ESSAYS IN BANKING AND FINANCE:

SECURITIZATION, SYSTEMIC RISK AND HEALTHCARE REFORM

by

GANG DONG

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ABSTRACT OF THE DISSERTATION

Essays in Banking and Finance:

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By GANG DONG

Dissertation Director:

Professor Darius Palia

This dissertation includes three essays. The first essay identifies the determinants of bank's risk contribution to systemic risk, and documents that banks with higher non-interest income (noncore activities like investment banking, venture capital and trading activities) have a higher contribution to systemic risk than traditional banking (deposit taking and lending). After decomposing total non-interest income into two components, trading income and investment banking and venture capital income, we find that both components are roughly equally related to systemic risk. These results are robust to endogeneity concerns when we use a difference-in-difference approach with the Lehman bankruptcy proxying for an exogenous shock. We also find that banks with higher trading income one-year prior to the recession earned lower returns during the recession period. No such significant effect was found for investment banking and venture capital income.

The second essay analyzes the effect of mortgage securitization on the real economy and housing market. I estimate the dynamic response of housing risk and real GDP to shocks of mortgage securitization and banks' ownership of mortgage-backed security (MBS), and test three hypotheses suggested in the extant literature. Using

structural vector autoregression (SVAR) methodology and cross-sectional analysis, I find that securitization reduces housing risk by completing the market. Interestingly, housing risk increases when commercial banks' ownership of MBS increases. This positive relationship is inconsistent with the agency view of securitization but is consistent with the neglected risk view of mortgage securitization (Gennaioli, Shleifer, and Vishny 2011). The causal inference is drawn from a quasi-experimental design using housing data of bordering CBSA regions in neighboring states with and without the passing of anti-predatory lending laws.

The third essay identifies the passing of the Patient Protection and Affordable Care Act (PPACA) as an exogenous shock and uses the event study method to estimate the stock market's reaction in terms of asset price changes in the health care sector. The stock market appears to view the passing of PPACA as good news to the home care and specialty outpatient services but bad news to the medical instrument and health insurance industries. This might suggest that the existing institutional structure of the insurance industry is biased against comprehensive health, and most growth opportunities exist in the home care and specialty outpatient services. Furthermore, the magnitude of the abnormal return is relatively larger for firms with higher profit and R&D investment, but smaller for firms held by healthcare-specialized institutional investors, which is consistent with the literature that price changes are partially due to information revelation efforts by sophisticated institutional investors.

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CHAPTER 1: Banks' Non-Interest Income and Systemic Risk

(jointly with Markus Brunnermeier and Darius Palia)

1.1 Introduction

The recent financial crisis of 2007-2009 was a showcase of large risk spillovers from one bank to another heightening systemic risk. But all banking activities are not necessarily the same. One group of banking activities, namely, deposit taking and lending make banks special to information-intensive borrowers and crucial for capital allocation in the economy.[1]

However, prior the crisis, banks have increasingly earned a higher proportion of their profits from non-interest income compared to interest income.[2] Non-interest income includes activities such as income from trading and securitization, investment banking and advisory fees, brokerage commissions, venture capital, and fiduciary income, and gains on non-hedging derivatives. These activities are different from the traditional deposit taking and lending functions of banks. In these activities banks are competing with other capital market intermediaries such as hedge funds, mutual funds, investment banks, insurance companies and private equity funds, all of whom do not have federal deposit insurance. Table I shows the mean non-interest income to interest income ratio has increased from 0.18 in 1989 to 0.59 in 2007 for the 10-largest banks (by market capitalization in 2000, the middle of our sample). Figure 1.1 shows big increases in the average non-interest income to interest income ratio starting around

[1] Bernanke (1983), Fama (1985), Diamond (1984), James (1987), Gorton and Pennachi (1990), Calomiris and Kahn (1991), and Kashyap, Rajan, and Stein (2002) as well as the bank lending channel for the transmission of monetary policy studied in Bernanke and Blinder (1988), Stein (1988) and Kashyap, Stein and Wilcox (1993) focus on this role of banking.

[2] When we refer to interest income we are using *net* interest income, which is defined as total interest income less total interest expense (both of which are disclosed on a bank's Income Statement).

2000 and lasting to 2008. This effect is more pronounced when we use a value-weighted portfolio than an equally-weighted portfolio.

*** Table I and Figure 1.1 ***

This paper examines the contribution of such non-interest income to *systemic* bank risk. In order to capture systemic risk in the banking sector we use two prominent measures of systemic risk. The first is the Δ*CoVaR* measure of Adrian and Brunnermeier (2008; from now on referred to as AB). AB defines *CoVaR* as the value at risk of the banking system conditional on an individual bank being in distress. More formally, Δ*CoVaR* is the difference between the *CoVaR* conditional on a bank being in distress and the *CoVaR* conditional on a bank operating in its median state. The second measure of systemic risk is *SES* or the Systemic Expected Shortfall measure of Acharya, Pedersen, Philippon, and Richardson (2010; from now on defined as APPR). APPR define *SES* to be the expected amount that a bank is undercapitalized in a systemic event in which the entire financial system is undercapitalized. Note that Δ*CoVaR* measures the externality a bank causes on the system, while SES focuses how much a bank is exposed to a potential systemic crisis.

In this paper, we begin by estimating these two measures of systemic risk for all commercial banks for the period 1986 to 2008. We examine four primary issues: (1) Is there a relationship between systemic risk and a bank's non-interest income? (2) From 2001 onwards, banks were required to report detailed breakdowns of their non-interest income. We categorize such items into two sub-groups, namely, trading income, and investment banking/venture capital income, respectively. We examine if any sub-group has a significant effect on systemic risk. (3) We hence check if the above two results are driven by endogeneity concerns, namely that significant omitted variables are correlated with both non-interest income and systemic risk. (4) Finally, we examine if there is a relationship in the levels of *pre-crisis* non-interest income and the bank's stock returns earned *during the crisis*.

Our results are the following:

1. Systemic risk is higher for banks with a higher non-interest income to interest income ratio. Specifically, a one standard deviation increase to a bank's non-interest income to interest income ratio increases its systemic risk contribution by 11.6% in $\Delta CoVaR$ and 5.4% in SES. This suggests that activities that are *not* traditionally linked with banks (such as deposit taking and lending) are associated with a larger contribution to systemic risk.
2. Glamour banks (those with a high market-to-book ratio) and more highly levered banks contributed more to systemic risk. Generally, larger banks contributed more than proportionally to systemic risk, which is consistent with the findings in AB.
3. After decomposing total non-interest income into two components, trading income and investment banking/venture income, we find that both components are roughly equally related to ex ante systemic risk. A one standard deviation increase to a bank's trading income increases its systemic risk contribution by 5% in $\Delta CoVaR$ and 3.5% in *SES,* whereas a one standard deviation shock to its investment banking and venture capital income increases its systemic risk contribution by 4.5% in $\Delta CoVaR$ and 2.5% in *SES*.

4. The difference-in-difference results show that banks with larger non-interest income contributed more to systemic risk than banks with low non-interest income after the Lehman shock. We find similar results for banks with the highest trading or investment banking/venture capital income compared to their counterparts with the lowest trading or investment banking/venture capital income. This suggests that our results are not driven by omitted variables(s) that happen to be correlated with both non-traditional income and systemic risk.
5. When we examine realized ex post risk, we find that banks with higher trading income one-year before the recession earned lower returns during the recession period. No such significant effect was found for investment banking and venture capital income of commercial banks. We also find that larger banks earned lower stock returns during the recession.

These results are robust to alternative proxies of non-interest income, excluding the largest banks and to defining systemic risks with respect to the market portfolio. Our finding that procyclical non-traditional activities (such as investment banking, venture capital and private equity income) can increase systemic risk is consistent with a number of papers. In the model of Shleifer and Vishny (2010), activities where bankers have less 'skin in the game' are overfunded when asset values are high which leads to higher systemic risk.[3] Similarly, Song and Thakor (2007) suggest that these transaction based activities can lead to higher risk. While not explicitly focusing on traditional and investment banking activities, Wagner (2010) theoretically argues that diversification can led to higher systemic risk because undertaking similar activities increase the

[3] Our non-traditional banking activities are similar to banking activities such as loan securitization or syndication wherein the banker does not own the entire loan (d < 1 in their model).

likelihood of failing at the same time. Our results are also consistent with Fang, Ivashina and Lerner (2010) who find private equity investments by banks to be highly procyclical, and to perform worse than those of nonbank-affiliated private equity investments.

In section 2 of this paper we describe the related literature and Section 3 explains our data and methodology. Section 4 presents or empirical results and in Section 5 we conclude.

1.2 Related Literature

Recent papers have proposed complementary measures of systemic risk other than Δ*CoVaR* and *SES.* Bisias, Flood, Lo and Valavanis (2012) provde an overview of the growing numbers of systemic risk measures. Allen, Bali and Tang (2010) propose the *CATFIN* measure which is the principal components of the 1% *VaR* and expected shortfall, using estimates of the generalized Pareto distribution, skewed generalized error distribution, and a non-parametric distribution. Brownlees and Engle (2010) define marginal expected shortfall (*MES*) as the expected loss of a bank's equity value if the overall market declined substantially. Tarashev, Borio, and Tsatsaronis (2010) suggest Shapley values based on a bank's of default probabilities, size, and exposure to common risks could be used to assess regulatory taxes on each bank. Billio, et al. (2010) use principal components analysis and linear and nonlinear Granger causality tests and find interconnectedness between the returns of hedge funds, brokers, banks, and insurance companies. Chan-Lau (2010) proposes the *CoRisk* measure which captures the extent to which the risk of one institution changes in response to changes in the risk of another institution while controlling for common risk factors. Huang, Zhou, and Zhu (2009,

2010) propose the deposit insurance premium (*DIP*) measure which is a bank's expected loss conditional on the financial system being in distress exceeding a threshold level.

Prior empirical papers that have examined whether diversification has been beneficial or detrimental to the risk of an *individual bank* (Saunders and Walter 1994, and DeYoung and Roland 2001 provide detailed literature reviews). While our study focuses on the effect of such diversifying activities on a bank's contribution to systemic risk, the literature on individual bank risk shows mixed evidence. On the one hand, Stiroh (2004, 2006) and Fraser, Madura, and Weigand (2002) find that non-interest income is associated with more volatile bank returns. DeYoung and Roland (2001) find fee-based activities are associated with increased revenue and earnings variability. Acharya, Hassan and Saunders (2006) find diseconomies of scope when a risky Italian bank expands into additional sectors. On the other hand, White (1986) finds that banks with a security affiliate in the pre-Glass Steagall period had a lower probability of default. In samples of international banks, Demurgic-Kunt and Huizinga (2010) find that bank risk decreases up to the 25th percentile of non-interest income and then increases, whereas De Jonghe (2010) finds non-interest income to monotonically increase systemic tail risk. All these studies focus on the risk of a particular bank, but not necessarily on the externality a bank imposes on the financial system.

A number of papers have used the $\Delta CoVaR$ measure in other contexts. Among them are Wong and Fong (2010), who examine $\Delta CoVaR$ for credit default swaps of Asia-Pacific banks, whereas Gauthier, Lehar and Souissi (2010) use it for Canadian institutions. Adams, Fuss and Gropp (2010) study risk spillovers among financial institutions including hedge funds, and Zhou (2009) uses extreme value theory rather than quantile regressions to get a measure of *CoVaR*.

1.3 Data, Methodology, and Variables Used

1.3.1 Data

We focus on all publicly traded bank holding companies in the U.S., namely, with SIC codes 60 to 67 (financial institutions) and filing Federal Reserve FR Y-9C report in each quarter. This report collects basic financial data from a domestic bank holding company (BHC) on a consolidated basis in the form of a balance sheet, an income statement, and detailed supporting schedules, including a schedule of off balance-sheet items. By focusing on commercial banks we do not include insurance companies, investment banks, investment management companies, and brokers. Our sample is from 1986 to 2008, and consists of an unbalanced panel of 538 unique banks. Four of these banks have zero non-interest income. We obtain a bank's daily equity returns from CRSP which we use to convert into weekly returns. Financial statement data is from Compustat and from Federal Reserve form FR Y-9C filed by a bank with the Federal Reserve. T-bill and LIBOR rates are from the Federal Reserve Bank of New York and real estate market returns are from the Federal Housing Finance Agency. The dates of recessions are obtained from the NBER (http://www.nber.org/cycles/cyclesmain.html). Detailed sources for each specific variable used in our estimation are given in Table II.

*** Table II ***

1.3.2 Systemic Risk using ΔCoVaR

We describe below how we calculate the $\Delta CoVaR$ measure of Adrian and Brunnermeier (2008). Such a measure is calculated one period forward and captures the marginal contribution of a bank to overall systemic risk. AB stress that rather than using a bank's risk in isolation which is typically measured by its *VaR* regulation should also include the bank's contribution to systemic risk measured by their $\Delta CoVaR$s. Importantly, in order to avoid procyclicality and the "volatility paradox" regulation should be based on reliably observed variables that predict future $\Delta CoVaR$s (in our regressions by one-quarter ahead).

Value-at-Risk (VaR)[4] measures the worst expected loss over a specific time interval at a given confidence level. In the context of this paper, VaR_q^i is defined as the percentage R^i of asset value that bank i might lose with q% probability over a pre-set horizon T:

$$Probability(R^i \leq VaR_q^i) = q \tag{1}$$

Thus by definition the value of *VaR* is negative in general.[5] Like AB, we do not flip the sign as a large part of the risk literature does. Another way of expressing this is that VaR_q^i is the q% quantile of the potential asset return in percentage term (R^i) that can occur to bank i during a specified time period T. The confidence level (quantile) q and the time period T are the two major parameters in a traditional risk measure using *VaR*.

[4] See Philippe (2006, 2009) for a detailed definition, discussion and application of *VaR*.

[5] Empirically the value of *VaR* can also be positive. For example, *VaR* is used to measure the investment risk in an AAA coupon bond. Assume that the bond was sold at discount and the market interest rate is continuously falling, but never below the coupon rate during the life the investment. Then the q% quantile of the potential bond return is positive, because the bond price increases when the market interest rate is falling.

We consider 1% quantile and weekly asset return/loss R^i in this paper, and the *VaR* of bank i is $Probability(R^i \le VaR^i_{1\%}) = 1\%$.

Let $CoVaR_q^{system|i}$ denote the Value at Risk of the entire financial system (portfolio) conditional upon bank i being in distress (in other words, the loss of bank i is at its level of VaR_q^i). That is, $CoVaR_q^{system|i}$ which essentially is a measure of systemic risk is the q% quantile of this conditional probability distribution:

$$Probability(R^{system} \le CoVaR_q^{system|i} \mid R^i = VaR_q^i) = q \qquad (2)$$

Similarly, let $CoVaR_q^{system|i,median}$ denote the financial system's *VaR* conditional on bank i operating in its median state (in other words, the return of bank i is at its median level). That is, $CoVaR_q^{system|i,median}$ measures the systemic risk when business is normal for bank i:

$$Probability(R^{system} \le CoVaR_q^{system|i,median} \mid R^i = median^i) = q \qquad (3)$$

Bank i's contribution to systemic risk can be defined as the difference between the financial system's *VaR* conditional on bank i in distress ($CoVaR_q^{system|i}$), and the financial system's *VaR* conditional on bank i functioning in its median state ($CoVaR_q^{system|i,median}$):

$$\Delta CoVaR_q^i = CoVaR_q^{system|i} - CoVaR_q^{system|i,median} \qquad (4)$$

In the above equation, the first term on the right hand side measures the systemic risk when bank i's return is in its q% quantile (distress state), and the second term measures the systemic risk when bank i's return is at its median level (normal state).

To estimate this measure of individual bank's systemic risk contribution $\Delta CoVaR_q^i$, we need to calculate two conditional *VaR*s for each bank, namely

$CoVaR_q^{system|i}$ and $CoVaR_q^{system|i,median}$. For the systemic risk conditional on bank i in distress ($CoVaR_q^{system|i}$), run a 1% quantile regression[6] using the weekly data to estimate the coefficients α^i, β^i, $\alpha^{system|i}$, $\beta^{system|i}$ and $\gamma^{system|i}$:

$$R_t^i = \alpha^i + \beta^i Z_{t-1} + \varepsilon^i \tag{5}$$

$$R_t^{system} = \alpha^{system|i} + \beta^{system|i} Z_{t-1} + \gamma^{system|i} R_{t-1}^i + \varepsilon^{system|i} \tag{6}$$

and run a 50% quantile (median) regression to estimate the coefficients $\alpha^{i,median}$ and $\beta^{i,median}$:

$$R_t^i = \alpha^{i,median} + \beta^{i,median} Z_{t-1} + \varepsilon^{i,median} \tag{7}$$

where R_t^i is the weekly growth rate of the market-valued assets of bank i at time t:[7]

$$R_t^i = \frac{MV_t^i \times Leverage_t^i}{MV_{t-1}^i \times Leverage_{t-1}^i} - 1 \tag{8}$$

and R_t^{system} is the weekly growth rate of the market-valued total assets of all N banks ($i = j = 1,2,3...,N$) in the financial system at time t:

$$R_t^{system} = \sum_{i=1}^{N} \frac{MV_{t-1}^i \times Leverage_{t-1}^i \times R_t^i}{\sum_{j=1}^{N} MV_{t-1}^j \times Leverage_{t-1}^j} \tag{9}$$

In equation (8) and (9), MV_t^i is the market value of bank i's equity at time t, and $Leverage_t^i$ is bank i's leverage defined as the ratio of total asset and equity market value at time t: $Leverage_t^i = Asset_t^i / MV_t^i$. It is noted that when we calculate the asset return of the entire financial system in equation (9), the individual bank's asset return is value-

[6] See Appendix A for a detailed explanation of quantile regressions.
[7] Market value of total asset is estimated by taking the product of market value of equity (MV) and financial leverage (Asset/Equity).

weighted by its total asset proxied by the product of equity market value (MV) and leverage at time *t-1*.

Z_{t-1} in equation (7) is the vector of macroeconomic and finance factors in the previous week, including market return, equity volatility, liquidity risk, interest rate risk, term structure, default risk and real-estate return. We obtain the value-weighted market returns from the database of S&P 500 Index CRSP Indices Daily. We use the weekly value-weighted equity returns (excluding ADRs) with all distributions to proxy for the market return. Volatility is the standard deviation of log market returns. Liquidity risk is the difference between the three-month LIBOR rate and the three-month T-bill rate. For the next three interest rate variables we calculate the changes from this week *t* to *t-1*. Interest rate risk is the change in the three-month T-bill rate. Term structure is the change in the slope of the yield curve (yield spread between the 10-year T-bond rate and the three-month T-bill rate. Default risk is the change in the credit spread between the 10-year BAA corporate bonds and the 10-year T-bond rate. All interest rate data is obtained from the U.S. Federal Reserve website and Compustat Daily Treasury database. Real estate return is proxied by the Federal Housing Finance Agency's FHFA House Price Index for all 50 U.S. states.

Hence we predict an individual bank's *VaR* and median asset return using the coefficients $\hat{\alpha}^i$, $\hat{\beta}^i$, $\hat{\alpha}^{i,median}$ and $\hat{\beta}^{i,median}$ estimated from the quantile regressions of equation (5) and (7):

$$VaR^i_{q,t} = \hat{R}^i_t = \hat{\alpha}^i + \hat{\beta}^i Z_{t-1} \tag{10}$$

$$R^{i,median}_t = \hat{R}^i_t = \hat{\alpha}^{i,median} + \hat{\beta}^{i,median} Z_{t-1} \tag{11}$$

The vector of state (macroeconomic and finance) variables Z_{t-1} is the same as in equation (5) and (7). After obtaining the unconditional *VaR*s of an individual bank i ($VaR_{q,t}^{i}$) and that bank's asset return in its median state ($R_{t}^{i,median}$) from equation (10) and (11), we predict the systemic risk conditional on bank i in distress ($CoVaR_{q}^{system|i}$) using the coefficients $\hat{\alpha}^{system|i}$, $\hat{\beta}^{system|i}$, $\hat{\gamma}^{system|i}$ estimated from the quantile regression of equation (6) . Specifically,

$$CoVaR_{q,t}^{system|i} = \hat{R}_{t}^{system} = \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} Z_{t-1} + \hat{\gamma}^{system|i} VaR_{q,t}^{i} \tag{12}$$

Similarly, we can calculate the systemic risk conditional on bank i functioning in its median state ($CoVaR_{q}^{system|i,median}$) as :

$$CoVaR_{q,t}^{system|i,median} = \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} Z_{t-1} + \hat{\gamma}^{system|i} R_{t}^{i,median} \tag{13}$$

Bank i's contribution to systemic risk is the difference between the financial system's *VaR* if bank i is at risk and the financial system's *VaR* if bank i is in its median state:

$$\Delta CoVaR_{q,t}^{i} = CoVaR_{q,t}^{system|i} - CoVaR_{q,t}^{system|i,median} \tag{14}$$

Note that this is same as equation (4) with an additional subscript t to denote the time-varying nature of the systemic risk in the banking system. As shown in the quantile regressions of equation (5) and (7), we are interested in the *VaR* at the 1% confident level, therefore the systemic risk of individual bank at q=1% can be written as:

$$\Delta CoVaR_{1\%,t}^{i} = CoVaR_{1\%,t}^{system|i} - CoVaR_{1\%,t}^{system|i,median} \tag{15}$$

1.3.3 Systemic Risk using SES

Acharya, Pedersen, Philippon and Richardson (2010) propose the systemic expected shortfall (*SES*) measure to capture a bank's exposure given that there is a systemic crisis. *SES* is defined as the expected amount that a bank is undercapitalized in a future systemic event in which the overall financial system is undercapitalized. In general, *SES* increases in the bank's expected losses during a crisis. Note that the *SES* reverses the conditioning. Instead of focusing on the return distribution of the banking system conditional on the distress of a particular bank, SES focuses on the bank i's return distribution given that the whole system is in distress. AB's *CoVaR* framework refers to this form of conditioning as "exposure *CoVaR*", as it measures which financial institution is most exposed to a systemic crisis and not which financial institution contributes most to a systemic crisis.

We define below the *SES* measure and discuss its implementation.[8] Let s_1^i be bank *i*'s equity capital at time 1, then the bank's expected shortfall (*ES*) in default is:

$$ES^i = E[s_1^i \mid s_1^i \le 0] \tag{16}$$

The bank *i*'s systemic expected shortfall (*SES*) is the amount of bank *i*'s equity capital s_1^i drops below its target level, which is a fraction k^i of its asset a^i, in case of a systemic crisis when aggregate banking capital S_1 at time 1 is less than *k* times the aggregate bank asset *A*:

$$SES^i = E[s_1^i - k^i a^i \mid S_1 \le kA] \tag{17}$$

[8] Our estimation of *SES* is slightly different from APPR (2010). APPR calculates *annual* realized *SES* using equity return data during the 2007-08 crisis, whereas we calculate *quarterly* realized *SES* with equity return data from 1986 to 2008.

where $S_1 = \sum_{j=1}^{N} s_1^j$ and $A = \sum_{j=1}^{N} a^j$ for all N banks in the entire financial system. To control for each bank's size, SES^i is scaled by bank i's initial equity capital s_0^i at time 0 and the banking system's equity capital is scaled by the banking system's initial equity capital S_0:

$$SES^i(\%) = \frac{SES^i}{s_0^i} = E\left[\frac{s_1^i}{s_0^i} - k^i \frac{a^i}{s_0^i} \middle| \frac{S_1}{S_0} \le k \frac{A}{S_0}\right] \tag{18}$$

where $S_0 = \sum_{j=1}^{N} s_0^j$ for N banks in the entire financial system. This percentage return measure of the systemic expected shortfall can be estimated as:

$$SES^i(\%) = E\left[r^i - k^i \times lev^i \middle| R \le k \times LEV\right] \tag{19}$$

where $r^i = \frac{s_1^i}{s_0^i}$ is the stock return of bank i, $R = \frac{S_1}{S_0}$ is the portfolio return of all banks, $lev^i = \frac{a^i}{s_0^i}$ is the leverage of bank i, and $LEV = \frac{A}{S_0}$ is the aggregate leverage of all banks.

Following the empirical analysis of APPR (2010), the systemic crisis event (when aggregate banking capital at time t is less than k_t times the aggregate bank leverage) is the five-percent worst days for the aggregate equity return of the entire banking system:

$$R_t \le k_t \times LEV_t \tag{20}$$

However, the problem is that we do not have ex ante knowledge about bank i's target fraction or threshold of capital (k_t^i). As proposed in APPR (2010), we circumvent the problem by using the realized *SES*. It is the stock return of bank i during the systemic crisis event (the worst 5% market return days at calendar quarter t). We will follow this measure of realized *SES* in the rest of the paper.

1.3.4 Independent Variables

To investigate the relationship between the bank characteristics and lagged bank's contribution to systemic risk, we run OLS regressions with quarterly fixed-effects of the individual bank's systemic risk contribution ($\Delta CoVaR$ or *SES*) on the following bank-specific variables: market to book (*M2B*), financial leverage (*LEV*), total asset (*AT*), and our main variable of analysis namely non-interest income to interest income (*N2I*).

$$SystemicRisk_t = \phi_0 + \phi_1 M2B_{t-1} + \phi_2 LEV_{t-1} + \phi_3 AT_{t-1} + \phi_4 AT_{t-1}^{\ 2} + \phi_5 N2I_{t-1} + \varepsilon_t \tag{22}$$

We focus on the impact of bank's *N2I* ratio (non-interest income to interest income ratio) on its systemic risk contribution.

From 2001 onwards, we can decompose *N2I* into two components, namely, trading income to interest income (*T2I*), and investment banking/venture capital income to interest income (*IBVC2I*). [9] We regress the individual bank's systemic risk contribution ($\Delta CoVaR$ or *SES*) on its *T2I* and *IBVC2I* ratios along with other control variables and include quarterly fixed-effects.

$$SystemicRisk_t = \phi_0 + \phi_1 M2B_{t-1} + \phi_2 LEV_{t-1} + \phi_3 AT_{t-1} + \phi_4 AT_{t-1}^{\ 2} + \phi_5 T2I_{t-1} + \phi_6 IBVC2I_{t-1} + \varepsilon_t \tag{23}$$

Trading income includes trading revenue, net securitization income, gain (loss) of loan sales and gain (loss) of real estate sales. Investment banking and venture capital income includes investment banking and advisory fees, brokerage commissions and

[9] We also included a component that included all other non-interest income items such as fiduciary income, deposit service charges, net servicing fees, service charges for safe deposit box and sales of money orders, rental income, credit card fees, gains on non-hedging derivatives . This component was not significant in any of the regressions so we dropped it from all our regressions.

venture capital revenue. The detailed definitions and sources of the accounting ratios are listed in Table II.

*** Table II ***

Table III presents the summary statistics. When we compare our results to those found in AB, we find that the average $\Delta CoVaR$ of individual banks to be lower (mean=-1.58% and median=-1.39%) than the average portfolio's $\Delta CoVaR$ found in AB (mean=-1.615% and median not reported). Comparing our results to APPR, we find an average (median) quarterly *SES* of -3.35% (-2.72%) for the years 1986-2008, whereas AAPR find an average (median) annual *SES* of -47% (-46%) for the crisis years 2007-08. As in the previous literature, we also find that banks are highly levered with an average debt-to-asset ratio of 92.1%. The average asset size of the banks is $ 15.7 billion and the median asset size is $ 1.86 billion. We find that the average ratio of non-interest income to interest income across all bank years to be 0.23, and the median ratio is 0.19.

*** Table III ***

In Table IV we find that the correlation between the two systemic risk measures $\Delta CoVaR$ and *SES* is 0.15, suggesting that these two measures capture some similar patterns in systemic risk. The correlation matrix reports no large correlation between the various independent variables. We find that higher leverage and size leads to higher systemic risk and the impact of market-to-book is much smaller. Finally we find that banks with a higher ratio of non-interest income to interest income are correlated with higher systemic risk.

*** Table IV ***

1.4 Empirical Results

Whereas the above correlations were suggestive, we hence run a multivariate regression, the results of which are given in Table V. The dependent variables are the two measures of systemic risk $\Delta CoVaR$ and *SES*. Columns 1-2 are the $\Delta CoVaR$ regressions, and columns 3-4 are the *SES* regressions. All independent variables are estimated with a one quarter lag, and also include quarter fixed-effects which are not reported. The *t*-statistics are calculated using Newey-West standard errors which rectifies for heteroskedasticity.

*** Table V ***

We first examine columns 1 and 3 where we only include our main variable of analysis, namely, the ratio of non-interest income to interest income. In doing so, we ensure that our results are not due to some spurious correlation between the various independent variables. We find that the ratio of non-interest income to interest income is significantly negative to both $\Delta CoVaR$ and *SES*, suggesting that it contributes adversely to systemic risk. In columns 2 and 4 we include the other four independent variables to check if our results change. We still find that non-interest income to interest income ratio is significantly negative to both $\Delta CoVaR$ and *SES*, although their economic magnitude is smaller. Specifically, a one standard deviation shock to a bank's non-interest income to interest income ratio increases systemic risk defined as $\Delta CoVaR$ by 11.6%, and by 5.4% when systemic risk is defined as *SES*.[10] Examining the bank-specific control variables we find that glamour banks, more highly levered banks, and larger banks are associated with higher systemic risk.

From 2001 onwards, we can decompose the ratio of non-interest income to interest income into trading income to interest income (*T2I*) and investment banking and venture capital income to interest income (*IBVC2I*), respectively. Federal Reserve form FR Y-9C only gives these detailed data after 2001. Trading income includes trading revenue, net securitization income, gain (loss) of loan sales and gain (loss) of real estate sales. Investment banking and venture capital includes investment banking and advisory fees, brokerage commission and venture capital revenue. We find in Table VI that both trading and investment banking and venture capital income are statistically negative and of equal magnitude. A one standard deviation shock to a bank's trading income increases systemic risk contribution defined as $\Delta CoVaR$ (as *SES*) by 5% (by 3.5%), whereas a one standard deviation shock to its investment banking and venture capital income increases its systemic risk contribution by 4.5%. (by 2.5%).

*** Table VI ***

Given that non-interest income consists generally of items which are marked to market, and interest income includes items such as interest on loans and deposits which

[10] Similar results are found when we use realized values of $\Delta CoVaR$.

are at historical cost, we examine if our results are driven by fair-value accounting issues. Investment banking consists of advisory fees and underwriting commissions which are not marked to market, whereas venture capital includes revenues from holdings in companies in which banks have taken to market and which are generally marked to market. If our results are driven by marked to market issues, the regression coefficient of venture capital should be negative and larger (in absolute terms) than the regression coefficient of investment banking. We find the same economic magnitude (results not reported), suggesting that mark to market accounting does not explain the contribution of non-interest income to systemic risk, and is generally consistent with the results in Laux and Leunz (2010) and studies cited therein.

We now examine if the above results are driven by endogeneity concerns. Specifically, are significant omitted variable(s) correlated with both non-interest income and systemic risk driving our results spuriously? In order to do so, we consider the bankruptcy filing of Lehman Brothers on September 15, 2011 (2008Q3) as an exogenous shock. We employ a difference-in-differences (DID) approach (see Meyer 1995, and Angrist and Krueger 1999 for detailed explanations of this methodology). We specifically analyze whether banks with different non-traditional income contribute differently to systemic risk measures when they face the unexpected shock of Lehman Brothers bankruptcy. Accordingly, banks with more non-traditional banking income (from trading and investment banking/venture capital) are defined as the treatment group, and banks with less non-traditional banking activities are the control or non-treated group. We rank all commercial banks based on their non-traditional banking income to interest income ratio in the year 2007Q2 and Q3 (average over the two quarters of the ratio of trading, investment banking and venture capital income to interest income). The dummy variable of *Top-quartile* is set to unity if the sum of a bank's non-traditional income is in the top-quartile (75-percentile and above), and zero if it is in the bottom-quartile (25-percentile and below). The dummy variable of *Post-Lehman Bankruptcy* is set to unity if the date is 2008Q4 (the quarter after the bankruptcy filing of Lehman Brothers), and zero if the date is 2007Q4 (one year before the bankruptcy filing of Lehman Brothers). A third dummy variable *Top-quartile×Post-Lehman Bankruptcy* is the cross-product of the previous two dummy variables.

The DID regression results are reported in the Panel A of Table VII wherein columns 1-2 are the $\Delta CoVaR$ regressions, and columns 3-4 are the *SES* regressions. The coefficient estimates of the cross-product dummy (*Top-quartile×Post-Lehman Bankruptcy*) in all DID specifications are significantly negative, suggesting that a bank with larger non-interest income after the Lehman shock contributed more to systemic risk. Not surprisingly, we find that the Lehman bankruptcy increased systemic risk.

*** Table VII ***

To investigate the different impact from a bank's trading and investment banking/ venture capital incomes on its systemic risk contribution, we create two new dummy variables, one for trading income and the other for investment banking/venture capital income. The dummy variable of *Post-Lehman Bankruptcy* is defined as before. Panel B of Table VII reports the DID regression results with the two non-interest income categories. In columns 1, 2, 5 and 6, the dummy variable of *Top-quartile Trading Bank* is set to unity if a bank's trading income is in the top-quartile (75^{th} percentile and above), and zero if it is in the bottom-quartile (25^{th} percentile and below). A third dummy variable of *Top-quartile Trading Bank×Post-Lehman Bankruptcy* is the cross-product of the previous two dummy variables. In columns 3, 4, 7 and 8, the dummy variable of *Top-quartile IBVC Bank* is set to unity if a bank's investment banking and venture capital income is in the top-quartile (75^{th} percentile and above), and zero if it is in the bottom-quartile (25^{th} percentile and below). A third dummy variable of *Top-quartile IBVC Bank×Post-Lehman Bankruptcy* is the cross-product of the previous two dummy variables. Once again the coefficient estimates of the cross-product dummy (*Top-quartile ×Post-Lehman Bankruptcy*) in all DID specifications are significantly negative, suggesting that a bank with larger trading or investment banking/venture capital income after the Lehman shock contributed more to systemic risk.

In summary, the difference-in-difference results show that banks with larger non-interest income after the Lehman shock contributed more to systemic risk than banks with low non-interest income. We find similar results for banks with the highest trading or investment banking/venture capital income compared to their counterparts with the lowest trading or investment banking/venture capital income. This suggests that our results are not driven by omitted variables(s) that happen to be correlated with both non-traditional income and systemic risk.

We now examine if there is a relationship in the levels of *pre-crisis* non-interest income and the bank's stock returns earned *during the crisis*. Doing so, allows us to predict (using the different components of non-interest income) bank performance during the crisis period. Given that the existing literature has yet to define a wellaccepted explicit empirical proxy for ex ante systemic risk, doing so also mitigates the criticism that measures of systemic risk are prone to severe measurement issues.

We specifically examine if banks with higher trading and/or investment banking income in the one-year before the crisis had more negative returns during the crisis. In doing so, we are looking at a sort of predictive regression. We run a regression with the bank's stock return during the latest recession period (defined by NBER as December 2007 to June 2009) as the dependent variable, and categorize banks by their trading income (or investment banking/venture capital income) into four quartiles in the year before the latest recession (2006Q3-2007Q3). We use a dummy variable for the highest quartile of each component of non-interest income.[11] In column (1) of Table VIII we find size to be negatively related to crisis returns, confirming the common intuition that large banks got into trouble in the crisis. We find no significant effect for leverage. In column (2) we include the dummy variables for each component of non-interest income. We find that banks with higher trading income one-year before the recession earned lower returns during the recession period. No such significant effect was found for investment banking and venture income.

*** Table VIII ***

In columns (3) and (4) we add two control variables to our regressions that have suggested to have resulted in bad performance during the crisis. The first variable is pre-crisis short-term funding, defined as debt whose maturity is less than one year divided by the sum of short-term debt, long-term debt, deposits and other liabilities (Fahlenbrach, Prilmeier, and Stulz 2011). The second variable is the ratio of loan commitments to loan

[11] See Appendix B for a list of such banks.

commitments and total loans (Shockley and Thakor 1997, Gatev, Schuermann, and Strahan 2009). In column (3) we find that the pre-crisis level of these variables is insignificantly related to the bank's returns during the crisis. The correlation between trading income (investment banking/venture capital income) and short-term funding is 0.21 (-0.01), and for loan commitments 0.26 (0.1), respectively. The correlation between short-term funding and loan commitments is 0.21. These low correlations suggest no evidence of multicollinearity in our regressions, which is also confirmed by a low condition number of 2.67 (see, Belsley, Kuh, and Welsch 1980). In column (4), we still find that banks with higher trading income one-year before the recession earned lower returns during the recession period. No such significant effect was found for investment banking and venture income.[12]

Robustness Tests: We run a number of robustness tests. First, we examine if our result is driven by the numerator (non-interest income) and not the denominator (net interest income). In Table IX, we re-estimate our regressions using the ratio of non-interest income to total assets instead of non-interest income to interest income. We find that non-interest income is once again negatively related suggesting that it contributes adversely to systemic risk when we also include net interest income to total assets as a separate regressor. No statistically significant result is found for net interest income for $\Delta CoVaR$. When we include net interest income for *SES* we find a statistically significant relationship. However, in a univariate regression it is statistically insignificant (results not reported). In Table X, we find a negative relationship for trading income, and an

[12] We also examined the 18 firms that were analyzed by the Federal Reserve for capital adequacy in late February 2009 under the Supervisory Capital Assessment Program (SCAP). Our sample size was reduced to 15 as three firms were not commercial banks (Goldman Sachs, Morgan Stanley, and American Express). Given the small sample size of 15 we did not find any significant results (results not reported but available from the authors).

insignificant relationship for investment banking and venture capital income. These results suggest that it is non-traditional income (namely, non-interest income) that contributes adversely to systemic risk, and not traditional income (namely, net interest income).

*** Tables IX and X***

Second, we examine if our results are driven by size. Although we controlled for both size and size squared in our previous regressions, we drop the top five-percentile by asset size of the largest banks in each quarter and redo our regressions. The results of such an analysis are given in Table XI. Consistent with our previous results we find that non-interest income is negatively related to both measures of systemic risk. We also find that trading income and investment banking/venture capital are negatively related to systemic risk, consistent with our previous results. This suggests that our result on non-interest income is not driven by bank size.

*** Table XI ***

Third, we examine if our results hold if we use CRSP equity returns (by calculating the value-weighted return of all stocks listed in CRSP monthly database for each calendar quarter[13]) as our proxy for market risk rather than the value-weighted bank stock portfolio. In Table XII, we reestimate our regressions using the ratio of non-interest income to interest income. We find that non-interest income is once again

[13] The results also hold if CRSP equity returns are equally-weighted.

negatively related suggesting that it contributes adversely to systemic risk, and the economic significance is slightly larger. Similar relationships are found for trading income and for investment banking and venture capital income in Table XIII. These results suggest that non-traditional income (namely, non-interest income) contributes adversely to systemic risk whether we use the bank portfolio or total market portfolio as our proxy for market risk.

*** Tables XII and XIII ***

1.5 Conclusions

The recent financial crisis showed that negative externalities from one bank to another created significant systemic risk. This resulted in significant infusions of funds from the Federal Reserve and the Treasury given that deposit taking and lending make banks special to information-intensive borrowers and for the bank lending channel transmission mechanism of monetary policy. But banks have increasingly earned a higher proportion of their profits from non-interest income from activities such as trading, investment banking, venture capital and advisory fees. This paper examines the contribution of such non-interest income to *systemic* bank risk.

Using two prominent measures of systemic risk (namely, ΔCoVaR measure of Adrian and Brunnermeier 2008, and the Systemic Expected Shortfall measure of Acharya, Pedersen, Philippon and Richardson 2010), we find banks with a higher non-interest income to interest income ratio to have a higher contribution to systemic risk. This suggests that activities that are not traditionally associated with banks (such as deposit taking and lending) are associated with a larger systemic risk. We also find that banks with a higher market-to-book ratio, higher leverage, and larger asset size, contributed more to systemic risk. When we decompose the total non-interest income into two components, we find trading income and investment banking/venture capital income to be significantly and equally related to systemic risk. In order to address endogeniety concerns, we also use a difference-in-difference approach assuming Lehman Brothers bankruptcy as an exogenous shock. We find that banks with larger non-interest income after the Lehman shock contributed more to systemic risk than banks with low non-interest income. Similar results are found for banks with the highest trading or investment banking/venture capital income. This suggests that our results are not driven by omitted variable(s) that happen to be correlated with non-traditional income and systemic risk. Finally, we find that banks with higher trading income one-year before the recession earned lower returns during the recession period. No such significant effect was found for investment banking and venture capital income. We also find that larger banks earned lower stock returns during the recession.

Appendix A: Quantile Regression

OLS regression models the relationship between the independent variable X and the conditional mean of a dependent variable Y given $X = X_1, X_2, \ldots X_n$. In contrast, quantile regression[14] models the relationship between X and the conditional quantiles of Y given $X = X_1, X_2, \ldots X_n$, thus it provides a more complete picture of the conditional

[14] Koenker and Hallock (2001) provide a general introduction of quantile regression. Bassett and Koenker (1978) and Koenker and Bassett (1978) discuss the finite sample and asymptotic properties of quantile regression. Koenker (2005) is a comprehensive reference of the subject with applications in economics and finance.

distribution of Y given X when the lower or upper quantile is of interest. It is especially useful in applications of Value at Risk (*VaR*), where the lowest 1% quantile is an important measure of risk.

Consider the quantile regression in equation (5): $R_t^i = \alpha^i + \beta^i Z_{t-1} + \varepsilon^i$, the dependent variable Y is bank i 's weekly asset return (R_t^i) and the independent variable X is the exogenous state (macroeconomic and finance) variables (Z_{t-1}) of the previous period. The predicted value ($\hat{R}_t^i$) using the coefficient estimates ($\hat{\alpha}^i$ and $\hat{\beta}^i$) from the 1%-quantile regression and the lagged state variable (Z_{t-1}) is bank i 's VaR at 1% confident level in that week: $VaR_{1\%,t}^i = \hat{R}_t^i = \hat{\alpha}^i + \hat{\beta}^i Z_{t-1}$. Similarly the predicted value ($\hat{R}_t^{system}$) in equation (12) using the coefficient estimates ($\hat{\alpha}^{system|i}$, $\hat{\beta}^{system|i}$ and $\hat{\gamma}^{system|i}$) from equation (6), the lagged state variable (Z_{t-1}), and the $VaR_{1\%,t}^i$ calculated above is the financial system's VaR ($CoVaR_{q,t}^{system|i}$) conditional on bank i 's return being at its lowest 1% quantile (VaR_t^i): $CoVaR_{1\%,t}^{system|i} = \hat{R}_t^{system} = \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} Z_{t-1} + \hat{\gamma}^{system|i} VaR_{1\%,t}^i$.

Note that the 50% quantile regression is also called median regression. Like the conditional mean regression (OLS), the conditional median regression can represent the relationship between the central location of the dependent variable *Y* and the independent variable *X*. However, when the distribution of *Y* is skewed, the mean can be challenging to interpret while the median remains highly informative[15]. As a consequence, it is appropriate in our study to use median regression to estimate the financial system's risk ($CoVaR_{1\%}^{system|i,median}$) when an individual bank is operating in its median state. The

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[15] The asymmetric properties of stock return distributions have been studied in Fama (1965), Officer (1972), and Praetz (1972).

predicted value ($\hat{R}_t^i$) using the coefficient estimates ($\hat{\alpha}^{i,median}$ and $\hat{\beta}^{i,median}$) from the 1%-quantile regression in equation (7) and the lagged state variable (Z_{t-1}) is bank i's median return: $R_t^{i,median} = \hat{\alpha}^{i,median} + \hat{\beta}^{i,median} Z_{t-1}$.

Following the same method, the financial system's risk conditional on bank i operating in its median state ($CoVaR_{1\%}^{system|i,median}$) is calculated using the coefficient estimates $\hat{\alpha}^{system|i}$, $\hat{\beta}^{system|i}$, $\hat{\gamma}^{system|i}$ from equation (6), the state variable (Z_{t-1}), and the median return of bank i ($R_t^{i,median}$): $CoVaR_{q,t}^{system|i,median} = \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} Z_{t-1} + \hat{\gamma}^{system|i} R_t^{i,median}$.

Finally, the measure of bank i's contribution of systemic risk ($\Delta CoVaR$) is the difference between $CoVaR_{q,t}^{system|i}$ and $CoVaR_{1\%}^{system|i,median}$: $\Delta CoVaR_{1\%,t}^{i} = CoVaR_{1\%,t}^{system|i} - CoVaR_{1\%,t}^{system|i,median}$. It is obvious that the calculation can be simplified to: $\Delta CoVaR_{1\%,t}^{i} = \beta^{system|i}(VaR_{1\%,t}^{i} - R_t^{i,median})$ as shown in Adrian and Brunnermeier (2008).

Appendix B: Names of Banks in the Top Quartile

This table lists alphabetically the banks in the top quartile of trading income to interest income (T2I) and investment banking/venture capital income to interest income (IBVC2I) ratios in the year before the latest recession (2006Q3-2007Q3).

NAME	Top 25% T2I	Top 25% IBVC2I
ACCESS NATIONAL CORPORATION	Yes	
ALABAMA NATIONAL BANCORPORATION	Yes	Yes
ALLIANCE BANKSHARES CORPORATION	Yes	
AMERICANWEST BANCORPORATION	Yes	
AMERISERV FINANCIAL, INC		Yes
AUBURN NATIONAL BANCORPORATION, INC.	Yes	
BANCFIRST CORPORATION		Yes
BANCTRUST FINANCIAL GROUP, INC.	Yes	
BANK OF AMERICA CORPORATION	Yes	Yes
BANK OF NEW YORK COMPANY, INC., THE	Yes	Yes
BANNER CORPORATION	Yes	
BB&T CORPORATION		Yes
BOK FINANCIAL CORPORATION	Yes	
BOSTON PRIVATE FINANCIAL HOLDINGS, INC.		Yes
BRIDGE CAPITAL HOLDINGS	Yes	
BRYN MAWR BANK CORPORATION	Yes	
C&F FINANCIAL CORPORATION	Yes	
CAPITAL BANK CORPORATION	Yes	
CAPITAL ONE FINANCIAL CORPORATION	Yes	
CARDINAL FINANCIAL CORPORATION	Yes	
CENTRUE FINANCIAL CORPORATION	Yes	
CHARLES SCHWAB CORPORATION, THE	Yes	Yes
CITIGROUP INC.	Yes	Yes
CITY NATIONAL CORPORATION		Yes
COAST FINANCIAL HOLDINGS, INC	Yes	
COBIZ FINANCIAL INC.		Yes
COBIZ INC.		Yes
COLUMBIA BANCORP	Yes	
COMERICA INCORPORATED	Yes	Yes
COMMERCE BANCORP, INC.		Yes
COMMERCE BANCSHARES, INC.		Yes
COMMUNITY BANKS, INC.		Yes
COMMUNITY BANKSHARES, INC.	Yes	
COMMUNITY CENTRAL BANK CORPORATION	Yes	
COMMUNITY TRUST BANCORP, INC.		Yes
COMPASS BANCSHARES, INC.		Yes
COOPERATIVE BANKSHARES, INC.	Yes	
COUNTRYWIDE FINANCIAL CORPORATION	Yes	
CULLEN/FROST BANKERS, INC.		Yes
EAGLE BANCORP, INC.	Yes	
FIDELITY SOUTHERN CORPORATION	Yes	
FIFTH THIRD BANCORP	Yes	Yes
FINANCIAL INSTITUTIONS, INC.		Yes
FIRST BUSEY CORPORATION		Yes
FIRST CHARTER CORPORATION		Yes

(Continued next page)

NAME	Top 25% T2I	Top 25% IBVC2I
FIRST COMMUNITY BANCORP	Yes	
FIRST FINANCIAL BANCORP		Yes
FIRST FINANCIAL BANKSHARES, INC.	Yes	
FIRST HORIZON NATIONAL CORPORATION	Yes	Yes
FIRST INDIANA CORPORATION	Yes	
FIRST MARINER BANCORP	Yes	
FIRST STATE BANCORPORATION	Yes	
FNB UNITED CORP.	Yes	
FRANKLIN RESOURCES, INC.	Yes	Yes
FREMONT BANCORPORATION	Yes	Yes
FULTON FINANCIAL CORPORATION	Yes	Yes
GLACIER BANCORP, INC.	Yes	
GREATER COMMUNITY BANCORP		Yes
HABERSHAM BANCORP	Yes	
HANCOCK HOLDING COMPANY		Yes
HANMI FINANCIAL CORPORATION	Yes	
HARLEYSVILLE NATIONAL CORPORATION		Yes
HERITAGE COMMERCE CORP	Yes	
HOME FEDERAL BANCORP	Yes	
HORIZON BANCORP	Yes	
HUNTINGTON BANCSHARES INCORPORATED	Yes	Yes
IBERIABANK CORPORATION	Yes	Yes
INDEPENDENT BANK CORPORATION	Yes	
INTERNATIONAL BANCSHARES CORPORATION		Yes
JPMORGAN CHASE & CO.	Yes	Yes
KEYCORP	Yes	Yes
LAKELAND BANCORP, INC.		Yes
LANDMARK BANCORP, INC.	Yes	
LEESPORT FINANCIAL CORP.	Yes	
M&T BANK CORPORATION		Yes
MELLON FINANCIAL CORPORATION	Yes	Yes
MERCANTILE BANKSHARES CORPORATION		Yes
MIDDLEBURG FINANCIAL CORPORATION		Yes
MIDWESTONE FINANCIAL GROUP, INC		Yes
MONROE BANCORP	Yes	
NARA BANCORP, INC.	Yes	
NATIONAL CITY CORPORATION	Yes	Yes
NATIONAL PENN BANCSHARES, INC.		Yes
NB&T FINANCIAL GROUP, INC.		Yes
NEW YORK COMMUNITY BANCORP, INC.		Yes
NORTHERN TRUST CORPORATION	Yes	
OAK HILL FINANCIAL, INC.		Yes
OLD NATIONAL BANCORP		Yes
OLD SECOND BANCORP, INC.	Yes	
ORIENTAL FINANCIAL GROUP INC.		Yes
PACIFIC CAPITAL BANCORP	Yes	Yes
PENNS WOODS BANCORP, INC.	Yes	
PEOPLES BANCTRUST COMPANY, INC., THE		Yes
PLACER SIERRA BANCSHARES		Yes
PNC FINANCIAL SERVICES GROUP, INC., THE	Yes	Yes
POPULAR, INC.	Yes	Yes
PREMIERWEST BANCORP		Yes
REGIONS FINANCIAL CORPORATION		Yes
RENASANT CORPORATION	Yes	
ROYAL BANCSHARES OF PENNSYLVANIA, INC.	Yes	

(Continued next page)

NAME	Top 25% T2I	Top 25% IBVC2I
RURBAN FINANCIAL CORP.	Yes	
SANDY SPRING BANCORP, INC.		Yes
SANTANDER BANCORP		Yes
SEACOAST BANKING CORPORATION OF FLORIDA	Yes	
SIMMONS FIRST NATIONAL CORPORATION		Yes
SKY FINANCIAL GROUP, INC.	Yes	Yes
SOUTH FINANCIAL GROUP, INC., THE		Yes
SOUTH FINANCIAL GROUP, THE		Yes
SOUTHERN COMMUNITY FINANCIAL CORPORATION		Yes
SOUTHWEST BANCORP, INC.	Yes	
STATE STREET CORPORATION	Yes	Yes
STERLING BANCSHARES, INC.		Yes
STERLING FINANCIAL CORPORATION		Yes
SUNTRUST BANKS, INC.		Yes
SUSQUEHANNA BANCSHARES, INC.	Yes	Yes
SVB FINANCIAL GROUP	Yes	Yes
SYNOVUS FINANCIAL CORP.		Yes
TAYLOR CAPITAL GROUP, INC.		Yes
TIB FINANCIAL CORP.	Yes	
TOMPKINS FINANCIAL CORPORATION		Yes
TOMPKINS TRUSTCO, INC.		Yes
TRUSTMARK CORPORATION		Yes
U.S. BANCORP		Yes
UCBH HOLDINGS, INC.	Yes	
UMB FINANCIAL CORPORATION	Yes	Yes
UMPQUA HOLDINGS CORPORATION	Yes	
UNION BANKSHARES CORPORATION	Yes	
UNIONBANCAL CORPORATION	Yes	Yes
UNITY BANCORP, INC.	Yes	
VALLEY NATIONAL BANCORP	Yes	Yes
VIRGINIA COMMERCE BANCORP, INC.	Yes	
VIRGINIA FINANCIAL GROUP, INC.	Yes	
WACHOVIA CORPORATION		Yes
WASHINGTON TRUST BANCORP, INC.		Yes
WELLS FARGO & COMPANY	Yes	Yes
WESBANCO, INC.		Yes
WEST BANCORPORATION, INC.		Yes
WEST COAST BANCORP	Yes	
WILMINGTON TRUST CORPORATION		Yes
WILSHIRE BANCORP, INC.	Yes	
WINTRUST FINANCIAL CORPORATION	Yes	Yes
ZIONS BANCORPORATION		Yes

Figure 1.1 Average non-interest to interest income ratio over the sample period

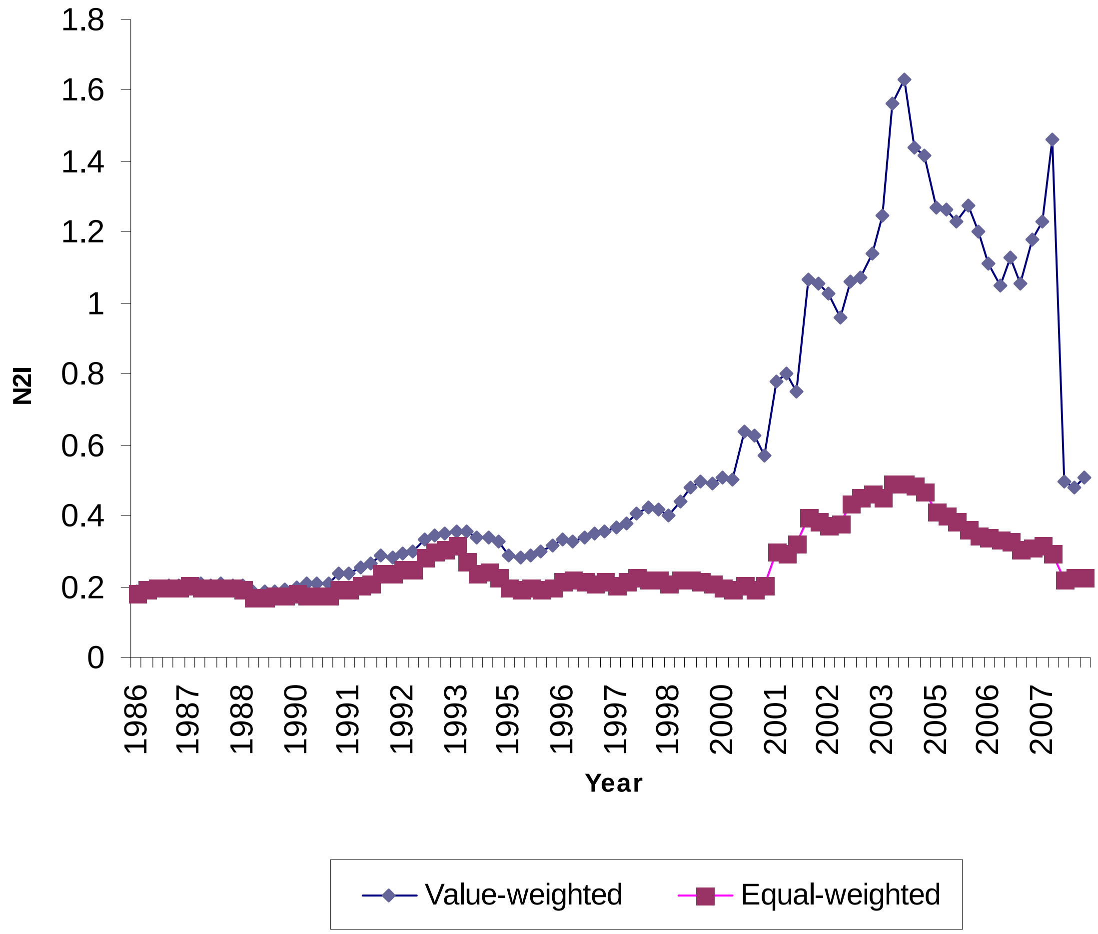

Table 1.1 Non-interest income to interest income ratio of the 10 largest commercial banks

Bank Name	1989	2000	2007
Citigroup	0.21	0.89	0.50
Bank of America	0.21	0.38	0.48
Chase	0.16	0.67	0.76
Wachovia	0.14	0.35	0.38
Wells Fargo	0.19	0.57	0.53
Suntrust	0.18	0.27	0.35
US Bank	0.18	0.50	0.55
National City	0.19	0.38	0.31
Bank of New York Mellon	0.21	0.67	1.39
PNC Financial	0.13	0.68	0.69
Average	0.18	0.53	0.59

Non-interest income ratio to interest income ratio (N2I) is defined below and the data are taken from the Federal Reserve Bank reporting form FR Y9C:

$$N2I = \frac{Noninterest\ Income}{Net\ Interest\ Income} = \frac{BHCK\,4079}{BHCK\,4107}$$

Citigroup was Citibank in 1989 before the merger with Travelers Group. Bank of America was called BankAmerica in 1989 before the merger with NationsBank. US Bank was First Bank System in 1989 before the combination with Colorado National Bank and West One Bank. Bank of New York Mellon was called Bank of New York in 1989 before the merger with Mellon Financial.

Table 2.2 Variable definitions

Variable	Name	Calculation	Sources
ΔCoVaR	Financial institution's contribution to systemic risk	From equation (15)	
SES	Systemic expected shortfall	From equation (21)	
R^i	Weekly asset return of individual bank	$\frac{MV_t^i \times LEV_t^i}{MV_{t-1}^i \times LEV_{t-1}^i} - 1$	CRSP Daily Stocks, Compustat Fundamentals Quarterly
R^s	Weekly asset return of all banks	$\sum_i \frac{MV_{t-1}^i \times LEV_{t-1}^i}{\sum_j MV_{t-1}^j \times LEV_{t-1}^j} R^i$	CRSP Daily Stocks, Compustat Fundamentals Quarterly
M2B	Market to book	MV / equity book value	CRSP Daily Stocks, Compustat Fundamentals Quarterly
MV	Market value of equity	Price × Shares outstanding	CRSP Daily Stocks
LEV	Leverage	Total asset / equity book value	Compustat Fundamentals Quarterly
AT	Logarithm of total book asset	Log(Total Asset)	U.S. Federal Reserve FRY-9C Report
AT^2	Square term of AT	$[\text{Log(Total Asset)}]^2$	U.S. Federal Reserve FRY-9C Report
N2I	Non-interest income to interest income	Non-interest income / Interest Income	U.S. Federal Reserve FRY-9C Report
T2I	Trading income to interest income	Trading income includes trading revenue, net securitization income, gain(loss) of loan sales and gain(loss) of real estate sales. (2001 onwards)	U.S. Federal Reserve FRY-9C Report
IBVC2I	IBVC income to interest income	IBVC income includes investment banking/advisory fee, brokerage commission and venture capital revenue. (2001 onwards)	U.S. Federal Reserve FRY-9C Report

Table 3.3 Summary statistics

Variable	Mean	Median	Standard Deviation
$\Delta CoVaR$	-1.58%	-1.39%	1.93%
SES	-3.35%	-2.72%	3.20%
Market to Book	1.80	1.62	1.21
Leverage	12.57	12.15	3.66
Log (Total Assets)	14.73	14.43	1.61
Non-interest Income to Interest Income	0.23	0.19	0.35

See Table 1 for data definition and Section 3 of the paper and for further details.

Table 4.4 Correlations between the various variables

	$\Delta CoVaR$	*SES*	Market to Book	Leverage	Log(Total Assets)
SES	0.15				
Market to Book	-0.02	0.01			
Leverage	-0.14	-0.09	-0.02		
Log(Total Assets)	-0.25	-0.14	0.09	0.13	
Non-interest Income to Interest Income	-0.07	-0.04	0.17	-0.05	0.26

Table 5.5 Regression of a bank's systemic risk on firm characteristics

In regression model (1) and (2) the dependent variable is $\Delta CoVaR$, which is the difference between *CoVaR* conditional on the bank being under distress and the *CoVaR* in the median state of the bank. In model (3) and (4) the dependent variable is Realized *SES*, systemic expected shortfall. The independent variables include one quarter lagged firm characteristics such as market to book, leverage, total asset, squared total asset, and non-interest income to interest income ratio.

Dependent Variable:	$\Delta CoVaR_t$		Realized SES_t	
	(1)	(2)	(3)	(4)
Market to Book $_{t-1}$		-0.0296***		-0.0632***
		(-3.25)		(-3.77)
Leverage $_{t-1}$		-0.0411***		-0.0704***
		(-2.76)		(-7.12)
Log (Total Asset) $_{t-1}$		0.0354		-0.209***
		(1.14)		(-5.54)
Log (Total Asset) squared $_{t-1}$		-0.00953***		0.0032
		(-9.21)		(0.23)
Non-interest Income to Interest Income $_{t-1}$	-0.525***	-0.168***	-0.514***	-0.216***
	(-5.07)	(-4.08)	(-4.71)	(-5.18)
Quarterly fixed-effects	Yes	Yes	Yes	Yes
N	23,085	23,085	23,085	23,085
Adjusted R-square	0.06	0.12	0.34	0.35
F-test	207.09	233.40	426.14	474.24

t-test based on Newey-West standard error is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 6.6 Regression of a bank's systemic risk on different components of non-interest income

In regression model (1) and (2) the dependent variable is Δ*CoVaR*, which is the difference between *CoVaR* conditional on the bank being under distress and the *CoVaR* in the median state of the bank. In model (3) and (4) the dependent variable is Realized *SES*, systemic expected shortfall. The independent variables include one quarter lagged firm characteristics such as market to book, leverage, total asset, squared total asset, trading income to interest income, and IBVC income to interest income ratio. Trading income includes trading revenue, net securitization income, gain(loss) of loan sales and gain (loss) of real estate sales. IBVC income includes investment banking/advisory fee, brokerage commission and venture capital revenue. All these detail accounting items are reported in FR Y-9C since 2001.

Dependent Variable:	$\Delta CoVaR_t$		Realized SES_t	
	(1)	(2)	(3)	(4)
Market to Book $_{t-1}$		-0.0827***		-0.0455
		(-3.61)		(-1.40)
Leverage $_{t-1}$		-0.0229***		-0.00314
		(-2.64)		(-0.27)
Log (Total Asset) $_{t-1}$		-1.191***		-3.116***
		(-6.55)		(-11.02)
Log (Total Asset) squared $_{t-1}$		0.0303***		0.0886***
		(5.05)		(9.74)
Trading Income to Interest Income $_{t-1}$	-0.751***	-0.258**	-1.106***	-0.631**
	(-4.93)	(-2.28)	(-3.99)	(-2.37)
IBVC Income to Interest Income $_{t-1}$	-0.186***	-0.122**	-0.218***	-0.12***
	(-2.73)	(-2.00)	(-3.55)	(-2.95)
Quarterly fixed-effects	Yes	Yes	Yes	Yes
N	9,603	9,603	9,603	9,603
Adjusted R-square	0.14	0.25	0.48	0.51
F-test	246.44	270.20	545.15	573.46

t-test based on Newey-West standard error is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 7.7 DID regression of a bank's systemic risk prior- and post- Lehman bankruptcy

We consider the bankruptcy filing of Lehman Brothers on September 15, 2011 (2008Q3) as an exogenous shock. We employ a difference-in-differences (DID) approach (see Meyer 1995, and Angrist and Krueger 1999 for detailed explanations of this methodology). Banks with more non-traditional banking income are defined as the treatment group, and banks with less trading and investment banking/venture capital (IBVC) activities are the control or non-treated group.

In Panel A, we rank all commercial banks based on their non-traditional banking income to interest income ratio in the year 2007Q2 and Q3 (average over the two quarters of the ratio of trading, investment banking and venture capital income to interest income). The dummy variable of *Top-quartile* is set to unity if the sum of a bank's non-traditional income is in the top-quartile (75-percentile and above), and zero if it is in the bottom-quartile (25-percentile and below). The dummy variable of *Post-Lehman Bankruptcy* is set to unity if the date is 2008Q4 (the quarter after the bankruptcy filing of Lehman Brothers), and zero if the date is 2007Q4 (one year before the bankruptcy filing of Lehman Brothers). A third dummy variable *Top-quartile×Post-Lehman Bankruptcy* is the cross-product of the previous two dummy variables. The DID regression equation is:

$$SystemicRisk = \phi_0 + \phi_1 M2B + \phi_2 LEV + \phi_3 AT + \phi_4 AT^2 + \phi_5 TopQuartile + \phi_6 PostLehman + \phi_7 TopQuartile \times PostLehman + \varepsilon_t$$

According to Meyer (1995) and Angrist and Krueger (1999), the coefficient ϕ_7 of the *Top-quartile Bank×Post-Lehman Bankruptcy* dummy is the effect that we want to estimate. In regression model (1) and (2) the dependent variable of systemic risk is $\Delta CoVaR$, which is the difference between *CoVaR* conditional on the bank being under distress and the *CoVaR* in the median state of the bank. In model (3) and (4) the dependent variable of systemic risk is Realized *SES*, systemic expected shortfall. The independent variables include firm characteristics such as market to book, leverage, total asset, squared total asset, top-quartile bank dummy, post-Lehman bankruptcy dummy, and cross-product dummy of the previous two dummy variables. Trading income includes trading revenue, net securitization income, gain (loss) of loan sales and gain (loss) of real estate sales. IBVC income includes investment banking/advisory fee, brokerage commission and venture capital revenue. All these detail accounting items are reported in FR Y-9C since 2001.

Panel A.

Dependent Variable:	$\Delta CoVaR_t$		Realized SES_t	
	(1)	(2)	(3)	(4)
Market to Book		0.155 (0.64)		1.335*** (2.78)
Leverage		-0.0674* (-1.72)		-0.0738 (-0.90)
Log (Total Asset)		-1.157 (-0.99)		-11.42*** (-4.94)
Log (Total Asset) squared		0.0205 (0.59)		0.312*** (4.51)
Post-Lehman Bankruptcy Dummy	-0.874** (-1.99)	-0.669* (-1.70)	-6.719*** (-7.43)	-5.960*** (-6.94)
Top-quartile Bank Dummy	-1.298*** (-2.98)	-0.488 (-1.10)	-0.934 (-1.04)	1.186 (1.35)
Top Quartile Bank × Post-Lehman Bankruptcy Dummy	-1.126* (-1.81)	-1.247** (-2.07)	-3.033** (-2.36)	-2.989** (-2.50)
Constant	-1.309*** (-4.28)	11.58 (1.22)	-5.143*** (-8.15)	93.11*** (4.94)
N	281	281	281	281
Adjusted R-square	0.18	0.26	0.39	0.50
F-test	19.60	13.64	60.73	38.59

t-test is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

In Panel B, we rank the banks' trading and IBVC incomes in 2007 separately. The dummy variable of *Post-Lehman Bankruptcy* is set to unity if the date is 2008Q4 (the quarter after the bankruptcy filing of Lehman Brothers) and zero if the date is 2007Q4 (one year before the bankruptcy filing of Lehman Brothers). In model (1), (2), (5) and (6), the dummy variable of *Top-quartile Trading Bank* is set to unity if a bank's trading income is in the top-quartile (75-percentile and above) and zero if it is in the bottom-quartile (25-percentile and below). A third dummy variable of *Top-quartile Trading Bank×Post-Lehman Bankruptcy* is the cross-product of the previous two dummy variables. In model (3), (4), (7) and (8), the dummy variable of *Top-quartile IBVC Bank* is set to unity if a bank's IBVC income is in the top-quartile (75-percentile and above) and zero if it is in the bottom-quartile (25-percentile and below). A third dummy variable of *Top-quartile IBVC Bank×Post-Lehman Bankruptcy* is the cross-product of the previous two dummy variables.

Panel B.

Dependent Variable:	$\Delta CoVaR_t$				Realized SES_t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market to Book		-0.16		0.17		0.83		1.01***
		(-0.62)		(0.93)		(1.61)		(2.59)
Leverage		-0.021		-0.009		-0.03		-0.12*
		(-0.65)		(-0.28)		(-0.49)		(-1.83)
Log (Total Asset)		-0.65		-2.63***		-11.62***		-12.1***
		(-0.57)		(-2.82)		(-5.14)		(-6.28)
Log (Total Asset) squared		0.0039		0.06**		0.31***		0.33***
		(0.12)		(2.18)		(4.60)		(5.74)
Post-Lehman Bankruptcy Dummy	-0.92**	-0.91**	-1.19***	-1.02***	-6.73***	-6.18***	-7.69***	-6.89***
	(-2.15)	(-2.16)	(-4.16)	(-3.61)	(-7.53)	(-7.45)	(-12.69)	(-11.71)
Top-quartile Trading Bank Dummy	-1.17***	-0.52			-0.56	1.15		
	(-2.74)	(-1.26)			(-0.64)	(1.41)		
Top Quartile Trading Bank × Post-Lehman Bankruptcy Dummy	-0.99*	-1.03*			-2.99**	-2.90**		
	(-1.72)	(-1.78)			(-2.36)	(-2.54)		
Top-quartile IBVC Bank Dummy			-0.72**	0.50			-1.22*	1.17
			(-2.01)	(1.33)			(-1.71)	(1.51)
Top Quartile IBVC Bank × Post-Lehman Bankruptcy Dummy			-1.05**	-1.07**			-2.20**	-2.43**
			(-2.02)	(-2.16)			(-1.99)	(-2.36)
Constant	-1.29***	7.71	-1.85***	23.13***	-4.76***	96.26***	-4.89***	100***
	(-4.29)	(0.83)	(-9.19)	(3.03)	(-7.64)	(5.24)	(-11.55)	(6.35)
N	281	281	281	281	281	281	281	281
Adjusted R-square	0.16	0.26	0.13	0.24	0.40	0.52	0.39	0.49
F-test	17.58	13.64	21.54	19.00	60.58	42.77	96.93	59.88

t-test is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 8.8 Regression of a bank's return during the crisis on its pre-crisis firm characteristics

The dependent variable is the bank's equity return from December 2007 to June 2009, the recession period defined by the NBER's Business Cycle Dating Committee. The independent variables include the log total asset, financial leverage, short-term funding, loan commitment, dummy variables for firms in top and bottom 25%tile of trading income to interest income ratio and IBVC (investment banking and venture capital) income to interest income ratio. Financial leverage is the ratio of total asset to book equity, short-term funding is the ratio of 1-year maturing debts to total liabilities, loan commitment is the unused commitments divided by the sum of commitments and total loans. All independent variables are averages during the period of 2006Q4 to 2007Q3 which is one year prior to the NBER recession period. Trading income includes trading revenue, net securitization income, gain (loss) of loan sales and gain(loss) of real estate sales. IBVC income includes investment banking/advisory fee, brokerage commission and venture capital revenue.

Dependent Variable: Return $_t$	(1)	(2)	(3)	(4)
Log (Total Asset) $_{t-1}$	-0.0305**	-0.0364**	-0.0321*	-0.0397**
	(-2.43)	(-2.50)	(-1.87)	(-2.19)
Leverage $_{t-1}$	0.0115	0.0124	0.0085	0.0098
	(1.46)	(1.58)	(1.04)	(1.21)
Short-term Funding $_{t-1}$			0.476	0.407
			(1.59)	(1.37)
Loan Commitment $_{t-1}$			-0.183	-0.117
			(-0.73)	(-0.46)
Dummy of top 25%tile Trading Income to Interest Income $_{t-1}$		-0.0940**		-0.0827*
		(-2.07)		(-1.77)
Dummy of top 25%tile IBVC Income to Interest Income $_{t-1}$		0.0851		0.0834
		(1.60)		(1.56)
Intercept	-0.110	-0.0280	-0.0526	0.0391
	(-0.52)	(-0.13)	(-0.21)	(0.16)
N	281	281	281	281
Adjusted R-square	0.03	0.06	0.03	0.06
F-test	4.23	3.85	2.97	2.93

t-test is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 9.9 Regression of a bank's return during the crisis on its pre-crisis firm characteristics

In regression model (1), (2) and (3) the dependent variable is $\Delta CoVaR$, which is the difference between *CoVaR* conditional on the bank being under distress and the *CoVaR* in the median state of the bank. In model (4), (5) and (6) the dependent variable is Realized *SES*, systemic expected shortfall. The independent variables include one quarter lagged firm characteristics such as market to book, leverage, total asset, squared total asset, net interest income to total asset, and non-interest income to total asset.

Dependent Variable:		$\Delta CoVaR_t$			Realized SES_t	
	(1)	(2)	(3)	(4)	(5)	(6)
Market to Book $_{t-1}$		-0.0252***	-0.0284***		-0.0559***	-0.0450***
		(-2.76)	(-2.76)		(-3.32)	(-2.61)
Leverage $_{t-1}$		-0.0414***	-0.0396**		-0.0709***	-0.0772***
		(-2.79)	(-2.49)		(-7.20)	(-7.55)
Log (Total Asset) $_{t-1}$		0.0346	0.0157		-0.211***	-0.147***
		(1.12)	(0.40)		(-5.61)	(-3.53)
Log (Total Asset) squared $_{t-1}$		-0.0094***	-0.00864***		0.00059	-0.00195
		(-9.15)	(-6.54)		(0.43)	(-1.30)
Net Interest Income to Total Asset $_{t-1}$			5.535			-18.61***
			(1.34)			(-4.05)
Non-interest Income to Total Asset $_{t-1}$	-21.66***	-7.512***	-7.405***	-22.74***	-10.73***	-11.09***
	(-11.16)	(-5.61)	(-5.40)	(-8.97)	(-5.89)	(-6.06)
Quarterly fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
N	23,085	23,085	23,085	23,085	23,085	23,085
Adjusted R-square	0.06	0.12	0.46	0.33	0.35	0.68
F-test	208.04	234.72	234.46	427.75	476.32	471.14

t-test based on Newey-West standard error is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 10.10 Robustness test: Different components of non-interest income to total assets

In regression model (1) and (2) the dependent variable is $\Delta CoVaR$, which is the difference between *CoVaR* conditional on the bank being under distress and the *CoVaR* in the median state of the bank. In model (3) and (4) the dependent variable is Realized *SES*, systemic expected shortfall. The independent variables include one quarter lagged firm characteristics such as market to book, leverage, total asset, squared total asset, trading income to total asset, and IBVC income to total asset ratio. Trading income includes trading revenue, net securitization income, gain (loss) of loan sales and gain(loss) of real estate sales. IBVC income includes investment banking/advisory fee, brokerage commission and venture capital revenue. All these detail accounting items are reported in FR Y-9C since 2001.

Dependent Variable:	$\Delta CoVaR_t$		Realized SES_t	
	(1)	(2)	(3)	(4)
Market to Book $_{t-1}$		-0.0825***		-0.0458
		(-3.61)		(-1.41)
Leverage $_{t-1}$		-0.0231***		-0.00347
		(-2.65)		(-0.29)
Log (Total Asset) $_{t-1}$		-1.193***		-3.116***
		(-6.60)		(-11.06)
Log (Total Asset) squared $_{t-1}$		0.03***		0.0886***
		(5.10)		(9.78)
Trading Income to Total Asset $_{t-1}$	-14.29***	-6.83***	-23.58***	-16.08***
	(-4.09)	(-2.56)	(-3.69)	(-2.71)
IBVC Income to Total Asset $_{t-1}$	-13.37***	-7.584***	-15.14***	-7.446***
	(-3.49)	(-2.82)	(-2.69)	(-2.41)
Quarterly fixed-effects	Yes	Yes	Yes	Yes
N	9,603	9,603	9,603	9,603
Adjusted R-square	0.14	0.25	0.48	0.51
F-test	246.44	270.66	545.15	573.35

t-test based on Newey-West standard error is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 11.11 Robustness test: Regression of a bank's systemic risk on non-interest income without top 5-percentile banks

This sample excludes banks of total assets within top 5 percentile. In regression model (1) to (4) the dependent variable is Δ*CoVaR*, which is the difference between *CoVaR* conditional on the bank being under distress and the *CoVaR* in the median state of the bank. In model (5) to (8) the dependent variable is Realized *SES*, systemic expected shortfall. The independent variables include one quarter lagged firm characteristics such as market to book, leverage, total asset, squared total asset, non-interest income to interest income ratio, trading income to interest income, and IBVC income to interest income ratio. Trading income includes trading revenue, net securitization income, gain(loss) of loan sales and gain (loss) of real estate sales. IBVC income includes investment banking/advisory fee, brokerage commission and venture capital revenue. All these detail accounting items are reported in FR Y-9C since 2001.

Dependent Variable:	$\Delta CoVaR_t$				Realized SES_t			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market to Book $_{t-1}$		-0.018**		-0.067***		-0.057***		-0.05
		(-2.23)		(-3.23)		(-3.35)		(-1.63)
Leverage $_{t-1}$		-0.041***		-0.021**		-0.071***		0.0001
		(-2.62)		(-2.57)		(-6.99)		(0.01)
Log (Total Asset) $_{t-1}$		0.12***		-1.05***		-0.22***		-5.39***
		(3.66)		(-3.49)		(-5.34)		(-11.31)
Log (Total Asset) squared $_{t-1}$		-0.014***		0.024**		0.0009		0.16***
		(-11.25)		(2.38)		(0.58)		(10.33)
Non-interest Income to Interest Income $_{t-1}$	-0.45***	-0.17***			-0.43***	-0.24***		
	(-4.76)	(-4.11)			(-4.45)	(-5.32)		
Trading Income to Interest Income $_{t-1}$			-0.70***	-0.38***			-0.89***	-0.86***
			(-4.29)	(-2.95)			(-3.03)	(-3.09)
IBVC Income to Interest Income $_{t-1}$			-0.16**	-0.10*			-0.21***	-0.14***
			(-2.51)	(-1.69)			(-3.74)	(-3.11)
Quarterly fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22,099	22,099	9.139	9.139	22,099	22,099	9.139	9.139
Adjusted R-square	0.42	0.45	0.60	0.66	0.67	0.69	0.73	0.74
F-test	194.11	227.53	232.99	273.62	397.17	451.84	504.94	561.64

t-test based on Newey-West standard error is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 12.12 Robustness test: Regression of a bank's systemic risk estimated using CRSP market return on a bank's non-interest income

In regression model (1) and (2) the dependent variable is $\Delta CoVaR$, which is the difference between *CoVaR* conditional on the bank being under distress and the *CoVaR* in the median state of the bank. In model (3) and (4) the dependent variable is Realized *SES*, systemic expected shortfall. The independent variables include one quarter lagged firm characteristics such as market to book, leverage, total asset, squared total asset, and non-interest income to interest income ratio.

Dependent Variable:	$\Delta CoVaR_t$		Realized SES_t	
	(1)	(2)	(3)	(4)
Market to Book $_{t-1}$		-0.183***		-0.0632***
		(-8.60)		(-3.14)
Leverage $_{t-1}$		-0.0142		-0.0704
		(-0.78)		(-0.61)
Log (Total Asset) $_{t-1}$		0.00528		-0.209***
		(0.15)		(-5.19)
Log (Total Asset) squared $_{t-1}$		0.0064***		0.00629***
		(5.30)		(3.22)
Non-interest Income to Interest Income $_{t-1}$	-0.783***	-0.433***	-0.447***	-0.216***
	(-4.00)	(-3.60)	(-4.92)	(-4.45)
Quarterly fixed-effects	Yes	Yes	Yes	Yes
N	23,085	23,085	23,085	23,085
Adjusted R-square	0.04	0.06	0.31	0.32
F-test	89.93	116.14	417.76	465.74

t-test based on Newey-West standard error is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 13.13 Robustness test: Regression of a bank's systemic risk estimated using CRSP market return on different components of non-interest income

In regression model (1) and (2) the dependent variable is Δ*CoVaR*, which is the difference between *CoVaR* conditional on the bank being under distress and the *CoVaR* in the median state of the bank. In model (3) and (4) the dependent variable is Realized *SES*, systemic expected shortfall. The independent variables include one quarter lagged firm characteristics such as market to book, leverage, total asset, squared total asset, trading income to interest income, and IBVC income to interest income ratio. Trading income includes trading revenue, net securitization income, gain (loss) of loan sales and gain(loss) of real estate sales. IBVC income includes investment banking/advisory fee, brokerage commission and venture capital revenue. All these detail accounting items are reported in FR Y-9C since 2001.

Dependent Variable:	$\Delta CoVaR_t$		Realized SES_t	
	(1)	(2)	(3)	(4)
Market to Book $_{t-1}$		-0.184***		-0.0285
		(-4.61)		(-0.93)
Leverage $_{t-1}$		-0.0161		0.0167
		(-1.03)		(0.79)
Log (Total Asset) $_{t-1}$		-0.66**		-2.887***
		(-1.99)		(-10.32)
Log (Total Asset) squared $_{t-1}$		0.0122		0.0833***
		(1.21)		(9.23)
Trading Income to Interest Income $_{t-1}$	-1.531*	-0.887	-1.187***	-0.819***
	(-1.81)	(-1.12)	(-3.77)	(-2.58)
IBVC Income to Interest Income $_{t-1}$	-0.219**	-0.131**	-0.201***	-0.109***
	(-2.07)	(-2.01)	(-4.07)	(-2.89)
Quarterly fixed-effects	Yes	Yes	Yes	Yes
N	9,603	9,603	9,603	9,603
Adjusted R-square	0.03	0.05	0.45	0.48
F-test	27.34	47.03	535.00	552.77

t-test based on Newey-West standard error is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

CHAPTER 2: Mortgage Securitization: The Good, the Bad, or the Irrelevant?

2.1 Introduction

What is the impact of mortgage securitization on the real economy and housing risk, and how does commercial banks' participation in owning mortgage-back securities affect economic production and property price volatility? Most traditional explanations of the benefits of securitization emphasize the risk sharing from completing the market as in Koppl (2006) and Gaur, Seshadri and Subrahmanyam (2010).[1] Recently, an abundance of criticism, such as Blinder (2007) and Stiglitz (2007), has questioned the wisdom of the originate-to-distribute model of mortgage underwriting and focused on the detriments of securitization due to the conflicts inherent in the role of financial institutions assembling securitization pools and then selling them to investors (see Plantin 2010 for the agency problem). If securitization has transformed the credit markets by pooling and tranching cash flows over the past few decades, and monetary policy operates through the credit markets, securitization have important effects on the transmission mechanisms of monetary policy, and in turn on the banking sector and eventually on the real economy.[2] Alternatively, Gennaioli, Shleifer, and Vishny (2011) suggest that market participants have neglected the risks of mortgage securitization, which can increase financial fragility even in the absence of leverage. This paper applies three econometric methods, namely

[1] Krueger and Perri (2011) infer from their model that if markets are complete, in that agents can trade a complete set of perfectly enforceable insurance contracts, then complete risk sharing can be achieved solely via private markets, and redistributions of wealth via income taxes and government subsidies provide no additional insurance.

[2] See Estrella (2002), Altunbas, Gambacorta and Marques-Ibanez (2009) and Bernanke (2007) for detailed discussions of how securitization affects monetary policy's transmission mechanism and eventually real output via liquidity channel and credit channel.

time-series SVAR, cross-sectional OLS and quasi-experimental design, to test three views of securitization: risk sharing, agency problem and neglected risk.

Mortgage securitization is a process to transform illiquid mortgages including residential and commercial mortgages to liquid financial securities, mainly fixed income instruments and their derivatives. Securitization is often called structured finance process that distributes risk by aggregating mortgages in a pool, often by selling all mortgages to a special purpose vehicle (SPV), then issuing new securities backed by the mortgages and their cash flows. The securities are sold to investors who share the risk and reward from those assets. The mortgage-backed securities (MBS) market is large and growing. From 1980 to 2009 the outstanding size of the 1-4 family mortgage-backed security in U.S. has grown dramatically from 111 millions to 7 trillions, whereas the outstanding size of the underlying mortgage assets has grown from 1 trillion to 11 trillion.[3] Commercial banks play a important role in the U.S. mortgage securitization market, acting as both originators and investors. The quarterly time-series plot of the securitization rate of U.S. residential mortgages, commercial bank's MBS ownership and residential house price risk, a proxy for housing risk, is shown in Figure 2.1. There is a consistent upward trend in both securitization rate and banks' ownership in MBS over the last twenty years. However, their relationship with residential housing risk is less clear.[4]

[Insert Figure 2.1 here]

[3] Mortgage Market Statistical Annual (Volumes I & II) of Inside Mortgage (2010)

[4] Securitization rate is quarterly new residential MBS ($) divided by residential mortgage issuance ($). Bank MBS ownership is quarterly commercial bank's holding of MBS ($) divided by total MBS outstanding ($). Housing risk is quarterly volatility of the residential REIT portfolio return (equally-weighted).

The securitization of residential mortgage has become a subject of intense national interest and debate (see Blinder 2007 and Stiglitz 2007). Many have questioned the wisdom of the originate-to-distribute model of mortgage underwriting and others have focused on the conflicts inherent in the role of financial institutions assembling securitization pools and then selling them to investors. The dominant view prior to the current financial crisis was that securitization is beneficial for the financial market. This is because securitization transforms relatively illiquid individual mortgages into liquid and tradable mortgage-backed securities. MBS is frequently more efficient and lower cost source of financing in comparison with other bank and capital markets financing alternatives. It allows issuers to diversify their financing sources, by offering alternatives to more traditional forms of debt and equity financing. MBS issuers can remove assets from their balance sheet, which can help to improve various financial ratios, utilize capital more efficiently and achieve compliance with risk-based capital standards. Therefore theoretically, securitization should serve to reduce risk by spreading it more widely (see Morduch 1995, Ligon 1998, Asdrubali and Kim 2004, Levine and Zevos 1998, Becker and Hoffmann 2006, Shiller 1995, Athanasoulis and van Wincoop 2001, and Xu 2008 for economic literature on risk sharing) and furthermore, it helps complete the market in the sense of Arrow-Debreu (1954), as suggested by Gaur, Seshadri and Subrahmanyam (2010).

The ongoing financial crisis of 2007-09 triggered by the subprime mortgage delinquencies signaled the end of a favorable period of mortgage securitization and housing market boom. It seems to suggest some side-effects of mortgage securitization, mainly lax screening by mortgage lenders. The agency view suggests that mortgage securitization reduces banks' incentives to screen and monitor their borrowers in good times (see, for example, Plantin 2010). When conditions in the housing market changed adversely, lower-quality mortgages were greatly affected, which subsequently led to lower output. Such an agency view has been empirically confirmed by Keys, Mukherjee, Seru and Vig (2009 and 2010), Mian and Sufi (2009 and 2010), and Mian, Sufi and Trebbi (2008).

Alternatively, Gennaioli, Shleifer, and Vishny (2011) suggest that market participants think locally. This results in neglecting certain adverse possible risks of mortgage securitization, which can increase financial fragility even in the absence of leverage. New securities are over-issued when investors neglect low probability risks in accounting for the nature of financial innovation such as mortgage securitization. The market for new securities (MBS) is fragile because news about unattended risks (national house prices plunge and mortgage defaults rise) surprise investors. They then dump the "false substitutes" (MBS) and fly to the safety of traditional securities (T-bonds). The authors claim that such neglected risk explains why the sharp decline in home prices and increase in mortgage defaults came as a substantial surprise to the market in the summer of 2007.

Despite the empirical finding of Estrella (2002) that securitization has a significant effect on the degree to which a given change in monetary policy can influence real output, there has been no research systemically examining the relationships between securitization and housing risk, and differentiating between the agency and neglected risk views of securitization. This research uses a structural vector autoregression (SVAR) methodology to analyze the effect of mortgage securitization on the real economy and house price risk. I contribute new time-series causality evidence for a 27-year period from 1983 to 2009 in which securitization became the dominant source of financing for the U.S. residential mortgage market. I estimate the dynamic responses of house price risk and aggregate U.S. real GDP to shocks of mortgage securitization and banks' ownership of mortgage-backed security (MBS), and test three hypotheses suggested in the extant literature. I find that securitization reduces housing risk by completing the market. Interestingly, I also find that housing risk increases when commercial banks' ownership of MBS increases. This positive relationship is inconsistent with the agency view of securitization but is consistent with the neglected risk view of mortgage securitization (Gennaioli, Shleifer, and Vishny 2011). Robustness checks using cross-sectional regressions provide complementary evidences from the metropolitan statistical area (MSA)-level data. The causal inference is drawn from a quasi-experimental design using housing data of bordering CBSA regions in neighboring states with and without the passing of anti-predatory lending laws.

The remainder of the paper is organized as follows. Section II reviews the relevant prior research on securitization and financial innovation in general. Section III develops the hypotheses. Section IV presents the sample data and measurement choice. Section V introduces the time-series empirical method. Section VI evaluates the results. Section VII performs robustness checks using cross-sectional regressions on MSA-level data. Section VIII conducts the causality test using a quasi-experimental design to address the endogeneity concerns. Section IX concludes.

2.2 Related Literature

Understanding the economics of securitization in residential and commercial mortgages is of fundamental importance and there is an extensive literature addressing the theoretic benefits and empirical effects of MBS market. Important recent papers on the theory of securitization include Shin (2009), Allen and Carletti (2006), Chiesa (2008), and Gaur, Seshadri and Subrahmanyam (2010), Parlour and Plantin (2008), Makarov and Plantin (2011), Plantin (2010), and Malherbe (2010). This strand of theoretical literature focuses on two main themes: market completeness and asymmetric information.

The securitization literature identifies at least two mechanisms by which securitization help complete the financial market in the Arrow and Debreu (1954) sense. First, Allen and Carletti (2006) show that credit risk transfer can be beneficial when banks face uniform demand for liquidity. In this mechanism, securitization improves risk sharing among all investors, but it can also induce contagion due to systemic effects and lead to a Pareto reduction in welfare. Second, Gaur, Seshadri and Subrahmanyam (2010) suggest that pooling and tranching are valuable in reducing ambiguity surrounding the valuation of new real investment in incomplete market. In a complete market, there is no benefit from pooling and tranching, and the standard asset pricing model can price the traded assets. However in an incomplete market, the value of a real asset can not always be uniquely computed using capital market prices. By pooling and tranching cash flows of underlying assets, securitization help price discovery.

The securitization literature also provides insight into the asymmetric information problems including moral hazard and adverse selection that can arise in securitization. Gorton and Pennacchi (1995) give an early and fundamental discussion of the first problem of asymmetric information in credit risk transfer: moral hazard. An important characteristic that is often attributed to banks is a special ability to monitor borrowers that increases the probability of loan repayment. However, this monitoring can not be observed by outsiders, which leads to a moral hazard problem. With loan sales being the only instrument available in their model, Gorton and Pennacchi (1995) show how a bank can overcome the moral hazard problem by continuing to hold a fraction of the loan, and offering explicit guarantees on loan performance. This loan ownership structure after loan sales improves the incentive of the bank to keep monitoring the firm. They conclude that if a bank can implicitly commit to holding certain fraction of a loan, or to provide limited recourse, the moral hazard associated with loan sales is reduced.

Greenbaum and Thakor (1987) consider another problem of asymmetric information in credit risk transfer: adverse selection, by examining a bank's choice of whether to fund the loans by deposits or to sell the loans. With common knowledge of loan quality and laissez faire banking, the choice is irrelevant. With adverse selection, the high-quality loans are sold or securitized, and the low-quality loans are funded with deposits. Duffee and Zhou (2006) include both moral hazard and adverse selection problems by extending the model of Gorton and Pennacchi (1995). Because banks have better private information about the creditworthiness of their borrowers, their assessment of the loan default likelihood is likely to be different to outsiders' assessment. The authors show that credit derivatives, as an instrument of risk transfer, help alleviate the lemons problem that plagues the loan sales market. However when the asymmetric information problem is severe, credit risk transfer benefits the bank only if it makes a high-quality loan, and this benefit is overweighed by an increase in deadweight cost if the bank makes a low-quality loan. Therefore, bank profits fall on average across both high-quality and low-quality loan states. The authors conclude that although credit derivatives market is useful to banks in general, the introduction of credit derivatives market could shut down the loan sales market. The net effect depends on the severity of asymmetric information: the bank is better off if the problem is moral hazard, and the bank is worse off if the problem is adverse selection.

In recent research, Parlour and Plantin (2008) analyze credit risk transfer through the bank-borrower relationship. Different to the risk transfer instrument of credit derivatives in Duffee and Zhou (2006), Parlour and Plantin (2008) use loan sales as an instrument of credit risk transfer, and generate an adverse selection problem by a bank that has a stochastic discount shock and can exploit proprietary information. They find that a liquid market of credit risk transfer can arise, but the socially inefficient outcome may result. The endogenous degree of liquidity is not always socially efficient because there might be excessive trade in high-quality bonds but inefficient liquidity in low-quality bonds. Wagner and Marsh (2006) go beyond the credit risk transfer within the banking system to include cross-sector risk transfer. They argue that the incentive of banks to transfer credit risk is aligned with the regulatory objective of improving stability and welfare, and the risk transfer from banks to non-banks is more beneficial than the risk transfer among banks.

In regard to the linkage between securitization and financial stability, Shin (2010) points out that the importance of securitization for financial stability derives from the ability of the shadow banking system to increase total supply of credit to end borrowers[5].

[5] The financial crisis literature covers more general discussion on the roots and mechanisms of bubble and crash, such as Abreu and Brunnermeier (2003) on synchronization, Shileifer and Vishny (1997), Abreu and Brunnermeier (2003) and Brunnermeier and Nagel (2004) on limited arbitrage, Brunnemeier and Pedersen (2008) on funding liquidity due to margin requirement.

The prior literature has identified two mechanisms that securitization could drive the growth of credit. The first mechanism is from supply-side. Bernanke and Blinder (1988) and Kashyap and Stein (2000) emphasize the liquidity structure of the bank's balance sheet, and Van Den Heuvel (2002) stress the cushioning effect of the bank's regulatory capital to explain the fluctuation of the credit. The second mechanism to cause fluctuation in credit is due to the shifts in the demand for credit as in Bernanke and Gertler (1989) and Kiyotaki and Moore (1997). The changing strength of the borrower's balance sheet and the resulting change in the creditworthiness of the borrower drive the fluctuation of the credit. A negative shock reduces labor demand and lowers wage, and it in turns deteriorate individual's net worth, reduces debt capacity and amplifies the downturns. Shin (2010) extends this supply-side factor to explain the origin of the ongoing subprime crisis. The greater risk-taking capacity of the shadow banking system leads to an increased demand for new assets to fill the expanding balance sheets and leverage. Shin (2010) suggests a picture of an inflating balloon which fills up with new assets, and as the balloon expands, banks search for new assets to fill the balloon.

2.3 Hypotheses

There are three prevailing theoretical views of securitization which can be empirically tested. They are:

2.3.1 Securitization is Optimal

Securitization was traditionally meant to transfer risks from the banking sector to outside investors and thereby disperse financial risks across the economy. Mortgage-backed securities (MBSs) transform relatively illiquid, individual mortgages into liquid and tradable capital market instruments. It allows mortgage originators to replenish their funds, which can then be used for additional origination activities. MBS is more efficient and lower cost source of financing in comparison with other financing options, and allows issuers to diversify their financing sources, by offering alternatives to more traditional forms of debt and equity financing. MBS issuers can remove assets from their balance sheet, which can then serve to reduce credit risk and achieve compliance with risk-based capital standards.

Theoretically securitization helps complete the market as in the general equilibrium model of Arrow-Debreu (1954), in which there exists a market for every time period and forward prices for every commodity at all time periods and in all states. Similarly, Gaur, Seshadri and Subrahmanyam (2010) also consider an Arrow-Debreu economy with three agents (investors, firms and intermediaries) and argue that securitization improves matching of the return cash flows to the needs of investors in various states of the nature, in the context of an incomplete financial market, hence providing value enhancement through pooling and tranching. While their results are derived under the strict definition of arbitrage, the authors argue that similar results can also be obtained under approximate arbitrage. Koppl (2006) sets up a dynamic risk sharing model and uses approach of Lindahl's (1919) equilibrium to show that financial markets always allow for optimal risk sharing as long as markets are complete; default is prevented in equilibrium and intermediaries provide enforcement competitively. Hence by pooling and tranching payment cash flows of underlying mortgages, securitization helps price discovery and reduces financial market risk. Accordingly, this view hypothesizes that:

H1: A positive shock to the securitization rate of mortgage-backed securities reduces housing risk and increases aggregate output.

The housing risk, or equivalently the housing price risk, can be empirically measured using the daily return volatility of a portfolio of residential REITs. There is a strand of literature in real estate economics and finance that deals with measuring, pricing and hedging housing risk, for example, Meyer and Wieand (1996), Englund, Hwang and Quigley (2002), Cannon, Miller and Pandher (2006), Han (2010), and Favilukis, Ludvigson and Van Nieuwerburgh (2011). The detailed construction and testing of this house price risk is discussed in the following methodology section. In aggregate, nominal GDP measures the output in a given year using the prices prevailing during that period. However over time, the general level of prices rise due to inflation, leading to an increase in nominal GDP even if the volume of goods and services produced is unchanged. Thus real GDP is a better measure for the output because it only changes with the changing production level.

2.3.2 Securitization is Detrimental

There are two possible theoretical arguments that have been made in the exiting literature that suggest that securitization is detrimental to the overall economy by increasing overall risks of financial markets. The first argument proposes an agency-based view of mortgage securitization. Securitization was traditionally meant to transfer risks from the banking sector to outside investors and thereby disperse financial risks across the economy. Since the risks were meant to be transferred, securitization allowed banks to reduce regulatory capital, except on pieces they retained, typically the first-loss piece in order to ensure they had some “skin in the game”. Gorton and Pennacchi (1995) suggest that a bank holds a fraction of the loan and offer explicit guarantees on loan performance to overcome the moral hazard problem. Plantin (2010) argues that mortgage securitization reduces a bank’s incentives to screen and monitor their borrowers in the booming housing market of the early 2000s, and the subsequent degradation in mortgage quality beginning in 2006 amplified the market downturn. Acharya, Schnabl and Suarez (2010) analyze the asset-backed commercial paper conduits. They find that during the first year of the crisis, asset-backed commercial paper issuance fell and spreads increased, especially for conduits with weaker guarantees, riskier banks, and lower quality assets. Futher, banks with higher exposure to conduits had lower stock returns, and that losses from conduits remained with banks rather than outside investors. They conclude that banks used securitization to concentrate, rather than disperse financial risks in the banking sector, while reducing their capital requirements. This agency problem in securitization has also been investigated and confirmed using cross-sectional data by Keys, Mukherjee, Seru and Vig (2009 and 2010), Mian and Sufi (2009 and 2010), Mian, Sufi and Trebbi (2008), whereas my paper is focused on the time-series evidence using vector autoregression models. When agency problems prevail in the mortgage-backed security market, higher ownership by banks will imply lower aggregate risks in financial markets. Specifically, the testable hypothesis is:

H2: An unexpected reduction or negative shocks in banks' ownership of mortgage-backed securities increases house price risk and decreases aggregate output.

In the following methodology section, I construct a portfolio of residential REITs and estimate its historical quarterly volatility. To measure the output, I use quarterly real GDP instead of nominal GDP to avoid the fluctuation due to inflation.

The second argument for the detrimental effect of securitization articulated by Gennaioli, Shleifer, and Vishny (2011) suggest that market participants have <u>neglected the risks</u> of mortgage securitization, which can increase financial fragility even in the absence of leverage. They develop a two-period model of local thinking (Gennaioli and Shleifer 2010: not all states of nature are accounted for by agents in making decisions) to formalize the notion that not all contingencies are represented. New securities are over-issued when investors neglect low probability risks in accounting for the nature of financial innovation such as mortgage securitization. The market for new securities (MBS) is fragile because when news about unattended risks (national house prices plunge and mortgage defaults rise) catches investors by surprise, they dump the "false substitutes" (MBS) and fly to the safety of traditional securities (Treasury bonds). The authors claim that such neglected risk explains why the sharp decline in home prices and increase in mortgage defaults came as a substantial surprise to the market in the summer of 2007. To distinguish this hypothesis from the previous agency-based view, the neglected view argues that mistakes were made by financial institutions even though they had a large amount of "skin in the game." Such unforeseen or neglected risks that worked itself through a higher rate of securitization lead to a higher aggregate financial market risk, and in turn affect aggregate output in a negative way. Campbell, Lettau, Malkiel and Xu (2001), citing work by Lilien (1982), reason that stock market volatility is related to structural change in the economy. Structural change consumes resources, which depresses gross domestic product (GDP) growth. The empirical implication for this time-series causality testing is:

H3: A positive shock or unexpected increase in banks' ownership of mortgage-backed security increases house price risk and decreases aggregate output.

In this paper I use residential REITs' daily return volatility to proxy for house price risk, and real GDP for output in each calendar quarter.

2.3.3 Securitization is Irrelevant

If I find no significant results from the abovementioned causality tests, then the possible implication is that mortgage securitization is irrelevant to the overall risks of financial markets.

2.4. Data

I begin by obtaining time-series data from Inside Mortgage Finance Publications' *Mortgage Market Statistical Annual.* New mortgage issuance and commercial banks' holding in mortgage-backed securities are gathered through their surveys from 1980 to 2010. The quarterly banks' MBS ownership (variable name: *Bank MBS Holding*) is the ratio of aggregate holdings in MBS to the new mortgage issuance. The Federal Reserve

Board's *Flow of Funds* dataset provides the dollar amount of US mortgages held by nonfinancial firms, and the amount of mortgage-backed securities issued in each month. This dataset allows me to create the quarterly securitization rate (variable name: *Securitization Rate*) from 1970 to 2010.

To estimate the quarterly housing risk (variable name: *House Price Risk*), I first construct a portfolio of residential REITs from *Compustat* using firms in industry code GICS 4040 (specifically GICS 40402050 sub-industry) engaged in the acquisition, development, ownership, leasing, management and operation of residential mortgages and properties including multifamily homes, apartments, manufactured homes and student housing properties.[6] Then I calculate the equally-weighted daily log-returns of this REIT portfolio for each calendar quarter. Finally I estimate the standard deviation of the REIT portfolio's log-returns within the quarter.

To measure the output, I use quarterly Real Gross Domestic Product (variable name: *Real GDP*) instead of nominal GDP to avoid the fluctuation due to inflation. Real GDP is a macroeconomic measure of the value of output economy adjusted for price changes, that is, inflation or deflation. The adjustment transforms the money-value measure of nominal GDP into an index for quantity of total output. The historical data of GDP is taken from the Federal Reserve Economic Data (FRED) from the Federal Reserve Bank in St. Louis. The same data source also provides historical time-series data for three-month Treasury rate (variable name: *3-momth T-bill*) and spot oil price of West Texas Intermediate (variable: *Oil Price*).

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[6] GICS (Global Industry Classification Standard) is developed by Standard & Poor's and MSCI Barra. It consists of 10 sectors, 24 industry groups, 68 industries and 154 sub-industries.

By matching the year and quarter of all datasets, the time period of the entire time-series data sample is from the first quarter of 1983 to the fourth quarter of 2009. The variables are defined in Table I, the summary statistics of the real variables is shown in Table II, and the correlation matrix is in Table III.

[Insert Table I, II and III here]

The second data set is a panel with cross-sectional MSA (Metropolitan Statistical Area) and quarterly time-series data, and I collect MSA-level data of population, industrial firms, commercial banks and housing market for each MSA. The population (variable name: *Log population*) and other demographic data (including cross-mapping among zip codes, MSA codes, CBSA codes and state name abbreviations) are downloaded from Missouri Census Data Center (Geographic Correspondence Engine with Census 2000 Geography). The estimation of quarterly house price risk is different to the previous time-series data set that uses the portfolio returns of residential REITs. It is the standard deviation of 30-quarter house price returns in each of the 25 MSA regions that are part of the House Price Index owned and maintained by Federal Housing Finance Agency (FHFA). The seasonally-unadjusted quarterly HPI data is available from the first quarter of 1991 to the second quarter of 2011. To obtain the MSA-level house price risk, I first calculate the quarterly HPI returns for each MSA region, and then estimate the standard deviation of regional HPI returns for the prior 30 quarters employing the rolling-window technique. Because this estimation of standard deviation consumes data in the prior 30 quarters, the time span of the final sample for cross-sectional analysis is reduced to 2001Q1-2011Q2.

The firm characteristics data for non-banking industrials are taken from *Compustat*, and aggregated for each MSA in each calendar quarter. The variable names of quarterly MSA-level industrial data are *Log revenue*, *Sales-to-asset*, *Log total asset*, *market-to-book*, and *financial leverage* (total asset over book equity). Similarly, for each quarter, the bank characteristics data are taken from Federal Reserve FR Y-9C and aggregated for each MSA. The variables of quarterly MSA-level bank data include *Log bank total asset*, *Bank market-to-book*, B*ank financial leverage* (bank's total asset over its book equity), and *Bank ROA*(bank's net income over its total asset). The variable of *Securitization rate* is the total transferred mortgage ($) in a MSA divided by the sum of transferred mortgage and kept mortgage ($) in the same metropolitan region, and *Bank MBS holding* is all banks' MBS ownership ($) divided by the total transferred mortgage ($). Due to the fact that commercial banks were required to report their MBS holdings since 2001, the time period of the entire data sample is from the second quarter of 2001 to the fourth quarter of 2010. The detailed variable definition is shown in Table IV.

[Insert Table IV here]

The third data set for quasi-experimental design is similar to the second data set of panel data, but of CBSA (Core Based Statistical Area)[7] level rather than of MSA level. CBSA refers collectively to both metropolitan statistical areas (MSA) and micropolitan

[7] Core Based Statistical Area (CBSA) is a U.S. geographic area defined by the Office of Management and Budget (OMB) based around an urban center of at least 10,000 people and adjacent areas that are socioeconomically tied to the urban center by commuting.

areas. Micropolitan areas are based around Census Bureau-defined urban clusters of at least 10,000 and fewer than 50,000 people. Because there aren't house price data available for micropolitan areas, I use the monthly building permit's value of new residential constructions from U.S. Consensus Bureau to proxy for the monthly house price in each CBSA region. The estimation of CBSA-level housing risk is done by calculating the standard deviation of monthly log change of building permit's values for the prior 24 months in each metro- and micropolitan areas. The rest variables including industrial firms and banks are the same to the second data set of panel.

2.5 Methodology

2.5.1 Time-series Analysis

I begin by analyzing the time-series relationships in two macroeconomic models using a structural vector autoregression (SVAR) methodology. SVAR is appropriate for my analysis because it allows for investigation of important dynamic characteristics of the real economy by imposing structural restrictions from economic theory. Particularly useful in this research are the impulse response functions and variance decompositions. Impulse response function (IRF) describes how the economy reacts over time to exogenous impulses, which economists usually call *shocks*, and are often modeled in the context of a VAR. Impulses that are often treated as exogenous from a macroeconomic point of view include changes in government spending, tax rates, and other fiscal policy parameters; changes in the monetary base or other monetary policy parameters; changes in productivity or other technological parameters.

According to Sims (1980), all variables appearing in the structural VAR could be argued to be endogenous. Econometric theory places only weak restrictions on the reduced form coefficients and on which variables that should enter a reduced-form VAR. He furthermore suggests that empirical research should use small-scale models identified via a small number of constraints. SVARs provide a more systemic approach to imposing restrictions and could lead one to capture empirical regularities which remain hidden to standard regression approaches. However, a concern might arise in the aggregation of economic data: by aggregating economic activities into one single variable like the GDP and house price risk, the geographical characteristics such as the differences of market completeness or risk sharing capability across different locations are largely ignored. Later in this paper, I provide cross-sectional evidences to ensure that my results are robust to such aggregation issues.

Enders (2009), Lutkepohl (2010), Keating (1992), Bjornland (2000), and Sims (2002) provide textbook treatment of SVAR in technical detail. Sims (1982) and Freeman, Williams and Lin (1989) introduce its use in policy analysis, and their methodology is closely related to this research, because essentially the results of this paper will provide empirical evidence for whether a policy to support or discourage mortgage securitization is sound and necessary. In the following two subsections, I will use two SVAR systems to study the U.S. macroeconomy: one is a three-variable benchmark model without housing and banking sectors and the other is a six-variable model with housing and banking sectors.

2.5.1.1 Macroeconomy without housing or banking sectors (three-variable)

To better understand the real economy, I first examine the behavior of a single representative economy in which there are only three real variables: oil price, three-month T-bill rate and real GDP. Oil price represents the commodity price that can be the cost of production, whereas three-month T-bill rate is the cost of capital. Real GDP is a gross measure of output. This parsimonious model describes a representative economy that has a production function similar to the Cobb–Douglas function that is widely used to represent the relationship of an output to inputs. The reduced-form VAR of one lag can be written as the followings:

$$OilPrice_t = \beta_{10} + \beta_{11}OilPrice_{t-1} + \beta_{12}TBillRate_{t-1} + \beta_{13}GDP_{t-1} + \varepsilon_{1t} \quad (1)$$

$$TBillRate_t = \beta_{20} + \beta_{21}OilPrice_{t-1} + \beta_{22}TBillRate_{t-1} + \beta_{23}GDP_{t-1} + \varepsilon_{2t} \quad (2)$$

$$GDP_t = \beta_{30} + \beta_{31}OilPrice_{t-1} + \beta_{32}TBillRate_{t-1} + \beta_{33}GDP_{t-1} + \varepsilon_{3t} \quad (3)$$

Having specified the reduced-form VAR model, the appropriate lag length of this model has to be decided. It is common to choose the lag length based upon a priori knowledge. For example, monetary economists tend to use four lags due to the presence of seasonality in quarterly macroeconomic time-series data. However, a large lag length relatively to the number of observations will typically lead to an inefficient estimation of coefficients β_{ij} (for equation *i* and coefficient *j*). On the other hand, a short lag length will induce spuriously significant coefficients, as unexplained information is left in the disturbance terms ε_{it} (for equation *i* at time *t*). The alternative approach is to use a statistical method such as Akaike (1974) information criterion (AIC), Schwarz (1978) Bayesian information criterion (BIC)[8], and Hannan and Quinn (1979) information criterion (HQIC). It is actually preferred and recommended by many econometrics textbooks including Enders (2009) and Lutkepohl (2010).

[8] Akaike (1977) develops his own Bayesian formalism independent of Schwarz (1978), now often referred to as Akaike's Bayesian Information Criterion (ABIC).

Yule (1926), Granger and Newbold (1974) and Phillips (1986) have observed that the ordinary least square regression of two nonstationary variables may produce spurious regression results. Thus, it is necessary to test for stationarity of the variables before estimating the model. The results of augmented Dickey-Fuller (ADF) test and Phillips–Perron (PP) test (Panel A of Table V) indicate the existence of unit-root in the real variables in levels. By taking the first-difference on the real variables, the new time-series data becomes stationary, as the ADF and PP test results shown in Section B of Table V.

[Insert Table V here]

The results of Akaike information criterion (AIC), Schwarz-Bayesian information criterion (BIC), and Hannan-Quinn information criterion (HQIC) suggest the optimal length of lags to be 2. Therefore, the more appropriate specification of the reduced-form VAR is:

$$\begin{aligned}\Delta OilPrice_t = \beta_{10} + \beta_{11}\Delta OilPrice_{t-1} + \beta_{12}\Delta OilPrice_{t-2} + \beta_{13}\Delta TBillRate_{t-1} + \beta_{14}\Delta TBillRate_{t-2} \\ + \beta_{15}\Delta GDP_{t-1} + \beta_{16}\Delta GDP_{t-2} + \varepsilon_{1t}\end{aligned} \tag{4}$$

$$\begin{aligned}\Delta TBillRate_t = \beta_{20} + \beta_{21}\Delta TBillRate_{t-1} + \beta_{22}\Delta TBillRate_{t-2} + \beta_{23}\Delta OilPrice_{t-1} + \beta_{24}\Delta OilPrice_{t-2} \\ + \beta_{25}\Delta GDP_{t-1} + \beta_{26}\Delta GDP_{t-2} + \varepsilon_{2t}\end{aligned} \tag{5}$$

$$\begin{aligned}\Delta GDP_t = \beta_{30} + \beta_{31}\Delta GDP_{t-1} + \beta_{32}\Delta GDP_{t-2} + \beta_{33}\Delta OilPrice_{t-1} + \beta_{34}\Delta OilPrice_{t-2} \\ + \beta_{35}\Delta TBillRate_{t-1} + \beta_{36}\Delta TBillRate_{t-2} + \varepsilon_{3t}\end{aligned} \tag{6}$$

Or in matrix form:

$$Y = B' L(Y) + \varepsilon, \text{ and } \varepsilon \sim N(0, \Sigma) \tag{7}$$

where $Y = \begin{bmatrix} \Delta OilPrice \\ \Delta TBillRate \\ \Delta GDP \end{bmatrix}$ at time t, $L(.)$ is the lag operator ($t-1$ and $t-2$), B is the matrix of beta coefficients, ε is the vector of residuals, and Σ is the diagonal variance-covariance matrix.

The reduced-form VAR can be directly estimated through single equation regression methods like OLS, however, the lag structure in equations (4) through (6) is unrestricted and therefore uninterpretable without reference to theoretical economic structures.[9] In other words, there is no unique mapping from reduce-form VAR to structural VAR without imposing sufficient number of contemporaneous restrictions on the lag structure to identify the structural coefficients. Suppose that the structural model has 3 equations, one each for the commodity market, capital market and goods market. Let $e_{\text{Commodity}}$, e_{Capital} and $e_{\text{Production}}$ be the structural disturbances or shocks to the commodity market, capital market and goods market output respectively, and ε_t be the residuals in the reduced-form VAR of equations (4) through (6). This structural VAR can be written in matrix form as:

$$Y = B' L(Y) + A^{-1} e \text{, and } e \sim N(0, I) \tag{8}$$

where $Y = \begin{bmatrix} \Delta OilPrice \\ \Delta TBillRate \\ \Delta GDP \end{bmatrix}$ at time t, $L(.)$ is the lag operator ($t-1$ and $t-2$), B is the matrix of beta coefficients, A is the matrix of identification restrictions that guarantee the unique mapping between reduced-form VAR and structural VAR, e is the vector of

[9] Cooley and Leroy (1985) criticize the reduced-form VAR on the ground that traditional VAR uses identification restriction based upon a recursive contemporaneous structure known as Choleski decomposition which is statistical, but not necessarily consistent with economic theory. Therefore the estimated shocks are not pure economic shocks but rather linear combinations of the structural disturbances. The evidence presented in Runkle (1987) suggests that it is often so.

disturbances or shocks, and I is the identity matrix. By comparing equation (7) and (8), the following condition is obtained: $\varepsilon = A^{-1}e$ or $A\varepsilon = e$.

The covariance matrix for structural disturbances $e(\Sigma)$ is assumed to have unity on its diagonal, and zero elsewhere, namely, $e = \varepsilon$, or

$$e_{Commodity} = \varepsilon_1 \tag{9}$$
$$e_{Capital} = \varepsilon_2 \tag{10}$$
$$e_{Production} = \varepsilon_3 \tag{11}$$

Equations (9) through (11) can be transformed to matrix form:

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{bmatrix} = \begin{bmatrix} e_{Commodity} \\ e_{Capital} \\ e_{Production} \end{bmatrix} \tag{12}$$

Now the matrix of identification restriction is formally defined as:

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{13}$$

This special case of contemporaneous restrictions implies that each real variable ($OilPrice_t$, $TBillRate_t$, and GDP_t) is assigned to its own structural equation (commodity market, capital market and output) which ensures that the shocks can be given meaningful economic interpretations. For example, if the commodity price is predetermined, only the commodity (oil) producers can respond instantly to aggregate supply shocks $e_{Commodity}$, hence the residual ε_1 of the oil price equation (4). This is consistent with the aggregate supply function, but the model is still overidentified as explained below.

Sims (1986), Bernanke (1986) and Blanchard and Watson (1986) make use of economic theory to impose short-run structural restrictions (shocks only have temporary effects) on the observed values of residuals (ε_1, ε_2 and ε_3) to recover the underlying structural disturbances ($e_{Commodity}$, $e_{Capital}$ and $e_{Production}$).[10] Following their methodology, there are 3×(3−1)/2=3 restrictions required for exact-identification in this three-variable VAR model of equations (4) through (6). The special case of equation (13) has 6 restrictions, therefore it is overidentified. In order to exact-identify this VAR, I will need only 3 restrictions, or equivalently 3 zero in the A matrix of equation (13).

Now I specify the new restrictions as the followings. The first equation (14) of this three-variable VAR is treated in the same way as equation (9) because it represents the commodity (oil) price and is assumed exogenous, at least contemporaneously. It is an appropriate assumption for an open economy. Bernanke, Gertler, Watson, Sims and Friedman (1997) argue that oil price provides valid exogenous shocks and affects U.S. monetary policy and real economy for two reasons. First, periods dominated by oil price shocks are reasonably easy to identify empirically, and the case for exogeneity of at least the major oil price shocks is strong. Second, oil price shocks are perhaps the leading alternative to monetary policy as the key factor in postwar U.S. recessions.

The second equation (15) represents the money (capital) market. In a typical theoretical model of money market, money demand is assumed to depend contemporaneously on the interest rate, inflation, and income, whereas money supply is set by the central bank after observing the money value, inflation and output. In this parsimonious model, I do not consider the money demand and money supply separately. Instead, the equilibrium interest rate (secondary market rate of three-month Treasury Bill) is a proxy for the optimal or prevailing cost of capital and depends only on output in the

[10] Alternatively, Shapiro and Watson (1988) and Blanchard and Quah (1989) consider the shocks having permanent effects.

goods market. This assumption implicitly suggests that commodity prices affect the money market only with a lag. The third equation (16) represents the goods (output) market. I allow shocks of commodity price and capital cost to have a contemporaneous effect on the output.

$$e_{Commodity} = \varepsilon_1 \tag{14}$$

$$e_{Capital} = \varepsilon_2 + a_1\varepsilon_3 \tag{15}$$

$$e_{Production} = a_2\varepsilon_1 + a_3\varepsilon_2 + \varepsilon_2 \tag{16}$$

The restrictions of equations (14) through (16) can be written in matrix form:

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & a_1 \\ a_2 & a_3 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{bmatrix} = \begin{bmatrix} e_{Commodity} \\ e_{Capital} \\ e_{Production} \end{bmatrix} \tag{17}$$

where a_1, a_2 and a_3 are free-parameters in the sense that they are not restricted to be zero and their values are estimated from the data. The matrix of identification restrictions is defined as equation (18), and there are 3 zeros in the matrix suggesting 3 restrictions for exact-identification.

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & a_1 \\ a_2 & a_3 & 1 \end{bmatrix} \tag{18}$$

Having specified the new restriction matrix A, I can estimate the three-variable VAR and use the impulse-response functions (IRFs) and forecast-error variance decomposition to analyze the impact of one variable on another.

2.5.1.2 Macroeconomy with housing and banking sectors (six-variable)

In order to study the impact of mortgage securitization and the moral hazard problem between banks and MBS investors on the U.S. economy and specifically the U.S.

housing market, I will need to add three more variables to this three-variable model and construct a six-variable Structural VAR. These variables are proxies for the activities of housing market and mortgage securitization, and the banks' incentive to screen and monitor the mortgages that are being originated and securitized. The first variable is house price risk, the second variable is securitization rate, and the third variable is the aggregate ownership of securitized mortgages by all commercial banks (shortened as $Bank_t$ in the VAR). Housing risk, or equivalently house price risk, is the quarterly standard deviation of the returns of an equally-weighted residential REIT portfolio.[11] Mortgage-backed security or MBS is the financial instrument created by the securitization process, and actively traded among financial institutions including investment banks, insurance companies and hedge funds. The holding of MBS by commercial banks is sometime referenced as the "skin in the game" by market practitioners and academic researchers.

The results of Akaike information criterion (AIC), Schwarz-Bayesian information criterion (BIC), and Hannan-Quinn information criterion (HQIC) suggest the optimal lag length to be 1. The specification of this six-variable reduced-form VAR is:

$$\begin{aligned} OilPrice_t = \beta_{10} + \beta_{11} OilPrice_{t-1} + \beta_{12} Securitization_{t-1} + \beta_{13} TBillRate_{t-1} + \beta_{14} HouseRisk_{t-1} \\ + \beta_{15} GDP_{t-1} + \beta_{16} Bank_{t-1} + \varepsilon_{1t} \end{aligned} \tag{19}$$

$$\begin{aligned} TBillRate_t = \beta_{20} + \beta_{21} TBillRate_{t-1} + \beta_{22} OilPrice_{t-1} + \beta_{23} Securitization_{t-1} + \beta_{24} HouseRisk_{t-1} \\ + \beta_{25} GDP_{t-1} + \beta_{26} Bank_{t-1} + \varepsilon_{3t} \end{aligned} \tag{20}$$

$$\begin{aligned} Bank_t = \beta_{30} + \beta_{31} Bank_{t-1} + \beta_{32} OilPrice_{t-1} + \beta_{33} Securitization_{t-1} + \beta_{34} TBillRate_{t-1} \\ + \beta_{35} HouseRisk_{t-1} + \beta_{36} GDP_{t-1} + \varepsilon_{5t} \end{aligned} \tag{21}$$

[11] House price risk is defined in the previous data section, and see Table 1 for more details. Residential REITs are Compustat firms in GICS 4040 industry, specifically GICS 40402050 sub-industry, engaged in the acquisition, development, ownership, leasing, management and operation of residential mortgages and properties including multifamily homes, apartments, manufactured homes and student housing properties.

$$HouseRisk_t = \beta_{40} + \beta_{41}HouseRisk_{t-1} + \beta_{42}OilPrice_{t-1} + \beta_{43}Securitization_{t-1} + \beta_{44}TBillRate_{t-1} + \beta_{45}GDP_{t-1} + \beta_{46}Bank_{t-1} + \varepsilon_{4t} \quad (22)$$

$$Securitization_t = \beta_{50} + \beta_{51}Securitization_{t-1} + \beta_{52}OilPrice_{t-1} + \beta_{53}TBillRate_{t-1} + \beta_{54}HouseRisk_{t-1} + \beta_{55}GDP_{t-1} + \beta_{56}Bank_{t-1} + \varepsilon_{2t} \quad (23)$$

$$GDP_t = \beta_{60} + \beta_{61}GDP_{t-1} + \beta_{62}OilPrice_{t-1} + \beta_{63}Securitization_{t-1} + \beta_{64}TBillRate_{t-1} + \beta_{65}HouseRisk_{t-1} + \beta_{66}Bank_{t-1} + \varepsilon_{5t} \quad (24)$$

Following the identification method of Sims (1986), Bernanke (1986) and Blanchard and Watson (1986), There are 6×(6−1)/2=15 restrictions required for exact-identification in this six-variable VAR model of equations (19) through (24). I will specify restrictions in the order of the identification equations. The equation (25) represents the commodity (oil) price and equation (26) represents the money (capital) market. These two restrictions suggests that oil price shocks are exogenous and monetary policy is only affected by commodity price and output. This is based on the results of Bernanke, Gertler, Watson, Sims and Friedman (1997).

$$e_{Commodity} = \varepsilon_1 \quad (25)$$
$$e_{Capital} = a_1\varepsilon_1 + \varepsilon_2 + a_2\varepsilon_6 \quad (26)$$
$$e_{Bank} = a_3\varepsilon_2 + \varepsilon_3 + a_4\varepsilon_4 + a_5\varepsilon_5 \quad (27)$$
$$e_{Housing} = a_6\varepsilon_1 + a_7\varepsilon_2 + a_8\varepsilon_3 + \varepsilon_4 + a_9\varepsilon_5 \quad (28)$$
$$e_{Securitization} = a_{10}\varepsilon_2 + a_{11}\varepsilon_3 + a_{12}\varepsilon_4 + \varepsilon_5 \quad (29)$$
$$e_{Production} = a_{13}\varepsilon_1 + a_{14}\varepsilon_2 + a_{15}\varepsilon_4 + \varepsilon_6 \quad (30)$$

The equation (27) represents the banking market and the change of commercial banks' holdings in mortgage-backed security is assumed to contemporaneously depend on the interest rate, house price risk and securitization activities. This restriction implies that any unexpected rising and falling of construction cost as proxied by the commodity price will only have lagged (not contemporaneous) effect on the securitization market.

The equation (28) is the restriction for the shocks of house price risk. I allow cost of production (commodity price), interest rate, banks' MBS ownership and securitization activities to have a contemporaneous effect on house price risk. In a typical theoretical model of financial innovation, securitization is assumed to be endogenous and depend on the cost of capital (interest rate), banks' incentive (MBS ownership) and housing market activities (house price risk). This is the restriction in equation (29), which also suggests that production cost (commodity price) and aggregate output (real GDP) affect the securitization market only with a lag. The restrictions in (28) and (29) imply that the securitization and housing market affect depend on each other contemporaneously in both directions. It is an appropriate assumption for output to be affected by many economic activities including those of the commodity market (oil price), capital market (interest rate) and housing market (house price risk). The restriction for the goods market is specified in equation (30). The identification restrictions of equations (25) through (30) can be written in matrix form:

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ a_1 & 1 & 0 & 0 & 0 & a_2 \\ 0 & a_3 & 1 & a_4 & a_5 & 0 \\ a_6 & a_7 & a_8 & 1 & a_9 & 0 \\ 0 & a_{10} & a_{11} & a_{12} & 1 & 0 \\ a_{13} & a_{14} & 0 & a_{15} & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \end{bmatrix} = \begin{bmatrix} e_{Commodity} \\ e_{Capital} \\ e_{Bank} \\ e_{Housing} \\ e_{Securitization} \\ e_{Production} \end{bmatrix} \tag{31}$$

where a_1 to a_{15} are free-parameters in the sense that they are not restricted to be zero and their values are estimated from the data. The matrix of identification restrictions is defined as the following, and there are 15 zeros in the matrix suggesting 15 restrictions for exact-identification.

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ a_1 & 1 & 0 & 0 & 0 & a_2 \\ 0 & a_3 & 1 & a_4 & a_5 & 0 \\ a_6 & a_7 & a_8 & 1 & a_9 & 0 \\ 0 & a_{10} & a_{11} & a_{12} & 1 & 0 \\ a_{13} & a_{14} & 0 & a_{15} & 0 & 1 \end{bmatrix} \tag{32}$$

2.5.2 Cross-sectional Analysis

The dynamic time-series method of causality analysis used in the previous section is essentially to forecast future events based on known past events to predict data points before they are measured. It describes how the real economy and housing market react over time to exogenous impulses, which economists usually call shocks. These shocks are treated as exogenous from a macroeconomic point of view, and include changes in the commodity market, changes in the money market and changes in the banking market. A time-series model generally reflects the fact that observations close together in time will be more closely related than observations further apart. However, a concern arises in the aggregation of economic data. By aggregating economic activities into one single variable like the GDP and house price risk, the geographical characteristics such as the differences of market completeness or risk sharing capability across different locations are largely ignored.

As a robustness check, this section provides cross-sectional evidence of how mortgage securitization and commercial banks' ownership of mortgage-backed security in each geographic region affect local real economy.

I collect regional data for each MSA, a five-digit Core-Based Statistical Area code including metropolitan and micropolitan areas. The variables of all firms excluding financial institutions in a MSA are total population, sales revenue, sales-to-asset ratio, total asset, market-to-book ratio, and financial leverage (total asset over book equity). The variables of financial institutions in each MSA include total asset, market-to-book ratio, financial leverage, ROA, mortgage securitization rate, and banks' MBS ownership. Due to the fact that commercial banks were required to report their MBS holdings since 2001, the time period of the entire data sample is from the second quarter of 2001 to the fourth quarter of 2010.

There are three econometric specifications of pooled regressions. The first regression (33) has the aggregate log sales revenue of all non-financial firms in each MSA as the dependent variable, and the second one (34) has the aggregate sales-to-asset ratio of all non-financial firms in each MSA on the left hand side. The right-hand side independent variables include log population, log total asset, market-to-book, financial leverage, log bank asset, bank market-to-book, bank leverage, bank ROA, mortgage securitization rate, and banks' MBS ownership in each MSA region.

$$\begin{aligned}\log(Revenue) = \beta_0 + \beta_1 \log(Population) + \beta_2 Asset + \beta_3 M2B + \beta_4 Leverage \\ + \beta_5 BankAsset + \beta_6 BankM2B + \beta_7 BankLeverage + \beta_8 BankROA \\ + \beta_9 SecuritizationRate + \beta_{10} BankMBSOwnership + \varepsilon \end{aligned} \tag{33}$$

$$\begin{aligned}\log(Sales2Asset) = \beta_0 + \beta_1 \log(Population) + \beta_2 Asset + \beta_3 M2B + \beta_4 Leverage \\ + \beta_5 BankAsset + \beta_6 BankM2B + \beta_7 BankLeverage + \beta_8 BankROA \\ + \beta_9 SecuritizationRate + \beta_{10} BankMBSOwnership + \varepsilon \end{aligned} \tag{34}$$

The entire sample is ranked according to the numbers of banks and firms within each MSA. When both the number of firms and the number of banks in a MSA are in the top quartile of the entire sample, such MSA is categorized as Large MSA. Similarly, when both the number of firms and the number of banks in a MSA are in the bottom quartile, it is categorized as Small MSA. In both regressions, robust standard error is used.

The third specification (35) uses the house price risk as the dependent variable. House price risk is defined as the standard deviation of 30-quarter house price returns in each of the 25 MSA regions that are part of the House Price Index owned and maintained by Federal Housing Finance Agency (FHFA).

$$\begin{aligned}\log(HousePriceRisk) = {} & \beta_0 + \beta_1 \log(Population) + \beta_2 Asset + \beta_3 M2B + \beta_4 Leverage \\ & + \beta_5 ROA + \beta_6 BankAsset + \beta_7 BankM2B + \beta_8 BankLeverage + \beta_9 BankROA \\ & + \beta_{10} SecuritizationRate + \beta_{11} BankMBSOwnership + \varepsilon \qquad (35)\end{aligned}$$

The seasonally-unadjusted quarterly HPI data is available from the first quarter of 1991 to the second quarter of 2011. The right-hand side independent variables are similar to the previous regression specifications: log population, log total asset, market-to-book, financial leverage, log bank asset, bank market-to-book, bank leverage, bank ROA, mortgage securitization rate, and banks' MBS holdings in each MSA region.

It should be noted that the economic interpretation of statistical significance in correlations among the regional securitization activities, housing risks and outputs deserves caution because the cross-sectional result does not provide "true" causal evidence as in either Sims (1980, 1982, 1986)'s time-series prediction or Rubin (1974, 1978)'s causality. The first econometric method in this paper is based upon Sims' time-series prediction which is essentially the Granger (1969) Causality, whereas the third method that I am about to discuss below is to specifically address the Rubin causality through the use of a quasi-experimental design which assigns intervention (treatment) and control (non-treatment) status at the bordering CBSA regions, and examines outcomes (changes of house price risk) at the metropolitan and metropolitan levels before and after conducting the intervention or treatment.

2.5.3 Quasi-experimental Design

This section aims to draw the causal inference with observational data by examining whether the cross-sectional results are driven by endogeneity concerns such that some omitted variables correlated with securitization, output and house price risk are driving the results spuriously, or the securitization does have causal impact on risk sharing in the real economy and housing market. In order to do so, I consider the passing of anti-predatory lending laws in the 10 states in year 2002 and 2003 as an exogenous shock or treatment. [12] I employ a matched sample difference-in-differences (DID) approach and pooled DID regression (see Meyer 1995, and Angrist and Krueger 1999 for detailed explanations of this methodology). I specifically analyze the housing and securitization data in neighboring CBSAs along the borders between the states that has passed the anti-predatory lending laws and those have not.

It has been argued in law literature that the predatory lending practice was caused by the over-supply of credit which was in turn due to securitization. For example, Eggert (2002) suggests that the growing securitization of residential mortgages and the troubling rise of the subprime mortgage industry create a fertile environment for predatory lending. With the advent of securitization, residential mortgages no longer were held until maturity by their originator and instead came to be transferred almost immediately upon their creation. With the access to capital markets that securitization provided, lenders dramatically expanded the amount of lending made available to borrowers with less than

[12] Arkansas, Georgia, Illinois, Maine, Massachusetts, North Carolina, New York, New Jersey, New Mexico and South Carolina are among the states considered to have the strongest laws. For example New Jersey (2004) states that the law is known as the New Jersey Homeowners Security Act, and signed in May 2003 and took effect in November 2003. It is a result of ongoing consultations with consumer groups and lenders in the state of New Jersey, and provides substantial protection against abusive provisions in high-cost loans, the most flagrant of predatory practices.

perfect credit, and the subprime loan market expanded rapidly. With these developments, and while protected from risk of loss both by contractual arrangements with the originators of loans and by the holder in due course doctrine, the capital markets began supplying funds to lenders who used the same deceptive practices in the residential mortgage industry that their predecessor consumer credit lenders had used in the past. [13]

Given the argument that the predatory lending is potentially associated with securitization due to supply-side effect, the passing of anti-predatory lending laws on the state level will have negative impact on the securitization activities within the jurisdictional territory of the state, but no impact on the securitization in the neighboring state. Specifically, I consider the passing of anti-predatory lending laws in the 10 states in year 2002 and 2003 as a treatment, and this negative shock is intended to reduce the securitization activities in the effected states, and conduct two difference-in-differences (DID) analyses.

2.5.3.1 Univariate Difference-in-difference

In the first DID test using univariate statistics, CBSA regions within the borderline of a state in which the law is passed in 2002 and 2003 are defined as the *treatment* group, and CBSA regions within the borderline of a neighboring state in which the law is NOT passed are the *control* or *non-treated* group. I collected the housing data and industrial output data from year 2001 to 2005. There are 101 pairs of bordering CBSAs in the original sample (see Appendix for the list of CBSAs and states), but because many CBSAs are small and don't have housing data available, the final sample

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[13] See also Engel and McCoy (2002, 2006) and Julia (2006). Azmy (2005) analyzes both the supply-side and demand-side effects.

size is reduced to 18 pairs of CBSAs. The difference-in-difference (DID) method requires taking two differences. The first-difference is taken for the house price risks in each CBSA region before (the averages of 2000 and 2001) and after (the averages of 2004 and 2005) the shock and the second-difference is taken for the first-differences between the two bordering CBSA regions.

2.5.3.2 Multivariate Difference-in-Difference

In the second DID analysis using multivariave statistics, CBSA regions in a state with the law passed in 2002 and 2003 are defined as the treatment group, and CBSA regions in a state without the law passed are the control or non-treated group. The dummy variable of *WithLaw* is set to unity if the state has the anti-predatory lending law passed, and zero if it doesn't. The dummy variable of *PostLaw* is set to unity if the year is 2004 or 2005, and zero if the year is 2000 or 2001. A third dummy variable *WithLaw×PostLaw* is the cross-product of the previous two dummy variables. The DID regression equation is:

$$Risk = \phi_0 + \phi_1 WithLaw + \phi_2 PostLaw + \phi_3 WithLaw \times PostLaw + \phi Controls + \varepsilon_t \qquad (36)$$

According to Meyer (1995) and Angrist and Krueger (1999), the coefficient ϕ_3 of the *WithLaw×PostLaw* dummy is the effect that needs to be estimated. The dependent variables is house price risk which is the standard deviation (%) of percentage returns of new residential house values in each CBSA region in year 2000, 2001, 2004 and 2005, and the independent variables include log population, log total asset, market-to-book, financial leverage, ROA, log bank asset, bank market-to-book, bank leverage, bank ROA, and three dummy variables in each CBSA region.

It should be noted that this specific quasi-experimental design can only provide causal evidence in the sense of Rubin (1974, 1978) that mortgage securitization help reduce the risk of housing market. However, it has no explanation power for the impact of commercial banks' ownership of mortgage-backed securities the volatility of property prices.

2.6 Results

I begin by alayzing the SVAR for the macroecomy (3-variable baseline) model for studying the behavior of a single representative economy includes three real variables: oil price, three-month T-bill rate and real GDP. They represent the commodity market (as a proxy for cost of production), money market (as a proxy for cost of capital) and aggregate output respectively. The data are first-differenced. Statistical tests suggest that first-difference makes the data stationary (See Table V in the previous Methodology section). After obtained first-differenced time-series data, the first stage is to estimate the reduced-form VAR. The variance-covariance matrix from this reduced-form VAR is used to estimate the structural VAR in the second stage. Two lags are used for this three-variable VAR model based on the test results of AIC, BIC and HQIC, and the sample period is from the first quarter of 1983 to the fourth quarter of 2009.

The parameter (β) estimates for the reduced-form three-variable VAR in equations (4) through (6) are not reported because their economic interpretation is ambiguous without appropriate restrictions.[14] Table VI shows the free-parameters (a)

[14] The evidence presented in Runkle (1987) suggests that it is often difficult to draw strong conclusions about the interrelationship of interest rates, money, prices, and output from unrestricted VARs. They often do not tell much about interesting macroeconomic questions.

estimates for the identification restrictions of the structural VAR in equations (14) through (16), or equation (18) in matrix form.

[Insert Table VI here]

Figure 2.2 plots the impulse-response functions (IRF) with 95% confidential interval bands.

[Insert Figure 2.2 here]

Impulse response function (IRF) describes how the economy reacts over time to exogenous impulses, which economists usually call *shocks*, and are often modeled in the context of a VAR. Impulses that are often treated as exogenous from a macroeconomic point of view include changes in government spending, tax rates, and other fiscal policy parameters; changes in the monetary base or other monetary policy parameters; changes in productivity or other technological parameters. In this baseline three-variable VAR, IRF is the reaction of endogenous macroeconomic variables such as commodity (oil) price, output (real GDP) and interest rate (3-month Treasury Bill) at the time of the shock and over subsequent quarters in time.

The shock in commodity (oil) price raises the real GDP initially in the first quarter, but reduces the output in the subsequent two quarters, and after the fourth quarter the output returns to normal.[15] The coefficient estimates of the reduced-form VAR in Table

[15] Hooker (1996) investigates the Granger-causality between oil price shocks and U.S. GDP changes and shows that a one-time, one-standard deviation increase in oil prices typically led to GDP growth roughly

VI confirms the relationship because the GDP equation in column (3) has a positive coefficient for the one-quarter lagged oil price change but a negative coefficient for the two-quarter lagged oil price change. Interest rate shock has the similar pattern of impact on output. On the other hand, the commodity price shock has no impact on the interest rate as measured by the three-month Treasury rate due to the fact that its IRF's 95% confident interval of includes zero. Similarly, shocks in output as measured by the real GDP do not affect the commodity price change and interest rate change in a significant way. The forecast-error variance decomposition (FEVD) is shown in Figure 2.3. FEVD indicates the amount of information each variable contributes to the other variables in a vector autoregression (VAR) models, or in other words, it determines how much of the forecast error variance of each of the variable can be explained by exogenous shocks to the other variables. The interest rate shock gradually explains most of output's variability. Comparing to the commodity price shock, the interest rate shock is more important for the real GDP.

[Insert Figure 2.3 here]

To study the impact of mortgage securitization and the moral hazard problem between banks and investors of securitized mortgages on the real economy and U.S. housing market, the six-variable VAR model adds three new variables relevant to the housing market, mortgage market and incentive to screen and monitor the mortgages that are being originated and securitized: (i) mortgage securitization rate, (ii) house price risk,

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0.6 percentage points lower in the third and fourth quarters after the shock, returning to its undisturbed rate in a slowly damping cyclical pattern.

a measure for the risk in the housing market, (iii) The new variable is the aggregate ownership of securitized mortgages by all commercial banks (shortened as $Bank_t$ in the VAR). Table VII shows the free-parameters (a) estimates for the identification restrictions of the structural VAR in equations (25) through (30), or equation (32) in matrix form.

[Insert Table VII here]

Figure 2.4 plots the impulse-response functions (IRF) with 95% confidential interval bands.

[Insert Figure 2.4 here]

These graphs illustrate the reaction of commodity (oil) price, mortgage securitization rate, interest rate (3-month Treasury Bill), housing risk (residential REITs' price risk), output (real GDP) and banks' MBS ownership at the time of the shock and over subsequent ten quarters in time. Specifically, positive shocks in the securitization market reduce the housing risk and increase aggregate output in a statistically significant way as indicated by the 95% confidential interval bands. A one standard deviation positive shock to the securitization rate causes $8 billion increase in real GDP, or roughly 0.08%, and 1.5% reduction in house price risks. The impact to the housing market is long-lasting: it takes about four quarters (one year) for house price risk to return to normal after the initial securitization shock, whereas it takes only about one quarter for output to return to normal. The shock in housing market contemporaneously increases the interest rate and reduces the output, but the effect is very weak because zero falls inside the 95% confidence interval. Interestingly, the same kind of shock has a long-term effect on the securitization market: the securitization rate increases in response to the rising house price risk and the effect lasts for more than ten quarters. The forecast-error variance decomposition (FEVD) in Figure 2.5 shows that shocks of securitization market, money market (interest rate) and banking market have significant explanation power over the variation of real GDP. They also gradually explain the variation of housing market. These findings support the "good" view of mortgage securitization (Hypothesis H1).

The shock of banks' ownership of MBS increases the housing risk for three quarters and reduces the aggregate output briefly (one quarter). A one standard deviation positive shock to commercial banks' MBS holdings causes 1% increase in house price risks, and \$6 billion reduction in real GDP, or roughly 0.06%. On the other hand, the only shock contemporaneously affects the banks' ownership of MBS is the shock from securitization market.[16] The rising securitization rate suddenly pushes up the banks' holding of mortgage-backed security and this effect disappears in just about one quarter. None of the other macroeconomic shocks in commodity price, interest rate, house price risk and output matters for banks' ownership of MBS. The forecast-error variance decomposition (FEVD) in Figure 2.5 shows that most variations in securitization market are explained by the shocks of interest rate and house price risk. Shocks of securitization rate and interest rate can explain most of the variability in banks' holdings of mortgage-backed security, whereas the risk of housing market only has insignificant explanatory

[16] Other IRFs that affect banks' MBS ownership have zero falling inside the 95% confidence interval band.

power for the changes in commercial banks' MBS ownership. These findings support the "bad" view of mortgage securitization, particularly the neglected risk hypothesis H3.

[Insert Figure 2.5 here]

In sum, the time-series evidence using structural VAR suggests that residential mortgage securitization does help complete the market by reducing housing risk and improving output. The influence of "skin in the game" from the commercial banks' MBS ownership on the securitization activities seems to be insignificant. There are evidences that shocks in banks' holdings of MBS actually increase the risk of residential housing market and makes real GDP decline.

As a robustness check and to provide complementary evidences, I run several cross-sectional regressions using the data of metropolitan statistical area (MSA)-level. There are three econometric specifications of pooled regressions. The first regression has the aggregate log sales revenue of all non-financial firms in each MSA as the dependent variable, and the second one (34) has the aggregate sales-to-asset ratio of all non-financial firms in each MSA on the left hand side. The right-hand side independent variables include log population, log total asset, market-to-book, financial leverage, log bank asset, bank market-to-book, bank leverage, bank ROA, mortgage securitization rate, and banks' MBS ownership in each MSA region.

The entire sample is ranked according to the numbers of banks and firms within each MSA. When both the number of firms and the number of banks in a MSA are in the top quartile of the entire sample, such MSA is categorized as Large MSA. Similarly, when both the number of firms and the number of banks in a MSA are in the bottom quartile, it is categorized as Small MSA. In both regressions, robust standard error is used. The results are shown in Table VIII and Table IX.

[Insert Table VIII and IX here]

The significantly positive sign of the coefficient for securitization rate indicates that regions with banks engaging in more mortgage securitization produces more sales revenue, whereas the negative sign of the coefficient for banks' MBS ownership suggests that more "skin in the game" actually has negative impact on regional output after controlling for total asset, productivity and leverage of both firms and banks in each MSA region. This finding is consistent with Gennaioli, Shleifer, and Vishny (2011) that market participants might have neglected the risks of mortgage securitization as in, which could potentially increase financial fragility even in the absence of financial leverage. More interestingly, the coefficient estimate of mortgage securitization rate for the small MSA regions is almost 20 times of the coefficient estimate of securitization rate for the large MSA regions. This clearly suggests that firms in high-density metropolitans like Chicago, New York and Los Angeles have better risk sharing than small cities, so that the benefit of mortgage securitization to the goods market is marginal. Allen and Gale (1994) make a similar point: "Insurance against unemployment cannot be purchased on the private market. For these individuals, existing outside the financial world of Wall Street and the City of London, markets are now less complete than they were before..." Related to this topic, Lustig and Van Nieuwerburgh (2004) use panel data from 23 U.S.

metropolitan areas, and find that times in which collateral is scarce are associated with significantly less risk-sharing. They reason that when the value of housing relative to human wealth falls, loan collateral shrinks, borrowing (risk-sharing) declines, and the sensitivity of consumption to income increases.

The third specification uses the house price risk as the dependent variable. The right-hand side independent variables are similar to the previous regression specifications: log population, log total asset, market-to-book, financial leverage, log bank asset, bank market-to-book, bank leverage, bank ROA, mortgage securitization rate, and banks' MBS holdings in each MSA region. The results are reported in Table X.

[Insert Table X here]

The negative coefficient estimate of mortgage securitization rate suggests that regions with more active securitization has lower risk in housing market than regions with less active securitization, whereas the positive coefficient estimate of banks' MBS ownership indicates the negative effect of banks' involvement in securitization on housing market due to increasing volatility in house prices. Specifically, a one standard deviation positive shock to securitization rate in a MSA region reduces its house price risk by 8.7% and increases its industrial (non-banking industry) output by 13.5%, whereas the same magnitude shock to commercial banks' MBS holdings increases regional property price's volatility by 89% and reduces regional industrial output by 29%.

These findings are consistent with the results (supporting the risk sharing hypothesis of Koppl 2006 and Gaur, Seshadri and Subrahmanyam 2010, and the neglected risk view of Gennaioli, Shleifer, and Vishny 2011, but not the agency view of Gorton and Pennacchi 1995 and Plantin 2010) of the previous two specifications that use MSA-level revenue and sales-to-asset ratio as the dependent variable. To some extent, this cross-sectional result supports Greenbaum and Thakor (1987)'s proposition with adverse selection that the high-quality loans are sold or securitized, and the low-quality loans are funded with deposits. The banks in the regions with more high-quality loans are more likely to securitize and this high securitization rate might reflect stronger regional economy, whereas the banks in the regions with more low-quality loans are less likely to securitize and this low securitization rate might reflect weaker regional economy. The economic interpretation of such statistically significant correlations among the regional securitization activities, housing risks and outputs deserves more caution because the cross-sectional result does not provide "true" causal evidence as in either Rubin (1974, 1978)'s causality or Sims (1980, 1982, 1986)'s time-series prediction.

To specifically address the causality question I employ a quasi-experimental design by examining whether the above results are driven by endogeneity concerns such that some omitted variables correlated with securitization, output and house price risk are driving the results spuriously, or the securitization does have causal impact on risk sharing in the real economy and housing market. In order to do so, I consider the passing of anti-predatory lending laws in the 10 states in year 2002 and 2003 as an exogenous shock or treatment. [17] I employ a matched sample difference-in-differences (DID)

[17] Arkansas, Georgia, Illinois, Maine, Massachusetts, North Carolina, New York, New Jersey, New Mexico and South Carolina are among the states considered to have the strongest laws. For example New Jersey (2004) states that the law is known as the New Jersey Homeowners Security Act, and signed in May 2003 and took effect in November 2003. It is a result of ongoing consultations with consumer groups and lenders in the state of New Jersey, and provides substantial protection against abusive provisions in high-cost loans, the most flagrant of predatory practices.

approach and pooled DID regression, and specifically analyze the housing and securitization data in neighboring CBSAs along the borders between the states that has passed the anti-predatory lending laws and those have not.

Given the argument that the predatory lending is potentially associated with securitization due to supply- -side effect, the passing of anti-predatory lending laws on the state level will have negative impact on the securitization activities within the jurisdictional territory of the state, but no impact on the securitization in the neighboring state. Specifically, I consider the passing of anti-predatory lending laws in the 10 states in year 2002 and 2003 as a treatment, and this negative shock is intended to reduce the securitization activities in the effected states, and conduct two difference-in-differences (DID) analyses.

In the first DID test using univariate statistics, CBSA regions within the borderline of a state in which the law is passed in 2002 and 2003 are defined as the *treatment* group, and CBSA regions within the borderline of a neighboring state in which the law is NOT passed are the *control* or *non-treated* group. The difference-in-difference (DID) method requires taking two differences. The first-difference is taken for the house price risks in each CBSA region before (the averages of 2000 and 2001) and after (the averages of 2004 and 2005) the shock and the second-difference is taken for the first-differences between the two bordering CBSA regions. The DID result is reported in Table XI. The statistically significant positive t-test (paired-sample) suggests an increase in residential house price risks due to the reduction of mortgage securitization activities in the 10 *treated* states after the passing of anti-predatory lending laws.

[Insert Table XI here]

In the second DID analysis using multivariave statistics, CBSA regions in a state with the law passed in 2002 and 2003 are defined as the treatment group, and CBSA regions in a state without the law passed are the control or non-treated group. The dummy variable of *WithLaw* is set to unity if the state has the anti-predatory lending law passed, and zero if it doesn't. The dummy variable of *PostLaw* is set to unity if the year is 2004 or 2005, and zero if the year is 2000 or 2001. A third dummy variable *WithLaw×PostLaw* is the cross-product of the previous two dummy variables. According to Meyer (1995) and Angrist and Krueger (1999), the coefficient ϕ_3 of the *WithLaw×PostLaw* dummy is the effect that needs to be estimated. According to the results shown in Table XII, the coefficient estimates of the cross-product dummy (*WithLaw×PostLaw*) in all regression specifications are significantly positive, suggesting that a CBSA region with its anti-predatory lending law passed has more house price risk due to the reduction of residential mortgage securitization activities. It can be inferred from this quasi-experimental design that securitization mitigates real-estate risk and potentially reduces the house price risk.

[Insert Table XII here]

It should be noted that this specific quasi-experimental design can only provide causal evidence in the sense of Rubin (1974, 1978) that mortgage securitization help reduce the risk of housing market. However, it has no explanation power for the impact of commercial banks' ownership of mortgage-backed securities the volatility of property prices.

2.7 Conclusions

This research analyzes the effect of mortgage securitization on the real economy and housing market. If securitization has transformed the credit markets by pooling and tranching cash flows from mortgage assets over the past few decades, and monetary policy operates through the credit markets, securitization must have important effects on the transmission mechanisms of monetary policy, and in turn on the banking sector and eventually on the real economy. Despite the empirical finding of Estrella (2002) that securitization has a significant effect on the degree to which a given change in monetary policy can influence real output, there has been no research systemically examining the relationships between securitization and housing market, and differentiating between the agency and neglected risk views of securitization.

I estimate the dynamic response of house price risk and aggregate U.S. real GDP to shocks of mortgage securitization and banks' ownership of mortgage-backed security (MBS), and test three hypotheses suggested in the extant literature. Using a structural vector autoregression (SVAR) methodology, I find that residential mortgage securitization reduces housing risk as suggested by the risk sharing hypothesis because securitization helps complete the market (Koppl 2006, Gaur, Seshadri and Subrahmanyam 2010). U.S. house price risk is reduced by 1.5% during the subsequent four quarters after a one standard deviation positive shock to mortgage securitization rate. The same shock increases aggregate output by roughly 0.1% or $8 billion in real GDP for the subsequent quarters. Thus, the mortgage securitization boom of the mid-2000s in the U.S. seems to cause the output to go up and housing risk to go down, supporting the hypothesis that securitization, as a risk transfer mechanism, benefits the financial market participants by improving market completeness through matching cash flows to investors' need in various states of the nature.

Interestingly, I also find that when commercial banks' ownership of MBS increases, housing risk increases and aggregate output decreases for three quarters and one quarter respectively. Specifically, a one standard deviation positive shock to banks' MBS holdings increases the volatility of property price by 1% and reduces the real GDP by 0.06% or $6 billions. This positive relationship between the housing risk and banks' MBS holdings is inconsistent with the agency view of securitization but is consistent with the neglected risk view of mortgage securitization (Gennaioli, Shleifer, and Vishny 2011). [18]

To address the concern that geographical characteristics such as the differences of market completeness or risk sharing capability across different locations are largely ignored due to the aggregation of economic data into one single variable like the real GDP and house price risk, I run several robustness checks using cross-sectional regressions. I collect regional economic, housing and financial market data for each metropolitan and micropolitan area. The results provide complementary evidences to support the neglected risk view of mortgage securitization.

Finally, I design a quasi-experimental study to find causal evidence that securitization affects risk sharing that enables economic agents, mainly industrial firms,

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[18] The evidence here is inconsistent to the agency view of securitization as in Gorton and Pennacchi (1995) and Plantin (2010).

investors and banks, to insulate their business activities from regional housing market shocks, I consider the passing of anti-predatory lending laws in the 10 US states in year 2002 and 2003 as an exogenous shock or treatment. I employ a matched sample difference-in-differences (DID) approach and pooled DID regression. I specifically analyze the housing and securitization data in neighboring CBSAs along the borders between the states that has passed the anti-predatory lending laws and those have not, and the evidence suggests that securitization mitigates real-estate risk and potential reduces the volatility of property prices.

The double-edged sword effect of mortgage securitization on the real economy and housing market as the evidences shown in this paper still leaves us with an open question: to what extent will the participation of the shadow banking system in mortgage securitization affect output and asset risk, as the commercial banks seems to have done? The answer will depend on what role the hedge funds, insurance companies and investment banks are playing, whether they act like a “monitor” with an agency problem, or they act like an “investor” neglecting the risk of MBS. Of course, to answer this question would involve the massive and difficult task of collecting MBS ownership data of hedge funds and investment banks. I leave such issues for future research.

Appendix. List of Bordering CBSA Regions

This is the list of bordering CBSA regions in neighboring states with and without anti-predatory lending laws passed around 2003

With Law		Without Law		With Law		Without Law		With Law		Without Law	
CBSA	State	CBSA	State	CBSA	State	CBSA	State	CBSA	State	CBSA	State
16980	IL	33340	WI	49340	MA	28300	NH	48340	AR	32820	TN
16980	IL	39540	WI	14460	MA	31700	NH	48340	AR	17260	MS
16980	IL	48580	WI	14460	MA	18180	NH	48340	AR	17380	MS
16980	IL	33140	IN	14460	MA	29060	NH	20980	AR	33740	LA
40420	IL	27500	WI	38860	ME	29060	NH	31620	AR	33380	LA
23300	IL	33820	WI	38860	ME	13620	NH	22220	AR	33060	OK
44580	IL	17540	IA	38860	ME	30100	NH	22900	AR	45140	OK
19340	IL	34700	IA	21020	NC	47260	VA	22900	AR	34780	OK
23660	IL	15460	IA	28620	NC	47260	VA	22140	NM	20420	CO
39500	IL	25300	MO	40260	NC	40060	VA	17580	NM	25820	TX
27300	IL	41180	MO	24660	NC	19260	VA	38780	NM	30220	TX
44100	IL	41180	MO	20500	NC	19260	VA	26020	NM	11380	TX
20820	IL	41180	MO	24660	NC	32300	VA	16100	NM	37780	TX
16060	IL	16020	MO	14380	NC	27740	TN	10460	NM	21340	TX
32060	IL	37140	KY	11700	NC	27740	TN	29740	NM	21340	TX
34500	IL	21780	IN	11700	NC	24620	TN	43500	NM	40940	TX
25380	IL	21780	IN	11700	NC	35460	TN	43500	NM	43420	TX
16660	IL	45460	IN	19140	GA	17420	TN				
19180	IL	29140	IN	19140	GA	16860	TN				
27460	NY	21500	PA	44900	GA	16860	TN				
27460	NY	47620	PA	44900	GA	22840	AL				
36460	NY	14620	PA	40660	GA	11500	AL				
21300	NY	42380	PA	16340	GA	11500	AL				
13780	NY	42380	PA	29300	GA	46740	AL				
35620	NJ	20700	PA	17980	GA	12220	AL				
35620	NJ	10900	PA	17980	GA	21640	AL				
35620	NJ	37980	PA	12460	GA	45220	FL				
35620	NJ	14860	CT	45620	GA	45220	FL				
45940	NJ	37980	PA	46660	GA	45220	FL				
12100	NJ	37980	PA	46660	GA	29380	FL				
47220	NJ	37980	PA	48180	GA	27260	FL				
39100	NY	45860	CT	41220	GA	27260	FL				
10580	NY	13540	VT	22220	AR	27900	MO				
24020	NY	13540	VT	25460	AR	14700	MO				
24020	NY	40860	VT	34260	AR	48460	MO				
38460	NY	15540	VT	37500	AR	28380	MO				
38340	MA	45860	CT	27860	AR	28380	MO				
44140	MA	25540	CT	14180	AR	28380	MO				
49340	MA	48740	CT	14180	AR	20540	TN				
49340	MA	39300	CT	27860	AR	32820	TN				
14460	MA	39300	CT	14180	AR	32820	TN				
38340	MA	13540	VT	22620	AR	32820	TN				

Table 14.1 Variable definitions of time-series data

Variable Name	Definition	Data Sources
Oil	Spot Oil Price: Quarterly price of West Texas Intermediate	FRED, Federal Reserve Bank of St. Louis
Securitization	Quarterly new residential MBS ($)divided by residential mortgage issuance ($)	Flow of Funds, Federal Reserve Board of Governors
Tbill	3-Month Treasury Bill: Quarterly average of secondary Market Rate	FRED, Federal Reserve Bank of St. Louis
Risk	House Price Risk: Quarterly volatility of the residential REIT portfolio return(equally-weighted)	Compustat and CRSP
GDP	Real Gross Domestic Product: Quarterly average	FRED, Federal Reserve Bank of St. Louis
Bank	Quarterly commercial bank's holding of MBS ($) divided by total MBS outstanding ($)	Mortgage Market Statistical Annual, Inside Mortgage Finance Publications

Table 15.2 Summary statistics of time-series data

Variable	N	Mean	SD	Min	Max	Median
Oil Price	108	33.81	23.45	11.28	133.93	25.52
Securitization Rate	108	58.22%	15.72%	19.64%	100%	57.23%
3-month T-bill Rate	108	4.59%	2.53%	0.06%	10.32%	4.93%
House Price Risk	108	0.82%	0.75%	0.38%	6.05%	0.6%
Real GDP	108	9837	2310	5866	13326	9584
Bank MBS Holding	108	14.44%	3.46%	6.2%	21.55%	14.7%

Table 16.3 Correlation matrix of time-series data

Variable	Oil Price	Securitization Rate	3-month T-bill	House Price Risk	Real GDP
Securitization Rate	0.64				
3-month T-bill	–0.44	–0.72			
House Price Risk	0.43	0.49	–0.42		
Real GDP	0.73	0.69	–0.70	0.36	
Bank MBS Holding	0.36	0.56	–0.75	0.13	0.71

Table 17.4 Variable definitions of MSA-level data

Variable Name	Definition	Data Sources
Revenue	Sales revenue of all non-financial firms in each MSA	Compustat
Sales-to-Asset	Revenue divided by total asset of non-financial firms	Compustat
House Price Risk	Standard deviation of 30-quarter house price returns in each of the 25 MSA regions that are part of the House Price Index owned and maintained by Federal Housing Finance Agency (FHFA)	FHFA
Population	Total population within each MSA	Missouri Census Data Center
Total Asset	Total asset of all non-financial firms within each MSA	Compustat
M2B	Market equity value of all non-financial firms divided by book equity	CRSP
Leverage	Total asset divided by book equity	Compustat
Bank Asset	Total asset of all commercial banks within each MSA	FR Y9C
Bank M2B	Market equity value of all commercial banks divided by book equity	FR Y9C
Bank Leverage	Total asset divided by book equity	FR Y9C
Bank ROA	Net income divided by total asset	FR Y9C
Securitization Rate	Transferred mortgage ($) divided by the sum of Transferred mortgage and kept mortgage ($)	FR Y9C
Bank MBS Holding	Bank’s MBS holding ($) divided by transferred mortgage ($)	FR Y9C

Table 18.5 Time-series stationarity tests

Unit-root test tests whether a time-series variable is non-stationary using an autoregressive model. A well-known test that is valid in large samples is the augmented Dickey–Fuller test. Another test is the Phillips–Perron test. The null hypothesis is there exists a unit root in the time-series data.

Panel A. Unit-root test on level data:

Variable	Augmented Dickey–Fuller (ADF) Test Statistic	Phillips–Perron (PP) Test Statistic
Oil Price	-1.291 (0.6331)	-0.984 (0.7589)
Securitization Rate	-2.623* (0.0882)	-2.356 (0.1544)
3-month T-bill Rate	-0.647 (0.8600)	-1.370 (0.5966)
House Price Risk	-3.719*** (0.0038)	-3.669*** (-0.0046)
Real GDP	-1.477 (0.5450)	-1.097 (0.7161)
Bank MBS Holding	-1.562 (0.5024)	-1.733 (0.4142)

Mackinnon approximate p-value is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Panel B. Unit-root test on first-differenced level data (except House Price Risk):

Variable	Augmented Dickey–Fuller (ADF) Test Statistic	Phillips–Perron (PP) Test Statistic
Oil Price	-8.827*** (0.0000)	-8.696*** (0.0000)
Securitization Rate	-12.816*** (0.0000)	-13.576*** (0.0000)
3-month T-bill Rate	-5.591*** (0.0000)	-5.630*** (0.0000)
Real GDP	-5.891*** (0.0000)	-6.001*** (0.0000)
Bank MBS Holding	-8.061*** (0.0000)	-8.058*** (0.0000)

Mackinnon approximate p-value is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 19.6 Structural VAR restrictions of baseline model: Macroeconomic system

The restrictions are in the form of a 3 by 3 matrix, thus there are $\frac{3\times(3-1)}{2}$ = 3 restrictions and 3 free-parameters (a_1 to a_3) for exact-identification:

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & a_1 \\ a_2 & a_3 & 1 \end{bmatrix}$$

The estimates of free-parameters (a_1 to a_3) for the structural VAR restrictions are shown below:

Restriction	(1) ΔOil Price	(2) Δ3-month T-bill	(3) ΔReal GDP
ΔOil Price	1	0	0
Δ3-month T-bill	0	1	0.00507* (1.65)
ΔReal GDP	-2.492*** (-26.13)	-24.55*** (-228.93)	1

t-test is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 20.7 Structural VAR restrictions of six-variable VAR model: Macro, mortgage securitization rate, house price risk, and banks' MBS holding

The restrictions are in the form of a 6 by 6 matrix, thus there are $\frac{6\times(6-1)}{2}$ = 15 restrictions and 15 free-parameters (a_1 to a_{15}) for exact-identification:

$$A=\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ a_1 & 1 & 0 & 0 & 0 & a_2 \\ 0 & a_3 & 1 & a_4 & a_5 & 0 \\ a_6 & a_7 & a_8 & 1 & a_9 & 0 \\ 0 & a_{10} & a_{11} & a_{12} & 1 & 0 \\ a_{13} & a_{14} & 0 & a_{15} & 0 & 1 \end{bmatrix}$$

The estimates of the free-parameters (a_1 to a_{15}) for the structural VAR restrictions are shown below:

Restriction	(1) ΔOil Price	(2) Δ3-month T-bill	(3) Δ Bank MBS Holding	(4) House Price Risk	(5) ΔSecuritization Rate	(6) ΔReal GDP
ΔOil Price	1	0	0	0	0	0
Δ3-month T-bill	-0.0431 (-0.428)	1	0	0	0	0.00991*** (4.398)
ΔBank MBS Holding	0	-0.950*** (-4.791)	1	-34.46*** (-6.913)	33.67 (1.109)	0
House Price Risk	-0.00759 (-0.0755)	0.0947 (0.648)	-0.0864 (-0.425)	1	-211.8*** (-13.74)	0
ΔSecuritization Rate	0	1.198*** (6.312)	0.993*** (7.110)	34.84*** (7.072)	1	0
ΔReal GDP	-2.073*** (-20.62)	-23.32*** (-119.6)	0	730.9*** (148.0)	0	1

t-test is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 21.8 MSA-level sales revenue, securitization rate and banks' MBS holding

The dependent variables is the log revenue of all non-financial firms in each MSA (a five-digit Core-Based Statistical Area code including metropolitan and micropolitan areas) region, and the independent variables include log population, log total asset, market-to-book, financial leverage, log bank asset, bank market-to-book, bank leverage, bank ROA, mortgage securitization rate, and banks' MBS holding in each MSA region. The entire sample is ranked according to the numbers of banks and firms within each MSA. When both the number of firms and the number of banks in a MSA are in the top quartile of the entire sample, such MSA is categorized as Large MSA. Similarly, when both the number of firms and the number of banks in a MSA are in the bottom quartile, it is categorized as a Small MSA.

Dependent variable:	All MSAs		Large MSAs		Small MSAs	
log(Revenue)	(1)	(2)	(3)	(4)	(5)	(6)
log(Population)		0.0512* (1.702)		-0.0985*** (-2.656)		0.594*** (4.884)
log(Total asset)	0.907*** (96.92)	0.886*** (57.08)	0.897*** (17.03)	0.923*** (23.47)	0.978*** (15.29)	0.743*** (10.67)
Market-to-book	0.126*** (8.760)	0.133*** (9.007)	0.180*** (3.542)	0.154*** (3.021)	-0.0640 (-0.683)	0.00955 (0.135)
Financial Leverage	-0.0732* (-1.840)	-0.0737* (-1.893)	-0.0426 (-0.525)	-0.0172 (-0.232)	-0.0822 (-1.226)	-0.0645 (-0.994)
log(Bank's total asset)	0.0107* (1.692)	0.00404 (0.521)	0.00328 (0.136)	-0.00291 (-0.154)	-0.327*** (-3.946)	-0.335*** (-4.641)
Bank's market-to-book	0.135*** (4.770)	0.129*** (4.813)	0.183*** (6.011)	0.142*** (4.155)	0.549*** (4.644)	0.0742 (0.560)
Bank's financial leverage	-0.00579 (-0.914)	-0.00552 (-0.901)	-0.0307*** (-5.146)	-0.0244*** (-3.641)	-0.0813** (-2.067)	-0.0322 (-1.012)
Bank's ROA	-7.304*** (-2.781)	-6.646*** (-2.609)	1.655 (0.562)	1.983 (0.672)	-32.19*** (-3.242)	-9.228 (-1.074)
Securitization rate	0.0249*** (2.846)	0.0190** (2.118)	0.0166* (1.872)	0.0202** (2.478)	0.584*** (3.747)	0.666*** (5.500)
Bank's MBS holding	-0.0882*** (-5.516)	-0.0859*** (-5.250)	-0.0457*** (-2.940)	-0.0644*** (-3.710)	-0.228 (-0.735)	-0.490* (-1.694)
Quarterly FE	Yes	Yes	Yes	Yes	Yes	Yes
N	664	664	143	143	87	87
R-square	0.99	0.99	0.99	0.99	0.99	0.99

t-test using robust standard error is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 22.9 MSA-level sales-to-asset, securitization rate and banks' MBS holding

The dependent variables is the sales-to-asset ratio of all non-financial firms in each MSA (a five-digit Core-Based Statistical Area code including metropolitan and micropolitan areas) region, and the independent variables include log population, log total asset, market-to-book, financial leverage, log bank asset, bank market-to-book, bank leverage, bank ROA, mortgage securitization rate, and banks' MBS holding in each MSA region. The entire sample is ranked according to the numbers of banks and firms within each MSA. When both the number of firms and the number of banks in a MSA are in the top quartile of the entire sample, such MSA is categorized as Large MSA. Similarly, when both the number of firms and the number of banks in a MSA are in the bottom quartile, it is categorized as a Small MSA.

Dependent variable:	All MSAs		Large MSAs		Small MSAs	
Sales-to-asset	(1)	(2)	(3)	(4)	(5)	(6)
log(Population)		0.00589 (0.815)		-0.0297*** (-2.665)		0.139*** (5.822)
log(Total asset)	-0.0233*** (-10.83)	-0.0257*** (-6.533)	-0.00972 (-0.630)	-0.00183 (-0.163)	-0.00522 (-0.343)	-0.0599*** (-4.149)
Market-to-book	0.0274*** (8.643)	0.0283*** (8.865)	0.0453*** (3.037)	0.0373** (2.542)	-0.0153 (-0.760)	0.00185 (0.123)
Financial Leverage	-0.0161* (-1.715)	-0.0161* (-1.740)	-0.0351 (-1.424)	-0.0274 (-1.254)	-0.0149 (-1.102)	-0.0107 (-0.833)
log(Bank's total asset)	0.00314** (2.191)	0.00237 (1.265)	0.000274 (0.0397)	-0.00160 (-0.302)	-0.0632*** (-3.412)	-0.0651*** (-4.053)
Bank's market-to-book	0.0262*** (4.034)	0.0256*** (3.991)	0.0453*** (4.993)	0.0329*** (3.413)	0.110*** (3.927)	-0.000745 (-0.0251)
Bank's financial leverage	0.000343 (0.294)	0.000374 (0.324)	-0.00730*** (-4.505)	-0.00540*** (-2.945)	-0.0114 (-1.387)	8.82e-05 (0.0136)
Bank's ROA	-1.233** (-2.234)	-1.158** (-2.120)	1.153 (1.375)	1.253 (1.488)	-5.347** (-2.639)	0.0109 (0.00627)
Securitization rate	0.00473** (2.312)	0.00405* (1.889)	0.00406* (1.680)	0.00514** (2.441)	0.126*** (3.618)	0.145*** (5.479)
Bank's MBS holding	-0.0234*** (-6.041)	-0.0232*** (-5.752)	-0.0144*** (-3.310)	-0.0201*** (-4.096)	-0.0265 (-0.337)	-0.0877 (-1.255)
Quarterly FE	Yes	Yes	Yes	Yes	Yes	Yes
N	664	664	143	143	87	87
R-square	0.95	0.95	0.99	0.99	0.96	0.97

t-test using robust standard error is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 23.10 MSA-level house price risk, securitization rate and banks' MBS holding

The dependent variables is house price risk which is defined as the standard deviation of 30-quarter house price returns in each MSA region (There are 25 MSAs that are part of the House Price Index owned and maintained by Federal Housing Finance Agency), and the independent variables include log population, log total asset, market-to-book, financial leverage, ROA, log bank asset, bank market-to-book, bank leverage, bank ROA, mortgage securitization rate, and banks' MBS holding in each MSA region.

Dependent variable: House price risk	(1)	(2)	(3)	(4)	(5)	(6)
log(Population)		-0.359*** (-2.662)		-0.456*** (-4.772)		-0.271** (-2.135)
log(Total asset)	-0.110*** (-5.050)	-0.0489 (-1.547)			-0.123*** (-5.467)	-0.0783** (-2.558)
Market-to-book	-0.0663** (-2.313)	-0.0416 (-1.402)			-0.00501 (-0.170)	0.0124 (0.409)
Financial Leverage	0.0889** (2.594)	0.119*** (3.345)			0.0801** (2.507)	0.101*** (3.055)
ROA	-0.288 (-0.124)	-0.191 (-0.0835)			-0.459 (-0.207)	-0.331 (-0.150)
log(Bank's total asset)			-0.0222 (-1.517)	-0.0397*** (-2.772)	-0.0393*** (-2.725)	-0.0429*** (-2.981)
Bank's market-to-book			0.0299 (0.527)	0.0599 (1.105)	0.103* (1.845)	0.0940* (1.701)
Bank's financial leverage			0.0553*** (5.263)	0.0397*** (3.792)	0.0465*** (4.621)	0.0423*** (4.169)
Bank's ROA			6.229 (0.829)	7.847 (1.100)	6.072 (0.872)	6.071 (0.880)
Securitization rate	-0.244*** (-3.696)	-0.176** (-2.516)	-0.330*** (-5.027)	-0.127* (-1.683)	-0.173** (-2.523)	-0.117* (-1.652)
Bank's MBS holding	0.328** (1.974)	0.275* (1.667)	0.450** (2.364)	0.398** (2.198)	0.285 (1.613)	0.271 (1.546)
Quarterly FE	Yes	Yes	Yes	Yes	Yes	Yes
N	233	233	233	233	233	233
R-square	0.948	0.950	0.948	0.953	0.958	0.959

t-test using robust standard error is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 24.11 Difference-in-differences of house price risk between bordering CBSA regions in neighboring sates with different levels of anti-predatory lending laws

Arkansas, Georgia, Illinois, Maine, Massachusetts, North Carolina, New York, New Jersey, New Mexico and South Carolina are among the states considered to have the strongest laws that were passed and enforced in 2002 and 2003. For example New Jersey (2004) states that the law is known as the New Jersey Homeowners Security Act, and signed in May 2003 and took effect in November 2003. The states without anti-predatory laws that are neighboring to the 10 states with anti-predatory laws at that time include Alabama, Arizona, Colorado, Connecticut, Delaware, Florida, Indiana, Iowa, Kentucky, Missouri, New Hampshire, Pennsylvania, Tennessee, Texas, Vermont, Virginia and Wisconsin.

In this quasi-experimental design, the passing of anti-predatory lending laws in the above 10 states in year 2002 and 2003 is considered as an exogenous shock or treatment. CBSA regions within the borderline of a state in which the law is passed in 2002 and 2003 are defined as the treatment group, and CBSA regions within the borderline of a neighboring state in which the law is not passed are the control or non-treated group. The first-difference is taken for the house price risks in each CBSA region before (the averages of 2001 and 2002) and after (the averages of 2004 and 2005) the shock and the second-difference is taken for the first-differences between the two bordering CBSA regions. There are 101 pairs of bordering CBSAs in the original sample, but because many CBSAs are small and don't have housing data available, the final sample size is reduced to 18 pairs of CBSAs.

Regions in states with Anti-predatory Lending Laws			Bordering regions in states without Anti-predatory Lending Laws			$\Delta(\Delta\text{Risk})$
CBSA	State	Region	CBSA	State	Region	
11700	NC	Asheville	27740	TN	Johnson City	0.097
14460	MA	Boston-Cambridge-Quincy	31700	NH	Manchester-Nashua	0.156
14460	MA	Boston-Cambridge-Quincy	39300	CT	Providence-New Bedford-Fall River	0.485
16980	IL	Chicago-Naperville-Joliet	33340	WI	Milwaukee-Waukesha-West Allis	-0.067
16980	IL	Chicago-Naperville-Joliet	39540	WI	Racine	0.076
17980	GA	Columbus, GA	12220	AL	Auburn-Opelika	-0.130
24660	NC	Greensboro-High Point	19260	VA	Danville	-0.106
27860	AR	Jonesboro	32820	TN	Memphis	0.001
29740	NM	Las Cruces	21340	TX	El Paso	0.210
35620	NJ	New York-North New Jersey	10900	PA	Allentown-Bethlehem-Easton	0.618
35620	NJ	New York-North New Jersey	14860	CT	Bridgeport-Stamford-Norwalk	1.007
35620	NJ	New York-North New Jersey	37980	PA	Philadelphia-Wilmington	0.613
40420	IL	Rockford	27500	WI	Janesville	0.055
44100	IL	Springfield	41180	MO	St. Louis	0.124
44140	MA	Springfield	25540	CT	Hartford-West Hartford-East Hartford	0.162
45940	NJ	Trenton-Ewing	37980	PA	Philadelphia-Wilmington	-0.589
47220	NJ	Vineland-Millville-Bridgeton	37980	PA	Philadelphia-Wilmington	0.540
49340	MA	Worcester	39300	CT	Providence-New Bedford-Fall River	0.025
					Mean DiD of house price risk	0.182
					Paired t-test	(2.08)**
					p-value	0.05

t-test is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 25.12 Difference-in-differences regressions of house price risk in US sates with and without anti-predatory lending laws

The passing of anti-predatory lending laws in 10 US states in year 2002 and 2003 is considered as an exogenous shock or treatment, and the negative shock is intended to reduce the securitization activities in the effected states due to the supply-side effect (see Eggert 2002, Engel and McCoy 2002 2006, and Julia 2006). CBSA regions in a state with the law passed in 2002 and 2003 are defined as the treatment group, and CBSA regions in a state without the law passed are the control or non-treated group.
The dummy variable of *WithLaw* is set to unity if the state has the anti-predatory lending law passed, and zero if it doesn't. The dummy variable of *PostLaw* is set to unity if the year is 2004 or 2005, and zero if the year is 2000 or 2001. A third dummy variable *WithLaw×PostLaw* is the cross-product of the previous two dummy variables. The DID regression equation is:

$$Risk = \phi_0 + \phi_1 WithLaw + \phi_2 PostLaw + \phi_3 WithLaw \times PostLaw + \phi Controls + \varepsilon_t$$

According to Meyer (1995) and Angrist and Krueger (1999), the coefficient ϕ_3 of the *WithLaw×PostLaw* dummy is the effect that needs to be estimated. The dependent variables is house price risk which is the standard deviation (%) of percentage returns of new residential house values in each CBSA region in year 2000, 2001, 2004 and 2005, and the independent variables include log population, log total asset, market-to-book, financial leverage, ROA, log bank asset, bank market-to-book, bank leverage, bank ROA, and three dummy variables in each CBSA region.

Dependent variable: House price risk (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Population)		5.090** (1.996)		11.15* (1.692)		7.541* (1.877)		17.65* (1.687)
log(Total asset)			0.442 (0.307)	-4.308* (-1.765)			-0.516 (-0.208)	-7.567* (-1.690)
Market-to-book			2.552 (1.127)	4.864** (2.403)			2.105 (0.636)	5.928* (1.878)
Financial Leverage			- 7.662*** (-3.556)	- 6.756*** (-3.248)			-2.241 (-0.712)	-2.129 (-0.771)
ROA			-217.6* (-1.924)	- 310.4*** (-3.419)			-38.18 (-0.209)	-150.9 (-1.031)
log(Bank's total asset)			3.030** (2.101)	1.528 (0.871)			5.052** (2.445)	1.719 (0.712)
Bank's market-to-book			-4.049 (-0.726)	-5.268 (-0.883)			-3.346 (-0.437)	-2.556 (-0.358)
Bank's financial leverage			-2.633 (-1.414)	-2.941 (-1.562)			-2.956 (-1.550)	-3.277 (-1.617)
Bank's ROA			598.6 (0.343)	283.4 (0.182)			132.5 (0.0605)	-1,443 (-0.706)
PostLaw	-11.62** (-2.487)	-11.99** (-2.570)	-13.12* (-1.984)	-10.57** (-2.002)	-11.87** (-2.496)	-12.48** (-2.639)	-14.58** (-2.024)	-9.568* (-1.798)
WithLaw	-10.57* (-1.883)	-11.78** (-2.029)	-9.496* (-1.973)	-8.193* (-1.979)	23.32*** (3.249)	-98.19* (-1.764)	-25.20 (-0.607)	-153.1 (-1.595)
PostLaw × WithLaw	16.00* (1.677)	16.61* (1.732)	20.28** (2.030)	21.14** (2.039)	19.22 (1.630)	18.71 (1.596)	20.21* (1.705)	19.88* (1.746)
Constant	35.46*** (7.827)	-40.61 (-1.134)	29.65 (1.091)	-57.46 (-0.935)				
State FE	No	No	No	No	Yes	Yes	Yes	Yes
N	89	89	89	89	89	89	89	89
R-square	0.070	0.114	0.313	0.354	0.811	0.823	0.848	0.864

t-test using robust standard error is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Figure 2.1 Quarterly time-series plot of securitization rate, bank MBS ownership and housing risk

Securitization rate is quarterly new residential MBS ($) divided by residential mortgage issuance ($). Bank MBS ownership is quarterly commercial bank's holding of MBS ($) divided by total MBS outstanding ($). Housing risk is quarterly volatility of the residential REIT portfolio return (equally-weighted).

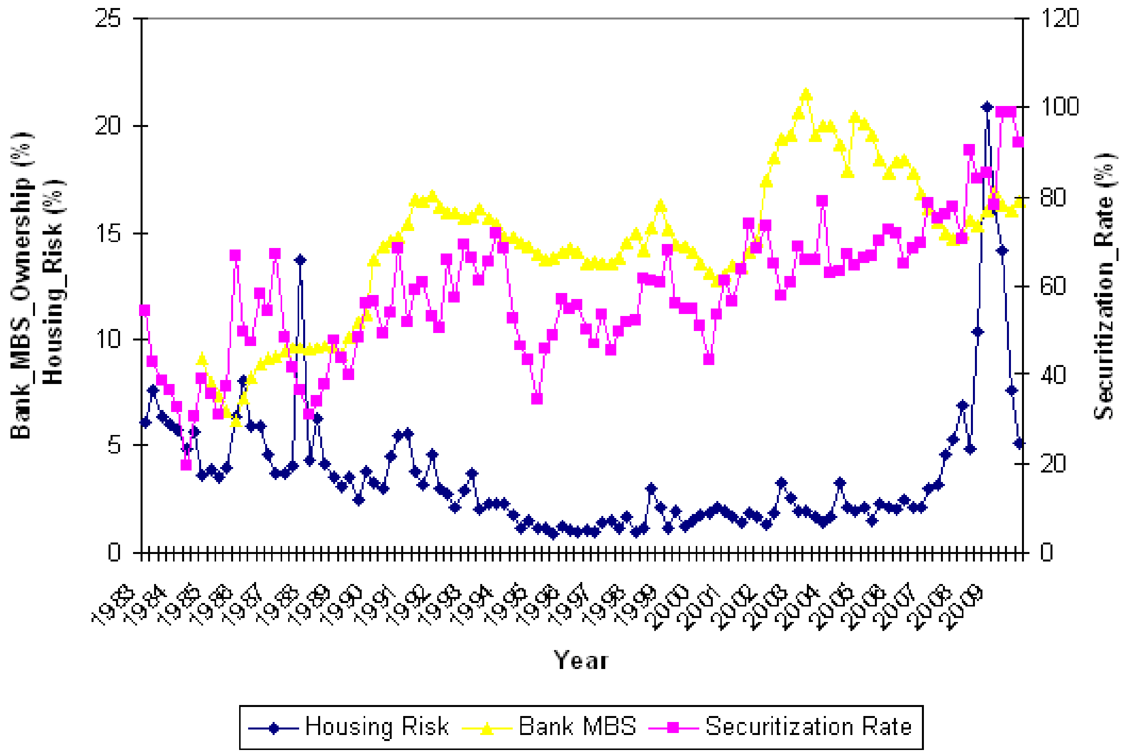


Figure 3.2 Impulse-Response Function (IRF) of baseline three-variable VAR model: Macroeconomic system

The dependent variables of this VAR model are quarterly oil price change, three-month T-bill change, and real GDP change. The independent variables are the one-quarter lagged dependent variables. IRF is the reaction of endogenous macroeconomic variables such as commodity (oil) price, output (real GDP) and interest rate (3-month Treasury Bill) at the time of the shock and over subsequent quarters in time.

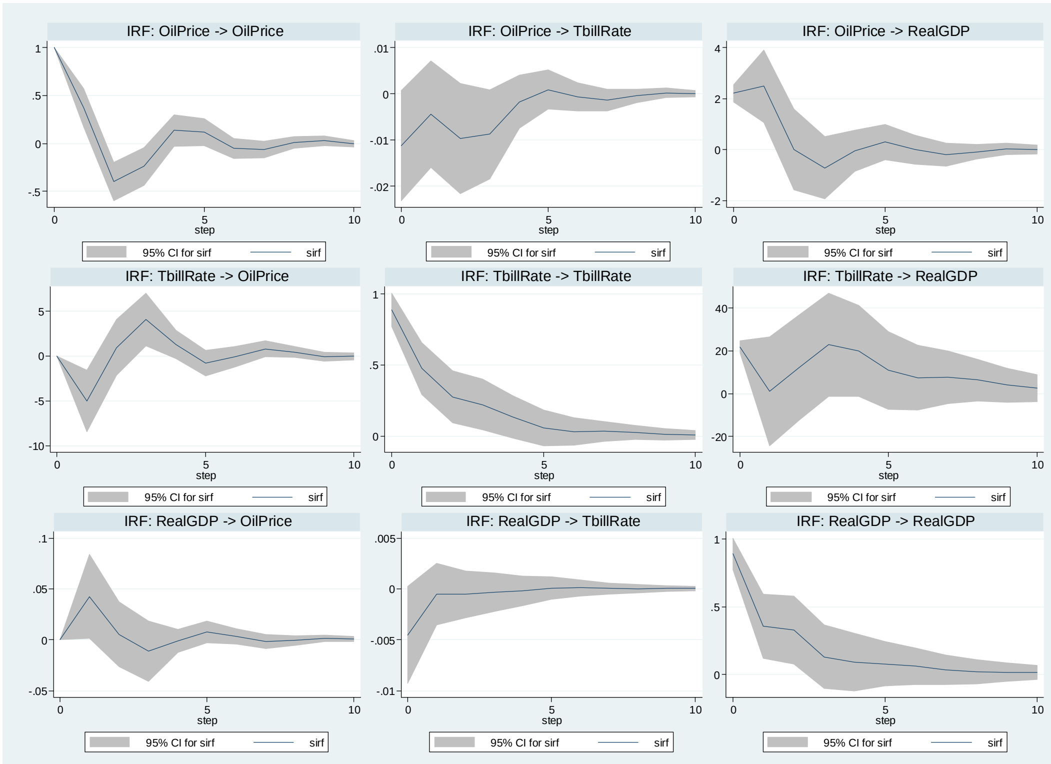


Figure 4.3 Risk Forecast-Error Variance Decomposition (FEVD) of baseline three-variable VAR model: Macroeconomic system

The dependent variables of this VAR model are quarterly oil price change, three-month T-bill change, and real GDP change. The independent variables are the one-quarter lagged dependent variables. FEVD indicates the amount of information each variable contributes to the other variables in a vector autoregression (VAR) models, or in other words, it determines how much of the forecast error variance of each of the variable can be explained by exogenous shocks to the other variables.

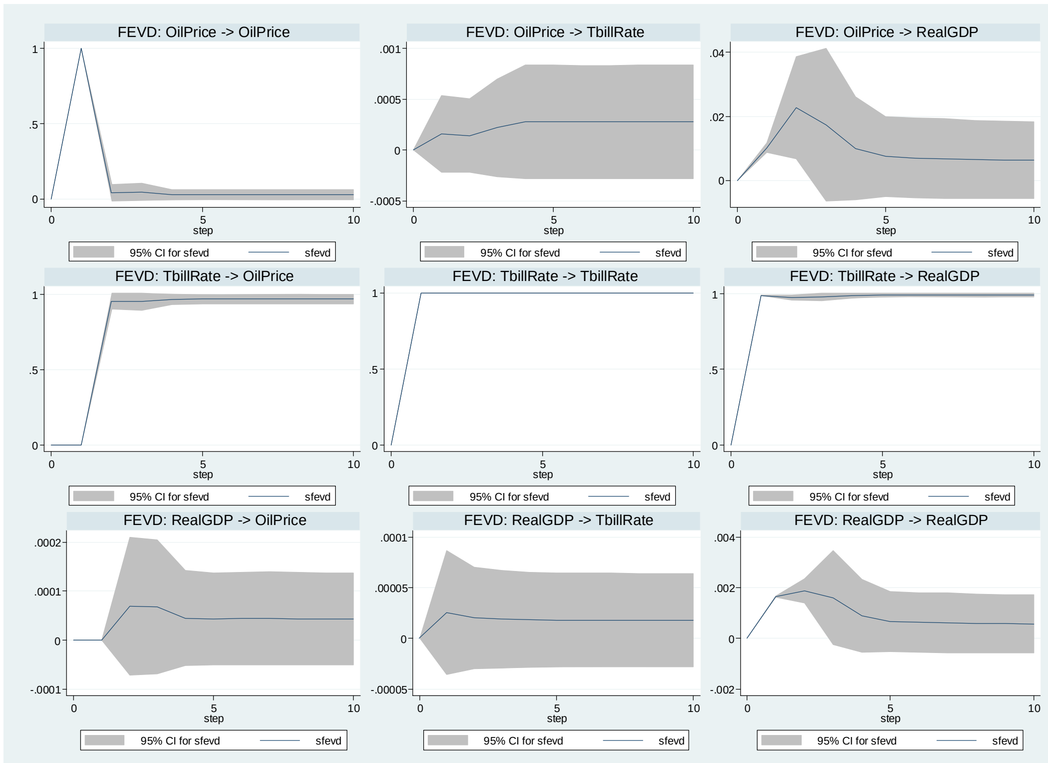


Figure 5.4 Impulse-Response Function (IRF) of six-variable VAR model: Macro, mortgage securitization rate, house price risk, and banks' MBS holding

The dependent variables of this VAR model are quarterly oil price change, securitization rate change, three-month T-bill change, house price risk (quarterly return volatility of the equally-weighted residential REIT portfolio), real GDP change and banks' MBS holding change. The independent variables are the one-quarter lagged dependent variables.

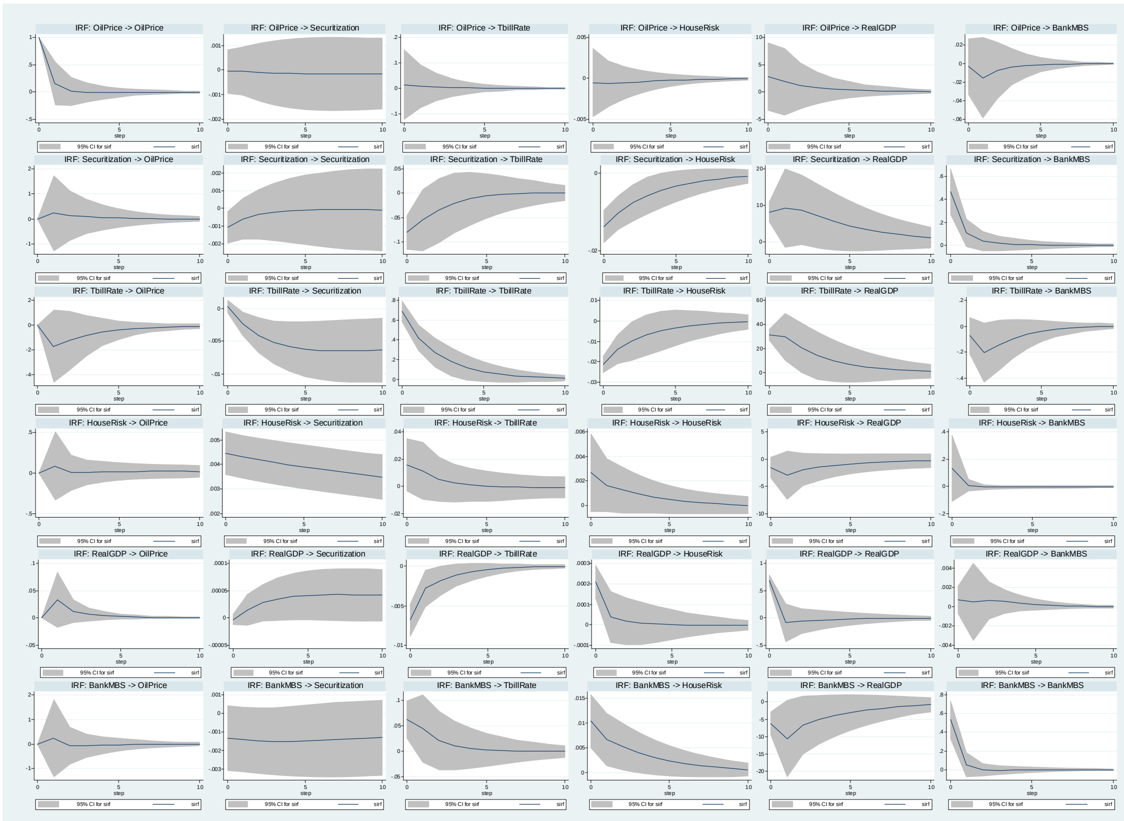


Figure 6.5 Forecast-Error Variance Decomposition (FEVD) of six-variable VAR model: Macro, mortgage securitization rate, house price risk, and banks' MBS holding

The dependent variables of this VAR model are quarterly oil price change, securitization rate change, three-month T-bill change, house price risk (quarterly return volatility of the equally-weighted residential REIT portfolio), real GDP change and banks' MBS holding change. The independent variables are the one-quarter lagged dependent variables.

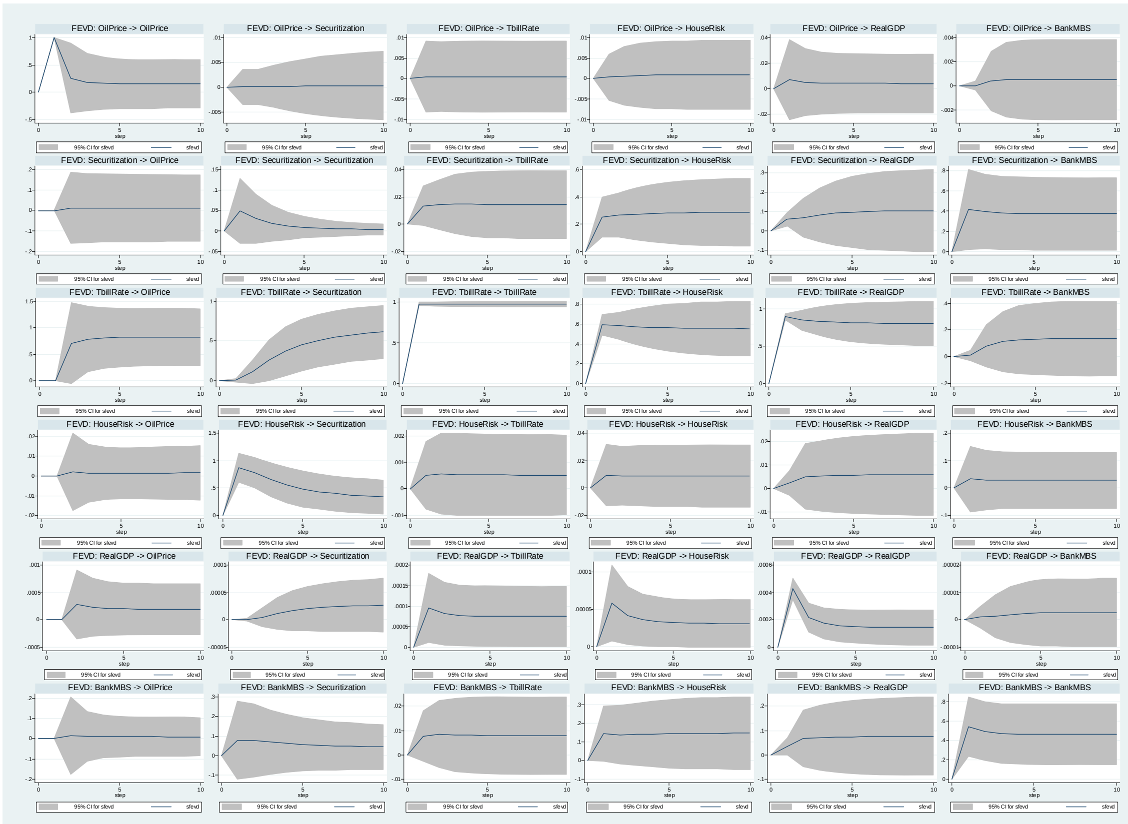
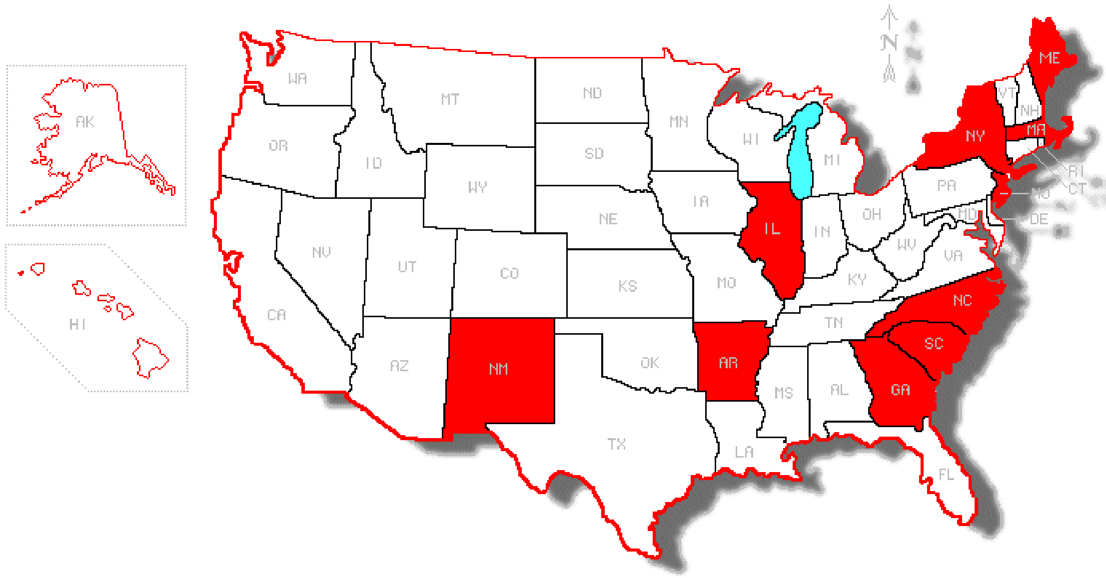


Figure 7.6 States with anti-predatory lending laws

Arkansas, Georgia, Illinois, Maine, Massachusetts, North Carolina, New York, New Jersey, New Mexico and South Carolina are among the states considered to have the strongest anti-predatory laws that were passed in year 2002 and 2003. These 10 states are colored in read on the map, and other states without anti-predatory laws passed in 2002 and 2003 are colored in white on the map. The states without anti-predatory laws that are neighboring to the 10 states with anti-predatory laws are: Alabama, Arizona, Colorado, Connecticut, Delaware, Florida, Indiana, Iowa, Kentucky, Missouri, New Hampshire, Pennsylvania, Tennessee, Texas, Vermont, Virginia and Wisconsin.



CHAPTER 3: Health Care Reform and the Stock Market: Economic Impact, Growth Opportunity and Institutional Ownership

3.1 Introduction

Health care reform in the United States has a long history, of which the most recent results were two federal statutes enacted in 2010: the Patient Protection and Affordable Care Act (PPACA) and the Health Care and Education Reconciliation Act of 2010 which amended the PPACA. PPACA became law with President Obama's signature on March 23, 2010. It represents the most significant transformation of the American health care system since Medicare and Medicaid. It is argued that PPACA will fundamentally change nearly every aspect of health care, from insurance to the final delivery of care. It is interesting to study how the stock market reacts to this lengthy and complex legislation related to the healthcare sector because the divisive and heated debates have led to massive confusion about the impact of PPACA.

This paper investigates the impact of the Act by examining its implicit economic effects on the healthcare sector and how institutional investors react differently to this event. Estimating the economic effects of healthcare reform on the real sector is complicated by the endogeneity of government policy decisions and the fact that business strategies react to numerous other variables. This paper identifies the passing of PPACA as an exogenous shock and uses the event study method to estimate the stock market's reaction in terms of asset price changes in the healthcare sector. The results indicate that the stock market views the passing of PPACA as good news to the home healthcare and specialty outpatient services but bad news to the medical instrument and health insurance industries. Furthermore, the magnitude of the abnormal return is relatively larger for firms with higher profit and R&D investment, but smaller for firms held by healthcare-specialized institutional investors. This is consistent with the prior findings that price changes are partially due to information revelation efforts by institutional investors, such that the passing of PPACA might come as less a surprise for sophisticated investors, as in El-Gazzar (1998), and Bartov, Radhakrishnan and Krinsky (2000).

PPACA introduces a comprehensive system of mandated health insurance with reforms designed to eliminate some of the worst practices of the insurance companies such as pre-condition screening and premium loadings, and annual coverage caps. It also encourages price competition by the creation of a web based health insurance exchange where consumers can compare prices and purchase plans. The system preserves private insurance and private health care providers and provides more subsidies to enable the poor to buy insurance. The newly implemented health law has major advances; however, it is deficient on cost controls, creates extreme regulatory burdens, potentially raises taxes, and empowers regulators and the insurers. Manchikanti, Caraway, Parr, Fellows and Hirsch (2010) suggest the key issues to be reducing the regulatory burden on the public and providers.

Before formally developing the testing hypotheses, we have to understand the essentials of this Act. PPACA requires insurers to offer the same premium to all applicants of the same age and geographical location without regard to most pre-existing conditions. It mandates individuals to have health insurance, and creates insurance exchanges to offer a marketplace where individuals and small businesses can buy insurance at lowest price. Insurance companies are required to spend 80% to 85% of premium dollars on eligible expenses. Co-payments, co-insurance, and deductibles are eliminated for select health care insurance benefits considered to be part of an essential benefits package. Changes are enacted that allow a restructuring of Medicare reimbursement from fee-for-service to bundled payments. The perceived major impact on practicing physicians in PPACA is the growing authority in association with further discounts in physician reimbursement. Additional support is provided for medical research and the National Institutes of Health. [1]

These mandates make clear that insurance companies could suffer from severe market competition along with hospitals who could suffer from bundled payments. The impact to clinics and physicians would be mixed because on one hand their reimbursement might be discounted by growing regulation and, on the other hand, the number of patient visits might increase due to universal health care. In this research, I identify the passing of PPACA as an exogenous shock and use the event study method to study the stock market's reaction in terms of asset price changes in the healthcare sector. The results suggest that the stock market views the passing of PPACA as good news to the home healthcare and specialty outpatient services but bad news to the medical instrument and health insurance industries.

A standard finding in the literature of financial market (Daniel, Hirshleifer and Subrahmanyam 2001, Kandel and Pearson 1995, Kim and Verrecchia 1991) is that, in equilibrium, stock price reflects a weighted average of investors' assessments of a firm's future earnings where the weigh on the sophisticated investors' view is increasing in the sophisticated investors' holdings. Institutional investors have strong incentives to search for private information about companies in their portfolios and their and industry peers

[1] Kaiser Family Foundation (2010) provides a summary of the law, and changes made to the law by subsequent legislation, with focus on provisions to expand coverage, control health care costs, and improve health care delivery system.

because of their fiduciary responsibilities and large resource bases.[2] Large institutional ownership may induce a high level of voluntary disclosure (El-Gazzar 1998)[3] or facilitate active corporate restructuring and accelerate the approvals required for restructuring plans (Bethel and Liebeskind 1993).[4] Greater private information acquisition and greater levels of disciplinary effects suggest that the content of the news about a firm with higher institutional ownership is partially preempted in predisclosure market prices. Besides the informational and disciplinary effects on firm performance, institutional investors can also increase managerial incentives to innovate by reducing the career risk of risky projects, according to Aghion, Van Reenen and Zingales (2010). If all these effects exist in the healthcare sector, the passing of PPACA might come as less a surprise to stock market participants due to sophisticated investors' efforts in information revelation, disciplining and motivating management.

In addition to the finding that stock market reacted positively to the passing of the US healthcare reform, this paper tests the hypothesis that the market price response to such news is smaller for stocks with sophisticated institutional holdings. The empirical tests provide evidence that the higher the healthcare-specialized institutional ownership, the lower the market reaction to the news after controlling for various firm characteristics.

The remainder of the paper is organized as follows. Section II reviews the relevant prior research. Section III presents the sample data and the empirical methodology. Section IV evaluates the results. Section V concludes.

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[2] Gompers and Metrick (2001) first document a positive relation between institutional ownership and future stock returns, and attribute this relation to temporal demand shocks rather than institutions' informational advantage. Yan and Zhang (2009) argue that such relationship is driven by short-term institution investors because they have access to better information on their investments than other market participants.

[3] However, Eng and Mak (2003) show that ownership structure and board composition but not blockholder ownership affect disclosure.

[4] Admati and Pfleiderer (2009) develop a theoretical model and find that the credible threat of exit by large shareholder on the basis of private information often reduces agency costs.

3.2 Related Literature

The last serious attempt of healthcare system reform was the Clinton Health Security Plan in 1993. [5] The resulting legislation of PPACA is a complex stew of changes in reforming the financing and improving delivery, and provisions that differ in the degree to which they are government-led or market-oriented. One of the most contentious points of debate about this Act was the role of regulation to the market. [6] Enthoven and Singer (1995) argue that health-care coverage based on avoidance of risk does not encourage competition and that only competition will motivate physicians to offer high-quality care to patients, and hence market-based reforms are necessary. Herzlinger (2007) suggests the consumer-driven health-care as one type of market-driven approach by allowing consumers to choose the innovators with their dollars, and the innovators take risks to satisfy consumers. These attempts reflect a faith that the market will work itself out for the benefit of the consumer when the system is restructured to encourage competition. PPACA does seem to inject competition into the system.

Critics of market-based reforms contend that this approach transforms professional ethics into commercial ethics, which places the interests of the seller, in this case the physician, over and above the interests of patients and society at large (see Berenson and Cassel 2009.) Enthoven and Singer (1995) propose a system of incentives

[5] See Schroeder (1993) for more discussions about the 1993 healthcare reform proposed by President Bill Clinton.

[6] Blumenthal (1996) asks for the "competitive revolution" of health care, in terms of the ownership and financing of health-care organizations.

that encourages all actors to minimize costs without sacrificing quality care, rather than a free market, because a health-care system is driven purely by market forces. [7]

Given the massive scale of the health-care delivery system, there is no way to completely avoid disruption and uncertainties in the process of enacting reforms. In a study of the economic impact of environmental regulation on firm innovation, Jaffe and Palmer (1997) present three distinct variants of the so-called Porter (1991) Hypothesis. Lanoie, Laurent-Lucchetti, Johnstone and Ambec (2011) provide empirical evidence that environmental regulation stimulates environmental innovations in a long run. Hinings and Greenwood (1988) claim that the inability to maneuver the uncertainties of implementing strategic change is a major obstacle for achieving intended outcomes. More recently, Hinings, Casebeer, Reay, Golden-Biddle, Pablo and Greenwood (2003) argue that change is more difficult the greater the degree of loose coupling between healthcare systems, organizations, and professions, which is characteristic of U.S. health care. However, the complexity of the healthcare delivery system also poses an opportunity for both old and new market players to innovate new products and services. (Ferlie, Pettigrew, Ashburner and Fitzgerald 1996)

Passage of health-care reform was itself an unexpected event, given the variety of political and organizational forces arrayed against it. Steinmo and Watts (1995) suggest that existing institutional structure might be biased against comprehensive health insurance, whereas Barer (1995) argue that public health insurance is inefficient.

Although the main focus of the paper is to study the PPACA’s economic impact, the comprehensive nature of the data set also allows me to examine the relation between institutional ownership and their informational roles in the stock market. Institutional

[7] The Secure Choice plan in Luft’s (2008) is an attempt.

investors have strong incentives to search for private information about companies in their portfolios and their and industry peers because of their fiduciary responsibilities and large resource bases (Gompers and Metrick 2001). A large body of literature has studied the behavior of institutional ownership and its impact on asset prices and returns, the informational role of institutional investors remains under investigation.[8] Gompers and Metrick (2001) document a positive relation between institutional ownership and future stock returns, and attribute this relation to temporal demand shocks rather than institutions' informational advantage. Nofsinger and Sias (1999) find that changes in institutional ownership forecast next year's returns, suggesting that institutional trading contains information about future returns. In contrast, Cai and Zheng (2004) report that institutional trading has negative predictive ability for next quarter's returns. Bennett, Sias, and Starks (2003) show that the evidence of institutions' ability to forecast returns is sensitive to how institutional trading is measured. Yan and Zhang (2009) argue that the positive relation between institutional ownership and future stock returns documented in Gompers and Metrick (2001) is driven by short-term institutional investors. Their empirical evidence that changes in short-term institutional ownership predict future returns supports the argument that short-term institutions are better informed and they trade actively to exploit their informational advantage.

Large institutional ownership may induce a high level of voluntary disclosure (El-Gazzar 1998), facilitate active corporate restructuring and accelerate the approvals required for restructuring plans (Bethel and Liebeskind 1993). Greater private

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[8] Research on institutional preferences includes Del Guercio (1996), Falkenstein (1996), Gompers and Metrick (2001), and Bennett, Sias, and Starks (2003). Papers on institutional trading patterns and their impact on stock returns include Lakonishok, Shliefer and Vishny (1992), Grinblatt, Titman and Wermers (1995), Nofsinger and Sias (1999), Wermers (1999), Badrinath and Wahal (2001), Bennett, Sias and Starks (2003), Griffin, Harris and Topaloglu (2003), and Cai and Zheng (2004)

information acquisition and greater levels of disciplinary effects suggest that the content of the news about a firm with higher institutional ownership is partially preempted in predisclosure market prices. Besides the informational and disciplinary effects on firm performance, institutional investors can also increase managerial incentives to innovate by reducing the career risk of risky projects, according to Aghion, Van Reenen and Zingales (2010). However, the empirical results regarding institutional investors' informational, disciplinary and incentive role are mixed (Bartov, Radhakrishnan and Krinsky 2000). One potential reason for the mixed results is that most studies in this literature focus on all institutional investors as a group. While institutional investors share some important commonalities, they are far from homogeneous. An important dimension of heterogeneity is the investment specialization. Institutions may have different investment objectives and areas of expertise. Most institutions are simply large diversified investors (Admati, Pfleiderer and Zechner 1994) achieving optimal risk sharing but might have potential problem of limited attention (Hirshleifer and Teoh 2003), whereas some other institutions are localized or industry-focused investors targeting a narrow niche (Clifford 2008 and Chen, Harford and Li 2007).

To study the impact of healthcare reform on the healthcare sector, I examine the excess returns caused by the passing of PPACA on March 22, 2010. Prior research has used event study methodology to estimate the economic impact of monetary policy (see Dale 1993, Thornton 1998, and Thornton and Garfinkel 1995,) foreign exchange policy (for example, Catte, Galli and Rebecchini 1994, Dominguez and Frankel 1993, and Fatum and Hutchison 2003,) and tax policy as in Berger (1993), Cutler (1988), and Gilligan and Krehbiel (1988). The motivation of applying event study in policy research is that if the financial market is efficiency (Efficient Market Hypothesis), then stock prices represent rational assessments of fundamental values. The large event study literature rests on this premise. In this context of this paper, the hypothesis of market efficiency will help reveal some of the difficulties and opportunities faced by the health care sector.

In addition to the event study of how stock market reacted to the passing of the US healthcare reform, this paper tests the hypothesis that the market price response to such news is smaller for stocks with sophisticated institutional holdings. If sophisticated investors have special knowledge and expertise of investing in healthcare sector, the passing of PPACA might come as less a surprise to stock market participants due to their efforts in information revelation, disciplining and motivating management. The empirical tests provide evidence that the higher the healthcare-specialized institutional ownership, the lower the market reaction to the news after controlling for various firm characteristics.

3.3 Methodology and Data

I used the market model of Fama, Fisher, Jensen and Roll (1969) to measure these firms' stock returns.[9] To capture the effect of the event on stock i, I control for the normal relation between the return on stock i during the day t, R_{it}, and the return on a broad stock market index, the CRSP market portfolio, during day t, R_{mt}.

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{1}$$

The coefficient $\beta_i = \text{cov}(R_i, R_m) / \text{var}(R_m)$ is the share of the return that can not be fully diversified. The excess return is then the residual, ε_{it}. This residual from the market

[9] Kothari and Warner (2007) provide a comprehensive survey on event study econometrics. Campbell, Lo, and MacKinlay (1996) have a careful and broad outline of key research design issues in event study.

model is used as an estimator of the abnormal return for stock *i* during the event day. This method removes the effects of economy wide factors from the return on firm *i*'s stock, leaving the portion of the return attributable to firm specific information, i.e., the error term in equation (1), which contains the effect of the passing of the health reform policy. The event date (*t*) is March 22, 2010, and the event period is from 30 days before the event to 30 days after. I estimate the coefficient (β_i) using the returns from 255 days to 46 days prior the event date. The event period is purposely excluded from the period used to estimate the market model parameters; because Ball and Brown (1968) point out that if it is included, the coefficient estimates are biased as the disturbances which contain the effects of the event and related occurrences are not mean zero.

The estimator of the average abnormal return on day *i*, AAR_t, is defined as

$$AAR_t = \sum_{i=1}^{N_t} \frac{AR_{it}}{N_t} \tag{2}$$

where AR_{it} is the estimator of the abnormal return for stock *i* and is N_t the number of firms in the sample on the event date *t*. The estimates of the average abnormal returns are summed across days to measure the average cumulative effect on the sample securities of company specific information reaching the market from day t_1, to day t_2, where $t_1 = -30$ and $t_2 = +30$ as defined earlier. That is $CAR_{(t1,t2)}$, the estimator of the cumulative average abnormal return, is given by

$$CAR_{(t_1,t_2)} = \sum_{t=t_1}^{t_2} AAR_t \tag{3}$$

As a robustness check, I also use the market-adjusted return to calculate the *CAR*. The market-adjusted return subtracts R_{mt} from R_{it}. This method is simpler than estimating market model abnormal returns because it is done in one step, rather than two. That is, when the market model is used, parameters are estimated in the first step and abnormal returns are estimated during the event period in the second step. When the market-adjusted return is used, no statistical parameters are estimated. However, its abnormal return estimators have considerably greater variance than the market model disturbances according to Chandra, Moriarity and Willinger (1990), and the abnormal return estimates are generally biased.

To test the hypothesis that the market price response to the passing of PPACA is smaller for stocks with sophisticated institutional holdings, I run the following cross-sectional regression:

$$\begin{aligned} CAR = \beta_0 + \beta_1 Log(Asset) + \beta_2 M2B + \beta_3 Leverage + \beta_4 Capex + \beta_5 PPS + \beta_6 RoA + \beta_7 R\&D \\ + \beta_8 Cash + FE(Time) + FE(Industry) + \varepsilon \end{aligned} \quad (4)$$

where CAR is the cumulative abnormal return (-1,1), M2B is market to book value, Capex is capital expenditure, PPS is pay-for-performance sensitivities for all employees, RoA is return on asset, R&D is research and development expenses divided by total asset, and Cash is cash and liquid asset holdings divided by total asset. I conduct OLS regressions with and without the fixed effects of time and industry and use clustered robust standard errors to estimate the t-statistics for coefficient. To control for the outliners, I also run median regression using the same control variables.

The firm sample includes all U.S. healthcare-related companies in Compustat/CRSP databases. These companies include doctor clinics, drug wholesalers and retailers, hospitals, insurers, medical product manufacturers, nursing homes, pharmaceuticals, etc. See Table I for the complete list of SIC codes.

[Insert Table I Here]

Due to the fact that the number of companies is small in some industries, I combine the industries of four-digit SIC codes and create 12 industries using three-digit SIC codes. The final sample has 351 firms in total with the majority being pharmaceuticals and medical product manufacturers, and the number of firms in each three-digit SIC industry is shown in Table II.

[Insert Table II Here]

3.4 Results

The average abnormal return (AAR) for 351 U.S. healthcare-related firms is +1.7% on March 22, 2010, one day after PPACA was passed the House of Representatives and one day prior being signed into law by President Barack Obama. However, the cumulative abnormal return (CAR) during the event window, 30 days prior to the event date to 30 days after, is about -4% using either the equally weighted or value weighted market model. Most losses of stock returns occur from 20 days prior to the event to 10 days after the event. The CAR estimation using market adjusted returns reports opposite results. This inconsistency in the abnormal return could be due to the biased estimator of market adjusted returns because the average beta of the sample firms is not one.[10] The time-series plot of CAR is shown in Figure 1:

[Insert Figure 1 Here]

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[10] See Binder (1998) for discussions in more technical details.

The stock market appears to view the passing of PPACA as good news but the overall healthcare reform as bad news to the healthcare sectors based on the evidence of the entire event window. To study what industries will benefit and what industries will be hurt by this new policy from Wall Street's perspective, I construct 12 sub-industries using three-digit SIC codes as shown in Table II. The mean cumulative abnormal returns are estimated for three event windows: (-30, -2), (-1, 0) and (1, 30). The CAR of the prior-event window reflects the normal situation because it is uncertain whether PPACA will be passed and eventually signed into law, although some expectation might be built up in the stock market. The CARs of the event-date window and the post-event window are the stock market's reaction of whether the passing of the act benefits or harms healthcare-related companies. The reason I separate the event window and the post-event windows is due to the concerns of market efficiency. The mean cumulative abnormal returns of 12 industries are reported in Table III.

[Insert Table III Here]

Most of the prior-event CARs are zero except for medical product and wholesale-drug industries which have negative returns. The event-date CARs are significantly positive for retail-drug, insurance, hospital, home care service and specialty facility industries, but some of the gains are offset by the negative returns during the post-event period, such as in retail-drug, insurance, hospital industries. More interestingly, medical instrument and ophthalmic good manufacturers have negative CARs during the post-event period but not on the event day.

To address the concern that stock market participants have inside information about the politics of PPACA, I repeat the CAR estimation for two different periods, when the act was passed in the Senate on December 24, 2009 with amendment, and when it was introduced in the House and passed the House on October 8, 2009. The time-series plots of CAR for both events are shown in Figure 2 and 3:

[Insert Figure 2 and 3 Here]

Again, the inconsistency between the results of market model and market adjusted returns could be due to the biased estimator of market adjusted returns because the average beta of the sample firms is not one. Table IV and V report the CAR estimations for these two events respectively.

[Insert Table IV and V Here]

Surprisingly the Wall Street did not respond to the passing of the Act in the Senate: only medical product manufacturers report significantly negative cumulative abnormal returns during the post-event period. When PPACA was first introduced and passed the House, the stock market appears to view it as good news for hospitals and ophthalmic good makers but apparently bad news for medical product manufacturers and nursing facilities. The reaction to the insurance companies is mixed with losses on the event day but gains during the post-event period.

To test the hypothesis that the market price response to the passing of PPACA is smaller for stocks with sophisticated institutional holdings, I first conduct two benchmark regressions without using the variables of institutional ownership: one pooled regression with date from all three event days, and the other regression with only the last event when the Act was finally passed the House. The results are shown in Table VI and VII.

[Insert Table VI and VII Here]

The significantly positive coefficients of ROA and R&D suggest that the magnitude of the abnormal return is relatively larger for firms with higher profit and R&D investment after controlling for the size (log asset), growth expectation (market to book), leverage (asset to equity), incentive (employee pay-for-performance sensitivities), capital expenditure, and liquidity (cash to asset). The dummy variable for March 22, 2010 is significantly positive which is consistent with the previous finding that stock market reacted strongly on the day when the Act was finally passed the House. Then, I add the institutional ownership data of both larger investors and institutions with specialization in healthcare sector. The results are reported in Table VIII and IX.

[Insert Table VIII and IX Here]

The coefficient estimate of large institutional ownership is positive whereas the coefficient estimate of healthcare-specialized institutional ownership is negative. Since the first variable measures the large diversification-driven investors' holdings and second variable measures the sophisticated or expert investors' holdings, the market price response to such news is smaller for stocks with sophisticated institutional ownership. This is consistent with the hypothesis that the efforts in information revelation, disciplining and motivating management by sophisticated investors have made the passing of PPACA less surprising to stock market participants. To further control for the outliners, I also run two median regressions (50-percentile quantile regression) using the same control variables and the results are shown in Table X and XI.

[Insert Table VIII and IX Here]

The results of median regressions are in general consistent with those of OLS regressions.

3.5 Conclusions

I conclude by noting that estimating the economic impact of health care policy on the real sector is complicated by the endogeneity of government policy decisions and the fact that business strategies react to numerous other variables. This paper identifies the passing of PPACA as an exogenous shock and uses the event study method to estimate the stock market's reaction in terms of asset price changes in the healthcare sector. The motivation of applying event study in this research is that if the financial market is efficiency, then stock price changes represent rational assessments of some of the difficulties and opportunities faced by the health- care sector. The empirical results show that Wall Street appears to view the passing of PPACA as good news to the home healthcare and specialty outpatient services but bad news to the medical instrument and health insurance industries. This might suggest that the existing institutional structure of the insurance industry is biased against comprehensive health insurance as claimed by Steinmo and Watts (1995), whereas most growth opportunities exist in the home health care and specialty outpatient services as implicated by Ferlie et al. (1996). Furthermore, the magnitude of the abnormal return is relatively larger for firms with higher profit and R&D investment, but smaller for firms held by healthcare-specialized institutional investors, which is consistent with the literature that price changes are partially due to information revelation efforts by institutional investors (El-Gazzar 1998, Bartov, Radhakrishnan and Krinsky 2000), such that the passing of PPACA might come as less a surprise for sophisticated institutions.

Table 26.1 Summary Statistics and Standard Industrial Classification (SIC) Codes

Section A. Variable Definition and Summary Statistics

Variable	Name	Definition	Mean	Standard Deviation
lat	Log Asset	log(total asset)	5.80	2.29
m2b	Market to Book	(price x shares)/book equity	3.31	3.19
lev	Leverage	total asset/book equity	2.21	1.78
capx	Capital Expenditure	capital expenditure	0.0256	0.0263
pps	Pay-for-performance sensitivities	(employee stock+options)/total shares outstanding	0.146	0.0954
roa	Return on Asset	net income / total asset	-0.0736	0.313
rd	R&D	research & development expense / total asset	0.105	0.1676
ch	Cash	cash / total asset	0.317	0.271
lio	Large Institutional Ownership	Stock ownership by top-quartile institutions [*]	0.453	0.329
hio	Healthcare-specialized Institution Ownership	Stock ownership by top-quartile healthcare-specialized institutions [+]	0.102	0.101

[*] Financial institutions are ranked by the market values of stock holdings.
[+] Financial institutions are ranking by the market value of investments in healthcare sector based on the SIC codes in Section B.

Section B. SIC Codes

The Standard Industrial Classification Codes that appear in a company's disseminated EDGAR filings indicate the company's type of business. Industrial companies of the following 4-digit SIC codes are included in the sample.

4-digit SIC Code	Industry Name
2833	MEDICINAL CHEMICALS & BOTANICAL PRODUCTS
2834	PHARMACEUTICAL PREPARATIONS
3841	SURGICAL & MEDICAL INSTRUMENTS & APPARATUS
3842	ORTHOPEDIC, PROSTHETIC & SURGICAL APPLIANCES & SUPPLIES
3844	X-RAY APPARATUS & TUBES & RELATED IRRADIATION APPARATUS
3845	ELECTROMEDICAL & ELECTROTHERAPEUTIC APPARATUS
3851	OPHTHALMIC GOODS
5122	WHOLESALE-DRUGS, PROPRIETARIES & DRUGGISTS' SUNDRIES
5912	RETAIL-DRUG STORES AND PROPRIETARY STORES
6321	ACCIDENT & HEALTH INSURANCE
6324	HOSPITAL & MEDICAL SERVICE PLANS
8011	SERVICES-OFFICES & CLINICS OF DOCTORS OF MEDICINE
8050	SERVICES-NURSING & PERSONAL CARE FACILITIES
8051	SERVICES-SKILLED NURSING CARE FACILITIES
8060	SERVICES-HOSPITALS
8062	SERVICES-GENERAL MEDICAL & SURGICAL HOSPITALS
8071	SERVICES-MEDICAL LABORATORIES
8082	SERVICES-HOME HEALTH CARE SERVICES
8090	SERVICES-MISC HEALTH & ALLIED SERVICES
8093	SERVICES-SPECIALTY OUTPATIENT FACILITIES

Table 27.2 Correlations and 3-digit SIC Codes

Section A. Correlation Matrix

	lat	m2b	lev	capx	pps	roa	rd	ch	lio
m2b	-0.2167								
lev	0.2586	0.3782							
capx	0.0371	-0.0349	0.016						
pps	-0.2942	0.0891	-0.1292	-0.0486					
roa	0.4702	-0.3477	-0.0356	0.1306	-0.1619				
rd	-0.3924	0.4194	-0.0932	-0.173	0.2732	-0.617			
ch	-0.4523	0.3446	-0.2165	-0.2844	0.2832	-0.3758	0.6326		
lio	0.5744	-0.1162	0.0666	0.0322	0.0143	0.3208	-0.2315	-0.1954	
hio	0.2735	0.0529	0.0397	-0.079	0.0895	0.1328	0.0076	0.0514	0.5444

Section B. 3-digit SIC Codes

This table lists the three-digit SIC codes after combining some sub-industries of the 4-digit SIC codes.

3-digit SIC Code	Industry Name	Number of Firms
283	MEDICINAL CHEMICALS, BOTANICAL PRODUCTS & PHARMACEUTICAL PREPARATIONS	156
384	MEDICAL INSTRUMENTS & APPARATUS	99
385	OPHTHALMIC GOODS	5
512	WHOLESALE-DRUGS, PROPRIETARIES & DRUGGISTS' SUNDRIES	10
591	RETAIL-DRUG STORES AND PROPRIETARY STORES	5
632	ACCIDENT/HEALTH INSURANCE & HOSPITAL/MEDICAL SERVICE PLANS	21
801	OFFICES & CLINICS OF DOCTORS OF MEDICINE	5
805	NURSING & PERSONAL CARE FACILITIES	5
806	HOSPITALS	11
807	MEDICAL LABORATORIES	9
808	HOME HEALTH CARE SERVICES	9
809	MISC HEALTH, ALLIED SERVICES & SPECIALTY OUTPATIENT FACILITIES	16
TOTAL		351

Table 28.3 Cumulative abnormal returns of health care industries on March 22, 2010

The Patient Protection and Affordable Care Act (PPACA) was passed the House of Representatives on Sunday, March 21, 2010, by a vote of 219–212, with 34 Democrats and all 178 Republicans voting against the bill.
In this table the cumulative abnormal returns (CARs) are calculated for three windows. The column (1) is the CAR from 30 days through 2 days prior the event date, which is the day that the PPACA was passed the House of Representatives. The column (2) is the CAR from 1 day prior the event date through the event date. The column (3) is the CAR from 1 day through 30 days post the event.
Firms are categorized to 12 industries using the three-digit Standard Industrial Classification Codes (SIC).

Industry	(1) CAR(-30,-2)	(2) CAR(-1,1)	(3) CAR(2,30)
MEDICINAL CHEMICALS, BOTANICAL PRODUCTS & PHARMACEUTICAL PREPARATIONS	-4.51%*** (-2.62)	0.45% (1.08)	-1.15% (-0.49)
MEDICAL INSTRUMENTS & APPARATUS	1.70% (0.64)	0.20% (0.61)	-3.35%** (-1.96)
OPHTHALMIC GOODS	3.18% (0.45)	-1.54% (-0.59)	-13.23%*** (-5.42)
WHOLESALE-DRUGS, PROPRIETARIES & DRUGGISTS' SUNDRIES	-5.62%** (-2.56)	0.55% (1.03)	6.85% (0.9)
RETAIL-DRUG STORES AND PROPRIETARY STORES	-0.11% (-0.02)	2.10%** (2.5)	-11.32% (-1.68)
ACCIDENT/HEALTH INSURANCE & HOSPITAL/MEDICAL SERVICE PLANS	2.59% (1.14)	1.84%** (1.97)	-11.13%*** (-5.03)
OFFICES & CLINICS OF DOCTORS OF MEDICINE	-4.27% (-0.94)	1.63% (0.45)	-3.50% (-0.82)
NURSING & PERSONAL CARE FACILITIES	-1.48% (-0.18)	1.79% (1.54)	-6.67% (-1.6)
HOSPITALS	2.50% (0.41)	8.23%*** (3.00)	-9.80%** (-2.58)
MEDICAL LABORATORIES	3.23% (1.02)	0.73% (0.79)	10.76% (1.61)
HOME HEALTH CARE SERVICES	-2.73% (-0.69)	1.77%** (2.22)	-4.89% (-0.63)
MISC HEALTH, ALLIED SERVICES & SPECIALTY OUTPATIENT FACILITIES	-1.87% (-0.46)	2.54%*** (3.22)	0.21% (0.05)

t-test is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 29.4 Cumulative abnormal returns of health care industries on December 24, 2009

The Patient Protection and Affordable Care Act (PPACA) was passed the Senate on Friday, December 24, 2009, by a vote of 60–39 with all Democrats and two Independents voting for, and all Republicans voting against.
In this table the cumulative abnormal returns (CARs) are calculated for three windows. The column (1) is the CAR from 30 days through 2 days prior the event date, which is the day that the PPACA was passed the House of Representatives. The column (2) is the CAR from 1 day prior the event date through 1 day post the event date. The column (3) is the CAR from 2 days through 30 days post the event.
Firms are categorized to 12 industries using the three-digit Standard Industrial Classification Codes (SIC).

Industry	(1) CAR(-30,-2)	(2) CAR(-1,1)	(3) CAR(2,30)
MEDICINAL CHEMICALS, BOTANICAL PRODUCTS & PHARMACEUTICAL PREPARATIONS	-0.34% (-0.12)	-0.61% (-1.56)	-6.25%*** (-3.04)
MEDICAL INSTRUMENTS & APPARATUS	0.44% (0.25)	0.06% (0.17)	2.04% (1.00)
OPHTHALMIC GOODS	8.33% (1.76)	1.67% (0.62)	-1.65% (-0.88)
WHOLESALE-DRUGS, PROPRIETARIES & DRUGGISTS' SUNDRIES	3.78% (0.70)	-0.88% (-0.70)	3.29% (0.66)
RETAIL-DRUG STORES AND PROPRIETARY STORES	1.21% (0.35)	-2.54% (-1.54)	-3.47% (-1.05)
ACCIDENT/HEALTH INSURANCE & HOSPITAL/MEDICAL SERVICE PLANS	8.43%*** (3.93)	-0.46% (-1.16)	3.94% (1.53)
OFFICES & CLINICS OF DOCTORS OF MEDICINE	-2.58% (-0.53)	-0.10% (-0.14)	-1.99% (-0.18)
NURSING & PERSONAL CARE FACILITIES	-4.30% (-0.72)	0.53% (0.45)	-3.10% (-0.64)
HOSPITALS	1.63% (0.36)	0.95% (1.43)	-4.90%** (-2.92)
MEDICAL LABORATORIES	3.07% (0.58)	1.10% (0.88)	3.02% (0.57)
HOME HEALTH CARE SERVICES	-4.52% (-0.4)	1.24% (1.25)	-8.51% (-1.68)
MISC HEALTH, ALLIED SERVICES & SPECIALTY OUTPATIENT FACILITIES	0.08% (0.02)	0.40% (0.62)	-2.91% (-1.51)

t-test is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 30.5 Cumulative abnormal returns of health care industries on October 8, 2009

The Patient Protection and Affordable Care Act (PPACA) was introduced in the House as the “Service Members Home Ownership Tax Act of 2009” by Charles Rangel (D–NY) on September 17, 2009 and passed the House on October 8, 2009.
In this table the cumulative abnormal returns (CARs) are calculated for three windows. The column (1) is the CAR from 30 days through 2 days prior the event date, which is the day that the PPACA was passed the House of Representatives. The column (2) is the CAR from 1 day prior the event date through 1 day post the event date. The column (3) is the CAR from 2 days through 30 days post the event.
Firms are categorized to 12 industries using the three-digit Standard Industrial Classification Codes (SIC).

Industry	(1) CAR(-30,-2)	(2) CAR(-1,1)	(3) CAR(2,30)
MEDICINAL CHEMICALS, BOTANICAL PRODUCTS & PHARMACEUTICAL PREPARATIONS	-0.48% (-0.16)	-0.91%** (-2.01)	-10.09%*** (-5.19)
MEDICAL INSTRUMENTS & APPARATUS	2.34% (1.01)	-0.27% (-0.79)	-2.23% (-1.06)
OPHTHALMIC GOODS	-3.30% (-1.36)	-0.15% (-0.08)	9.42%*** (4.66)
WHOLESALE-DRUGS, PROPRIETARIES & DRUGGISTS' SUNDRIES	3.78% (1.26)	-0.94% (-1.23)	10.90%* (2.09)
RETAIL-DRUG STORES AND PROPRIETARY STORES	-5.91% (-0.94)	1.42% (1.15)	-6.00% (-0.92)
ACCIDENT/HEALTH INSURANCE & HOSPITAL/MEDICAL SERVICE PLANS	-9.92%*** (-5.23)	-0.94%* (-1.92)	11.10%*** (3.97)
OFFICES & CLINICS OF DOCTORS OF MEDICINE	-6.39%** (-2.67)	-1.24% (-1.37)	-4.73% (-1.39)
NURSING & PERSONAL CARE FACILITIES	3.08% (0.33)	-1.53%** (-2.5)	-6.14% (-1.49)
HOSPITALS	-2.12% (-0.90)	2.73%** (2.99)	-3.34% (-0.71)
MEDICAL LABORATORIES	-5.65% (-0.75)	2.32% (1.78)	-0.41% (-0.11)
HOME HEALTH CARE SERVICES	-0.97% (-0.21)	-1.35% (-1.74)	-3.07% (-0.52)
MISC HEALTH, ALLIED SERVICES & SPECIALTY OUTPATIENT FACILITIES	5.31% (1.24)	-1.03% (-0.99)	-6.89% (-1.44)

t-test is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 31.6 Determinants of cumulative abnormal returns of health care industries

The Patient Protection and Affordable Care Act (PPACA) was introduced in the House as the "Service Members Home Ownership Tax Act of 2009" by Charles Rangel (D–NY) on September 17, 2009 and passed the House on October 8, 2009. It was passed the Senate on Friday, December 24, 2009, by a vote of 60–39 with all Democrats and two Independents voting for, and all Republicans voting against. Finally, it was passed the House of Representatives on Sunday, March 21, 2010, by a vote of 219–212, with 34 Democrats and all 178 Republicans voting against the bill.

The dependent variable is the CAR from 1 day prior to the event to 1 day post the event. Firms are categorized to 12 industries using the three-digit Standard Industrial Classification Codes (SIC).

Dependent variable: CAR (-1,1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log (Total Asset)	0.0264 (0.285)	0.0275 (0.299)	0.0395 (0.424)	0.0655 (0.760)	0.0666 (0.779)	0.0812 (1.038)	0.0533 (0.604)	0.0545 (0.622)	0.0725 (0.902)
Market-to-Book	0.00456 (0.0469)	0.00422 (0.0437)	0.0624 (0.910)	0.00452 (0.0471)	0.00409 (0.0429)	0.0557 (0.743)	-0.0145 (-0.143)	-0.0149 (-0.147)	0.0403 (0.516)
Leverage	-0.0857 (-0.395)	-0.0857 (-0.395)	-0.221 (-1.467)	-0.0736 (-0.376)	-0.0736 (-0.376)	-0.196 (-1.598)	-0.0548 (-0.277)	-0.0548 (-0.276)	-0.181 (-1.466)
Capital Expenditure	4.363 (1.142)	4.379 (1.154)	0.587 (0.111)	6.757** (2.463)	6.780** (2.474)	2.908 (0.539)	6.659** (2.335)	6.682** (2.350)	2.723 (0.503)
Pay-for-performance Sensitivity	-3.434 (-1.288)	-3.401 (-1.278)	-3.568 (-1.279)	-3.323 (-1.165)	-3.291 (-1.154)	-3.438 (-1.154)	-3.623 (-1.237)	-3.590 (-1.227)	-3.788 (-1.221)
Return-on-Asset	1.98*** (3.900)	1.97*** (3.864)	2.10*** (3.784)	1.40** (2.542)	1.39** (2.515)	1.49** (2.450)	1.87*** (3.210)	1.87*** (3.177)	2.00*** (3.210)
R&D-to-Asset	2.887* (2.026)	2.886** (2.301)	2.978** (2.364)				2.041* (1.985)	2.038** (2.203)	2.223** (2.219)
Cash-to-Asset				1.635 (1.230)	1.637 (1.230)	1.629 (1.128)	1.122 (1.019)	1.126 (1.020)	1.141 (0.989)
Constant	0.572 (0.575)	0.172 (0.207)	0.112 (0.141)	-0.0171 (-0.023)	-0.420 (-0.666)	-0.437 (-0.865)	0.104 (0.134)	-0.299 (-0.448)	-0.446 (-0.843)
Time Fixed-Effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry Fixed-Effects	No	No	Yes	No	No	Yes	No	No	Yes
N	1,070	1,070	1,070	1,070	1,070	1,070	1,070	1,070	1,070
R-square	0.013	0.020	0.043	0.013	0.019	0.042	0.014	0.021	0.044
F-test	2.00	2.34	2.34	1.98	2.33	2.32	1.94	2.26	2.30

t-test based on clustered robust standard errors is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 32.7 Determinants of cumulative abnormal returns of health care industries on March 22, 2010

The Patient Protection and Affordable Care Act (PPACA) was passed the House of Representatives on Sunday, March 21, 2010, by a vote of 219–212, with 34 Democrats and all 178 Republicans voting against the bill.

The dependent variable is the CAR from 1 day prior to the event to 1 day post the event. Firms are categorized to 12 industries using the three-digit Standard Industrial Classification Codes (SIC).

Dependent variable: CAR (-1,1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (Total Asset)	0.126 (0.715)	0.139 (0.742)	0.126 (0.713)	0.150 (0.804)	0.207 (0.975)	0.236 (1.049)	0.194 (0.883)	0.224 (0.980)
Market-to-Book	0.130 (0.731)	0.252 (1.658)	0.0571 (0.320)	0.195 (1.283)	0.0311 (0.169)	0.167 (0.926)	0.0102 (0.0578)	0.147 (0.884)
Leverage	0.0221 (0.0588)	-0.294 (-1.196)	0.109 (0.294)	-0.219 (-0.859)	0.165 (0.505)	-0.151 (-0.648)	0.186 (0.556)	-0.132 (-0.548)
Capital Expenditure	-1.575 (-0.130)	-9.819 (-0.677)	0.896 (0.0773)	-8.178 (-0.580)	6.682 (0.718)	-3.347 (-0.252)	6.587 (0.693)	-3.568 (-0.268)
Pay-for-performance Sensitivity	3.406* (1.804)	2.689 (1.514)	2.369 (1.141)	1.653 (0.841)	2.206 (0.876)	1.551 (0.580)	1.872 (0.785)	1.127 (0.462)
Return-on-Asset	0.931 (1.597)	1.273 (1.752)	2.055** (3.100)	2.355** (2.645)	1.276** (2.689)	1.512** (2.364)	1.795* (1.968)	2.137* (1.898)
R&D-to-Asset			4.358*** (5.322)	4.372*** (4.110)			2.231*** (3.050)	2.710*** (3.092)
Cash-to-Asset					3.376* (1.943)	3.101 (1.703)	2.820 (1.369)	2.508 (1.194)
Constant	-0.656	-0.233	-0.894	-0.783	-2.198	-1.999	-2.066	-2.002
	(-0.474)	(-0.182)	(-0.661)	(-0.595)	(-1.271)	(-1.259)	(-1.152)	(-1.275)
Industry Fixed-Effects	No	Yes	No	Yes	No	Yes	No	Yes
N	358	358	358	358	358	358	358	358
R-square	0.008	0.102	0.015	0.108	0.020	0.111	0.021	0.112
F-test	0.48	2.27	0.74	2.27	1.00	2.34	0.94	2.25

t-test based on clustered robust standard errors is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 33.8 Cumulative abnormal returns and institutional ownership

PPACA was introduced in the House on September 17, 2009 and passed the House on October 8, 2009. It was passed the Senate on Friday, December 24, 2009, and finally passed the House of Representatives on Sunday, March 21, 2010.

The dependent variable is the CAR from 1 day prior to the event to 1 day post the event. Firms are categorized to 12 industries using the three-digit Standard Industrial Classification Codes (SIC).

Dependent variable: CAR (-1,1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log (Total Asset)	-0.045 (-0.50)	-0.046 (-0.50)	-0.006 (-0.068)	0.107 (1.09)	0.108 (1.11)	0.132 (1.45)	-0.036 (-0.43)	-0.037 (-0.43)	-0.005 (-0.06)
Market-to-Book	-0.022 (-0.24)	-0.023 (-0.25)	0.031 (0.45)	-0.003 (-0.02)	-0.003 (-0.03)	0.055 (0.67)	-0.008 (-0.09)	-0.009 (-0.10)	0.046 (0.66)
Leverage	-0.035 (-0.18)	-0.035 (-0.18)	-0.165 (-1.41)	-0.062 (-0.30)	-0.062 (-0.30)	-0.19 (-1.51)	-0.033 (-0.17)	-0.033 (-0.17)	-0.170 (-1.40)
Capital Expenditure	6.41** (2.27)	6.43** (2.28)	2.70 (0.49)	6.146* (2.12)	6.167* (2.14)	2.049 (0.40)	5.226* (1.89)	5.238* (1.90)	1.539 (0.30)
Pay-for-performance Sensitivity	-4.324 (-1.58)	-4.303 (-1.57)	-4.341 (-1.52)	-3.120 (-1.10)	-3.086 (-1.09)	-3.144 (-1.03)	-4.028 (-1.64)	-4.004 (-1.63)	-3.960 (-1.51)
Return-on-Asset	1.82*** (3.28)	1.81*** (3.25)	1.94*** (3.24)	1.96*** (3.25)	1.95*** (3.22)	2.08*** (3.24)	1.94*** (3.51)	1.93*** (3.48)	2.00*** (3.40)
R&D-to-Asset	2.223** (2.22)	2.223** (2.22)	2.254** (2.27)	2.079* (2.00)	2.076* (2.00)	2.251** (2.21)	2.466** (2.44)	2.467** (2.44)	2.340** (2.33)
Cash-to-Asset	1.034 (0.91)	1.036 (0.91)	1.041 (0.86)	1.291 (1.23)	1.295 (1.23)	1.324 (1.22)	1.269 (1.20)	1.273 (1.20)	1.221 (1.10)
Large Institutional Ownership	1.067* (2.14)	1.084* (2.20)	0.795 (1.35)				2.05*** (3.35)	2.08*** (3.43)	1.81** (2.47)
Healthcare-specialized Institutional Ownership				-3.07** (-2.32)	-3.08** (-2.31)	-3.36** (-2.46)	-5.7*** (-3.44)	-5.8*** (-3.46)	-5.69** (-3.08)
Constant	0.291 (0.385)	-0.114 (-0.172)	-0.194 (-0.357)	-0.02 (-0.029)	-0.427 (-0.650)	-0.595 (-1.159)	0.225 (0.318)	-0.187 (-0.303)	-0.124 (-0.243)
Time Fixed-Effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry Fixed-Effects	No	No	Yes	No	No	Yes	No	No	Yes
N	1,070	1,070	1,070	1,070	1,070	1,070	1,070	1,070	1,070
R-square	0.017	0.023	0.045	0.017	0.024	0.047	0.024	0.031	0.052
F-test	2.02	2.31	2.25	2.04	2.32	2.35	2.61	2.80	2.349

t-test based on clustered robust standard errors is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 34.9 Cumulative abnormal returns (March 22, 2010) and institutional ownership

The Patient Protection and Affordable Care Act (PPACA) was passed the House of Representatives on Sunday, March 21, 2010, by a vote of 219–212, with 34 Democrats and all 178 Republicans voting against the bill.

The dependent variable is the CAR from 1 day prior to the event to 1 day post the event. Firms are categorized to 12 industries using the three-digit Standard Industrial Classification Codes (SIC).

Dependent variable: CAR (-1,1)	(1)	(2)	(3)	(4)	(5)	(6)
Log (Total Asset)	0.0965 (0.466)	0.185 (0.829)	0.275 (1.248)	0.314 (1.403)	0.106 (0.544)	0.184 (0.874)
Market-to-Book	0.00309 (0.0183)	0.143 (0.873)	0.0269 (0.145)	0.169 (0.931)	0.0216 (0.127)	0.163 (0.956)
Leverage	0.203 (0.636)	-0.124 (-0.537)	0.173 (0.506)	-0.155 (-0.607)	0.205 (0.629)	-0.131 (-0.562)
Capital Expenditure	6.285 (0.672)	-3.609 (-0.271)	5.698 (0.639)	-4.613 (-0.364)	4.429 (0.531)	-5.226 (-0.422)
Pay-for-performance Sensitivity	1.164 (0.491)	0.839 (0.337)	2.642 (1.006)	2.093 (0.759)	1.530 (0.691)	1.287 (0.553)
Return-on-Asset	1.753* (1.984)	2.109* (1.848)	1.924* (1.876)	2.260* (1.822)	1.915* (2.036)	2.195* (1.881)
R&D-to-Asset	2.409** (2.147)	2.723** (2.103)	2.298** (2.043)	2.760** (2.082)	2.747** (2.207)	2.834** (2.119)
Cash-to-Asset	2.722 (1.331)	2.452 (1.190)	3.064 (1.583)	2.781 (1.462)	3.001 (1.566)	2.658 (1.411)
Large Institutional Ownership	1.040** (2.248)	0.399** (2.391)			2.368** (2.635)	1.679** (1.998)
Healthcare-specialized Institutional Ownership			-4.718* (-1.888)	-5.055* (-1.956)	-7.799** (-2.213)	-7.183** (-2.099)
Constant	-1.867 (-1.060)	-1.866 (-1.269)	-2.245 (-1.271)	-2.223 (-1.457)	-1.907 (-1.124)	-1.743 (-1.229)
Industry Fixed-Effects	No	Yes	No	Yes	No	Yes
N	358	358	358	358	358	358
R-square	0.023	0.113	0.026	0.118	0.033	0.121
F-test	0.90	2.14	1.02	2.24	1.17	2.20

t-test based on clustered robust standard errors is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 35.10 Median regressions of cumulative abnormal returns

PPACA was introduced in the House on September 17, 2009 and passed the House on October 8, 2009. It was passed the Senate on Friday, December 24, 2009, and finally passed the House of Representatives on Sunday, March 21, 2010.

The dependent variable is the CAR from 1 day prior to the event to 1 day post the event. Firms are categorized to 12 industries using the three-digit Standard Industrial Classification Codes (SIC).

Dependent variable: CAR (-1,1)	(1) All Events	(2) All Events	(3) All Events	(4) 2010/3/22	(5) 2010/3/22
Log (Total Asset)	0.0861* (1.713)	0.0961* (1.832)	0.0931 (1.455)	0.131 (1.163)	0.0690 (0.769)
Market-to-Book	0.00676 (0.185)	0.00838 (0.223)	0.00349 (0.0751)	-0.0350 (-0.430)	-0.00291 (-0.0433)
Leverage	-0.122* (-1.959)	-0.160** (-2.485)	-0.138* (-1.678)	0.0767 (0.547)	0.0527 (0.461)
Capital Expenditure	3.434 (0.962)	4.042 (1.078)	3.604 (0.802)	9.365 (1.158)	-1.215 (-0.188)
Pay-for-performance Sensitivity	1.772* (1.764)	0.416 (0.397)	0.822 (0.658)	1.979 (0.888)	1.699 (0.949)
Return-on-Asset	1.410*** (3.569)	1.616*** (3.907)	1.618*** (3.360)	1.393** (2.595)	1.762** (2.519)
R&D-to-Asset	0.434 (1.518)	1.082** (2.235)	1.288** (2.224)	1.520* (1.811)	1.571** (2.038)
Cash-to-Asset	0.195 (0.401)	0.183 (0.361)	0.244 (0.401)	1.716 (1.595)	1.781** (2.057)
Constant	-0.595 (-1.366)	-0.563 (-1.183)	-0.783 (-1.267)	-1.171 (-1.201)	-0.679 (-0.820)
Time Fixed-Effects	No	Yes	Yes		
Industry Fixed-Effects	No	No	Yes	No	Yes
N	1,070	1,070	1,070	358	358
Pseudo R-square	0.0088	0.0174	0.0280	0.0141	0.0476
F-test	1.94	2.26	2.30	0.94	2.25

t-test is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Table 36.11 Median regressions of cumulative abnormal returns and institutional ownership

PPACA was introduced in the House on September 17, 2009 and passed the House on October 8, 2009. It was passed the Senate on Friday, December 24, 2009, and finally passed the House of Representatives on Sunday, March 21, 2010.

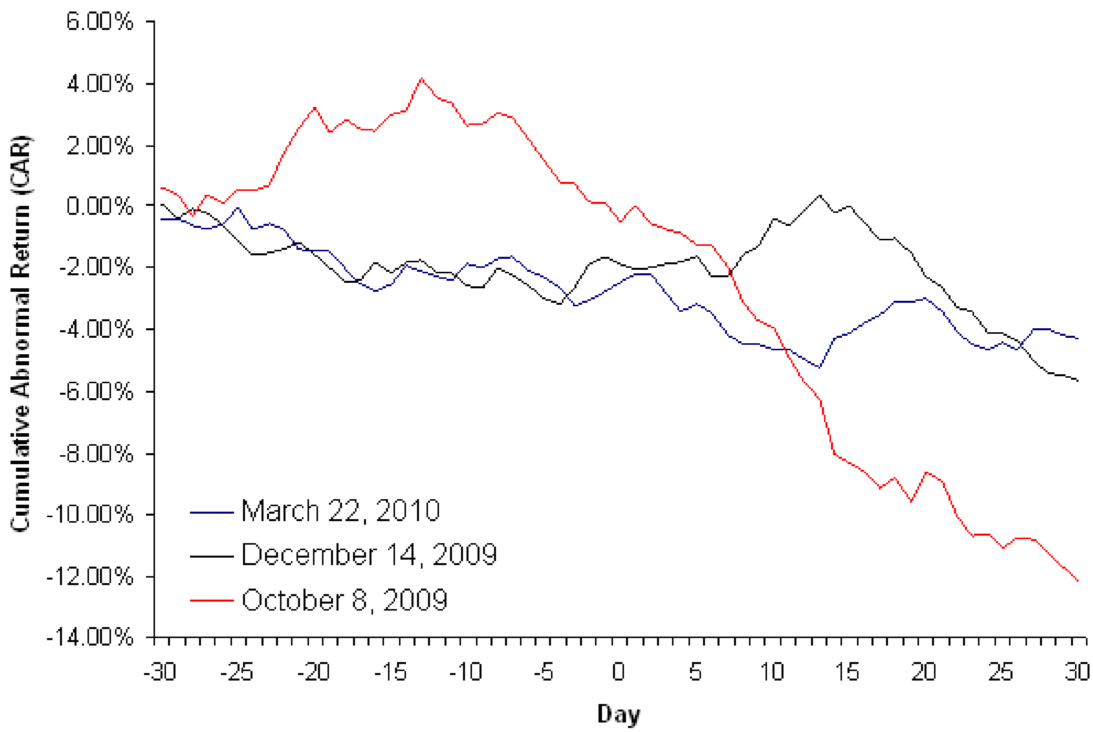
The dependent variable is the CAR from 1 day prior to the event to 1 day post the event. Firms are categorized to 12 industries using the three-digit Standard Industrial Classification Codes (SIC).

Dependent variable: CAR (-1,1)	(1) All Events	(2) All Events	(3) All Events	(4) 2010/3/22	(5) 2010/3/22
Log (Total Asset)	0.0302 (0.474)	0.0181 (0.249)	0.0319 (0.535)	0.0335 (0.255)	-0.0273 (-0.185)
Market-to-Book	-0.0148 (-0.374)	0.00362 (0.0821)	0.0126 (0.341)	-0.00968 (-0.126)	0.0380 (0.409)
Leverage	-0.121* (-1.814)	-0.0823 (-1.088)	-0.0668 (-1.026)	0.148 (1.078)	-0.00623 (-0.0400)
Capital Expenditure	4.606 (1.195)	5.737 (1.303)	3.316 (0.955)	5.728 (0.719)	-7.227 (-0.822)
Pay-for-performance Sensitivity	0.252 (0.227)	-0.839 (-0.670)	-0.374 (-0.376)	1.683 (0.741)	2.180 (0.855)
Return-on-Asset	1.574*** (3.712)	1.716*** (3.578)	1.811*** (4.799)	1.941** (2.222)	1.720* (1.794)
R&D-to-Asset	1.410 (1.559)	1.486** (2.460)	1.604** (1.962)	2.590** (2.419)	1.587* (1.756)
Cash-to-Asset	0.254 (0.486)	0.368 (0.621)	0.174 (0.371)	1.488 (1.372)	0.823 (0.684)
Large Institutional Ownership	1.367*** (3.240)	1.642*** (3.427)	1.122*** (2.899)	1.008** (2.172)	1.571* (1.824)
Healthcare-specialized Institutional Ownership	-2.613** (-2.213)	-2.923** (-2.186)	-2.559** (-2.471)	-0.884** (-2.373)	-2.324* (-1.888)
Constant	-0.567 (-1.198)	-0.772 (-1.378)	-0.634 (-1.292)	-1.182 (-1.216)	-0.0691 (-0.0582)
Time Fixed-Effects	No	Yes	Yes		
Industry Fixed-Effects	No	No	Yes	No	Yes
N	1,070	1,070	1,070	358	358
Pseudo R-square	0.0159	0.0241	0.0323	0.0177	0.0524
F-test	2.61	2.80	2.49	1.17	2.20

t-test is shown in the parenthesis with ***, ** and * indicating its statistical significant level of 1%, 5% and 10% respectively.

Figure 8.1 Cumulative abnormal returns of health care industries on March 22, 2010

The Patient Protection and Affordable Care Act (PPACA) was introduced in the House as the "Service Members Home Ownership Tax Act of 2009" by Charles Rangel (D–NY) on September 17, 2009 and passed the House on October 8, 2009. It was passed the Senate on Friday, December 24, 2009, by a vote of 60–39 with all Democrats and two Independents voting for, and all Republicans voting against. Finally, it was passed the House of Representatives on Sunday, March 21, 2010, by a vote of 219–212, with 34 Democrats and all 178 Republicans voting against the bill.



REFERENCE

Abreu, Dilip and Markus Brunnermeier, 2002, "Synchronization Risk and Delayed Arbitrage," Journal of Financial Economics, 66, 341-360.

Abreu, Dilip and Markus Brunnermeier, 2003, "Bubbles and Crashes," Econometrica, 71, 173-204.

Acharya, Viral, and Matthew Richardson, 2009, Restoring Financial Stability, John Wiley & Sons Inc.

Acharya, Viral, Iftekhar Hasan, and Anthony Saunders, 2006, "Should Banks Be Diversified? Evidence from Individual Bank Loan Portfolios," Journal of Business 79, 1355-1412.

Acharya, Viral, Lasse Pedersen, Thomas Philippon, and Mathew Richardson, 2010, "Measuring Systemic Risk," NYU Stern Working Paper.

Adams, Zeno, Roland Fuss, and Reint Gropp, 2010, "Modeling Spillover Effects among Financial Institutions: A State-Dependent Sensitivity Value-at-Risk (SDSVaR) Approach," EBS Working Paper.

Admati, Anat and Paul Pfleiderer, 2009, "The Wall Street Walk and Shareholder Activism: Exit as a Form of Voice," Review of Financial Studies, 22, 2645-2685.

Admati, Anat, Paul Pfleiderer and Josef Zechner, 1994, "Large Shareholder Activism, Risk Sharing, and Financial Market Equilibrium," Journal of Political Economy, 102, 1097-1130,

Adrian, Tobias, and Markus Brunnermeier, 2008, "CoVaR," Fed Reserve Bank of New York Staff Reports.

Aghion, Philippe, John Van Reenen and Luigi Zingales, 2010, "Innovation and Institutional Ownership," NBER Working Paper No. 14769.

Akaike, Hirotugu, 1974, "A New Look at the Statistical Model Identification," IEEE Transactions on Automatic Control, 19, 716–723.

Akaike, Hirotugu, 1977. "On Entropy Maximization Principle," Applications of Statistics, North-Holland, 27–41.

Allen, Franklin and Douglas Gale, 1994, Financial Innovation and Risk Sharing, MIT Press.

Allen, Franklin and Douglas Gale, 2000, "Financial Contagion," Journal of Political Economy, 108, 1-33.

Allen, Franklin and Elena Carletti, 2006, "Credit Risk Transfer and Contagion," Journal of Monetary Economics, 53, 89-111.

Allen, Linda, Turan Bali, and Yi Tang, 2010, "Does Systemic Risk in the Financial Sector Predict Future Economic Downturns?," Baruch College Working Paper.

Altunbas, Yener, Leonardo Gambacorta and David Marques-Ibanez, 2009, "Securitisation and the Bank Lending Channel," European Economic Review, 53, 996-1009.

Angrist, Joshua and Alan Krueger, 1999, "Empirical Strategies in Labor Economics," Handbook of Labor Economics (Orley Ashenfelter and David Card, eds.), 3A, 1277-1366.

Angrist, Joshua and Alan Krueger, 1999, "Empirical Strategies in Labor Economics," Handbook of Labor Economics (Orley Ashenfelter and David Card, eds.), 3A, 1277-1366.

Arrow, Kenneth and Gerard Debreu, 1954, "Existence of an Equilibrium for a Competitive Economy," Econometrica, 22, 265-290.

Asdrubali, Pierfederico and Soyoung Kim, 2004, "Dynamic Risk Sharing in the United States and Europe," Journal of Monetary Economics, 51, 809-836.

Athanasoulis, Stefano and Eric van Wincoop, 2001, "Risk Sharing Within The United States: What Do Financial Markets And Fiscal Federalism Accomplish?," Review of Economics and Statistics, 83, 688-698.

Azmy, Baher, 2005, "Squaring the Predatory Lending Circle: A Case for States as Laboratories of Experimentation," Florida Law Review, 57, 295-404.

Ball, Ray and Philip Brown, 1968, "An Empirical Evaluation of Accounting Income Numbers," Journal of Accounting Research, 6, 159–178.

Barer, Morris, 1995, "So Near, and Yet So Far: A Canadian Perspective on U.S. Health Care Reform," Journal of Health Politics, Policy and Law, 20, 463-476.

Bartov, Eli, Suresh Radhakrishnan and Itzhak Krinsky, 2000, "Investor Sophistication and Patterns in Stock Returns after Earnings Announcements," Accounting Review, 75, 43-63.

Bassett, Gilbert and Roger Koenker, 1978, "Asymptotic Theory of Least Absolute Error Regression," Journal of the American Statistical Association 73, 618-622.

Becker, Sascha and Mathias Hoffmann, 2006, "Intra- and International Risk-sharing in the Short Run and the Long Run," European Economic Review, 50, 777-806.

Belsley, David, Edwin Kuh, and Roy Welsch, 1980, Regression Diagnostics: Identifying Influential Data and Sources of Collinearity, John Wiley & Sons, Inc.

Bennett, James, Richard Sias and Laura Starks, 2003, “Greener Pastures and the Impact of Dynamic Institutional Preferences,” Review of Financial Studies, 16, 1203-1238.

Bernanke, Ben and Alan Blinder, 1988, “Credit, Money, and Aggregate Demand,” American Economic Review, 78, 435-439.

Bernanke, Ben and Mark Gertler, 1989, “Agency Costs, Net Worth, and Business Fluctuations,” American Economic Review, 79, 14-31.

Bernanke, Ben, 1983, “Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression,” American Economic Review 73, 257-276.

Bernanke, Ben, 1986, “Alternative Explanations of the Money-Income Correlation,” Carnegie-Rochester Conference Series on Public Policy, 25, 49-99.

Bernanke, Ben, 2007, “Housing, Housing Finance, and Monetary Policy,” Economic Symposium Conference Proceedings, Federal Reserve Bank of Kansas City.

Bernanke, Ben, and Alan Blinder, 1988, “Credit, Money, and Aggregate Demand,” American Economic Review 78, 435-439.

Bernanke, Ben, Mark Gertler, Mark Watson, Christopher Sims and Benjamin Friedman, 1997, Systematic Monetary Policy and the Effects of Oil Price Shocks, Brookings Papers on Economic Activity, 1997, 91-157.

Bethel, Jennifer and Julia Liebeskind, 1993, “The Effects of Ownership Structure on Corporate Restructuring,” Strategic Management Journal, 14, 15-31.

Billio, Monica, Mila Getmansky, Andrew Lo, and Loriana Pelizzon, 2010, “Econometric Measures of Systemic Risk in the Finance and Insurance Sectors,” NBER Paper No. 16223.

Binder, John, 1998, “The Event Study Methodology since 1969,” Review of Quantitative Finance and Accounting, 11, 111-137.

Bisias, Dimitrios, Mark Flood, Andrew Lo, Stavros Valavanis, 2012, "A Survey of Systemic Risk Analytics", Office of Financial Research Working Paper #0001.

Bjornland, Hilde, 2000, “VAR Models in Macroeconomic Research,” Statistical Norway Research Documents, October 2000/14.

Blanchard, Olivier and Danny Quah, 1989, “The Dynamic Effects of Aggregate Demand and Supply Disturbances,” American Economic Review, 79, 655-673.

Blanchard, Olivier and Mark Watson, 1986, "Are All Business Cycles Alike?," The American Business Cycle: Continuity and Change, University of Chicago Press, 123–160.

Blinder, Alan, 2007, "Six Fingers of Blame in the Mortgage Mess," The New York Times, September 30.

Blumenthal, David, 1996, "Effects of Market Reforms on Doctors and Their Patients," Health Affairs, 115, 170-184.

Brownlees, Christian, and Robert Engle, 2010, "Volatility, Correlation and Tails for Systemic Risk Measurement," NYU Stern Working Paper.

Brunnermeier, Markus and Lasse Pedersen, 2009, "Market Liquidity and Funding Liquidity," Review of Financial Studies, 22, 2201-2238.

Brunnermeier, Markus and Stefan Nagel, 2004, "Hedge Funds and the Technology Bubble," Journal of Finance, 59, 2013-2040.

Cai, Fang and Lu Zheng, 2004, "Institutional Trading and Stock Returns," Finance Research Letters, 1, 178-189.

Calomiris, Charles, and Charles Kahn, 1991, "The Role of Demandable Debt in Structuring Optimal Banking Arrangements," American Economic Review 81, 497-513.

Campbell, John, Andrew Lo and A. Craig MacKinlay, 1996, The Econometrics of Financial Markets, Princeton University Press.

Campbell, John, Martin Lettau, Burton Malkiel, and Yexiao Xu, 2001, "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk," Journal of Finance, 56, 1-43.

Cannon, Susanne, Norman Miller and Gurupdesh Pandher, 2006, "Risk and Return in the US Housing Market: A Cross-Sectional Asset Pricing Approach," 34, 519-552.

Catte, Pietro, Giampaolo Galli and Salvatore Rebecchini, 1994, "Concerted Interventions and the Dollar: An Analysis of Daily Data," The International Monetary System (Peter Kenen, Francesco Papadia and Fabrizio Saccomanni, Ed.,) Cambridge University Press, Cambridge.

Chandra, Ramesh, Shane Moriarity and G. Lee Willinger, 1990, "A Reexamination of the Power of Alternative Return-Generating Models and the Effect of Accounting for Cross-Sectional Dependencies in Event Studies," Journal of Accounting Research, 28, 398–408.

Chan-Lau, Jorge, 2010, "Regulatory Capital Charges for Too-Connected-to-Fail Institutions: A Practical Proposal," IMF Working Paper 10/98.

Chen, Xia, Jarrad Harford and Kai Li, 2007, "Monitoring: Which Institutions Matter?" Journal of Financial Economics, 86, 279–305.

Chiesa, Gabriella, 2008, "Optimal Credit Risk Transfer, Monitored Finance, and Banks," Journal of Financial Intermediation, 17, 464-477.

Clifford, Christopher, 2008, "Value Creation or Destruction? Hedge Funds as Shareholder Activists," Journal of Corporate Finance, 14, 323–336.

Cooley, Thomas and Stephen Leroy, 1985, "Atheoretical Macroeconometrics: A Critique," Journal of Monetary Economics, 16, 283-308.

Cutler, David, 1988, "Tax Reform and the Stock Market: An Asset Price Approach," American Economic Review, 78, 1107-1117.

Dale, Spencer, 1993, The Effect of Changes in Official U.K. Rates on Market Interest Rates since 1987, The Manchester School, 61, 76–94.

Daniel, Kent, David Hirshleifer and Avanidhar Subrahmanyam, 2001, "Overconfidence, Arbitrage, and Equilibrium Asset Pricing," Journal of Finance, 56, 921–965.

De Jonghe, Oliver, 2010, "Back to Basics in Banking? A Micro-Analysis of Banking System Stability," Journal of Financial Intermediation 19, 387-417.

Del Guercio, Diane, 1996, "The Distorting Effect of the Prudent-Man Laws on Institutional Equity Investment," Journal of Financial Economics, 40, 31-62.

Demirguc-Kunt, Asli and Harry Huizinga, 2010, "Bank Activity and Funding Strategies," Journal of Financial Economics 98, 626-650.

DeYoung, Robert, and Karin Roland, 2001, "Product Mix and Earnings Volatility at Commercial Banks: Evidence from a Degree of Total Leverage Model," Journal of Financial Intermediation 10, 54-84.

Diamond, Douglas, 1984, "Financial Intermediation and Delegated Monitoring," Review of Economic Studies 51, 393-414.

Dominguez, Kathryn and Jeffrey Frankel, 1993, "Does Foreign Exchange Intervention Work?" Institute for International Economics, Washington D.C.

Duffee, Gregory and Chunsheng Zhou, 2001, "Credit Derivatives in Banking: Useful Tools for Managing Risk?," Journal of Monetary Economics, 48, 25-54.

Eggert, Kurt, 2002, Held Up in Due Course: Predatory Lending, Securitization, and the Holder in Due Course Doctrine, Creighton Law Review, 35, 363-431.

El-Gazzar, Samir, 1998, “Predisclosure Information and Institutional Ownership: A Cross-Sectional Examination of Market Revaluations during Earnings Announcement Periods,” Accounting Review, 73, 119-129.

Enders, Walter, 2009, “Chapter 5: Multiequation Time-Series Model,” Applied Econometric Times Series, Wiley.

Eng, L.L., Y.T. Mak, 2003, “Corporate Governance and Voluntary Disclosure,” Journal of Accounting and Public Policy, 22, 325–345.

Engel, Kathleen and Patricia McCoy, 2002, “A Tale of Three Markets: The Law and Economics of Predatory Lending,” Texas Law Review, 80, 1255-1381.

Engel, Kathleen and Patricia McCoy, 2006, “Turning a Blind Eye: Wall Street Finance of Predatory Lending,” Fordham Law Review, 75, 2039-2103.

Englund, Peter, Min Hwang and John Quigley, 2002, “Hedging Housing Risk,” Journal of Real Estate Finance and Economics, 24, 167-200.

Enthoven, Alain and Sara Singer, 1995, “Market-based Reform: What to Regulate and by Whom,” Health Affairs, 14, 105-119.

Estrella, Arturo, 2002, “Securitization and the Efficacy of Monetary Policy,” Federal Reserve Bank of New York, Economic Policy Review, 9, 243-255.

Fahlenbrach, Rudiger, Robert Prilmeier, and Rene Stulz, 2011, “This Time Is the Same: Using Bank Performance in 1998 to Explain Bank Performance During the Recent Financial Crisis,” OSU Fisher College of Business Working Paper No. 2011-03-010.

Falkenstein, Eric, 1996, “Preferences for Stock Characteristics as Revealed by Mutual Fund Portfolio Holdings,” Journal of Finance, 51, 111-35.

Fama, Eugene, 1965, “The Behavior of Stock Market Prices,” Journal of Business 37, 34-105.

Fama, Eugene, 1985, “What's Different About Banks?,” Journal of Monetary Economics 15, 29-39.

Fama, Eugene, Lawrence Fisher, Michael Jensen and Richard Roll, 1969, “The Adjustment of Stock Prices to New Information,” International Economic Review, 10, 1–21.

Fang, Lily, Victoria Ivashina, and Josh Lerner, 2010, “Unstable Equity? Combining Banking with Private Equity Investing,” Harvard Business School Working Paper No. 10-106.

Fatum, Rasmus and Michael Hutchison, 2003, “Is Sterilised Foreign Exchange Intervention Effective After All? An Event Study Approach,” Economic Journal, 113, 390–411.

Favilukis, Jack, Sydney Ludvigson and Stijn Van Nieuwerburgh, 2011, “The Macroeconomic Effects of Housing Wealth, Housing Finance, and Limited Risk-Sharing in General Equilibrium,” NBER Working Paper No. 15988.

Ferlie, Ewan, Andrew Pettigrew, Lynn Ashburner and Louise Fitzgerald, 1996, The New Public Management in Action, Oxford University Press.

Fligstein, Neil and Adam Goldstein, 2010, “The Anatomy of the Mortgage Securitization Crisis,” Research in the Sociology of Organizations, 30, 29-70.

Fraser, Donald, Jeff Madura, and Robert Weigand, 2002, “Sources of Bank Interest Rate Risk,” Financial Review 37, 351-367.

Freeman, John, John Williams, and Tse-min Lin, 1989, “Vector Autoregression and the Study of Politics,” American Journal of Political Science, 33, 842-877.

Garfinkel, Michelle and Daniel Thornton, 1995, “The Information Content of the Federal Funds Rate: Is it Unique?” Journal of Money, Credit and Banking, 27, 838-847.

Gatev, Evan, Til Schuermann. And Phil Strahan, 2009, “Managing Bank Liquidity Risk: How Deposit Lending-Lending Synergies Vary with Market Conditions, Review of Financial Studies 22, 995-1020.

Gaur, Vishal, Sridhar Seshadri and Marti Subrahmanyam, 2010, “Securitization and Real Investment in Incomplete Markets,” Management Science.

Gauthier, Celine, Alfred Lehar, and Moez Souissi, 2010, “Macroprudential Capital Requirements and Systemic Risk,” Bank of Canada Working Paper 2010-4.

Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny, 2011, “Neglected Risks, Financial Innovation, and Financial Fragility,” Journal of Financial Economics, forthcoming.

Gilligan, Thomas and Keith Krehbiel, 1988, “Complex Rules and Congressional Outcomes: An Event Study of Energy Tax Legislation,” Journal of Politics, 625-654.

Gompers, Paul and Andrew Metrick, 2001, “Institutional Investors and Equity Prices,” Quarterly Journal of Economics, 116, 229-259.

Gorton, Gary and George Pennacchi, 1995, “Banks and Loan Sales Marketing Nonmarketable Assets,” Journal of Monetary Economics, 35, 389-411.

Gorton, Gary, and George Pennacchi, 1990, "Financial Intermediaries and Liquidity Creation," Journal of Finance 45, 49-71.

Granger, Clive and Paul Newbold, 1974, "Spurious Regressions in Econometrics," Journal of Econometrics, 2, 111-120.

Granger, Clive, 1969, "Investigating Causal Relations by Econometric Models and Cross-spectral Methods," Econometrica, 37, 424-438.

Greenbaum, Stuart and Anjan Thakor, 1987, "Bank Funding Modes: Securitization versus Deposits," Journal of Banking and Finance, 11, 379-401.

Griffin, John, Jeffrey Harris and Selim Topaloglu, 2003, "The Dynamics of Institutional and Individual Trading," Journal of Finance, 58, 2285-2320.

Grinblatt, Mark, Sheridan Titman and Russ Wermers, 1995, "Momentum, Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior," American Economic Review, 85, 1088-1105.

Han, Lu, 2010, "The Effects of Price Risk on Housing Demand: Empirical Evidence from U.S. Markets," Review of Financial Studies, 23, 3889-3928.

Hannan, Edward and Barry Quinn, 1979, "The Determination of the Order of an Autoregression," Journal of the Royal Statistical Society, 41, 190-195.

Herzlinger, Regina, 2007, Who Killed Health Care? America's $2 Trillion Medical Problem - and the Consumer-Driven Cure, McGraw-Hill.

Hinings, C. Robert, Ann Casebeer, Trish Reay, Karen Golden-Biddle, Amy Pablo and Royston Greenwood, 2003, "Regionalizing Healthcare in Alberta: Legislated Change, Uncertainty and Loose Coupling," British Journal of Management, 14, 15–30.

Hirshleifer, David and Siew Hong Teoh, 2003, "Limited Attention, Information Disclosure, and Financial Reporting," Journal of Accounting and Economics, 36, 337–386.

Hooker, Mark, 1996, "What Happened to the Oil Price-Macroeconomy Relationship?," Journal of Monetary Economics, 38, 195-213.

Huang, Xin, Hao Zhou, and Haibin Zhu, 2009, "A Framework for Assessing the Systemic Risk of Major Financial Institutions," Journal of Banking and Finance 33, 2036-2049.

Huang, Xin, Hao Zhou, and Haibin Zhu, 2010, "Systemic Risk Contributions," FRB Working Paper.

Ikeda, Shinsuke and Akihisa Shibata, 1992, "Fundamentals-dependent Bubbles in Stock Prices," Journal of Monetary Economics, 30, 143-168.

Inside Mortgage, 2010, Mortgage Market Statistical Annual: Volumes I & II, Inside Mortgage Finance Publications.

Jaffe, Adam and Karen Palmer, 1997, "Environmental Regulation and Innovation: A Panel Data Study," Review of Economics and Statistics, 79, 610–619.

James, Christopher, 1987, "Some Evidence on the Uniqueness of Bank Loans," Journal of Financial Economics 19, 217-235.

Jorion, Philippe, 2006, Value at Risk: The New Benchmark for Managing Financial Risk, McGraw-Hill.

Jorion, Philippe, 2009, Financial Risk Manager Handbook, 5th edition, Wiley.

Julia, Forrester, 2006, "Still Mortgaging the American Dream: Predatory Lending, Preemption, and Federally-Supported Lenders," University of Cincinnati Law Review, 74, 1303-1371.

Kaiser Family Foundation, 2010, Summary of New Health Reform Law, Focus on Health Reform, The Henry J. Kaiser Family Foundation, Menlo Park, California.

Kaminsky, Graciela, Carmen Reinhart and Carlos Vegh, 2003, "The Unholy Trinity of Financial Contagion," Journal of Economic Perspectives, 17, 51-74.

Kandel, Eugene and Neil D. Pearson, 1995, "Differential Interpretation of Public Signals and Trade in Speculative Markets," Journal of Political Economy, 103, 831–872.

Kashyap, Anil, Jeremy Stein, and David Wilcox, 1993, "Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance," American Economic Review 83, 78-98.

Kashyap, Anil, Raghuram Rajan, and Jeremy Stein, 2002, "Banks as Liquidity Providers: An Explanation for the Coexistence of Lending and Deposit-Taking," Journal of Finance 57, 33-73.

Keating, John, 1992, "Structural Approaches to Vector Autoregressions," Federal Reserve Bank of St. Louis Review, September, 37-57.

Keys, Benjamin, Tanmoy Mukherjee, Amit Seru and Vikrant Vig, 2009, "Financial Regulation and Securitization: Evidence from Subprime Mortgage Loans," Journal of Monetary Economics, 56, 700-720.

Keys, Benjamin, Tanmoy Mukherjee, Amit Seru and Vikrant Vig, 2010, "Did Securitization Lead to Lax Screening? Evidence from Subprime Loans," Quarterly Journal of Economics, 125, 307-362.

Kim, Oliver and Robert Verrecchia, 1991, "Trading Volume and Price Reactions to Public Announcements," Journal of Accounting Research, 29, 302-321.

Kiyotaki, Nobuhiro and John Moore, 1997, "Credit Cycles," Journal of Political Economy, 105, 211-248.

Kiyotaki, Nobuhiro and John Moore, 2002, "Balance-Sheet Contagion," American Economic Review, 92, 46-50.

Koenker, Roger, 2005, Quantile Regression, Cambridge University Press.

Koenker, Roger, and Gilbert Bassett, 1978, "Regression Quantiles," Econometrica 46, 33-50.

Koenker, Roger, and Kevin Hallock, 2001, "Quantile Regression," Journal of Economic Perspectives 15, 143-156.

Koppl, Thorsten, 2006, "Risk Sharing through Financial Markets with Endogenous Enforcement of Trades," Journal of Economic Dynamics and Control, 30, 1987-2014.

Kothari, S.P. and Jerold Warner, 2007, "Econometrics of Event Studies," Handbook of Corporate Finance: Empirical Corporate Finance (B. Espen Eckbo, Ed.,) Elsevier.

Krueger, Dirk and Fabrizio Perri, 2011, "Public versus Private Risk Sharing," Journal of Economic Theory, 146, 920-956.

Lakonishok, Josef, Andrei Shleifer and Robert Vishny, 1992, "The Impact of Institutional Trading on Stock Prices," Journal of Financial Economics, 32, 23-43.

Lanoie, Paul, Jérémy Laurent-Lucchetti, Nick Johnstone and Stefan Ambec, 2011, "Environmental Policy, Innovation and Performance: New Insights on the Porter Hypothesis," Journal of Economics & Management Strategy, 20, 803–842.

Laux, Christian, and Christian Leuz, 2010, "Did Fair-Value Accounting Issues Contribute to the Financial Crises," Journal of Economic Perspectives 24, 93-110.

Levine, Ross and Sara Zervos, 1998, "Stock Markets, Banks, and Economic Growth," American Economic Review, 88, 537-558.

Ligon, Ethan, 1998, "Risk Sharing and Information in Village Economics," Review of Economic Studies, 65, 847-64.

Lilien, David, 1982, "Sectoral Shifts and Cyclical Unemployment," Journal of Political Economy, 90, 777-793.

Lindahl, Eric, 1919, "Just Taxation - A Positive Solution," Classics in the Theory of Public Finance (Richard Musgrave and Alan Peacock, e.d.), Palgrave Macmillan, 1958.

Longstaff, Francis, 2010, "The Subprime Credit Crisis and Contagion in Financial Markets," Journal of Financial Economics, 97, 436-450.

Lustig, Hanno and Stijn Van Nieuwerburgh, 2010, "How Much Does Household Collateral Constrain Regional Risk Sharing?," Review of Economic Dynamics, 13, 265-294.

Lutkepohl, Helmut, 2010, "Chapter 9: Structural VARs and VECMs," New Introduction to Multiple Time Series Analysis, Springer.

Makarov, Igor and Guillaume Plantin, 2011, "Equilibrium Subprime Lending," Journal of Finance, Forthcoming.

Malherbe, Frederic, 2010, "Market Discipline and Securitization," London Business School Working Paper.

Manchikanti, Laxmaiah, David Caraway, Allan Parr, Bert Fellows and Joshua Hirsch, 2011, "Patient Protection and Affordable Care Act of 2010: Reforming the Health Care Reform for the New Decade," Pain Physician, 14, 35-67.

Meyer, Bruce, 1995, "Natural and Quasi-experiments in Economics," Journal of Business and Economic Statistics, 13, 151 – 161.

Meyer, Bruce, 1995, "Natural and Quasi-experiments in Economics," Journal of Business and Economic Statistics, 13, 151 – 161.

Meyer, Richard, Kenneth Wieand, 1996, "Risk and Return to Housing, Tenure Choice and the Value of Housing in an Asset Pricing Context," Real Estate Economics, 24, 113-131.

Mian, Atif and Amir Sufi and Francisco Trebbi, 2008, "The Political Economy of the US Mortgage Default Crisis," NBER Working Paper No. 14468.

Mian, Atif and Amir Sufi, 2009, "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis," Quarterly Journal of Economics, 122, 1449-1496.

Mian, Atif and Amir Sufi, 2010, "Household Leverage and the Recession of 2007 to 2009," NBER Working Paper No. 15892l.

Morduch, Jonathan, 1995, "Income Smoothing and Consumption Smoothing," Journal of Economic Perspectives, 9, 103-114.

New Jersey, 2004, "New Jersey's Predatory Lending Law Protecting Consumers," New Jersey Department of Banking and Insurance, News Release of December 21, 2004 (Holly Bakke, Commissioner).

Nofsinger, John and Richard Sias, 1999, "Herding and Feedback Trading by Institutional and Individual Investors," Journal of Finance, 54, 2263-2295.

Officer, R. R., 1972, "The Distribution of Stock Returns," Journal of the American Statistical Association 67, 807-812.

Parlour, Christine and Guillaume Plantin (2008), "Loan Sales and Relationship Banking," Journal of Finance, 63, 1291-1314.

Philip Berger, 1993, "Explicit and Implicit Tax Effects of the R&D Tax Credit," Journal of Accounting Research, 31, 131-171.

Phillips, Peter, 1986, "Understanding Spurious Regressions in Econometrics," Journal of Econometrics, 33, 311-340.

Plantin, Guillaume, 2010, "Good Securitization, Bad Securitization," Toulouse School of Economics and CEPR Working Paper.

Porter, Michael, "America's Green Strategy," 1991, Scientific American, 168.

Praetz, Peter, 1972, "The Distribution of Share Price Changes," Journal of Business 45, 49-55.

Rubin, Donald, 1974, Estimating Causal Effects of Treatments in Randomized and Non-Randomized Studies, Journal of Educational Psychology, 66, 688–701.

Rubin, Donald, 1978, Bayesian Inference for Causal Effects. The Role of Randomization. Annals of Statistics, 6, 34–58.

Runkle, David, 1987, "Vector Autoregressions and Reality," Journal of Business and Economic Statistics, 5, 437-442.

Schroeder, Steven, 1993, "The Clinton Health Care Plan: Fundamental or Incremental Reform?" Annuals of Internal Medicine, 119, 945-947.

Schwarz, Gideon, 1978, "Estimating the dimension of a model," Annals of Statistics, 6, 461–464.

Shapiro, Matthew and Mark Watson, 1988, "Sources of Business Cycle Fluctuations," NBER Macroeconomics Annual, 3, 111-148.

Shiller, Robert, 1995, "Aggregate Income Risks and Hedging Mechanisms," Quarterly Review of Economics and Finance, 35, 119-152.

Shin, Hyun Song, 2009, "Securitization and Financial Stability," Economic Journal, 119, 309-332.

Shleifer, Andrei and Robert Vishny, 1997, "The Limits of Arbitrage," Journal of Finance, 52, 35-55.

Shleifer, Andrei, and Robert Vishny, 2010, "Unstable Banking," Journal of Financial Economics 97, 306-318.

Shockley, Richard and Anjan Thakor, 1997, "Bank Loan Commitment Contracts: Data, Theory, and Tests," Journal of Money, Credit, and Banking 4, 517-534.

Sims, Christopher, 1980, "Macroeconomics and Reality," Econometrica, 48, 1-48.

Sims, Christopher, 1982, "Policy Analysis with Econometric Models," Brookings Papers on Economic Activity, 107-164.

Sims, Christopher, 1986, "Are Forecasting Models Usable for Policy Analysis?," Federal Reserve Bank of Minneapolis Quarterly Review, 10, 2-16.

Sims, Christopher, 2002, "Structural VAR's," Time Series Econometrics (Econ 513), Princeton University.

Song, Fenghua and Anjan Thakor, 2007, Relationship Banking, Fragility, and the Asset-Liability Matching Problem, Review of Financial Studies 6, 2129-2177.

Stein Jeremy, 1998, "An Adverse-Selection Model of Bank Asset and Liability Management with Implications for the Transmission of Monetary Policy", RAND Journal of Economics 29, 466-486.

Steinmo, Sven and Jon Watts, 1995, "It's the Institutions, Stupid! Why Comprehensive National Health Insurance Always Fails in America," Journal of Health Politics, Policy and Law, 20, 329-372.

Stiglitz, Joseph, 2007, "Houses of Cards," The Guardian, October 9.

Stiroh, Kevin, 2004, "Diversification in Banking: Is Noninterest Income the Answer?," Journal of Money, Credit and Banking 36, 853-882.

Stiroh, Kevin, 2006, “A Portfolio View of Banking with Interest and Noninterest Activities,” Journal of Money, Credit, and Banking 38, 2131-2161.

Tarashev, Nikola, Claudio Borio, and Kostas Tsatsaronis, 2010, “Attributing Systemic Risk to Individual Institutions: Methodology and Policy Applications,” BIS Working Papers 308.

Thornton, Daniel, 1998, “Tests of the Market’s Reaction to Federal Funds Rate Target Changes,” Federal Reserve Bank of St. Louis Review, 80, 25–36.

Wagner, Wolf and Ian Marsh, 2006, “Credit Risk Transfer and Financial Sector Stability,” Journal of Financial Stability, 173-193.

Wagner, Wolf, 2010, “Diversification at Financial Institutions and Systemic Crises,” Journal of Financial Intermediation 19, 373-386.

West, Kenneth, 1987, “A Specification Test for Speculative Bubbles,” Quarterly Journal of Economics, 102, 553-580.

Wong, Alfred, and Tom Fong, 2010, “Analyzing Interconnectivity among Economics,” Hong Kong Monetary Authority Working Paper 03/1003.

Wu, Yangru, 1997, “Rational Bubbles in the Stock Market: Accounting for the U.S. Stock-price Volatility,” Economic Inquiry, 35, 309-319.

Xu, Xinpeng, 2008, “Consumption Risk-Sharing in China,” Economica, 75, 326-341.

Yan, Xuemin and Zhe Zhang, 2009, “Institutional Investors and Equity Returns: Are Short-term Institutions Better Informed?” Review of Financial Studies, 22, 893-924.

Yule, G. Udny, 1926, “Why do We Sometimes Get Nonsense-Correlations between Time-Series? A Study in Sampling and the Nature of Time-Series,” Journal of the Royal Statistical Society, 89, 1-63.

Zhou, Chen, 2009, “Are Banks too Big to Fail?,” DNB Working Paper 232.

VITA

Gang Dong

1973	Born Nov 11 in Shanghai, China
1989-1992	Shanghai Yan'an High School (High school diploma)
1992-1996	Shanghai University (B.S. in Computer Engineering)
1996-1997	Hewlett Packard (Analyst)
1998	Singapore OCBC Bank (Analyst)
1998-2000	Capgemini, Denver (Analyst)
2000-2004	Reuters, Chicago (Analyst)
2001-2003	Illinois Institute of Technology (M.S. in Computer Science)
2004	Purdue University (M.S. Graduate Study)
2004-2006	Indiana University (M.B.A.)
2005	Bear Stearns, New York (Analyst)
2006-2010	Columbia University (P.D. in Industrial Engineering)
2006	Credit Suisse, New York (Analyst)
2007	Bank of New York, New York (Analyst)
2007-2012	Rutgers Business School, Newark and New Brunswick (Ph.D. in Finance)