports to determine how an individual bank holding company defines their expenses.[3]

[3]For example, Bank of America Merrill Lynch discussed data processing on page 259 of their 2014 Annual Report: "Data processing costs are allocated to the segments based on equipment usage. Item processing costs are allocated to the segments based on the volume of items processed for each segment."

The list above is not extensive; for many of the smaller costs used in our models there is no available description in the Microdata Reference Manual. Of the general cost definitions listed so far, however, only labor, capital, and total non-interest expenses are necessary to parametrize our models. This means that only personnel and employee benefits (which make up labor), as well as supplies and printing, equipment, occupancy, and software expenses (which make up capital) are necessary to conduct our research. We next present summary statistics of our cost decomposition data, as well as graphs which represent the cost efficiency in relation to asset size and time.

4.2 Determining Bank Size Categories

As was mentioned, the translog cost function is a poor estimator of returns to scale for the entire banking sector, which is heterogeneous. This means that it is necessary to only parametrize our model using commercial bank holding companies which are homogeneous. To determine homogeneity, we plot each bank's average assets over time against the relative size of the bank compared to its peers. We then essentially look for structural breaks in the graph. The commercial bank holding companies would then stay in their individual size categories throughout the entirety of the time series. Originally, we considered allowing commercial bank holding companies to change size category, however, this significantly reduced the availability of observations for the largest commercial bank holding companies prior to 2000. An example graph of our commercial bank holding companies sorted and plotted by average assets are shown below.

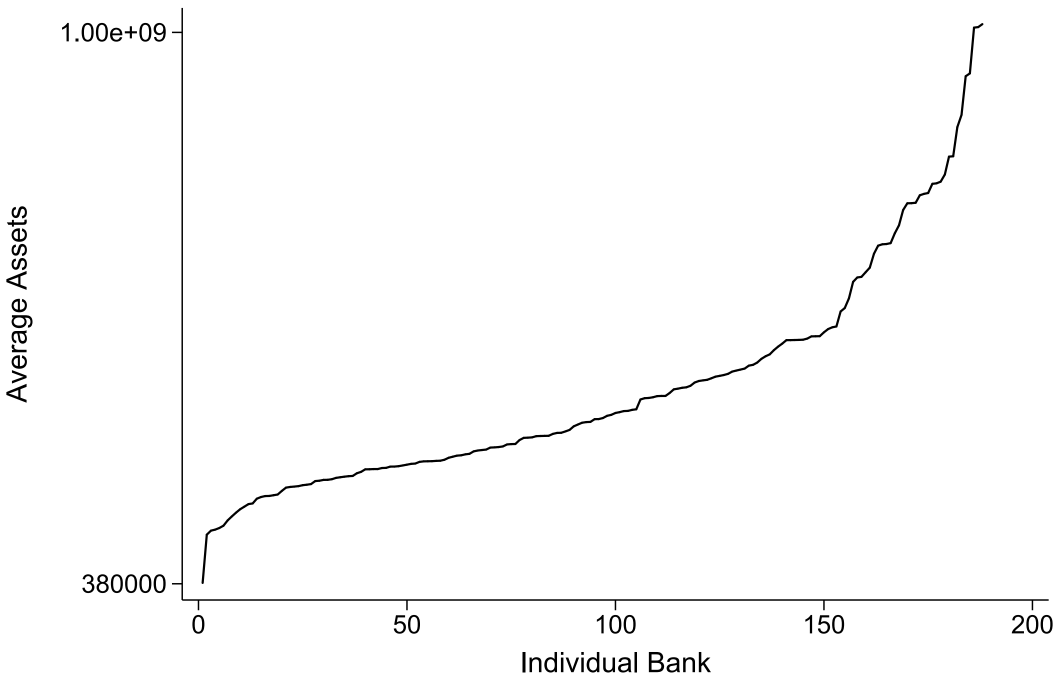


Figure 1: Average bank size against the bank's rank relative to peers.

Note that the y-axis of the above plot is logged to better show what occurs at smaller asset sizes. Based on this graph, clearly the smallest bank should be left out since it is not similar to other commercial bank holding companies that are also small. Because the graph goes nearly exponential on a logged scale, the graph also clearly shows that the largest commercial bank holding companies in the dataset are significantly larger than any of the other commercial bank holding companies. Another way to observe the difference in average asset size for each bank holding company is by looking at the growth rates of each bank compared to their neighbor.

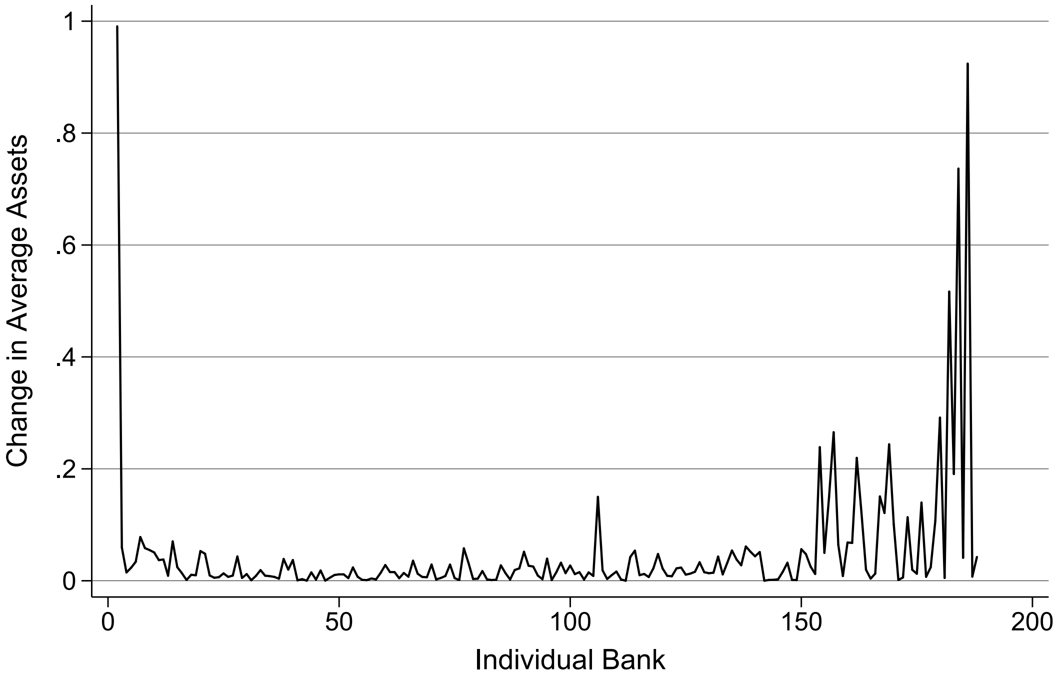


Figure 2: The growth in a bank holding company's actual size compared to its nearest neighbor against the bank's rank relative to peers.

Figure 2 displays the growth in average asset size for a given bank compared to their nearest neighbor. Note that, as was mentioned prior, the growth rate from the smallest bank holding company to the second smallest bank holding company is incredibly large, so the smallest bank holding company should clearly be dropped from the dataset. In addition, the growth rates for the largest bank holding companies are very large, especially when compared to the small and medium sized bank holding companies in the dataset. Based on these growth rates the bank holding companies can be separated into the groups specified in section 4.3.

4.3 Summary Statistics

Below are our tables showing the different summary statistics for Too-Big-To-Fail, large, medium, and small commercial bank holding companies. We determined whether a bank fell into each category by its average asset size. Commercial bank holding companies with an average asset size of over $20 billion made up the Too-Big-To-Fail group, between $2.5 billion and $20 billion made up the large group, between $500 million and $2.5 billion made up the medium group, and under $500 million made up the smallest bank category. Note that the number of commercial bank holding companies listed are how many cross-sections are in each panel dataset for the different bank size categories.

Table 2: Summary Statistics for Too-Big-Too-Fail Banks

Variable	Obs	Mean	Std. Dev.	Min	Max
Insurance Exp	0	.	.	.	.
Supp. and Print	0	.	.	.	.
Software Exp	32	106406	31925	53000	157000
Occupancy Exp	412	710902	612148	51200	2406000
Marketing Exp	221	321462	246331	10000	926000
Data Processing Exp	66	447955	223402	107000	856000
Loan Processing Exp	0	.	.	.	.
Prof. Services Exp	263	492191	507096	6424	2109000
Litigation Exp	0	.	.	.	.
Telecommunications Exp	301	411710	382001	32700	1646000
Travel Exp	0	.	.	.	.
Postal and Courier Exp	23	36820	13125	19324	67000
Card Processing Exp	0	.	.	.	.
Personnel Exp	435	3400753	2671402	108800	1.02e+07
Other Noninterest Exp	415	1611499	1744373	51000	1.31e+07
Total Noninterest Exp	526	6437326	5209732	253472	2.72e+07
Total Deposits	522	3.53e+08	3.48e+08	22000	1.32e+09
Gross Loans	465	3.22e+08	2.95e+08	475000	9.77e+08
Total Assets	546	7.68e+08	6.98e+08	2.12e+07	2.52e+09
Number of Banks	7				

Table 3: Summary Statistics for Large Banks

Variable	Obs	Mean	Std. Dev.	Min	Max
Insurance Exp	0	.	.	.	.
Supp. and Print	205	4779	2761	826	11872
Software Exp	171	47077	54013	3523	190000
Occupancy Exp	1673	77899	67253	681	447000
Marketing Exp	770	54175	79668	1060	511142
Data Processing Exp	315	58086	53740	4140	233000
Loan Processing Exp	48	49583	21035	26000	111000
Prof. Services Exp	857	54415	73099	220	518000
Litigation Exp	0	.	.	.	.
Telecommunications Exp	504	54993	59672	4126	266200
Travel Exp	0	.	.	.	.
Postal and Courier Exp	68	47027	31196	7432	81000
Card Processing Exp	70	115500	51452	44000	193000
Personnel Exp	1722	324001	260935	3430	1404000
Other Noninterest Exp	1113	116330	140158	1222	1218000
Total Noninterest Exp	1839	662793	589071	5520	7273350
Total Deposits	1685	4.95e+07	4.49e+07	452201	2.76e+08
Gross Loans	1504	4.87e+07	4.26e+07	1734832	2.44e+08
Total Assets	1832	7.54e+07	6.67e+07	2047633	3.89e+08
Number of Banks	25				

Table 4: Summary Statistics for Mid-Sized Banks

Variable	Obs	Mean	Std. Dev.	Min	Max
Insurance Exp	108	2791	1725	107	8589
Supp. and Print	432	2046	1729	366	6292
Software Exp	36	5646	3804	1704	11087
Occupancy Exp	3144	12366	12195	114	120213
Marketing Exp	1515	3131	2943	80	24870
Data Processing Exp	885	5605	5396	117	29071
Loan Processing Exp	208	4686	4342	577	40786
Prof. Services Exp	1453	4331	4083	242	29905
Litigation Exp	43	4008	2751	855	12806
Telecommunications Exp	632	3916	4406	129	31000
Travel Exp	114	2766	2138	622	10194
Postal and Courier Exp	400	3434	3669	165	15960
Card Processing Exp	71	5733	3913	1686	16018
Personnel Exp	3469	42467	39139	1028	362340
Other Noninterest Exp	2694	14170	13255	156	113300
Total Noninterest Exp	3665	81385	76686	1410	754678
Total Deposits	3553	7382313	5338367	301673	4.65e+07
Gross Loans	3389	6297472	4576498	43801	2.80e+07
Total Assets	3565	9973001	7160884	386737	5.00e+07
Number of Banks	54				

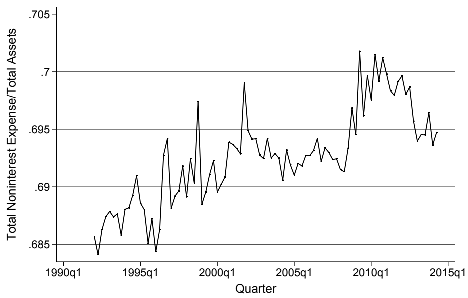
Table 5: Summary Statistics for Smallest Banks

Variable	Obs	Mean	Std. Dev.	Min	Max
Insurance Exp	156	637	610	11	3330
Supp. and Print	886	303	154	58	885
Software Exp	83	789	239	379	1575
Occupancy Exp	6204	2526	2616	41	42967
Marketing Exp	2477	657	564	0	10977
Data Processing Exp	2700	1052	1463	0	23161
Loan Processing Exp	38	281	204	61	1044
Prof. Services Exp	2232	1081	1060	6	10816
Litigation Exp	189	493	353	28	2001
Telecommunications Exp	1052	1300	2970	51	26122
Travel Exp	18	191	42	128	305
Postal and Courier Exp	561	480	300	25	1340
Card Processing Exp	268	730	582	90	2746
Personnel Exp	6709	10530	17476	67	395936
Other Noninterest Exp	5237	3530	3500	0	69911
Total Noninterest Exp	7140	19561	26843	1	482944
Total Deposits	6872	1792173	1289990	4801	1.20e+07
Gross Loans	6461	1573544	1158160	341	1.09e+07
Total Assets	6944	2332048	1725824	10161	1.53e+07
Number of Banks	101				

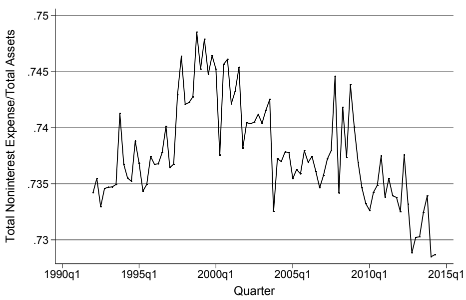
4.4 Cost Efficiency Over Time

To assess the range of cost efficiency over time, we plot the average value of total noninterest expenses divided by total assets for bank groups of different sizes. Interestingly, the small and medium commercial bank holding companies seem to follow a similar pattern, and the Too-Big-To-Fail and large commercial bank holding companies follow another. Whereas the small and medium commercial bank holding companies appear to become less cost efficient over time, the large and Too-Big-To-Fail commercial bank holding companies increase in cost efficiency over time. This impact is especially pronounced in the period just after the Great Recession. This is particularly interesting because the Dodd-Frank Act was enacted post-Great Recession. The change in cost efficiency just after Dodd-Frank qualitatively support the claim that Dodd-Frank legislation changed the drivers of cost efficiency.

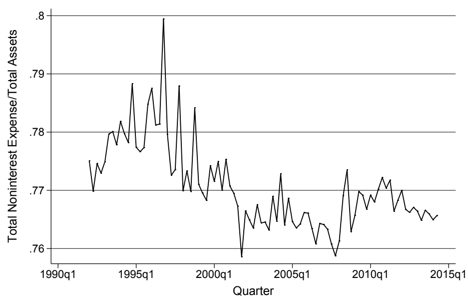
(a) Small Banks



(b) Medium Banks



(c) Large Banks

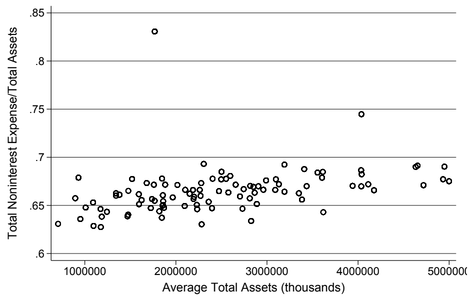


(d) Too-Big-To-Fail Banks

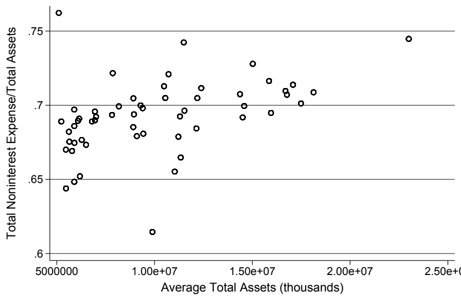
Figure 3: Cost Efficiency v Time Graphs, separated into different asset sizes.

4.5 Cost Efficiency and Asset Sizes

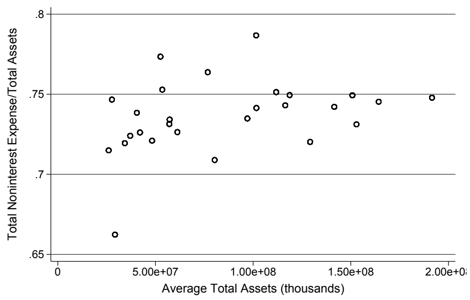
To qualitatively assess whether an increase in total assets increases efficiency we plot efficiency against total assets for each bank holding company below. Again, note that the y-axis measures cost divided by total assets, so lower values denote a higher cost efficiency. We note that there is a slight upward trend in the data for both the small and medium commercial bank holding companies and a possible downward trend for large and Too-Big-To-Fail commercial bank holding companies. This could mean that as smaller commercial bank holding companies increase their asset size they first become more inefficient, but afterwards become more efficient.



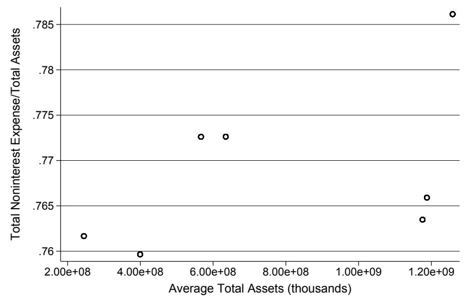
(a) Small Banks



(b) Medium Banks



(c) Large Banks



(d) Too-Big-To-Fail Banks

Figure 4: Cost Efficiency v Asset Graphs, separated into different asset sizes.

5 Empirical Models

5.1 Translog Cost Function

The translog cost function is a second order approximation to the cost function. As McAllister and McManus (1993) demonstrated, the translog cost function is suitable for homogeneous samples. Given that we use the largest commercial bank holding companies and divide them into four groups, our sample is very homogeneous and does not suffer from the approximation errors as much. Firstly, consider a general Cobb-Douglas production function:

$$Q = A \prod_{i=1}^{M} x_i^{\alpha_i} \tag{1}$$

Where A is the total factor productivity and M is the number of inputs that specify our given level of output, Q. The Lagrangian for the cost minimization problem is:

$$\mathcal{L} = \mathbf{p}'\mathbf{x} + \lambda \left(Q - \kappa \prod_{i=1}^{M} x_i^{\alpha_i} \right) \tag{2}$$

Where $\mathbf{x}$ and $\mathbf{p}$ are vectors of variable input quantities and their prices, respectively. The solution to this cost-minimization problem gives $x_i = x_i(Q, \mathbf{p})$. The product of the cost and quantity of each input will yield the total cost of that a particular input. Taking the summation of all operating costs then will give a bank's total noninterest expense. Thus, the bank's total cost function becomes[4]:

$$C^* = \sum_i p_i x_i(Q, \mathbf{p}) = C^*(Q, \mathbf{p}) \tag{3}$$

In the case of bank holding companies, a firm's total loans will serve as a measure of a bank's output. The inputs for a firm's production function are labor,

[4]For more information please refer to Greene (1990).

capital, and deposits. The amount of labor is specified by the sum of employee benefits and personnel costs. The amount of capital is a sum of the supplies and printing, software, occupancy, and equipment expenses. Unfortunately, the coefficients needed to parametrize our cost function cannot be solved for analytically, but their values can be approximated. We take the multivariate Taylor Series expansion of the natural log of the cost function about the point where the log of each input cost and the bank's outputs are all equal to zero (i.e. that each input is in equilibrium):

$$\begin{aligned}\ln C^* \approx \beta_o + \left(\frac{\partial \ln C}{\partial \ln Q}\right) \ln Q + \sum_m \left(\frac{\partial \ln C}{\partial \ln p_m}\right) \ln p_m + \sum_n \left(\frac{\partial^2 \ln C}{\partial \ln p_n \partial \ln Q}\right) \ln Q \ln p_n \\ + \frac{1}{2} \sum_m \sum_n \left(\frac{\partial^2 \ln C}{\partial \ln p_m \partial \ln p_n}\right) \ln p_m \ln p_n + \frac{1}{2} \left(\frac{\partial^2 \ln C}{\partial \ln Q^2}\right) \ln Q^2 + \ln A \quad (4)\end{aligned}$$

Where the vector **A** is included to represent the controls discussed in Section 4, bank fixed effects, and dummy variables for bank regulations[5]. The above expansion provides the empirical framework by which we will estimate the impacts of individual costs on the total cost function. Substituting in for the each partial derivative, equation (4) can be written into the following translog function:

$$\ln C^* \approx \beta_o + \beta_Q \ln Q + \sum_m \beta_m \ln p_m + \sum_n \tau_n \ln p_n \ln Q + \frac{1}{2} \sum_m \sum_n \delta_{mn} \ln p_m \ln p_n + \frac{1}{2} \gamma \ln Q^2 + \epsilon \ln A \quad (5)$$

Prior to finding the value of the coefficients in the regression, a number of restrictions must be put in place. Firstly, to ensure linear homogeneity, the sum of all the β_m coefficients must be 1. Put simply, this restriction ensures that, should

[5]Note that the dummy variables are given values of zero before a regulation was enacted and one in all periods thereafter.

each operating cost be multiplied by some scalar constant, the total cost will change by the same constant. In other words: $\lambda C = C(Q, \lambda\mathbf{p})$; the cost function must be homogeneous of degree one. From the arguments of linear homogeneity and symmetry, it follows that the τ and δ coefficients must also all sum to zero. If these coefficients on interacted price terms did not sum to zero, then the equation $\lambda C = C(Q, \lambda\mathbf{p})$ would no longer be satisfied.

5.1.1 Returns to Scale

After empirically solving for the estimated values of the coefficients, a partial derivative of $\ln C$ with respect to $\ln Q$ can be obtained:

$$\frac{\partial \ln C^*}{\partial \ln Q} = \beta_Q + \sum_n \tau_n \ln p_n + \gamma \ln Q \tag{6}$$

This partial derivative gives the change in cost resulting from an increase or decrease in output. If this number is one, then cost is perfectly correlated with output and commercial bank holding companies have constant returns to scale. Along the same argument a value higher than one yields decreasing returns to scale, and less than one yields increasing returns to scale. The standard expression for the scale effects can also be written as:

$$1 - \frac{\partial \ln C}{\partial \ln Q}$$

After this arithmetic, a negative number will yield decreasing returns to scale and a positive number will yield increasing returns to scale. Thus, using the translog cost function to calculate returns to scale is straightforward and only requires a simple partial derivative after the empirical model has been estimated.

5.2 Fourier Flexible Form

The translog cost function makes several assumptions which could lead to inaccurate values of returns to scale. In particular, the translog assumes a certain parametric form of the cost function; a form that is a quadratic in log-space. The Fourier flexible form represents a semi-nonparametric approach, which is useful when the true functional form of the cost function is unknown. Because sine and cosine functions are orthogonal within the 0 to 2π range, an infinite series of sines and cosines with varying frequencies can accurately represent any continuously and differentiable function. Because of computational and dimensionality limits, an infinite Fourier series (which would be a fully nonparametric estimate) is not feasible. A finite Fourier series, however, is semiparametric and (unlike the translog cost function) is a global approximation of the cost function. The Fourier flexible form used in this paper is presented below:

$$\ln C \approx \beta_o + \beta_Q \ln Q + \sum_m \beta_m \ln p_m + \sum_n \tau_n \ln p_n \ln Q + \frac{1}{2}\sum_m \sum_n \delta_{mn} \ln p_m \ln p_n + \frac{1}{2}\gamma \ln Q^2 + \sum_{i=1}^{N} [\zeta_i \sin(k_i V) + \phi_i \cos(k_i V)] + \epsilon A \quad (7)$$

Where k_i is a vector of integer values and V is a vector of the logged input and output quantities. In order for the Fourier flexible form to accurately measure returns to scale several criteria must be fulfilled. In particular, the input and output variables must be transformed so that they vary within the interval [0,2π]. These restrictions The more difficult step is choosing which integers make up the k_i vectors. There is not substantial literature on how to make this choice, so we follow the criteria laid out in Skolrud (2013). To ensure orthogonality between the cosine and sine terms, all values within the k_i vectors must be integers. In order to maintain linear homogeneity, the β, τ, and δ coefficients are subject to the same restrictions as an in the translog cost function. The addition of the vector V, however, means restrictions must also be imposed on the values of k_i. In particular, the sum of k_i integers which are multiplied with input prices must be equal to zero.[6] This restriction ensures that $\lambda C = C(Q, \lambda \mathbf{p})$ is still satisfied when using the Fourier flexible form. Similar to the translog cost function, returns to scale can be obtained from the Fourier flexible form by taking a partial derivative with respect to the natural log of output:

$$\frac{\partial \ln C}{\partial \ln Q} = \beta_Q + \sum_n \tau_n \ln p_n + \gamma \ln Q + \sum_{i=1}^{N} k_{i,Q} \left[\zeta_i \cos(k_i V) - \phi_i \sin(k_i V) \right] \tag{8}$$

Note that the $k_{i,Q}$ integer value (corresponding to the output quantity) is multiplied by the overall sum of sine and cosine due to the chain rule. Other than the trigonometric formulae, however, the equation for returns to scale looks similar to equation (6). Because the Fourier flexible form makes fewer assumptions than the translog cost function, we will compare these values to those obtained by the translog cost function to determine the accuracy of the translog.

5.3 Panel Vector Autoregression (PVAR)

VAR, or vector autoregressive models are those which project a given variable's current value as a function of its lagged values and lagged values of other variables. VAR models are particularly useful in that all input variables are treated as endogenously determined and interdependent. With purely time-series data the general equation for a vector autoregressive model can be written as:

$$X_t = \beta_0 + \Gamma_1 X_{t-1} + \Gamma_2 X_{t-2} + ... + \Gamma_m X_{t-m} + \epsilon_t \tag{9}$$

[6] For example, if the integer '1' is multiplied by a particular input cost then '-1' must be multiplied by another input cost. For more details on the necessary k_i restrictions, please refer to Skolrud (2013)

Where X_t is an $(nx1)$ vector of endogenous variables at some time 't'. The vectors on the right-hand side of the equation represent lagged values of the $(nx1)$ vector. The Γ's represent (nxn) coefficient matrices and the ϵ term is an i.i.d. $(nx1)$ vector of error terms. The number of lags is equal to m, the value of which is typically determined by qualitative rationale and statistical tests. Written in a more accessible format below is an example of an n-variable, 2-lag vector autoregression:

$$\begin{bmatrix} x_{1,t} \\ x_{2,t} \\ \vdots \\ x_{n,t} \end{bmatrix} = \beta_0 + \begin{bmatrix} \gamma^1_{1,1} & \gamma^1_{1,2} & \cdots & \gamma^1_{1,n} \\ \gamma^1_{2,1} & \gamma^1_{2,2} & \cdots & \gamma^1_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma^1_{n,1} & \gamma^1_{n,2} & \cdots & \gamma^1_{n,n} \end{bmatrix} \begin{bmatrix} x_{1,t-1} \\ x_{2,t-1} \\ \vdots \\ x_{n,t-1} \end{bmatrix} + \begin{bmatrix} \gamma^2_{1,1} & \gamma^2_{1,2} & \cdots & \gamma^2_{1,n} \\ \gamma^2_{2,1} & \gamma^2_{2,2} & \cdots & \gamma^2_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma^2_{n,1} & \gamma^2_{n,2} & \cdots & \gamma^2_{n,n} \end{bmatrix} \begin{bmatrix} x_{1,t-2} \\ x_{2,t-2} \\ \vdots \\ x_{n,t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \vdots \\ \epsilon_{n,t} \end{bmatrix} \tag{10}$$

It is straightforward to see that the above equation can be extrapolated to any number of lags given the addition of more matrices. Presented thus far have only been vector autoregressions for use with times series data. Given the fact that our data consists of 198 commercial bank holding companies across 24 years (our dataset is explained, in detail, in Section 4) we must extrapolate our time series model to work with a panel dataset. The econometric application of a PVAR model is slightly more complicated, but the theoretical extension to a panel dataset can be written compactly as:

$$X_{i,t} = \beta_{i,0} + \Gamma_{i,1} X_{i,t-1} + \Gamma_{i,2} X_{i,t-2} + ... + \Gamma_{i,m} X_{i,t-m} + \epsilon_{i,t} \tag{11}$$

For our purposes, the most useful information from the PVAR comes in the form of impulse response functions. In a purely mathematical sense, impulse response functions measure the response of current and future values of each variable to a shock, defined as a unit increase in the current value of one of the variables.

For our var model, the shock will be some change in row 'n' of the $(nx1)$ ϵ column vector. Because of the interpendencies that characterize a PVAR, this shock will likely impact all variables in X_t. The response over time of the X_t variables creates the impulse response functions. In general, the ϵ_n shock imposed is the size of the standard deviation of variable x_n. In addition, all variables are typically normalized to have a value equal to zero prior to the shock.

For commercial bank holding companies, PVAR is particularly interesting because the parameters that characterize an impulse response function will show the effects that an increase in assets have on cost efficiency and returns to scale. Kovner et al. (2014) find that commercial bank holding companies with larger asset bases achieve greater cost efficiency than their smaller peers, through a PVAR we can support or refute this claim. We can also take our analysis a step forward by observing whether assets affect returns to scale and cost efficiency differently with the inclusion of bank regulation dummy variables.

5.4 Bayesian Panel VAR

All forms of regression analysis contain bias based on a researcher's prior beliefs. Ideally, an econometrician would like to estimate a model that is as accurate as possible. In order to develop a strong model, the researcher will select variables and, in some cases, even the form of the model (when the model is parametric). While this is a typical approach in estimation, it does impose the researcher's biases on the model. The Bayesian form of estimation helps fix this issue by assuming that model parameters are random quantities. Bayesian analysis is contrasted by frequentist analysis, which instead assumes that the data is a random sample of the global data, but that the parameters are fixed and unknown. By assuming that the model's parameters are random, Bayesian analysis allows the researcher to incorporate prior knowledge in the estimation process. These 'priors' are a researcher's best estimate of the distribution of the model's parameters before any regressions have been run. These prior distributions are then updated in a series of simulations until a final posterior distribution is determined. This form of estimation gives a more robust result than frequentist analysis because Bayesian estimation uses both data on hand and the prior knowledge. It is also especially useful in our situation because Bayesian analysis will serve as a robustness check for our results obtained through a frequentist panel var.

Interpretations of the results of Bayesian analysis are also different than frequentist approaches. Bayesian inference provides a summary of the posterior distribution's mean and standard error. This distribution is estimated through Markov Chain Monte Carlo (MCMC) sampling. Rather than traditional confidence intervals, Bayesian analysis gives "credible intervals". For example, the interpretation of 95% credible interval means that for a certain parameter, the probability that the parameter lies in a certain range is 95%.

In Bayesian analysis the posterior has two components: a likelihood function which contains information about the parameters from observed data, and a prior which contains information about the parameters from other sources. The posterior distribution generally cannot be solved for analytically (typically it does not even have a closed form solution). Thus, to find the posterior solution one must use MCMC sampling to approximate the distribution. To assess the accuracy of the numerically-determined Bayesian solution, one must determine whether their estimations converge. Because the number of samplings is not finite, convergence can be determined to an arbitrary level of precision. Although the theoretical basis for Bayesian analysis is more complicated than for frequentist analysis, the form of a Bayesian PVAR is equivalent to that of equation (11), the only difference being the additional reliance on priors and the determination of a solution through estimation.

6 Results

6.1 Measurements of Returns to Scale

Here we implement the translog cost function discussed in Section 5.1. In order to avoid the problems resulting from the curse of dimensionality and listwise deletion we do not use all 15 operating expenses as inputs. Instead, we create a new variable which measures the total capital of a particular bank. This variable is created as the sum of the occupancy, equipment, software, and supplies expenses. In addition, we use the sum of personnel and employee benefits to represent labor. We represent the cost of deposits by a firm's total deposits and use all controls discussed in Section 4 as well as dummy variables representing each regulation. Recognizing that the translog model is a local approximation of the cost function, we estimate the translog cost function for commercial bank holding companies of different asset sizes separately. This allows the cost functions of fundamentally different commercial bank holding companies to take on different forms. The results of these four translog cost functions (for small commercial bank holding companies, medium commercial bank holding companies, large commercial bank holding companies, and Too-Big-To-Fail commercial bank holding companies[7]) suggest strongly increasing returns to scale for all commercial bank holding companies except those deemed Too-Big-To-Fail.

Table 6: Returns to Scale Measurements from Translog Cost Function

Size	$\partial \ln C / \partial \ln Q$
Too-Big-To-Fail Banks	.
Large Banks	0.294
Mid-Size Banks	0.857
Small Banks	0.660

[7]The size groups are as follows: small commercial bank holding companies are those with average assets under $500 million; medium commercial bank holding companies are those with average asset sizes between $500 million and $2.5 billion; large commercial bank holding companies are those with average asset sizes between $2.5 billion and $20 billion; and Too-Big-To-Fail commercial bank holding companies are those with average asset sizes greater then $20 billion.

Only seven commercial bank holding companies were large enough to be considered Too-Big-To-Fail, and for this size category each bank-specific estimate for returns to scale was found to be statistically insignificant at the 5% level. Nonetheless, our results support recent literature (that large commercial bank holding companies display increasing returns to scale). To find the average values for returns to scale of each size group we check the statistical significance of each of our $\partial \ln C/\partial \ln Q$ estimates. We accomplish this by nonlinear hypothesis testing at different values of $\partial \ln C/\partial \ln Q$. In our averages we exclude any $\partial \ln C/\partial \ln Q$ values where $p < |t|$ is less than 5%. This adds a higher degree of accuracy to our findings and rejects any estimates which have a significant probability of being statistically insignificant. We compare these results to theoretically more robust results obtained from the Fourier flexible form.

The Fourier flexible form is created using the same set of data as the translog cost function. We follow Skolrud's (2013) methodology and combine a 6^{th} order Fourier series expansion with the pre-existing translog cost function. The estimates of $\partial \ln C/\partial \ln Q$ are presented below.

Table 7: Returns to Scale Measurements from Fourier Flexible Form

Size	$\partial \ln C/\partial \ln Q$
Too-Big-To-Fail Banks	2.013
Large Banks	0.106
Mid-Size Banks	0.093
Small Banks	0.526

Our results here are similar to those obtained using the translog cost function except for medium commercial bank holding companies. In particular, we find that the largest commercial bank holding companies in our study actually exhibit decreasing returns to scale. Our results are consistent with earlier literature which find increasing returns to scale up to a particular size limit. Although each size category exhibits increasing returns to scale, the medium commercial bank holding companies exhibit the largest increases compared to large and small commercial bank holding companies showing a non-monotonic distribution of returns to scale. This difference might occur because medium commercial bank holding companies are more heterogeneous compared to other groups. The translog model, however, only estimates well with a local and homogeneous approximation, so if the medium commercial bank holding companies are heterogeneous then the translog results will provide flawed estimates. Therefore, we will describe our VAR findings based on Fourier flexible form results in the following section. We can also assess the role the banking regulations play in the cost function since we have explicitly included dummy variables for each regulation.

Table 8: The impact of different regulations on total cost.

Variables	Translog Cost Function[8]			Fourier Flexible Form		
	RN	GLB	DF	RN	GLB	DF
TBTF	-0.297	0.157	0.002	-0.858***	0.313	0.242
Large	0.069	-0.238**	0.151	0.039	-0.263***	-0.051
Medium	0.049	0.054	0.151***	0.020	0.029	-0.033
Small	-0.010	0.044	0.243***	0.064	0.071*	0.166***

Our results for TBTF, large, and small commercial bank holding companies are highly consistent between estimation technique. Interestingly, we find that the total costs of small commercial bank holding companies increased the most as a result of Dodd-Frank legislation. This is surprising because the Dodd-Frank legislation was marketed as a way to reduce banking risk, targeted specifically at the largest commercial bank holding companies in the US economy. In fact, for both the translog and Fourier flexible form models, neither the TBTF nor the large commercial bank holding companies saw an increase in their costs as a result of the legislation. The largest commercial bank holding companies, however, benefited the most from legislation which granted commercial bank holding companies more

[8]Note that standard errors for each regulation coefficient obtained through the translog cost function are listed in appendix A. Standard errors for each regulation coefficient obtained through the Fourier Flexible Form are listed in appendix B.

freedom (Riegle-Neal and the Gramm-Leach-Bliley Act). This is interesting because it appears that the largest commercial bank holding companies perform well no matter the regulatory environment. This allows us to conclude that restrictive bank regulations, even those which are targeted towards the largest commercial bank holding companies, have the most significant negative impact on the smallest commercial bank holding companies. One explanation for why this may be the case is because larger commercial bank holding companies have large, pre-existing compliance departments that were more likely to quickly interpret and implement the Dodd-Frank legislation. For smaller commercial bank holding companies, the compliance department is smaller and likely to be more focused. This could mean that after Dodd-Frank small commercial bank holding companies were forced to hire outside legal help to understand, and adhere to, the new legislation.

6.2 Panel VAR (PVAR) Results

PVAR allows the study of the effects of increases in size on cost efficiency and returns to scale. Moreover, each of these variables are interrelated, and thus endogenous, which makes the PVAR the best estimation model. The variables used in our PVAR are the natural logs of cost efficiency (we define this as total cost over total assets[9]), a bank's size (measured as total assets), and a bank's returns to scale (obtained using the translog cost function and Fourier flexible form). Although we can observe shocks to each endogenous variable, we are most interested in how a bank's returns to scale and cost efficiency respond to a growth in total assets. We include a bank's total assets because our results, as well as recent papers on the subject (such as Wheelock and Wilson (2012)), find that returns to scale differ for firms of different sizes; Kovner et al. (2014) come to the same conclusions about cost efficiency. Using a PVAR model, we quantitatively mea-

[9]It is important to note that total noninterest expenses divided by assets is actually a measure of cost inefficiency. Throughout the paper higher values always denote higher cost inefficiency

sure the effect that increases or decreases in size have on returns to scale and efficiency. Because we use a panel dataset, we address the issues relating to bank fixed effects by Helmert transforming our data. The use of vector autoregressive models in returns to scale and bank cost efficiency research is novel, and a significant contribution to the field. It should be noted that the RTS estimates used to parametrize the PVAR and Bayesian PVAR are based on the Fourier flexible form since the Fourier estimations are based on fewer assumptions.

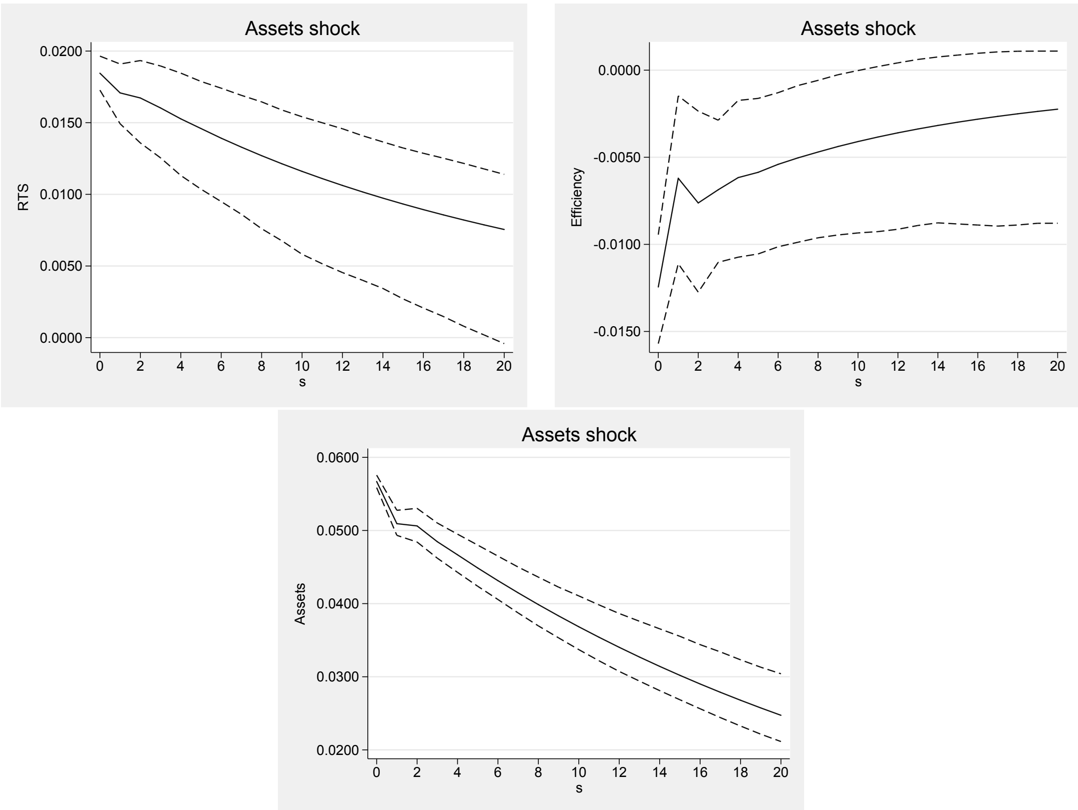


Figure 5: PVAR IRFs measuring cost efficiency, total assets, and returns to scale after a total asset shock.

Note that a shock to a firm's size both increases cost efficiency and decreases returns to scale. These results are statistically significant in the period directly after the shock, and the impulse response functions are stable. The cost efficiency findings are consistent with the recent research of Kovner et al. (2014), where the authors found that an increase in firm size was associated with an increase in cost efficiency. The returns to scale findings also fit in with recent literature. This PVAR model is based on data for small, medium, large, and Too-Big-To-Fail commercial bank holding companies, but for completeness PVARs should be separately parametrized for each size group. Unfortunately, limited data availability (especially after a number of RTS estimates are rejected) leads to significant divergence in the errors of the IRFs in later periods. The size of the errors makes it impossible to draw any conclusion of the difference in an asset shock across different group sizes. Nonetheless, the conclusions we draw here reinforce the theory that an increase in bank size does have a statistically significant effect on both cost efficiency and returns to scale. To determine the robustness of these results, we next consider a Bayesian Panel VAR.

6.3 Bayesian Panel VAR Results

We obtain posterior distributions for the Bayesian PVAR using Metropolis-Hastings MCMC sampling. The Metropolis-Hastings algorithm requires initial prior distributions for each coefficient in the Bayesian PVAR. The posterior distribution of these coefficients is then updated through a series of iterations. Ideally, the iterations should converge to a final posterior distribution after a finite number of repetitions. To deal with the issue of bank fixed effects, we again apply Helmert transformation to each of the variables used. Presented below are the prior and posterior coefficient distributions for each of the nine variables included in the Bayesian PVAR.

Table 9: Distributions where Total Assets is Dependent Variable

Variable	Prior (μ, σ^2)	Posterior (μ, σ^2)
L1.Total Assets	N(0,10xσ)	(0.863, 1.97e-04)
L2.Total Assets	N(0,10xσ)	(0.096, 3.49e-04)
L3.Total Assets	N(0,10xσ)	(0.007, 1.92e-04)
L1.RTS	N(0,10xσ)	(0.019, 1.81e-04)
L2.RTS	N(0,10xσ)	(0.000, 3.18e-04)
L3.RTS	N(0,10xσ)	(-0.030, 1.71e-04)
L1.Cost Efficiency	N(0,10xσ)	(-0.002, 2.72e-05)
L2.Cost Efficiency	N(0,10xσ)	(-0.012, 2.67e-05)
L3.Cost Efficiency	N(0,10xσ)	(0.009, 2.71e-05)

Table 10: Distributions where RTS is Dependent Variable

Variable	Prior (μ, σ^2)	Posterior (μ, σ^2)
L1.Total Assets	N(0,10xσ)	(0.008, 2.04e-04)
L2.Total Assets	N(0,10xσ)	(-0.030, 3.58e-04)
L3.Total Assets	N(0,10xσ)	(0.048, 1.93e-04)
L1.RTS	N(0,10xσ)	(0.905, 1.89e-04)
L2.RTS	N(0,10xσ)	(0.189, 3.26e-04)
L3.RTS	N(0,10xσ)	(-0.163, 1.74e-04)
L1.Cost Efficiency	N(0,10xσ)	(0.007, 2.73e-05)
L2.Cost Efficiency	N(0,10xσ)	(-0.002, 2.64e-05)
L3.Cost Efficiency	N(0,10xσ)	(-0.010, 2.70e-05)

Table 11: Distributions where Cost Efficiency is Dependent Variable

Variable	Prior (μ, σ^2)	Posterior (μ, σ^2)
L1.Total Assets	N(0,10xσ)	(-0.046, 0.001)
L2.Total Assets	N(0,10xσ)	(-0.011, 0.002)
L3.Total Assets	N(0,10xσ)	(0.028, 0.001)
L1.RTS	N(0,10xσ)	(-0.031, 0.001)
L2.RTS	N(0,10xσ)	(0.061, 0.002)
L3.RTS	N(0,10xσ)	(-0.015, 0.001)
L1.Cost Efficiency	N(0,10xσ)	(0.276, 1.70e-04)
L2.Cost Efficiency	N(0,10xσ)	(0.337, 1.66e-04)
L3.Cost Efficiency	N(0,10xσ)	(0.159, 1.68e-04)

The posterior distribution was based on 1,000,000 MCMC iterations (of which, the first 500,000 were discarded). As few as 100,000 iterations were also tested, and in all cases (with iterations between 1,000,000 and 100,000) all convergence criteria were met. Note that our priors are flat and noninformative, meaning our posterior distributions are obtained based primarily on the data. Posteriors obtained from flat priors should theoretically not resemble the priors in any way. Clearly, the results of our Bayesian PVAR validate this theory. Based on confirmation that the prior and posterior distributions are fundamentally different, a number of impulse response functions may once again be created.

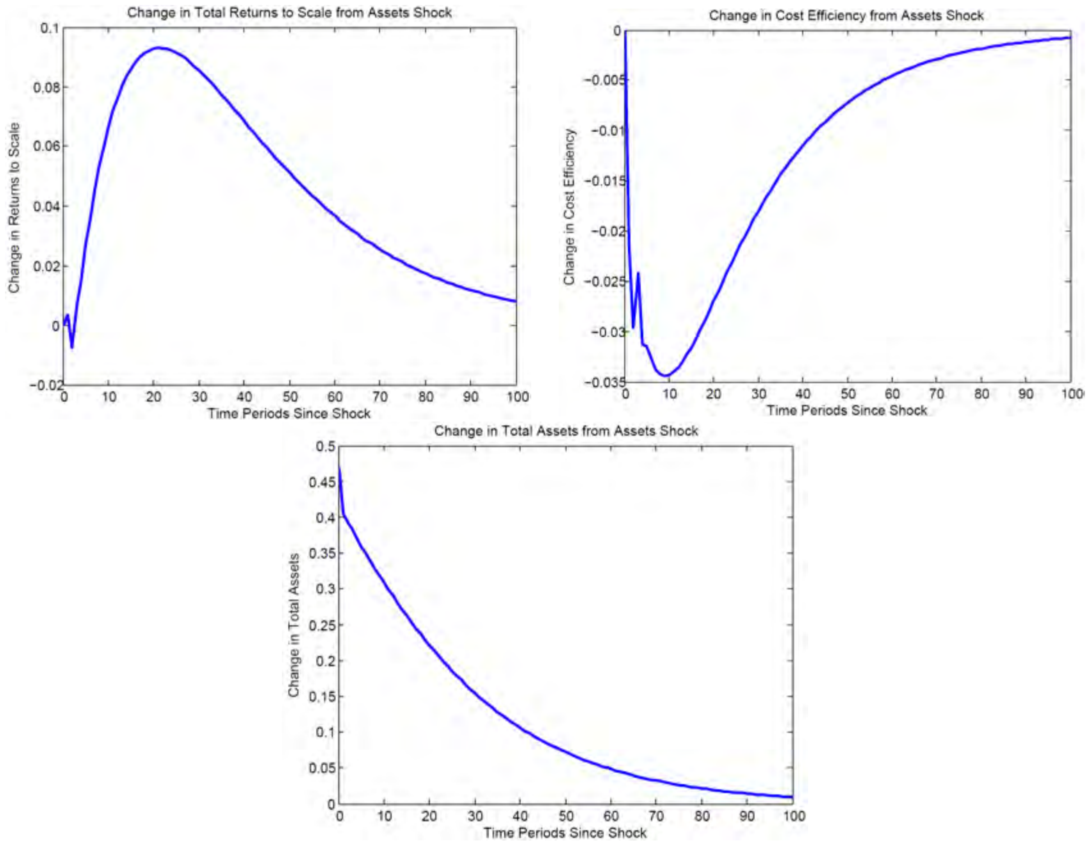


Figure 6: Bayesian PVAR IRFs measuring cost efficiency, total assets, and returns to scale after a total asset shock.

The conclusions drawn from the Bayesian PVAR IRFs are consistent with those drawn from the PVAR IRFs. Once again, we note that an increase in total assets both increases cost efficiency and decreases returns to scale. While the conclusions between estimation technique are similar, however, the magnitude and persistence of the shocks differs between models. With the Bayesian estimation, the effects of a shock in firm size appear to last nearly five times as long as the effects of shock with frequentist estimation. Note that our x-axis when considering the Bayesian PVAR is larger than for the PVAR because we show the entire effect of a total assets shock. Also, the effects of an asset shock also appear to be larger in the case of the PVAR. Despite these differences, it is important to note that the Bayesian results show that the PVAR conclusions are robust.

6.4 Robustness Checks

6.4.1 Robustness Checks of RTS Results

To generate estimates for the average returns to scale for each bank size group, a number of returns to scale estimates were rejected based on statistical significance. Rejection of the estimates was performed at the 5% level, but we also check the returns to scale estimates at the 10% level and without rejection. At the 10% level there is very little change in the RTS estimates for either the Fourier or translog model. Without rejection, however, there are substantial changes in the results and conclusions for the largest commercial bank holding companies (small and medium commercial bank holding companies generally saw smaller changes). Thus, we must reject the statistically insignificant returns to scale estimates, but whether we reject at the 5% or 10% level is unimportant.

We next test our results with a balanced panel dataset. We test our findings using balanced panel data from 2002:1 to 2007:3 to determine whether recessionary periods are leading to inaccurate results. Using the Fourier flexible form we find similar conclusions to our general model (unbalanced, using all available data). To determine whether our findings depend on the unbalanced nature of the dataset during recessionary periods we next test our findings using a balanced panel dataset from 1998:1 to 2014:2. We determine that our conclusions are robust regardless of whether we transform our dataset so that it is balanced.

6.4.2 Sensitivity Analysis of Bank Groups

To test whether the bank size categories affected the estimates for returns to scale (which would change the PVAR conclusions) we obtain returns to scale results using banks segmented into groups by their real assets. In average real assets, these size categories ranged from (in thousands) less than 2.93e06 for small bank holding companies; from 2.93e06 to 1.43e07 for medium bank holding companies; from 1.43e07 to 2.00e08 for large bank holding companies; and greater than 2.00e08 for the Too-Big-To Fail bank holding companies. The returns to scale results are listed in the appendix, but the overall conclusions do not change: all banks but the Too-Big-To-Fail generate increasing returns to scale. Note that these results are based on the translog cost function which should be more sensitive to group switching than the Fourier flexible form. The fact that we obtain consistent results means that we are confident in the group categories for our Fourier flexible form as well. As was previously mentioned, once banks are placed in a given size category they do not leave that group regardless of whether they grow larger or smaller. Using real assets and the size categories listed above, we check the number of banks that either grow too large for their size category or shrink too small at any point in time. We find that for small banks, 43 out of 77 would have switched groups; for medium banks, 69 out of 72 would have switched groups; for large banks, 22 out of 32 would have switched groups; and for TBTF banks, 7 out of 7 would have switched groups. Although many banks would have switched size categories at some point in time (if we had allowed them to do so), the fact that we changed the banks within size groups and still obtained consistent results means that the number which changed will not significantly impact our conclusions.

6.4.3 Robustness Checks of PVAR and Bayesian PVAR Results

Recognizing that our results could be influenced by the controls that we select, we run both the PVAR with and without macroeconomic controls. The conclusions drawn from running the PVAR without controls are the same as when the PVAR was run with controls. This finding shows that our conclusions are robust to the controls we select. Furthermore, in our Bayesian estimation we helmert transform our variables to address the issue of bank fixed effects. To see whether these bank fixed effects played a role in the impulse response functions we estimate the Bayesian PVAR with and without variables that are Helmert transformed. We do find a statistically significant change in the IRFs, which means that addressing the bank fixed effects is an important step in our estimation. This is to be expected since the commercial bank holding companies in our global sample are highly heterogeneous. Finally, we changed the Cholesky Ordering in our PVAR estimation. Our final model is based on the most conservative ordering,[10] but we do check other orders. We note that the model is robust to ordering: a change in the variable order has no significant impacts on the IRFs. These robustness checks add confidence that the conclusions drawn from the impulse response functions are sound.

As with our returns to scale robustness checks, we again determine whether our results change when we drop several commercial bank holding companies and convert our dataset so that it is balanced. We first check our PVAR results using data exclusively from 2002:1-2007:3 to parametrize our model. We find that our conclusions are robust regardless of the inclusion or exclusion of the recessionary periods. We next test whether our conclusions change using data from 1998:1-2014:2 (again using a balanced dataset). We find that our results are

[10] For our model, the most conservative order is Total Assets, Cost Efficiency, and Returns to Scale.

robust to whether or not our dataset is balanced or unbalanced. Note that the impulse response functions for several of these robustness checks are presented in the appendix.

7 Conclusion

Past papers measuring returns to scale reject the results of the translog cost function (Wheelock and Wilson (2012), Wheelock and Wilson (2015)). While our translog results are generally in-line with those obtained through the Fourier flexible form, the quantitative values are substantially different. It is important to note, however, that the Fourier flexible form is a more accurate estimate of returns to scale because it relies on fewer assumptions about the parametric form of the cost function. Despite their differences, both estimation techniques find results that are in agreement with older papers (Noulas et al. (1990), Hunter et al. (1990)), which find the largest commercial bank holding companies exhibit decreasing returns to scale. Due to our Too-Big-To-Fail group having the smallest number of commercial bank holding companies among all size groups considered, however, this result may not be as robust as those obtained for the other size groups. Nonetheless, our findings add to the debate over whether commercial bank holding companies with large asset sizes exhibit increases or decreases in returns to scale.

With respect to the PVAR and Bayesian PVAR results, we determine that an increase in bank size has a statistically significant impact on both returns to scale and cost efficiency. We note that an increase in firm size decreases returns to scale, but increases cost efficiency. This result is consistent with the findings of many papers on returns to scale and agrees with the empirical work by Kovner et al. (2014). We also obtain results that measure the impact which regulations have on a bank's total cost function. The largest commercial bank holding companies generally benefit from the most flexible regulations, whereas the smaller commercial bank holding companies are generally hurt by the most restrictive regulations. This is an interesting result because the most restrictive regulation (Dodd-Frank) is generally focused on the largest commercial bank holding companies. However, this regulation has the largest influence on the cost function of the smallest commercial bank holding companies. This result suggests that regulators must consider the auxiliary implications of regulations on commercial bank holding companies which may not be in their 'target' group.

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A Regression Results for the Translog Cost Function

The following sections show select coefficients estimated using the Translog Cost. Note that for all datasets the coefficient on labor is not shown because $\beta_{Lab} + \beta_{Cap} + \beta_{Dep} = 1$.

A.1 TBTF Banks

Table 12: Select Estimation results for Translog Cost Function for Too-Big-To-Fail Banks

Variable	**Coefficient**	**(Std. Err.)**
Capital	-.268**	(.109)
Total Deposits	.033	(.093)
Gross Loans	.053	(.091)
Gross Loans Squared	-.010	(.010)
Dodd-Frank Act	.002	(.186)
Gramm-Leach-Bliley Act	.157	(.206)
Riegle-Neal Act	-.297	(.203)
N	547	

A.2 Large Banks

Table 13: Select Estimation results for Translog Cost Function for Too-Big-To-Fail Banks

Variable	**Coefficient**	**(Std. Err.)**
Capital	-.002	(.065)
Total Deposits	1.081***	(.055)
Gross Loans	-.698***	(.056)
Gross Loans Squared	.057***	(.007)
Dodd-Frank Act	.069	(.087)
Gramm-Leach-Bliley Act	-.238**	(.099)
Riegle-Neal Act	.151	(.101)
N	1845	

A.3 Medium Banks

Table 14: Select Estimation results for Translog Cost Function for Too-Big-To-Fail Banks

Variable	**Coefficient**	**(Std. Err.)**
Capital	.116***	(.027)
Total Deposits	1.448***	(.025)
Gross Loans	-1.194***	(.021)
Gross Loans Squared	.119***	(.003)
Dodd-Frank Act	.151***	(.037)
Gramm-Leach-Bliley Act	.054	(.040)
Riegle-Neal Act	.049	(.043)
N	3916	

A.4 Small Banks

Table 15: Select Estimation results for Translog Cost Function for Too-Big-To-Fail Banks

Variable	Coefficient	(Std. Err.)
Capital	.110***	(.028)
Total Deposits	1.178***	(.026)
Gross Loans	-.955***	(.028)
Gross Loans Squared	.117***	(.004)
Dodd-Frank Act	.243***	(.037)
Gramm-Leach-Bliley Act	.044	(.042)
Riegle-Neal Act	-.010	(.052)
N	6924	

B Regression Results for the Fourier Flexible Form

The following sections show select coefficients estimated using the Fourier flexible form. Note that for all datasets the coefficient on labor is not shown because $\beta_{Lab} + \beta_{Cap} + \beta_{Dep} = 1$.

B.1 TBTF Banks

Table 16: Select Estimation results for Fourier Flexible Form for Too-Big-To-Fail Banks

Variable	Coefficient	(Std. Err.)
Capital	-.322	(.459)
Total Deposits	-.419	(.399)
Gross Loans	-121.012	(192.305)
Gross Loans Squared	38.580	(61.227)
Dodd-Frank Act	.242	(.234)
Gramm-Leach-Bliley Act	.313	(.261)
Riegle-Neal Act	-.858***	(.262)
N	547	

B.2 Large Banks

Table 17: Select Estimation results for Fourier Flexible Form for Large Banks

Variable	Coefficient	(Std. Err.)
Capital	.500***	(.116)
Total Deposits	.555***	(.090)
Gross Loans	-.114	(1.722)
Gross Loans Squared	.034	(.558)
Dodd-Frank Act	-.051	(.082)
Gramm-Leach-Bliley Act	-.263***	(.094)
Riegle-Neal Act	.039	(.099)
N	1845	

B.3 Medium Banks

Table 18: Select Estimation results for Fourier Flexible Form for Medium Banks

Variable	Coefficient	(Std. Err.)
Capital	-.360***	(.043)
Total Deposits	.433***	(.035)
Gross Loans	-.779	(.795)
Gross Loans Squared	.227	(.256)
Dodd-Frank Act	-.033	(.027)
Gramm-Leach-Bliley Act	.029	(.028)
Riegle-Neal Act	.020	(.031)
N	3916	

B.4 Small Banks

Table 19: Select Estimation results for Fourier Flexible Form for Small Banks

Variable	Coefficient	(Std. Err.)
Capital	.792***	(.062)
Total Deposits	.437***	(.049)
Gross Loans	-5.376	(26.146)
Gross Loans Squared	1.733	(8.334)
Dodd-Frank Act	.166***	(.035)
Gramm-Leach-Bliley Act	.071*	(.039)
Riegle-Neal Act	.064	(.049)
N	6924	

C Group Sensitivity and Returns to Scale

In order to test whether our size categories play a role in the returns to scale estimates for each bank group, we create new groups based on a bank's total real assets rather than total nominal assets. Because the translog cost function should be more susceptible to changes in the banks within each group we present estimation results from the translog cost function below. Our results are consistent with those presented in table 6.

Table 20: Returns to Scale Measurements from Translog Cost Function

Size	$\partial \ln C / \partial \ln Q$
Too-Big-To-Fail Banks	.
Large Banks	0.332
Mid-Size Banks	0.651
Small Banks	0.770

D PVAR with a Unbalanced 2002:1-2007:3 Dataset

Below are impulse response functions testing a PVAR which was parametrized using an unbalanced dataset for the period from the first quarter of 2002 through the third quarter of 2007. Note that the conclusions drawn here are the same as for the unbalanced dataset with all available years used (as shown in section 6.2).

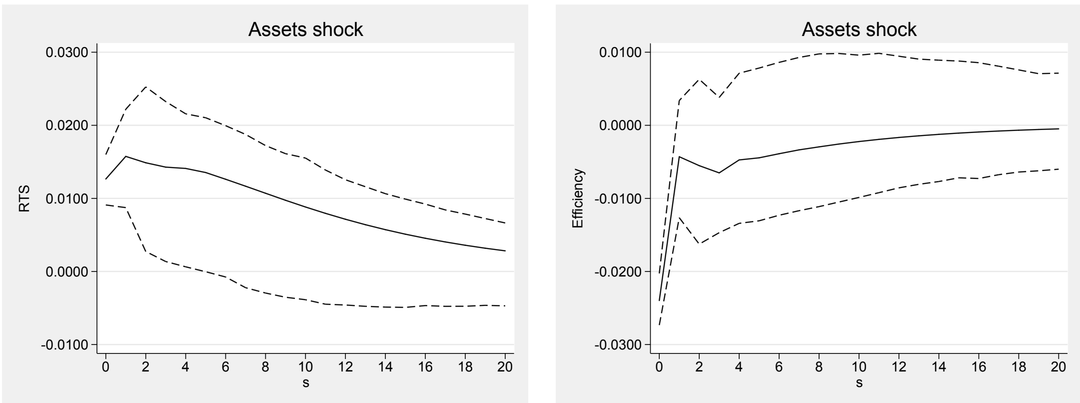

Figure 7: PVAR IRFs measuring cost efficiency and returns to scale after a total asset shock with an unbalanced dataset and data from 2002:1-2007:3.

E PVAR with a Balanced 1998:1-2014:2 Dataset

Below are impulse response functions testing a PVAR which was parametrized using an balanced dataset for the period from the first quarter of 1998 through the second quarter of 2014. Note that the conclusions drawn here are the same as for the unbalanced dataset with all available years used (as shown in section 6.2).

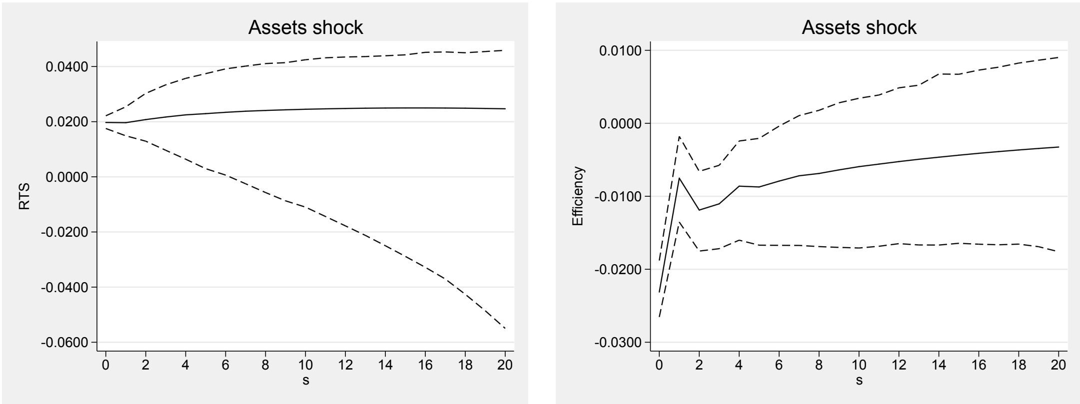

Figure 8: PVAR IRFs measuring cost efficiency and returns to scale after a total asset shock with a balanced dataset and data from 1998:1-2014:2.

F PVAR with Macroeconomic Controls Included

Below are impulse response functions testing a PVAR which was parametrized using the entire dataset from the third quarter of 1992 through the second quarter of 2014. The difference between these results and the model shown in the paper is that these PVARs do not include controls for the macroeconomy. Note that the conclusions drawn here are the same as for the model dataset which did not use macroeconomic controls (as shown in section 6.2).

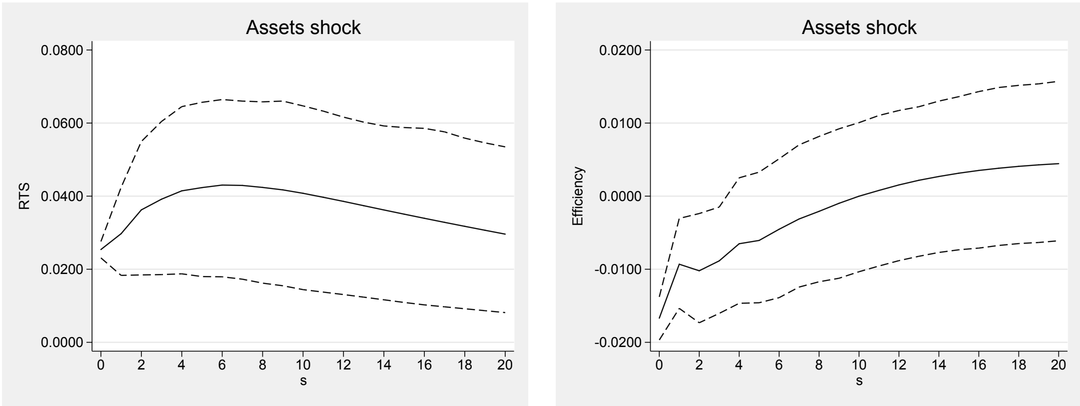

Figure 9: PVAR IRFs measuring cost efficiency and returns to scale after a total asset shock with the entire dataset, including macroeconomic controls.