Title

The Effect of Compliance Costs on Bank Failure: Building a Bank Failure Model forRegulatory Changes During a Recessionary Period

Author
Eddie, Andrew

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The Effect of Compliance Costs on Bank Failure: Building a Bank Failure Model for Regulatory Changes During a Recessionary Period

Andrew Eddie

Advisor: Dr. Peter Rupert

University of California, Santa Barbara

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Abstract

This reports studies what contributes to bank failure during the Great Recession and after the introduction of the Dodd-Frank Act using survival analysis. I show that measures of CAMELS ratings such as capital adequacy and solvency play large roles. I found that while a high efficiency ratio increases risk of failure for financial institutions, banks can mitigate this by focusing the burden of non-interest expenses on salary. While small banks (defined as having below one billion dollars in assets) had an overall lower failure risk, they also had higher relative risks of failure if they were inefficient than risks for large banks. However, small banks are shown to reap the rewards of a high salary ratio more than large banks. Salary ratio influenced post-Dodd-Frank bank failure more than it did pre-Dodd-Frank.

Special Thanks to Dr. Shelly Lundberg and Christine Braun

Introduction

Community banks are almost three time more likely than non-community banks to operate outside a metro area, and hold 46% of the financial industry's small loans to farms and businesses (Hammond and Stacey, 2014). Community banks hold the only banking offices in 629 U.S. counties, home to a total of six million people. This shows their economic importance to rural areas that rely on these banks for loans and other financial activities. However, the share of U.S. banking assets held by community banks have declined from 38% in 1984 to 14% in 2011. In that same period, the number of banks has decreased from 17,901 to 7,357. This decrease has partly been seen through mergers and consolidations of banks, but since the financial crisis of 2007-2008, there has been a spike in the failure rate of banks. After the recession, a legislative bill titled the Dodd-Frank Wall Street Reform and Consumer Protection Act. The stated aim of the bill is as followed:

"To promote the financial stability of the United States 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" (US Government Publishing Office)

With the introduction of the Dodd-Frank Act, compliance costs have increased tremendously due to added rules and restrictions imposed on banks. For the year 2014, two-thirds of compliance professionals expected compliance costs to increase even more. From 2010 to 2015 a total of 125 regulations totaling $29.3 billion in costs and 73 million man-hours have been placed upon financial institutions (Thomson Reuters' Annual Cost of Compliance Survey, 2015).

While these costs affect all banks, regulatory expenses absorb a larger percentage of small banks' budgets than those of larger banks. In 2014, banks with less than $100 million in assets had an average compliance cost of $163,800, or 8.7% of noninterest expenses, while banks with assets between $1 billion and $10 billion averaged $1.8 million, or 2.9% of noninterest expenses.

Since the start of the recession, which for the purpose of this paper is September 15th, 2008, when Lehman Brothers failed, until the end of collection, which is the fourth quarter of 2015, 517 depositing institutions have failed. Around half of those have occurred since the passing of the Dodd-Frank Act, which was officially signed into law on July 21st, 2010.

The purpose of this research is to develop a bank failure model that specifically targets the effects of increased regulation in a recessionary period. This paper utilizes the usefulness of survival analysis as its foundation for research. Furthermore, interaction terms between indicator variables allow for a difference-in-difference approach to discerning how risk was changed after the advent of the Dodd-Frank Act.

Literature Review

There has been an abundance on literature concerning bank failure in the past couple decades. Sinskey (1975) ran a multivariate regression on newly discovered "problem" banks against non-problem banks (control) to construct a set of rules that could be used to classify banks into these two groups. He found that factors such as asset composition, capital adequacy, and profitability are good discriminators between the two groups. This led to the internationally recognized rating system known as CAMELS (Capital Adequacy, Asset Quality, Management, Earnings, Liquidity, and Sensitivity) that has been used since 1979 to rate financial institutions.

Since then, many studies have been done to empirically test whether the use of CAMELS as an early warning system is beneficial. Thompson (1991) found that solvency and liquidity are the most important predictors of bank failure up to 30 months before failure. However, as the bank gets closer to failure, asset quality, earnings, and management quality play a bigger role. Hwang, Lee, and Liaw (1997) found the higher the equity capital, profitability, or liquidity of a bank, the lower the probability of failure.

Local economic conditions play a vital role in the collapse of community banks. Due to the sensitive nature of small banks with a low number of branches, they can be forced to close easier than banks that operate in multiple states. Meyer and Yeager (2001) found that out of 16 variables relating to state economic conditions, 15 of them were statistically correlated to the probability of bank failure. Some of these included unemployment rate, employment growth, and personal income growth. While the removal of inter-state branch restrictions allowed for banks to diversify their risk, local economic shocks were still found to heavily contribute to bank failure (Aubuchon and Wheelock 2010).

Since the recession of 2007-08, other factors of bank failure have been investigated. Antoniades (2015) found that exposure to the real estate sector during the recession was a primary factor in bank collapse, not liquidity, but more so for larger banks. While banks with more than $1 billion in assets fared worse than smaller banks, any institution that invested in the real estate sector, measured by illiquid assets, marketable securities, and off-balance sheet credit line portfolios, increased the probability of bank failure. In a study by Cole and White (2012), residential real estate holdings were not shown to be a factor in bank failure while proxies for CAMELS components and commercial real estate holdings were.

Regulatory Literature

In a study using seven measures of banking regulation, Klomp and de Haan (2013) found that among non-industrial countries, stricter regulation and supervision reduces banking risk. Barth et al. (2004) and Agoraki et al. (2011) find that the share of non-performing loans decreases when there is more private monitoring present. However, Cyree (2016) found that loans per employee and average pay decreased after the introduction of the Dodd-Frank Act. Dolar and Shughart (2007) use total non-interest expenditures as a proxy for compliance costs related to regulatory burden and find smaller institutions are at a disadvantage since costs are proportionally larger than for bigger banks after the PATRIOT Act of 2001 was enacted. Part of this study will try and relate Dolar and Shughart's findings to the passage of Dodd-Frank.

Data

Data was collected from publicly accessible databases. The Federal Deposit Insurance Corporation compiles and releases quarterly banking reports of every listed banking institution in the country. This provided all of the banking-related variables, such as asset size and the CAMELS ratios. It also continuously updates its list of failed banks going back to 2000.

Gross Domestic Product (GDP) was provided by the Bureau of Economic Analysis and is measured as the percent change from the preceding quarter in real terms. Long-term government bond yields were provided by the Organization for Economic Co-operation and Development (OECD). These variables are an attempt to control for national economic conditions.

Inflation rates were taken from the Bureau of Labor Statistics and were used to deflate salaries and total non-interest expenses.

Variables

To measure CAMELS ratings, I used quarterly banking information to create a series of independent variables. Capital adequacy is measured by Tier 1 and 2 Capital over risk-weighted assets, as well as equity over assets. Tier 1 capital is made up of shareholders' equity and retained earnings while tier 2 capital is revaluation reserves, hybrid capital instruments and subordinated term debt, general loan-loss reserves, and undisclosed reserves. Asset quality is measured by Bad Loans, which is a ratio of non-accrual loans divided by net loans. Management Quality is loans to insiders over assets. Earnings is measured by net income over assets, known as return on assets. Liquidity is measured by net loans over assets. Solvency is measured by loan loss allowance divided by assets due past 90 days and assets placed on nonaccrual status. It is also measured by equity over assets.

To account for the effect of compliance, I included two proxies; non-interest expenses divided by net income and salaries and benefits divided by non-interest expenses. Non-interest expenses divided by net income is a measure of efficiency, and will be referred to as such from now on.

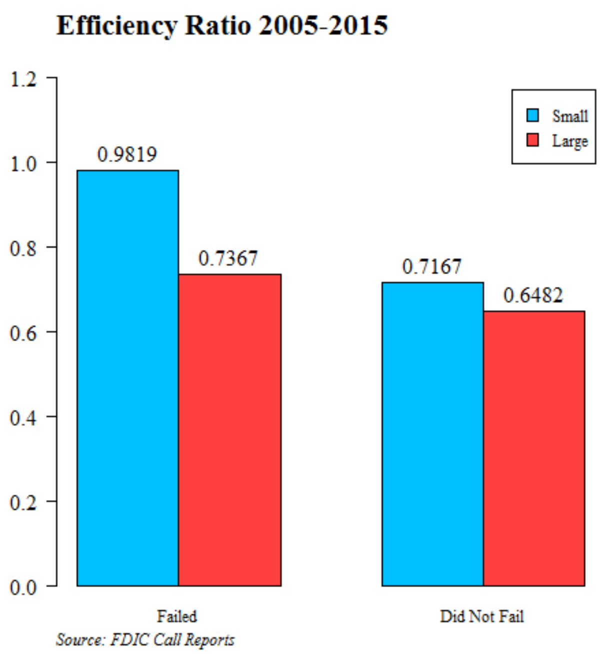
Macroeconomic variables are year-over-year change in gross domestic product (GDP) and 10-year bonds. These variables are used only in the survival analysis models.

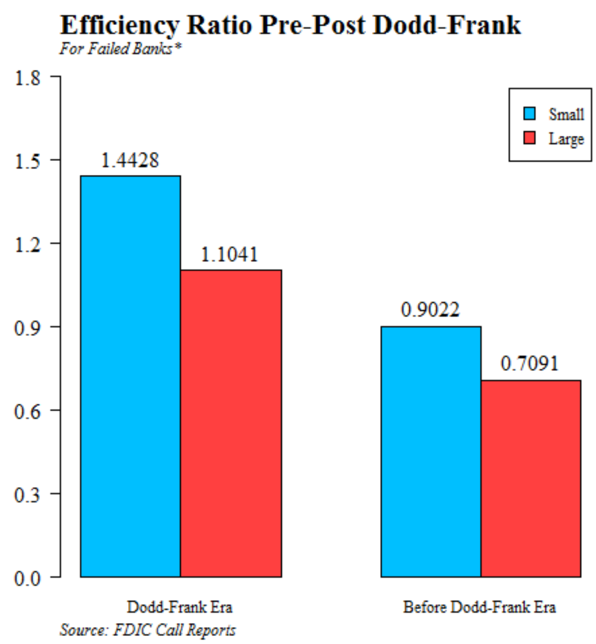
From initial descriptive statistics, some observations are noted. In the fourth quarter of 2011, return on assets reached a high over 1.1 percent. In the following years it stayed below 1 percent until the fourth quarter of 2014, implying a slow earnings period for financial institutions. The Basel standards for capital adequacy stayed below an average of 20% from the end of 2006 until the third quarter of 2010, implying that financial institutions felt confident in the years prior and during the recession. The year after Dodd-Frank was introduced capital adequacy has remained stable at around 21%. The non-interest expense ratio increased significantly when looking at the years prior to the recession and after, implying that financial institutions are spending more money on fixed costs, employee salaries and benefits, and regulatory costs. Time series graphs depicting the change in median return on assets and capital adequacy ratios are shown in this section, and a table of more descriptive statistics can be found in the Appendix.

Efficiency and Salary Ratio Trends

This sections aims to clarify how non-interest expenses play a role in explaining bank failure. In this experiment, non-interest expenses are included in the efficiency ratio; non-interest expenses over net income. Non-interest expenses include salaries and benefits, expenses of premises and fixed assets, gains or losses on other real estate owned, loans sales, fixed assets sales, amortization of intangible assets, and other itemized expenses. Salaries and benefits make up the majority of this category. Due to the compliance-heavy nature of the Dodd-Frank Act, I believe non-interest expenses would rise during this period as compliance personnel are added to each financial institution's workforce.

I created sets of graphs to visualize the trends in efficiency and salary ratio. The first set of columns are the means for efficiency for small and large banks that failed during this period, respectively. The second set are the means for non-failed banks. For small banks, the respective averages are 0.9819 and 0.7167. For large banks, the averages are 0.7367 and 0.6482. These data sets do not differ in averages to a high degree.





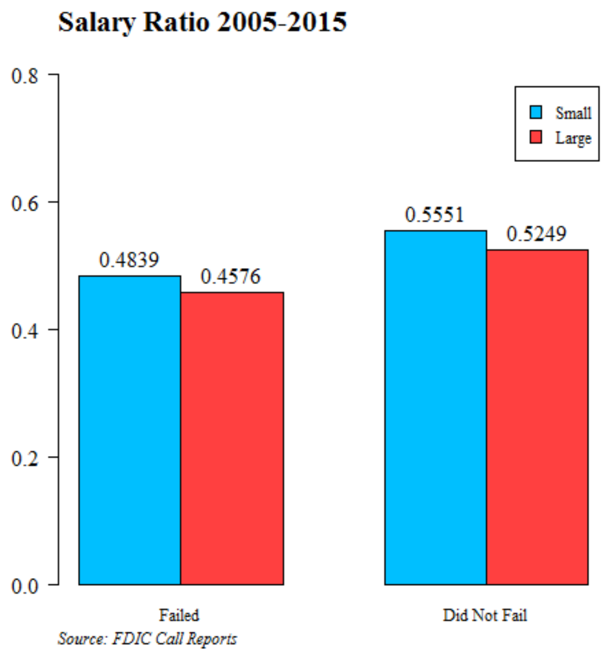
The next figure uses the same set, but separates the failed banks between pre-Dodd-Frank and post-Dodd-Frank. There is a stark difference in how the efficiency ratio is correlated with failure in these two time periods. Small banks that failed during Dodd-Frank had an average efficiency ratio of 1.4428, while the mean for non-failed small banks before that was 0.9022. For large banks, the averages were 1.1041 and 0.7091. This represents a drastic change in what causes bank failure in these two time periods.

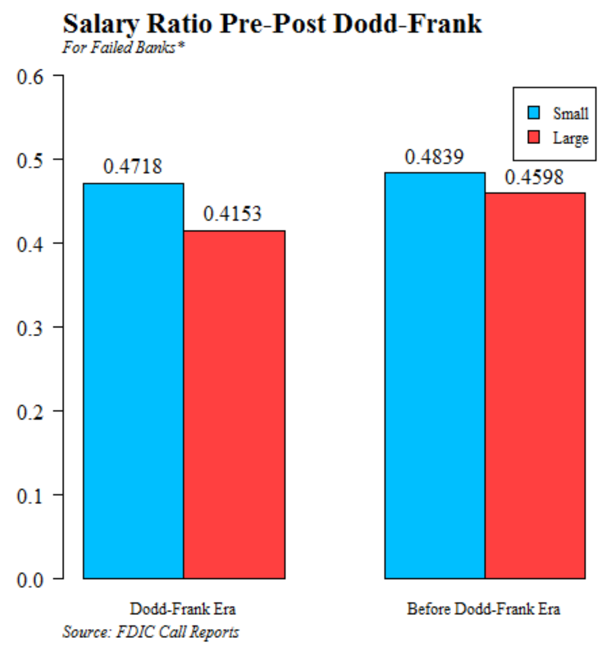
Salary Ratios

Small banks during this time period had an average salary ratio of 55.1 percent. For big banks, this average was 51.2 percent. These means correspond to both failed and non-failed banks. Looking at failed banks specifically, small and large banks had respective salary ratios of 48.4 and 45.8 percent. For non-failed banks, 55.5 and 52.5 percent. The similarity between these groups is that big banks spend a lower proportion of their non-interest expenses on salaries.

When looking at comparisons between pre and post-Dodd-Frank, banks that failed after Dodd-Frank had lower salary ratio averages than pre--Dodd-Frank failed banks. For small banks, the averages were 0.4718 and 0.4839. For large banks, 0.4153 and 0.4598. Combined with the fact that failed banks in Dodd-Frank had higher efficiency ratios, it is clear that these two ratios play vital roles in discovering how Dodd-Frank affected failure. These results below

When comparing real non-interest expenses, it is worth mentioning that for small banks, non-interest expenses changed very little over the length of the study. As for large banks, non-interest expenses were just returning to pre-recession levels towards the end of 2015.





Time trends are displayed in figures A, B, C, D in the Appendix. As 2015 consumer price index had not been released at the time of publishing, these graphs only contain the years 2005 through 2014.Both size groups tend to move in the same direction with regards to the efficiency and salary ratios. Small banks have consistently higher ratios. While the difference in salary ratio is only a few percent, the difference in efficiency can increase to over ten percent.

Methodology

Survival Analysis Model

The model used in this experiment is longitudinal survival analysis using quarterly discrete observations. Specifically, the model was a random-effects Weibull model. Weibull distribution was selected due to the increasing risk of failure that occurred in the study as the recession hit. Since the sample size did not include every bank listed under FDIC, a random-effects model was used for the general regression while a mixed-effect model was used for the interaction models. Survival analysis shows how different variables affect time to a specific event, which in this case is when a bank is deemed closed by the Federal Deposit Insurance Corporation. A key concept of survival analysis is the hazard function, which is shown below.

$$h(t) = \lim_{\Delta t \to 0} \frac{R(t) - R(t + \Delta t)}{\Delta t \cdot R(t)}.$$

The hazard function is defined as the event rate at time *t* conditional on survival until time *t* or later. In terms of bank failure, this means the rate of bank failures at a specified time. For this experiment, I chose to find hazard ratios for control and treatment groups. For a bank to be contained in a treatment group, it would need to follow certain criteria during a quarter. For example, if a bank has below $1 billion in assets at a time *t*, it would be assigned to the small bank group. This allows us to discern the relative hazard functions between a small bank and a large bank. The hazard ratio would provide the relative risk of failure for a small bank compared to a large bank at any given time.

When it comes to bank failure in terms of survival analysis, there are two possible events; a Type 1 event is a bank closure, and a Type 2 event is a bank merger. This project solely dealt with a Type 1 event, so any banks that merged during the event of the 11-year study was removed. As I did not want any left-censoring, I also removed any banks that were not open at the advent of the study but joined later. I understand this would cause bias in the study, as some banks that were close to failure would merge instead.

As an attempt to measure how Dodd-Frank changed the way banks fail, I found that creating interaction terms helped. Creating indicators for the Dodd-Frank period and measures of compliance and then interacting them allows for a variety of options. I was able to create six regression based off the main model that substituted continuous variables for factor variables. To find appropriate levels for these factor variables, I observed how these ratios differed for failed banks after Dodd-Frank was introduced.

Efficiency ratios for failed banks during the study averaged around 92 percent. This number was calculated using all failed banks, regardless of size. Since this was drastically different than non-failed banks' average of 71 percent, using a cutoff between these two numbers would provide significant results. After trying a few levels, I found that 90 percent gave the most significant results.

An indicator for salary was harder to determine as the difference between failed and non-failed banks was not as drastic as for efficiency. Respectively, the means were 48 and 55 percent. Using a number in between these two means provided insignificant results, so I went slightly above the non-failed mean and used 60 percent.

This model varied from previous failure models of the past. After constructing a usual early warnings signs model, I found indicators of the past used to detect such as net loans over deposits, net loans over assets, and real estate exposure, to be highly insignificant. As a robustness check, I removed some of these variables to check the validity of other indicators. For liquidity, for which net loans divided by deposits is typically used, I found solvency and capital adequacy as much more powerful indicators of any potential capital risk. To account for removing measures of asset quality such as exposure to the real estate market and loans due past 90 days, I added NONACCRUAL, a ratio of non-accrued loans divided by net loans. This accounts for any loan that is not accruing interest, which would include any risky real estate loans and loans due past 90 days.

To determine whether the variable DF, which was in place for every time period past the first quarter of 2010, was a good indicator of the immediate impact of the Dodd-Frank Act, I first only included DF for the first year of the act. I found this to be an insignificant variable. I only found DF to be significant when it was in place for the remaining time periods.

To control for any unrealistic outliers, I checked each variable included in the regression. Outliers were checked with quantiles. This process divides the range of the probability distribution into five markers along the range. Therefore I could examine the 0 and 100 percent markers for irregularities. Any data that was unlikely to be authentic was removed.

Hypotheses

Hypothesis 1: The Efficiency Ratio is a significant factor in bank failure during 2010 and 2011.

In a 2014 survey by Thomson Reuters, half of compliance professionals predicted compliance costs would increase in the coming year, a sentiment that had been the case for the previous years. After the introduction of Dodd-Frank, non-interest expenses for banks increased and I believe this is a key component in failure.

Hypothesis 2: Banks with a higher salary ratio before and after Dodd-Frank Act have a lower risk of failure.

A study by Hellerstein, Neumark, and Troske (1999) found that the higher pay of workers correlates with improved marginal productivity. Higher marginal productivity would result in lower risk of failure. In regards to the effects of compliance costs, Bace, Rozwell, Feiman, Kirwin (2006) found that about 15 percent of compliance costs are composed of staff costs.

Results

General Model Results

Main Regression

Capital Adequacy	**0.8239**
	(0.024)***
Solvency	**6.226**
	(1.925)***
Return on Assets	**1.067**
	(0.022)***
Equity to Assets	**0.717**
	(0.032)***
Efficiency	**1.001**
	(0.000)***
Salary Ratio	**0.988**
	(0.002)***
Bad Loans	**1.040**
	(0.007)***
Insider Loans	**0.914**
	(0.044)
GDP	**0.914**
	(0.022)***
Long-Term Yield	**2.312**
	(0.346)***
Log(Assets)	**1.086**
	(0.057)
Age	**0.991**
	(0.002)***
LN_P	**1.255**
	(0.103)***
Log Likelihood	63.7
# Observations	143,050
# Banks	3,941
# Failures	466

*** - 5 Percent
** - 1 Percent
* - 0.1 Percent

The model used in this experiment is shown here. Capital adequacy and solvency are the greatest financial measures of failure. A one percent increases in capital adequacy reduces risk by almost 18 percent. Solvency was given an indicator variable if a bank had above a one-to-one ratio. A ratio of one implies the bank has enough funds to cover any potential losses due to nonaccrual loans. If a bank goes over this ratio, either it does not have enough loan loss allowance, an indicator of poor management quality and risky behavior, or failing loans, an indicator of credit risk. In this study, if a bank has over a one-to-one ratio, it is 6.22 time more likely to fail than a bank who remain below this level. This implies that risky behavior or credit risk are major causes for bank failure. While increasing loan loss allowance reduces the amount of deposits that can be used for loans, taking safe protocols is shown to reduce failure by a large margin. Insider loans, a measure of management quality, proved to actually decrease the risk of bank failure, as a one percent increase reduces the risk of bank failure by nine percent. For earnings, a one percent increase in return on assets, measured by net income divided by assets, increases risk of failure by almost seven percent. Age has a large impact on bank failure, and a one year increase in longevity reduces bank failure by one percent. As some of the banks in this study have been around for over a century, this is a meaningful results. A bank founded in 1900, holding all else constant, is half as likely as a bank in 2000 to fail. Equity over assets, which measures how much of the bank is held by shareholders, proves to be one of the biggest indicators of bank failure. Just a one percent increase in this ratio reduces bank failure by 28 percent. A higher equity-to-assets ratio implies that the liabilities-to-assets ratio is smaller, as assets is equivalent to liabilities and equity. Having a lower liabilities-to-assets ratio puts the bank at lower risk of insolvency. A one percent increase in non-accrual loans to net loans increases risk of failure by four percent. This measure of asset quality, which was used instead of the preliminary measures of asset quality, proved the most substantial and significant of the variables.

Factor and Interaction Models

Results from using indicator variables for post-Dodd-Frank effects on failure variables indicate that banks that increased salary as a proportion of non-interest expenses fared much better than banks that did not. Efficiency is a key problem. While real interest-expenses did not rise over the decade studied, income fell, costing financial institutions profits they earned over previous periods. Banks that were not able to compete with decreased profits and increased regulation by shifting the bulk of expenses to salary and benefits had a higher risk of failure. Appendix A shows six additional regressions in addition to the normal bank failure model. These six regress the same model, but each also contains a two-way interaction term. The one-way terms are;

1. DF: Equal to one from the period from the second quarter of 2010 until the end of the study to indicate the period of the Dodd-Frank Act;
2. SALRATDUM: Equal to one if a financial institution has a salary to non-interest expenses ratio above 60%. This will be referred to as a “well-paid” bank versus a “poorly-paid” bank;
3. EFFDUM: Equal to one if a financial institution has a non-interest expenses to net income ratio above 90%. This will be referred to as an “inefficient” bank versus an “efficient”;
4. SB: Equal to one if a financial institution has total assets below one billion.

Two-Factor Interactions

In this section I ran six mixed-effects models consisting of the previously mentioned interaction terms to discover the effects of Dodd-Frank and to see how the other areas of interest interact with each other.

Dodd-Frank Interactions

Dodd-Frank Interactions

	COEFFICIENT	STD. ERROR	LOG LIK.
DF	0.773	0.155	-
SALRATDUM	0.518	0.305	-
DF*SALRATDUM	0.244	0.078***	61.8
DF	0.249	0.093***	-
EFFDUM	2.404	0.452***	-
DF*EFFDUM	1.872	0.464*	95.7
DF	0.275	0.117**	-
SMALLBANK	0.522	0.115**	-
DF*SMALLBANK	0.446	0.119**	69

*** - 5 Percent
** - 1 Percent
* - 0.1 Percent

Before Dodd-Frank, well-paid banks were 48 percent lower at risk of failing than poorly-paid banks. After Dodd-Frank, this number increased to 124 percent. This seems consistent with the overall increasing salary ratio trend shown in figure H as well as the decrease in salary ratios for failed banks during 2010-2015 when compared to the previous five years. There are a couple theories for this; Dodd-Frank increased compliance costs through a mixture of forced and unforced regulation. Banks that opted to hire more regulatory consultants fared better in this new market. Another possibility is that since failed banks in both periods had similar while the overall trend for all banks was increasing implies that failed banks were not paying the same share of expenses to their employees as the market was.

Before Dodd-Frank, efficient banks were 140 percent less likely to fail than inefficient banks. After Dodd-Frank, this number increased to 228 percent. This coincides with the general upwards trend in inefficiency. The averages for both size groups increased around 7.5 percent from 2005 to 2015. Banks that were able to keep costs low and profits high during a period of rising expenses were more stable during Dodd-Frank than before it.

Before Dodd-Frank, small banks were 48 percent less likely to fail than big banks. After Dodd-Frank, this number increased to 103 percent. Overall, the three indicators listed factored heavily into bank failure before Dodd-Frank as well as after.

Non-Dodd-Frank Interactions

Other Two-Way Interactions

	COEFFICIENT	STD. ERRO	LOG LIK.
SALRATDUM	0.122	0.132*	-
SB	0.692	0.133*	-
SALRATDUM*SB	0.230	0.076***	61.4
SALRATDUM	0.343	0.188*	-
EFF	3.455	0.557***	-
SALRATDUM*EFF	1.109	0.373	85.2
SB	0.662	0.209	-
EFF	3.396	1.112***	-
SB*EFF	2.264	0.667**	87.8

*** - 5 Percent
** - 1 Percent
* - 0.1 Percent

Inefficiency is a massive indicator of failure, and an inefficient but well-paid bank is still much more at risk than an inefficient bank that spends a large proportion of it expenses on salaries. However, well-paid but inefficient banks were 257 percent more likely to fail than well-paid but efficient banks. This is more apparent when comparing the difference in how salary affects the two levels of efficiency, as having a low salary ratio contributes less risk to inefficient banks than to efficient banks. Well-paid and efficient banks were 66 percent less likely to fail than efficient but poorly-paid banks.

A high salary ratio decreases the risk of failure in both size groups with significant results. Small, well-paid banks were 165 percent less likely to fail than small, poorly-paid banks, while the difference for large banks was 88 percent. More so, small, well-paid banks were 108 percent less likely to fail than large, well-paid banks. However, small, poorly-paid banks were just 31 percent less likely to fail than large, poorly-paid banks. Small banks that can also pay their employees well reap the rewards of doing so; higher pay would increase productivity (Helper, Noonan 2015).

Inefficiency plays a large role for bank failure regardless of size, but larger banks might be able to hang on if they are not doing so well by cutting expenses. Smaller banks would have a harder time cutting costs that would not affect the big business decisions of the bank. An efficient, small bank is 366 percent less likely to fail than an inefficient, small bank. An efficient, large bank is 240 percent less likely to fail than an inefficient, large bank. The benefits of efficiency are less pronounced for smaller banks than they are for large banks, and may explain the differing impact of Dodd-Frank on bank size. The ability of big banks to ride out a period of high expenses and/or low income is not as transferable to banks of smaller size. This correlates with Dolar and Shughart's findings on the Patriot Act disproportionately affecting small banks (2007). While the results become insignificant when running a three-way interaction, when including the finding that inefficiency became a bigger cause of risk after Dodd-Frank and that inefficiency hurts small banks more than large banks, it seems likely that the Dodd-Frank Act further increased the difference in failure risk between the size groups when looking at efficiency.

Conclusion

During the study, real expenses did not rise, but real income did not rise much either. Costs were not returning the same levels of profits as before, and many banks did not adjust to this change. This hit small banks harder than large banks. Looking just at size differences, small banks overall had better odds of surviving. But inefficient small banks had higher failure rates than inefficient large banks, and did not have much wiggle room when it came to cutting costs or scaling down operations. By looking at efficiency means for failed banks, both sizes saw massive increases after Dodd-Frank. Banks that closed in the five years after Dodd-Frank had costs well above their revenue, and this can be partially explained by rising compliance costs imposed on banks. However, while these differences were over 40 percent, the overall trend of efficiency ratios implies that these banks were not adjusting as others were in a new regulatory climate.

Furthermore, while average salary ratios were increasing among both size groups, failed banks in both time periods had similar averages. This reflects the results shown when interacting the Dodd-Frank and salary ratio indicators. Having a ratio above 60 percent after Dodd-Frank became a crucial indicator of the health of a bank. Before the act, well-paid banks had a 50 percent lower risk of failure; after the act, this more than doubled to almost 125 percent. Banks that were not able to meet this growing importance in salaries could not compete with banks that did.

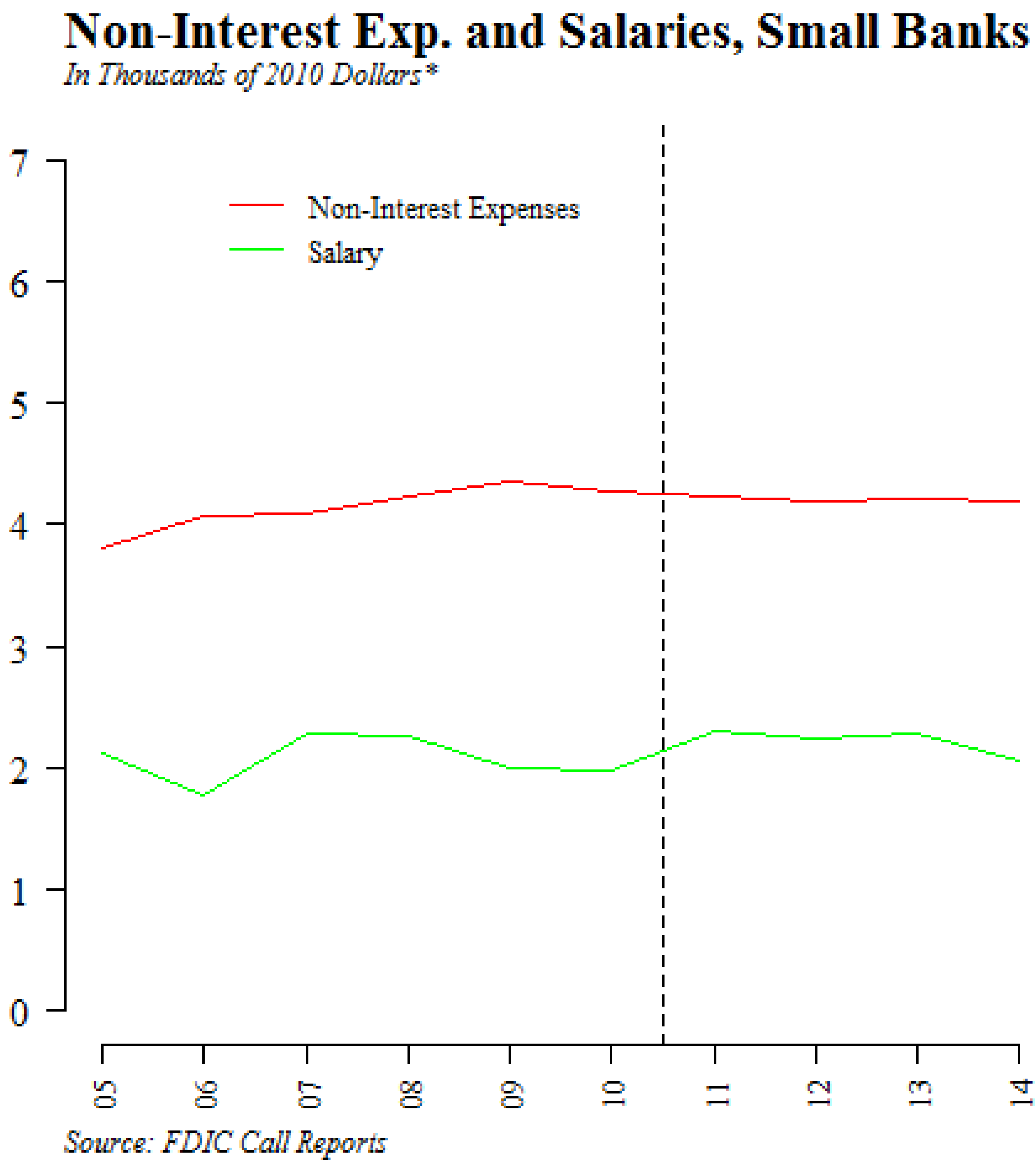
Looking at the effect of these ratios on bank size, efficiency plays a larger role for small banks, as they face higher risks if they are labeled inefficient compared to efficient banks in their size group. However, they also are rewarded more so than large banks for increasing their salary ratio.

Appendix

Variable Description

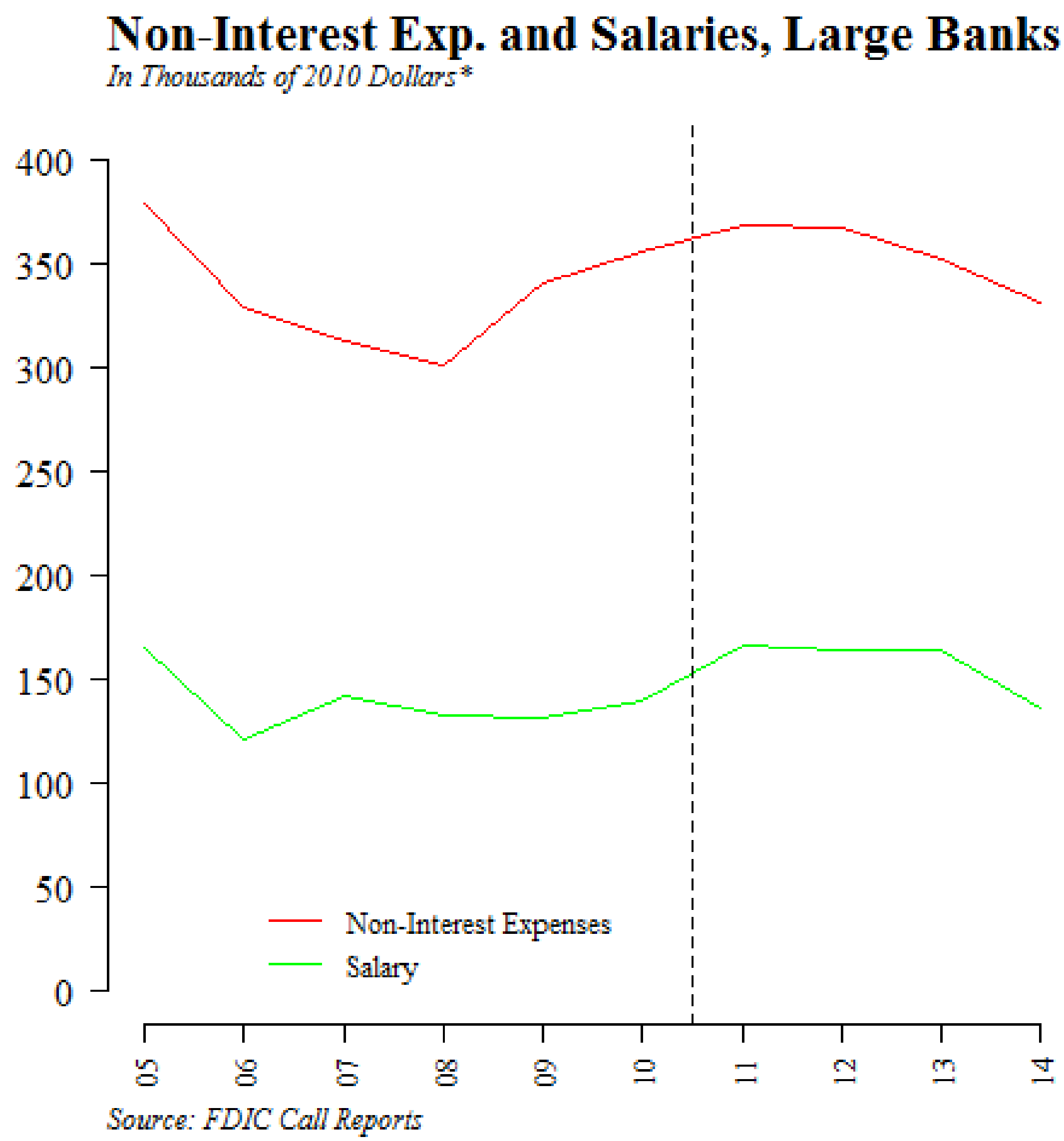
Variable	**Definition**
Capital Adequacy	Tier 1 Capital plus Tier 2 Capital Over Risk-Weighted Assets
Solvency	Loan Loss Allowance Over Nonaccrual Assets Plus Assets Past 90 Days
Return on Assets	Net Income Over Assets
Equity to Assets	Equity Over Assets
Efficiency	Non-Interest Expenses Over Net Income
Salary Ratio	Proportion of Non-Interest Expenses Composed of Salaries and Benefits
Bad Loans	Assets Past 90 Days or More Plus Assets Place on Nonaccrual Status Over Net Loans
Insider Loans	Loans to Executives, Managers, Shareholders, etc Over Net Loans
GDP	Percent Change From Preceding Period in Real Gross Domestic Product
Long-Term Yield	Long-term government bond yields
Log(Assets)	Natural Log of Total Assets Per Quarter (In Thousands)
Age	Age of Bank in Years Since Formation
LN_P	Indicates How Risk Increased or Decreased Throughout Timeline
DF	Indicator Variable Equal to 1 if the Observation Takes Place During Dodd-Frank Era
EFFDUM	Indicator Variable Equal to 1 if the Efficiency Ratio is Above 90 Percent
SALRATDUM	Indicator Variable Equal to 1 if the Salary Ratio is Above 60 Percent
SB	Indicator Variable Equal to 1 if Assets are Greater than 1 Billion

Figure A



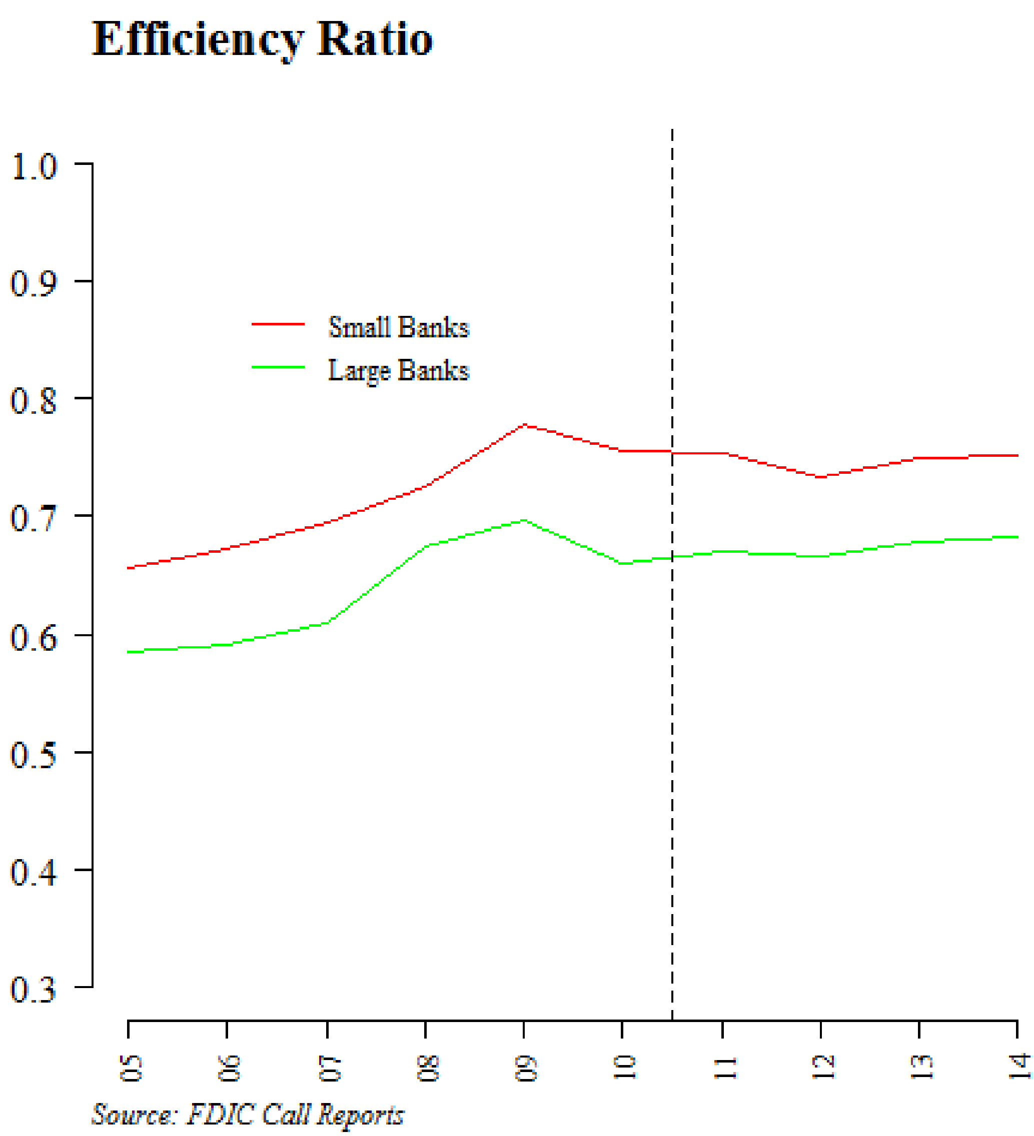
***Dashed line indicates when the Dodd-Frank Act was brought into effect**

Figure B



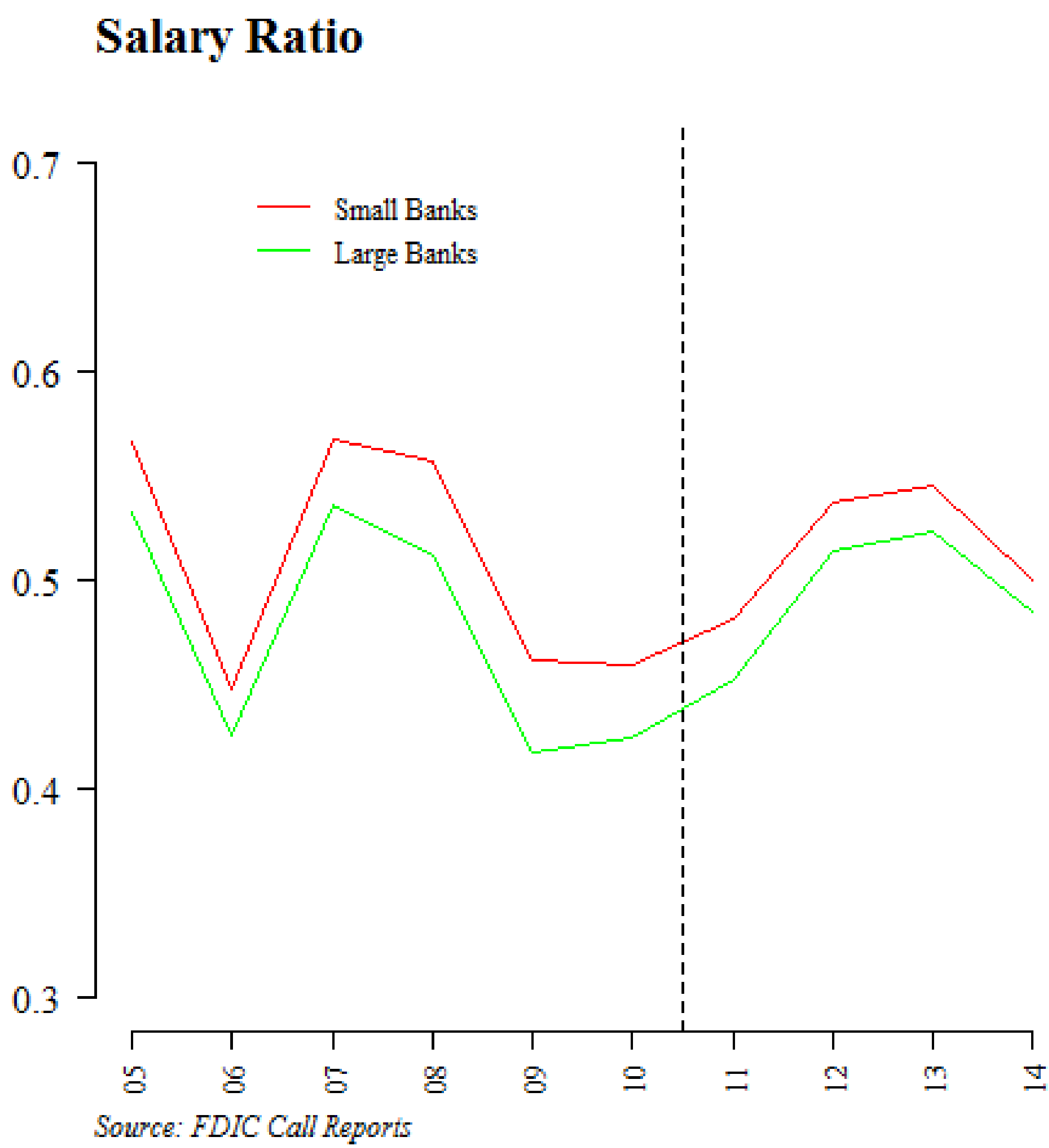
***Dashed line indicates when the Dodd-Frank Act was brought into effect**

Figure C



***Dashed line indicates when the Dodd-Frank Act was brought into effect**

Figure D



***Dashed line indicates when the Dodd-Frank Act was brought into effect**

Descriptive Statistics

Quarter	Cap. Ad.	Eq.-Assets	Non-Int.Exp	90+	LLC	ROA	Insider Loans	Loans-to-Assets
2005_Q1	0.217	0.117	0.716	0.003	0.691	0.007	0.020	0.618
2005_Q2	0.220	0.117	0.681	0.003	0.682	0.006	0.020	0.629
2005_Q3	0.216	0.116	0.669	0.003	0.702	0.009	0.020	0.635
2005_Q4	0.215	0.114	0.676	0.003	0.688	0.011	0.020	0.631
2006_Q1	0.217	0.114	0.675	0.003	0.681	0.003	0.020	0.633
2006_Q2	0.214	0.114	0.668	0.003	0.690	0.006	0.020	0.645
2006_Q3	0.200	0.117	0.666	0.003	0.753	0.009	0.020	0.647
2006_Q4	0.198	0.115	0.678	0.003	0.746	0.012	0.020	0.640
2007_Q1	0.198	0.116	0.691	0.003	0.793	0.003	0.020	0.639
2007_Q2	0.192	0.116	0.684	0.003	0.836	0.006	0.020	0.649
2007_Q3	0.193	0.118	0.683	0.003	0.908	0.009	0.021	0.651
2007_Q4	0.190	0.116	0.695	0.003	0.974	0.011	0.020	0.649
2008_Q1	0.190	0.116	0.709	0.003	1.101	0.003	0.020	0.640
2008_Q2	0.188	0.114	0.528	0.003	1.190	0.005	0.020	0.652
2008_Q3	0.188	0.114	0.694	0.003	1.298	0.007	0.020	0.658
2008_Q4	0.187	0.113	0.716	0.003	1.409	0.007	0.020	0.653
2009_Q1	0.188	0.113	0.726	0.004	1.583	0.002	0.020	0.642
2009_Q2	0.188	0.113	0.746	0.004	1.646	0.003	0.020	0.644
2009_Q3	0.189	0.115	0.732	0.004	1.790	0.004	0.020	0.641
2009_Q4	0.187	0.112	0.746	0.003	1.637	0.004	0.020	0.631
2010_Q1	0.191	0.113	0.720	0.004	1.693	0.002	0.020	0.622
2010_Q2	0.192	0.114	0.716	0.004	1.700	0.004	0.020	0.625
2010_Q3	0.202	0.115	0.714	0.003	1.686	0.005	0.020	0.620
2010_Q4	0.194	0.112	0.732	0.003	2.006	0.006	0.020	0.612
2011_Q1	0.197	0.112	0.726	0.003	1.713	0.002	0.020	0.595
2011_Q2	0.199	0.115	0.728	0.003	1.711	0.004	0.020	0.599
2011_Q3	0.200	0.116	0.716	0.003	1.551	0.006	0.020	0.595
2011_Q4	0.199	0.115	0.726	0.003	1.462	0.007	0.020	0.590
2012_Q1	0.203	0.115	0.715	0.003	2.571	0.002	0.020	0.575
2012_Q2	0.204	0.117	0.717	0.003	1.352	0.005	0.019	0.584
2012_Q3	0.206	0.118	0.715	0.003	1.433	0.007	0.020	0.585
2012_Q4	0.204	0.116	0.726	0.002	1.391	0.009	0.019	0.580
2013_Q1	0.208	0.116	0.737	0.002	1.441	0.002	0.020	0.569
2013_Q2	0.207	0.114	0.728	0.002	1.253	0.005	0.019	0.584
2013_Q3	0.208	0.114	0.727	0.002	1.216	0.007	0.019	0.588
2013_Q4	0.208	0.114	0.736	0.002	1.158	0.009	0.019	0.590
2014_Q1	0.209	0.115	0.737	0.002	1.143	0.002	0.019	0.583
2014_Q2	0.208	0.117	0.730	0.002	1.075	0.005	0.019	0.595
2014_Q3	0.209	0.118	0.707	0.002	1.268	0.008	0.019	0.601
2014_Q4	0.207	0.118	0.732	0.002	1.042	0.010	0.019	0.604
2015_Q1	0.212	0.119	0.727	0.002	1.006	0.003	0.019	0.599
2015_Q2	0.207	0.119	0.720	0.002	1.141	0.005	0.019	0.612
2015_Q3	0.207	0.121	0.719	0.002	1.061	0.008	0.018	0.617
2015_Q4	0.213	0.119	0.725	0.002	1.048	0.010	0.018	0.617

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