A Model of Bank Asset and Liability Management with Loan Commitments

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Abstract

This paper develops a simple model of bank asset and liability management with loan commitments, in which a bank faces a liquidity management problem due to stochastic loan commitment take-down. Consistent with the model's implications, our empirical research finds: (1) the use of loan commitments increased *after* interstate banking deregulation, which suggests that a bank's ability of tapping uninsured funds through cheaper external financing or internal capital markets is critical to its decision on the amount of loan commitments to be issued, (2) the ratio of C&I (Commercial and Industrial) loans to total loans increases with the amount of C&I loan commitments (as a share to total loans) during contractionary periods and this tendency is more pronounced for banks with more limited access to external financing. Following the model's implication, it suggests that banks tend to reduce the amount of its term loans to be issued in an attempt to deal with tighter financial constraints, caused by increased loan take-down. That is, loan commitments *crowd out* term loans during periods of financial distress, indicating the disproportionate impact on the borrowers of loan commitments and term loans, and (3) as a natural extension of the previous implication, the states with more intensive use of loan commitments suffer less from external shocks, displaying smaller economic fluctuations during contractionary periods. Neither state-specific industry structures nor other bank balance sheet variables can explain away this finding. Implications for the increased macroeconomic stability of U.S. economy from mid 80's, bank lending channel and risk-based capital regulations are discussed.

1 Introduction

Bank loan commitment, a formal contract by a bank to lend to a specific borrower up to a certain amount at prespecified terms, is widely used and its use is getting popular over time, as documented by many researchers (Morris and Sellon (1995), Shockley and Thakor (1997), Ergungor (2001)). As Figure 1 shows, the amount of unused loan commitment outstanding in off-balance sheets of commercial banks is almost as large as the amount of total loans made as of 1999:IV. Also, Federal Reserve Statistical Release E.2 as of 2005 May reports that the share of commercial and industrial (C&I) loans made under commitment amounts to 88 percent of total C&I loans made. Statistics gathered from the Federal Reserve's Report of Condition and Income, so called "Call Reports," document the increased use of loan commitments in all sizes of banks and regardless of bank holding company (BHC, henceforth) affiliation, as shown in Figure 2 and 3.

Considering this increased significance of loan commitments in economic activity, this paper develops a simple model of a bank's asset and liability choice with loan commitments, in order to address the questions of: (1) which factors affect the optimal amount of loan commitments for a bank? (2) what happens to a bank's loan composition in terms of loans made through commitment arrangements and non-commitment term loans when loan take-down increases? If any, do banks' responses differ depending on banks' characteristics? (3) do those reshufflings of bank loan portfolio, caused by loan commitment take-down, have any real effects to the economy?

Rather than taking an approach based on contract theory, a variant of famous "newsboy problem" in operation research literature is developed.[1] In our model, the amount of liquidity held by a bank is regarded as inventory in preparation for uncertain liquidity demand. Thus,

[1]For a newsboy who sells papers on a street corner, the demand is uncertain, and the newsboy must decide how many papers to buy from his supplier. If he buys too many papers, he is left with unsold papers that have no value at the end of the day; if he buys too few papers, he has lost the opportunity of making a higher profit. Like a newsboy, a bank with loan commitments needs to control the level of liquidity in face of uncertain liquidity demand. One caveat on the modeling strategy in this paper is that it does not pay much attention to the informationl value of loan commitments.

in the context of optimal inventory management, a bank who seeks to maximize its expected net income should consider: (1) the optimal allocation between loan commitments and non-commitment term loans for profitable investments, and (2) the optimal amount of liquidity to be held in preparation for stochastic loan take-down. One key assumption in the model is that the cost of denying obligations from loan commitments by invoking MAC (Material Adverse Changes) clauses and/or covenants is higher than that of cutting term loans, which seems very plausible considering the contractual property of loan commitments. Using the model's implications, we derive three testable implications.

Firstly, the model identifies the ability of tapping uninsured funds with lower cost as one of the key parameters in issuing loan commitments. By running two-step instrumental variable estimation with the measures of interstate banking used in Morgan, Rime, and Strahan (2004), it is shown that the ratio of unused loan commitments to total loans, as a proxy for the intensity of using loan commitments in banks' loan supply, increased *after* interstate banking deregulation. In addition, Call Reports show that larger banks and BHC-affiliated banks issue more loan commitments. These results suggest that a bank's ability of tapping uninsured funds through cheaper external financing or internal capital markets is critical to its decision on the amount of loan commitments to be issued.

Secondly, when the increased take-down drains the amount of liquidity held inside, a liquidity-constrained bank would respond to this by reducing its term loans and/or resorting to external financing. The model shows that a bank with more limited access to external financing tends to cut down more of its term loans to be issued.[2] That is, loan commitments may *crowd out* non-commitment terms loans since the latter has no legal obligations.[3] This implies that term loans are relatively more vulnerable to disruptions such as monetary policy tightening because they are likely to be topped off by the increased take-down from loan commitments, which will in turn make loan commitments more valuable especially when the

[2]It is natural to think that terminating relationship with firms or denying roll-over despite relationship banking will incur some damages to a bank. The model introduced below incorporates this factor and the amount of term loans eventually cut down will be decided by its relative cost to external financing cost.

[3]MAC (Material Adverse Change) clauses allow a bank to get out of its obligations from loan commitments. But, its use is fairly limited. This issue will be discussed in the following section.

amount of funds available in the economy is more limited.[4]

Due to the unavailability of data on *used* amount of loan commitments, we instead pursue an indirect and partial test by looking at the response of C&I loans to its corresponding loan commitments in bad times. Our empirical test shows that the ratio of C&I loans to total loans increases with the amount of C&I loan commitments outstanding in bad times.[5] Also, this effect is stronger for small stand-alone banks compared to small BHC-affiliated banks, because stand-alone banks do not have internal capital markets from which they can get funds in their financial distress. When increased loan take-down tightens banks' financial constraints, banks without cheaper sources of funds opt more for cutting its term loans rather than relying more on external financing or internal capital markets. This logic explains the differential responses of the two groups in response to loan take-down during tight periods.

Extending the previous implication, our third testable implication from the model is that monetary policy has a potential to disproportionately affect the borrowers of terms loans and loan commitments, which indicates the economic activities of loan commitment borrowers would be more stable. That is, firms which rely on higher proportion of loan commitments in its financing would exhibit less volatile economic activities because they have a relatively more guaranteed source of funds, especially in bad times.

The best way to test this reasoning empirically would be to obtain firm-level panel data which include not only firms' activities of production and sales but also their financial conditions with their choices of external financing and to match them with bank-level panel data.[6]

[4]However, this proposition cannot be interpreted to argue that term loans are inferior to loans made through loan commitments. While loan commitments provide an insurance device by becoming stable sources of funds to firms, term loans are another profitable investments to banks, over which they have more discretion so that they can control in case there are some disruptions to banks' financical position. In this regard, even though the use of loan commitments are increasing very fast in 1990's, loan commitments are not expected to completely replace term loans in the future.

[5]Call Reports data record an item of "other commitments," which are mainly obligations for commercial and industrial firms. I'll call this C&I loan commitments.

[6]*Quarterly Financial Report for Manufacturing, Mining and Trade Corporations*, published by the Census Bureau, provides summary financial statistics for all manufacturing corporations (except those with assets less than $250,000 at the time of sampling), and mining and trade corporations with $50 million and over

However, since those firm-level data matched with bank-level ones are not available, we instead test the hypothesis at state level. The bank-level Call Reports data are aggregated to state level and merged with macroeconomic variables and state-level industry characteristics. The empirical result shows that the states with higher loan commitment ratio to total loans exhibit less volatile economic activities during high interest rate periods. Alternatively, it can be said that loan commitments play a role of dampening external shocks especially when firms find it harder to get external funds. Other bank balance sheet variables such as the ratio of liquid assets to total assets and the bank equity share to total assets, which possibly play a role of buffer stock to external shocks, cannot explain this result. It also survives various robustness tests including endogeneity problem, choices of monetary policy measures and the like.

Empirical findings in this paper lead us to a couple of venues to explore. One is about the increased macroeconomic stability of U.S. economy observed from mid 80's. Morgan, Rime, and Strahan (2004) shows that, during the deregulation period of the infamous Douglas Amendment to the 1956 Bank Holding Company Act, interstate banking became common and the integration through BHC-member banks tends to dampen the impact of bank capital shocks to state economic activity. Considering that interstate banking allows more BHC-member banks to operate in the economy and those banks tend to issue more loan commitments with their advantages in managing liquidity, our finding may be one mechanism to explain their empirical result.[7]

Secondly, deeper understanding of how loan commitments affect banks' asset and liability managements will also help estimate the effect of the lending channel with more accuracy. To measure its impact, it is essential to identify the changes in loan *supply* in response to monetary policy shocks. However, it is very hard to identify the shift in loan supply schedule due to the concurrent changes in loan demand conditions.[8] In addition to this, take-down

in assets at the time of sampling. However, time periods available are from 1977 to 1991, which are not overlapped much with our sample period. Also, firm-level data are available only on yearly basis.

[7]In the empirical test below, we formally test if the use of loan commitments increased after interstate banking deregulation. The result shows that our conjecture discussed here is highly plausible.

[8]Empirical studies of Sofianos, Wachtel, and Melnik (1990), Morgan (1998), Kashyap and Stein (2000)

from loan commitments also makes this problem more intricate.

As an example, in the literature of the lending channel, it is well-known that loan growth rates of larger banks and BHC-affiliated banks are less responsive to monetary shocks comparing those of smaller banks and stand-alone banks, since larger banks have access to cheaper source of external funding and BHC-member banks have internal capital markets. But, considering that larger banks and BHC-affiliated banks are more heavily using loan commitments, these differential responses between the groups may partly come from different level of using loan commitments since term loans and commitment loans behave differently in response to monetary shocks, as documented in Morgan (1998). In this regard, empirical studies, without taking proper account of the role of loan commitments, may incorrectly estimate the responses of loan growth because of different level of loan commitment usage associated with bank sizes and BHC-affiliation.[9] Also, since the observed loan changes include the sum of loan take-down and the changes in new term loans, which might partly offset each other, VAR analysis with aggregated time series may face more severe problems of identifying the impact of monetary shocks to loan growth rates. This line of argument is not for invalidating the empirical studies on the lending channel. Rather it tries to point out the difficulties in gauging the size of the lending channel accurately. Enhancing our understanding on loan commitments will shed some light on the famous "black box," transmission mechanism of monetary policy.

The rest of the paper is organized as follows. The next section discusses the main implications of related literature, with some of institutional backgrounds. Section 3 presents the models, starting with a simple one-period model which highlights a bank's choice between term loans and loan commitments in the context of liquidity management, followed by an extended one which allows a bank to recall its term loans. Section 4 will test the model's

and Ashcraft (forthcoming) support the argument that loan supply is affected by monetary policy. Khwaja and Mian (2005) use unanticipated nuclear tests in Pakistan in 1998 as "natural experiments" and identifiy the supply side shocks. And they show that those supply shocks have significant and persistent real impacts to the economy.

[9] This issue can be discussed in the context of omitted variable problem. Covariance between loan takedown and monetary policy measure will affect the magnitude of bias.

implications along with robustness tests. The following section devotes some thoughts on the role of loan commitments on macroeconomic stability, its implication for bank lending channel and risk-based bank capital regulation. The final section concludes with the summary.

2 Related Literature

The main distinctive features of loan commitments which attract economists' interest are multiple fee structure and option-like exercise. Thus, many studies focus on explaining why loan commitments exists and how they are priced.

Morgan (1993) uses a model based on contract theory to see how incentive problems between lender and borrower affect the fee structure of loan commitments. His model predicts that the spread over the safe rate will increase with the size of commitment loan and the least-known firms with high monitoring cost benefit the most from using bank loan commitments. However, the reality is that a fixed spread for all sized loans is charged and relatively well-known firms use loan commitments more heavily. He leaves an open question about why the small firms which would benefit most from loan commitments use less of it. Shockley and Thakor (1997) scrutinize a micro data to make testable predictions that pricing structure of loan commitment is more complicated and delicate to firms whose assets are harder to value and whose credit quality is poor. Also, they predict the announcement of a loan commitment purchase should be greeted with an abnormal positive price reaction since obtaining a stable source of funds is regarded as a good news in the markets. Both predictions are confirmed in their empirical test.

As to credit risk from using loan commitments, Boot and Thakor (1991) formally establish that loan commitments may reduce banks' asset risk. And Avery and Berger (1991) shows that commitment loans tend to have slightly better than average performance, suggesting that either commitments generate little risk or that this risk is offset by the selection of safer borrowers to receive commitments.

Some may point out that loan commitment is rather discretionary due to MAC (Material

Advance Change) clauses, hence adding no credit or liquidity risk . Banks can get out of their obligations under certain circumstances, attesting MAC clauses. Nevertheless, in reality, it appears that courts have often obstructed banks' right to invoke MAC clauses and deny credit to a loan commitment owner, arguing that the banks had not acted in good faith (Edelstein (1991)). Additionally, if a bank concerns about its reputation by exercising MAC clauses and its long-term effect, invoking the clauses is costly. Therefore, being with MAC clauses does not entitle banks to full freedom of leaving obligations from loan commitments at any time. In this regard, it may be a wrong proposition that loan commitments with MAC clauses do not impose any credit or liquidity risk on banks.[10] Notwithstanding, it cannot be said that loan commitment is an unconditional obligation to firms all the time. An empirical study by Sufi (2005) shows that banks, recognizing that the line of credit can be prone to abusive use by corporate borrowers, closely monitor and extend the line of credit through covenants on firms' profitability. In this regard, it seems obnoxious to think that loan commitment lies between unconditional obligation of funding and term loans without commitment.

In terms of pricing loan commitments, a recent study by Chava (2004) presents interesting results. Using a pricing model and Dealscan database, he shows that banks offer loan commitments (on a stand-alone basis) to firms below the fair price and the extent of underpricing is significantly and positively related to the length of the relationship between the bank and the borrower. The empirical fact that loan commitments are widely used despite its negative price on a stand-alone basis implies the existence of informational value accruing from mutual relationships between lenders and borrowers

At macro level, Morgan (1998) reports that bank loans not made under commitment slow after tight policy, while loans under commitment accelerate or are not changed. In a similar context, Sofianos, Wachtel, and Melnik (1990) use VAR and find an evidence of a smaller impact of monetary policy on loans made under commitment agreements than on

[10] Boot and Thakor (1991) theorectically show that loan commitments lower the bank's asset portfolio risk. However, the result is based on rather a restrictve assumption that the bank's loan portfolio is observable to customers.

loans not made under commitment. They conclude loan commitments effectively insulate borrowers from the effect of credit rationing and force monetary policy to work exclusively through the interest channel.[11] In a similar study, Hirtle (1990) suggests that the size of loan commitment market is a proxy for the share of corporate borrowers that are no longer dependent on banks for credit. As the share of non-bank dependent corporate borrowers increases, monetary policy in the banking sector will have to work more exclusively through the interest channel. Our empirical finding is consistent with this assertion in terms of policy implication that the interest sensitivity of output decreases with the size of loan commitment market. However, given our finding that the ratio of C&I loans to total loans increases during contractionary periods and this increase is well-explained by the amount of loan commitments outstanding, loan commitment is more than a proxy for financial market developments, by becoming an actual source of funds to firms. This issue will be discussed more in the section of robustness check below.

Kashyap, Rajan, and Stein (2002) ask why the dominant proportions of loan commitments are issued by commercial banks, not by other types of financial intermediaries. Their key insight is that deposit withdrawal and loan commitment take-down are essentially the same in terms of liquidity provision. Hence, if those two liquidity demands are not perfectly correlated, dealing with two seemingly separate functions under one roof produces the synergy effect, allowing banks to hold less amount of buffer stock liquidity. Recent studies by Gatev and Strahan (2005) and Gatev, Schuermann, and Strahan (2005) confirms this by showing that, during 1998 crisis, banks experiencing a large inflow of transaction deposits provide liquidity to firms using commercial back up lines. Also they present an evidence that this deposit-lending synergy is more powerful during crisis, as nervous investors move their funds into banking sector.

[11] Both studies use the Federal Reserve Board's Loan Commitment Survey, which ran between January 1975 and June 1987. This survey records the loans under commitment, which are not available in Call Report data. Morgan (1998) uses Romer dates and federal funds rate as measures for monetary policy stance while Sofianos, Wachtel, and Melnik (1990) use a monetary aggregate of M1.

3 Model

This section introduces a simple one-period model to highlight the determinants of using loan commitments.[12] The simple case will show how the optimal amount of loan commitments is affected by the degree of adverse selection in capital markets, the degree of uncertainty in borrowers' liquidity demand and other parameters. Next, an extended version allows a bank to use an option of recalling term loans. When the amount of liquidity held inside falls short of the realized take-down from loan commitments, a bank needs to make up for the shortfall. In this situation, the options open to a bank are (1) to get uninsured funds through external financing and (2) to reduce the amount of term loans to be issued. The relative importance of these two options depends on their relative marginal costs. If a bank's external financing cost is higher compared to that of others, it will cut down more of its term loans if other things are being equal. This extended version will show that the ratio of loan commitments to term loans will increase in bad times and this effect is stronger for small banks or stand-alone banks, which are our testable implications in the next section.

3.1 Simple Case

The one-period model is designed to capture the following characteristics of a bank in a minimalist fashion: (1) a bank provides funds to its customers via term loan (N) or commitment loan (C); and (2) it should maintain a buffer stock of liquid assets (S) inside to meet the unexpected take-down of loan commitment; but (3) it is costly for a bank to raise external finance in case the amount of take-down is larger than the buffer stock of liquidity. Under this setting, a bank faces a problem of liquidity management. If it piles up too much liquidity inside, it loses more profitable investment opportunities through term loans or commitment loans. To the contrary, it incurs a penalty of more expensive external financing when the expected level of liquidity falls short of the realized take-down.

In the beginning of the period (period 0), a bank is endowed with deposit D, which is

[12] The framework is similar with the one in Kashyap, Rajan, and Stein (2002). Their focus is more on the synergy effect in saving liquidity by dealing with loan commitments and demand deposit under one roof.

to be optimally divided into term loans and commitment loans. A bank can make profits by issuing term loan with the rate of r_N and loan commitments. When a bank issues loan commitments, it receives a total contract fee $f(C)C$ where $f(C) = j - hC$ $(j, h > 0)$ and earns r_C per unit of realized take-down.[13] The actual take-down will be determined by a random variable $z \in [0, 1]$, which is realized following a bank's portfolio decision. We assume that z is uniformly distributed in the range of $[a, b]$ where $0 \leq a < b \leq 1$. The difference between term loans and loan commitments is that, in case of the latter, a bank should face the uncertainty of how much of funds will be taken down from loan commitment. If it fails to meet the realized take-down (zC) with the predetermined buffer stock (S_0), it should raise external finance as much as $B = \max[zC - S_0, 0]$ at the end of the period (period 1). In order to get a closed-form solution, cost function takes a simple form of $H(B) = \alpha(zC - S_0)$ when $zC > S_0$ with properties of $H'(B) > 0$ and $H(0) = 0$.[14] It is reasonable to assume $\alpha > r_N$ since α can be interpreted as the penalty cost of external financing incurred when it fails to predict the loan commitment take-down correctly. Also the parameter α measures the degree of adverse selection problem a bank faces in the capital markets. Thus, we expect α to be decreasing with the bank size because larger banks tend to suffer less from capital market imperfections.

A bank seeks to maximize its expected net income:

$$\max_{C,S_0} .E[r_N N + f(C)C + r_C zC - H(B)]$$

subject to

$$N + S_0 = D \tag{1}$$

$$N + zC + S_1 = D + B \tag{2}$$

[13] According to Ergungor (2001), the fee structure may include a commitment fee, which is an up-front fee paid when the contract is made, an annual service fee, which is paid on the borrowed amount, and a usage fee, which is levied on the unused amount. I assume that only commitment fee is charged.

[14] Stein (1998) derives a quadratic form of cost function in a more formal model where there is an adverse selection problem in a bank's uninsured liabilities. When we use a quadratic form, our main results remain untouched. However, closed-form solutions are not available in that case.

and

$$S_1 = \max\{S_0 - zC, 0\} \tag{3}$$

where equation (1) and (2) are balance sheet constraints for period 0 and 1 respectively. If the period 0 liquidity (S_0) is not sufficient for the take-down, additional fund needs to be obtained, but not through short sales. This is reflected in (3). Since external financing is necessary only when $zC > S_0$, expected external financing cost function is given by

$$\begin{aligned} E[H(B)] &= \int_a^b \alpha(zC - S_0)dF(z) \\ &= \alpha \int_{S_0/C}^b (zC - S_0)dF(z) + \alpha \int_0^{S_0/C} 0dF(z) \\ &= \alpha \int_{S_0/C}^b (zC - S_0)dF(z) \end{aligned}$$

Reformulating the maximization problem gives:

$$\max_{C,S_0}.E[r_N(D - S_0) + (j - hC)C + zr_C C] - \alpha \int_{S_0/C}^b (zC - S_0)dF(z)$$

The first order conditions are

$$[C] : r_C\mu_z + j - 2hC^* = \frac{\alpha}{2}(b^2 - \frac{S_0^{*2}}{C^{*2}})$$

$$[S_0] : r_N = \alpha(b - \frac{S_0^*}{C^*})$$

where μ_z is the mean value of z. These two first order conditions consist of a non-linear simultaneous equation system for the optimal level of loan commitment and liquidity to be held. By rearranging and solving for C^* and S_0^*, we obtain:

$$C^* = \frac{1}{2h}[\frac{r_N^2}{2\alpha} - r_N b + r_C\mu_z + j]$$

$$S_0^* = \frac{\alpha b - r_N}{\alpha}C^*$$

And the optimal amount of term loans N^* is determined with S_0^* in (1).

The comparative statics for some variables of interest shows very intuitive results. The first result is about the effect of external financing ability on loan commitments. As shown in (4),

$$\frac{\partial C^*}{\partial \alpha} = -\frac{r_N^2}{4h\alpha^2} < 0 \tag{4}$$

a bank which faces more severe adverse selection problem in the capital markets (higher α) tends to issue less loan commitments.

Other theoretical studies on the existence of loan commitments predict that small banks and small firms can benefit more from using them since information-intensive activity of using loan commitments may alleviate the agency problem. However, the data shows loan commitments prevail far more in large banks, as shown in line 12 of Table 1 and Figure 2. Consistent with these real world observations, (4) implies that the role of liquidity management in issuing loan commitments may be more important than informational values accrued from bilateral agreements. Note that this result is pertinent to supply side of loan commitments.

As one characteristics of demand side, it would be interesting to see the effect of uncertain take-down on loan commitment issuance. Letting $b \equiv b' + \varepsilon$ and $a \equiv a' - \varepsilon$, increasing ε is equivalent to increase the variance of z leaving its mean unchanged. The second comparative statics shows

$$\frac{\partial C^*}{\partial \varepsilon} = -\frac{r_N}{2h} < 0$$

which implies a bank with more uncertain liquidity demand from loan commitments tends to rely less on loan commitments. This explains why many banks imposes usage fees. By charging usage fees on the amount of *unused* loan commitments, it helps a bank better predict the actual amount of loan take-down and manage liquidity with more ease, narrowing the distance between a and b.

As to the optimal amount of liquidity held inside for unexpected take-down, there are two opposing forces. Higher external financing cost (higher α) makes a bank hold more liquidity given C^* while it also deters a bank from issuing loan commitments, leading to less demand for liquidity. (5) shows this intuition[15]:

$$\frac{\partial S_0^*}{\partial \alpha} = (1 - \frac{r_N}{\alpha})\frac{\partial C^*}{\partial \alpha} + \frac{r_N}{\alpha^2}C^* \lesseqgtr 0 \tag{5}$$

If the cost of external financing is so exorbitantly high that it is practically impossible to get funds from outside, a bank should pile up liquidity as much as the maximum amount of take-down, as shown in (6):

$$\lim_{\alpha \to \infty} S_0^* = bC^* \tag{6}$$

While it is possible to perform the comparative statics with all the parameters in the model, the first result provides our first prediction. for our empirical analysis.

Proposition 1 *A bank with less severe adverse selection problem in capital markets or with cheaper sources of external funds will issue more loan commitments. Following our notations,* $\partial C^*/\partial \alpha < 0$.

The above proposition implies that larger banks, which face less adverse selection problem in capital markets, and BHC-affiliated banks, which have internal capital markets, are expected to issue more loan commitments compared to smaller and stand-alone banks. We'll look at the evidences to confirm this prediction below.

3.2 Model with Recallable Term Loans

We'll extend the previous model by allowing a bank to recall its term loans. When there is a liquidity shortage, a bank is allowed to cancel part of its term loans which are initially promised (N_0). When recalling its term loans by the amount of ($N_0 - N_1$), it incurs the cost

[15] If the response of loan commitments is not too negative, we expect $\partial S_0^*/\partial \alpha$ to be positive. More formally, a sufficient condition for $\partial S_0^*/\partial \alpha > 0$ is

$$\frac{r_N}{\alpha(r_N - 1)} < \frac{\partial C^*/\partial \alpha}{C^*} < 0$$

That is, its says the elasticity of C^* to α is not too negative.

of $G(N_0 - N_1)$.[16] N_0 can be regarded as the optimal amount of term loans before take-down shock (z) is realized while N_1 is the optimal amount of term loans actually issued at period 1 after the realization of z between period 0 and 1.

A bank's maximization problem is:

$$\max . E[r_N N_0 + f(C)C + r_C zC - H(B) - G(N_0 - N_1)]$$

subject to

$$N_0 + S_0 = D$$

$$N_1 + zC + S_1 = D + B$$

and

$$S_1 = \max\{S_0 - zC, 0\}$$

If liquidity held inside meets the demand from take-down, there is no need for external financing or recalling term loans. In this case, N_1 is equal to N_0. If not, the excessive amount of liquidity demand, $\Delta \equiv (zC - S_0)$, should be dealt with external financing and recalling term loans. That is, when $zC > S_0$, it should be

$$\Delta \equiv zC - S_0 = B + (N_0 - N_1)$$

Alternatively,

$$N_1 = \min\{N_0, D + B - zC\}$$

Since this cost associated with external financing and recalling term loans arises only when $\Delta > 0$, we can think of a cost minimization problem for a given amount of excess demand Δ first and expect the minimized cost function to be a function of Δ. Regarding

[16] In the model, we implicitly assume that the cost of negating the legal obligation by invoking MAC (Material Adverse Change) clauses or using covenants on borrowers' profitability is infinite. However, as Sufi (2005) shows, loan commitments are rather flexible than our expectation and they are extended after banks' close monitoring. Nevertheless, an assumption that the cost of canceling loan commitments is higher than that of cutting term loans is sufficient for our model's implication to work.

the realized $\Delta > 0$ as constant, we face a problem of optimally dividing excess demand (Δ) into borrowing (B) and cutting term loans ($N_0 - N_1$):

$$\min_{B,N_1} .H(B) + G(N_0 - N_1)$$

subject to

$$\Delta = B + (N_0 - N_1)$$

Assuming $H(B) = \alpha B$ and $G(N_0 - N_1) = \gamma(N_0 - N_1)^2$ gives the closed form solutions of the optimal level of external financing and the amount of term loans cut down.[17] They are:

$$B^* = \Delta - \alpha/2\gamma \quad \text{and} \quad N_0^* - N_1^* = \alpha/2\gamma \quad \text{if } \Delta > 0 \tag{7}$$

where α is the marginal cost for external borrowing and γ is a measure of relative costs associated with cutting term loans. Plugging these in the objective function gives the minimized expected cost function. Considering that this optimized function is relevant only when $\Delta > 0$, our original problem becomes

$$\max_{C,S_0} .E[r_N(D - S_0) + fC + r_C zC] - \alpha \int_{S_o/C}^{1} (zC - S_0)dF(z) - \frac{\alpha^2}{4\gamma}(1 - \frac{S_0}{C})$$

assuming $z \in [0, 1]$ for simplicity. And this can be solved by differentiating with respect to C and S_0 as in the previous section, though the closed form solutions are not available in this case. Our concern is to see how much of term loans are reduced in response to a tightened financial constraint caused by increased loan take-down. Since Δ is to be optimally divided between B and $N_0 - N_1$ when $\Delta > 0$, the amount of term loans cut down depends on the marginal costs of external financing and recalling term loans. As a result, B^* and $(N_0^* - N_1^*)$ are functions of α and γ, and $(N_0^* - N_1^*)$ is an increasing function of α, as shown in (7).

The result implies that, for a given amount of Δ, a bank with higher α will recall more of its term loans because its ability of external financing is more limited. Following this,

[17] Assuming both $H(\cdot)$ and $G(\cdot)$ are quadratic, we have

$$B^* = \frac{\alpha}{\alpha + \gamma}\Delta \quad \text{and} \quad N_0^* - N_1^* = \frac{\gamma}{\alpha + \gamma}\Delta \quad \text{when } \Delta > 0$$

Except one special case in which both $H(\cdot)$ and $G(\cdot)$ are linear, both B^* and $N_0 - N_1^*$ are the functions of α.

one testable empirical implication is derived. In bad times when firms find it harder to get external funds, take-down from loan commitments (zC) increases and it causes a bank to cut down its term loans ($N_0 - N_1$) in an attempt to readjust its portfolio. Therefore, the ratio of loans made through commitment arrangements to term loans increases and this effect is expected to be bigger with higher amount of loan commitments outstanding. Let R be the ratio of loans made through commitment contracts to term loans. Then we expect:

$$\frac{\partial^2 R}{\partial MP \partial C} > 0 \tag{8}$$

and

$$\frac{\partial^3 R}{\partial MP \partial C \partial \alpha} > 0$$

where MP is a monetary policy index with higher values corresponding to higher interest rates.

Proposition 2 *In a bank's loan portfolio, the ratio of loans made under commitment to term loans increases with the amount of loan commitment outstanding in bad times (*$\partial^2 R/\partial MP \partial C > 0$*). And, this effect is more pronounced for smaller banks and stand-alone banks (*$\partial^3 R/\partial MP \partial C \partial \alpha > 0$*).*

The proposition says the ratio of commitment loans to term loans will increase during recessions due to increased loan take-down. Also the effect will be stronger for banks with more limited ability of tapping uninsured funds because the amount of term loans crowded by commitment loans is bigger for these banks. Extending this implication, it can be interpreted that borrowers of loan commitments and term loans are disproportionately affected by external shocks. This implication will be tested as our third prediction.

4 Empirical Analysis

4.1 Data

In the analysis below, I use quarterly data on the population of all insured commercial banks from the Federal Reserve's Report of Condition and Income, often called "Call Reports."

In making a consistent dataset, I heavily borrowed the variable definitions and exclusion criteria used in Kashyap and Stein (2000), Campello (2002) and Ashcraft (forthcoming). One must be careful in making consistent time-series data since there are changes in accounting practices and numerous bank mergers which bring jumps in balance sheet variables. The appendix provides a more detailed note on how to make the variables used here. Call Reports are available from 1976. However, the sample period in the analysis is limited to 1984:II-1999:IV due to the availability of loan commitments data, key variable in the analysis. Total unused commitment series is available from 1984:II while other commitment-related variables such as credit card lines and commitment to fund loans secured by real estate are available from 1990:I or 1991:I.

Call Reports data have a merit that it is a population of all commercial banks, not a sample. Also it has detailed information on bank balance sheets. However, there are some missing and incorrect numbers. To fix this and remove outliers, all the observations which are not considered as normal operations of banks are eliminated. In detail, observations of bank-quarter with asset growth in excess of 50 percent, those with commitments-to-total loans ratio exceeding 4, those with the ratio of total loans to asset below 10 percent, and those with total loan and C&I loan growth rates exceeding 100 percent are eliminated. Also the observations with the ratio of non-performing loans to total loans in excess of 50 percent and with the ratio of C&I loans to total loans exceeding 100 percent are dropped. To make regressions with four lags possible, all the bank entities with less than five consecutive quarters are removed from the sample, too. This screening dropped approximately 7.7% of observations, from the population of 812,970 bank-quarter observations.

Also, I use the most recent merger file from the Federal Reserve Bank of Chicago, used in Ashcraft (forthcoming), to exclude the bank-quarter observations which are involved in mergers since they may create jumps in balance sheet variables unrelated to real economic activity.

Table 1 presents the median values of balance sheet variables in each size/BHC (Bank Holding Company)-affiliation categories. Top 1 percent in terms of average assets during the sample period are categorized into 'large banks.' And banks between below 1 percent and top 5 percent are named as 'medium banks' and below 5 percent are defined as 'small banks.' If a bank is affiliated with BHC, it is a member of BHC. Otherwise, it is called stand-alone banks.

4.2 Prediction 1: Banks with Less Severe Agency Problem Issue More Loan Commitments

4.2.1 Empirical Specification

Our first prediction from the model is that banks with less severe agency problem in capital markets will use more loan commitments because ability of tapping into uninsured funds will help their liquidity management problem associated with loan commitments. Alternatively, we expect larger banks and BHC-affiliated banks to use more loan commitments because they have better external financing ability or internal capital markets. Using the model's notation, we expect $\partial C^{*}/\partial \alpha < 0$.

The bottom row of Table 1 shows the ratio of unused loan commitments to total loans by size and BHC membership as of 1985:I and 1999:IV. Though the loan commitment item collected in Call Reports is the *unused* amount of loan commitment, not the actual amount of commitment taken down, upward trend of unused commitments can be regarded as heavier use of loan commitments over time. It shows, as of 1999:IV, larger banks and BHC-affiliated banks, if they are in the same size group, use more loan commitments compared to smaller banks and stand-alone banks.

Even without considering the informational role of loan commitments, our simple model based on liquidity management approach can explain the real world observations. Figure 2 and 3 show that the larger banks and BHC-affiliated banks tend to use more loan commitments. Because larger banks and BHC-affiliated banks are deemed to face less severe adverse selection problem in the market for uninsured funds compared to smaller banks and stand-alone banks, this corresponds to the model's prediction that lower α motivates banks to use more loan commitment.

However, the conclusion based on summary statistics in Table 1, Figure 2 and Figure 3 may be indecisive because we do not have exogenous variations in α, our measure of a bank's adverse selection problem in external capital markets. In order to support our conjecture based on the figures and summary statistics, we test the hypothesis more formally using differences-in-differences estimation, taking interstate banking deregulation as a natural experiment for exogenous changes in agency cost.

The logic is that, if interstate banking deregulation from 1970's allows many banks to use internal capital markets through mergers, those banks would experience lower agency costs due to internal capital markets and tend to issue more loan commitments.[18] If this logic works, we expect to observe a 'jump' in using loan commitments at the time of bank deregulation, which will be captured by dummy variables taking one after deregulation. Also, the use of loan commitments is expected to increase as interstate banking pervades.

For more formal analysis, I borrow two variables from Morgan, Rime, and Strahan (2004). To measure bank integration, they use *interstate asset ratio* and *other state asset ratio*. The first one equals the fraction of bank assets in state i that are owned by a holding company that owns bank assets in one or more other states. The second measure equals total out-of-state assets held by holding companies operating in the states, divided by total assets in that state. They take other state asset ratio as given because it depends mostly on a state's size and location, factors that are largely exogenous with respect to the size of a fluctuation in a given state-year. That is, other state asset ratio is rather exogenous to economic conditions and the year of interstate banking deregulation.[19]

Using these measures, we test more formally to see if the use of loan commitments increases *after* interstate banking deregulation and if it goes with bank integration by estimating the following regression equation:

$$COM_{it} = c + \alpha_D D_k^i + \beta ISAR_{it} + \sum_{j=1}^{7} \phi_j IS_{i,t}^j + \alpha_i + u_{it}, \quad k = 3 \text{ or } 5 \tag{9}$$

where COM is the ratio of total loan commitments to total loans and $ISAR$ is interstate asset ratio. We include state-level industry income shares to control for state-specific industry

[18] Note that states deregulated in waves from 1970's, rather than all at once. For a brief history of U.S. bank deregulation, see Kroszner and Strahan (1999) and Morgan, Rime, and Strahan (2004).

[19] Morgan, Rime, and Strahan (2004) contain more detailed explanation on these measures.

structures. Following the definition in Morgan, Rime, and Strahan (2004), D_k^i is a dummy variable which switches on (from zero to one) k years after deregulation in state i. Note that D_k^i allows for delays between deregulation and the actual mergers that increase interstate bank affiliations.[20]

For estimation, we use two-stage IV estimation with the yearly data of 1984-1994.[21] As pointed out in Morgan, Rime, and Strahan (2004), there might be an endogeneity problem in interstate asset ratio ($ISAR$) because it can be affected by current economic conditions and the accompanying bank buy-out. For this reason, I run the same form of their first-stage regression for IV estimation:

$$ISAR_{it} = c + \psi_1 OSAR_{it} + \psi_2 D_1^i + \psi_3 D_k^i + \psi_4 D_B^i + v_{it}, \quad k = 3 \text{ or } 5 \tag{10}$$

where $OSAR$ is other state asset ratio, D_1 is a dummy for one year after deregulation and D_B is a dummy for intrastate branch deregulation. Equation (10) is exactly the same form of the first stage regression in Morgan, Rime, and Strahan (2004).

4.2.2 Results

Our focus is on the signs of α_D and β in (9) . $\alpha_D > 0$ implies that the use of loan commitments actually increases *after* deregulation while $\beta > 0$ means that it goes with the degree of bank integration across states. We use fixed effect panel regression with IVs and pooled OLS with IVs. In case of pooled OLS with IVs, robust standard errors, clustered by states to allow for correlation across states, are also reported following a suggestion in Bertrand, Duflo, and Mullinaithan (2004).

The empirical result supports our hypothesis. Table 2 shows that, for estimates of α_D, all the estimates from fixed effect panel regression with IVs and pooled OLS with IVs are positive and they are strongly significant, implying that the use of loan commitments increases after deregulation. When we look at the case with robust standard errors, statistical significance

[20] In the original paper, they use only D_5. To check the sensitivity of the result on the delay periods, I also try D_3.

[21] The reason for not extending over 1994 is that the year of 1994 is the last year in their sample period.

gets lower but their p-values are still around 0.1. According to the estimates, the ratio of loan commitments to total loans increases by 3.8% to 5.3% after deregulation.

Kroszner and Strahan (1999) find deregulation occurs earlier in states with fewer small banks, in states where small banks are financially weaker, and in states with more small, presumably bank-dependent, firms. Also, a larger insurance industry delays deregulation when banks may compete in the sale of insurance products. Their study suggests the possible endogeneity of deregulation timing. Though how such endogeneity affects our estimates is not clear, I check the effect of states which deregulate earlier or later compared to other states by running the same regression without those states.[22] Whether those early or late states are excluded from regression does not change our result in Table 2 considerably, adding more support for our initial result.

Also, for the coefficient of interstate asset ratio ($ISAR$), all the estimates come up with positive signs and all of them are statistically significant at 10% level. Following this, we conclude that the use of loan commitments goes together with interstate asset ratio, a measure of bank integration across states, and it actually increases after deregulation, possibly via interstate banking.

4.3 Prediction 2: Loan Commitments Crowd Out Term Loans in Bad Times

4.3.1 Empirical Specification

Following the model's implication, we are going to test if loan commitments crowd out term loans in bad times. In the estimation, one significant obstacle is that Call Reports do not record the amount of loan take-down in a separate item. Only Available is the unused amount of loan commitments in off-balance sheet and loans which are the sum of loan take-down and term loans. If we can observe the amount of loan take-down, our empirical test

[22] Five 'early states' which deregulate earlier are Maine (1978), Arkansas (1982), New York (1982), Connecticut (1983) and Massachusetts (1983) while five 'late states' are Nebraska (1990), Iowa (1991), North Dakota (1991), Kansas (1992) and Montana (1993). The numbers in parentheses are years of deregulation.

would be easier and its interpretation would be more straightforward. For example, if such data are available, we can directly test if the ratio of loans made under commitments to non-commitment term loans increases in bad times and if this tendency is more pronounced for banks with more limited access to external financing. Unfortunately, this approach is not readily implementable due to the unavailability of such data. To bypass this problem, we are going to pursue rather an indirect and partial test of this hypothesis, by looking at one category of loans, C&I loans.

While we look at CI loans due to data unavailability, there are at least three advantages of using C&I loans for our test. Firstly, there is a corresponding loan commitment category for C&I loans in Call Reports, which is an item of RCFD3818. RCFD3818 is also called "other unused commitments" among the subcategories of loan commitments and they are mainly obligations to supply loans to commercial and industrial firms. Thus, loan take-down from "other unused commitments" will be added to C&I loans. Secondly, as recent Federal Reserve Statistical Releases indicate, most of C&I loans are made through loan commitments. In this regard, we don't have worry much about the amount of C&I *term loans* to be crowded out by C&I loan commitments and can focus more on the effect of C&I loan commitments to the relative shares between C&I loans and loans in other categories. Lastly, since C&I loans are known to be closely related to business cycles, the changes in the share of C&I loans to total loans may have macroeconomic implications.

Following the logic discussed in the previous section, if loan take-down from C&I loan commitments increases during tight periods and forces a bank to reduce its term loans in other loan categories, we expect: (1) the share of C&I loans to total loans is increasing with the amount of C&I loan commitments outstanding in bad times. That is, ∂^2(C&I loans/total loans)$/\partial MP \partial COM > 0$ where COM is "other unused commitments" for C&I loans. And (2) to the amount the increased C&I loan commitment take-down discourages a bank to issue new term loans, this effect of increasing the share of C&I loans to total loans will be bigger since it make total loans (or total loans minus C&I loans) shrink or increase less compared to C&I loans. Based on this reasoning, we expect ∂^3(C&I loans/total loans)$/\partial MP \partial COM \partial \alpha > 0$. In this regard, our dependent variable will be the ratio of C&I

loans to total loans and one of explanatory variables will be a measure of intensity in using loan commitments in issuing C&I loans.

For the correct identification of these two effects, it is essential to make sure that we have only variations from the ability of external financing (α) and not from the loan demand conditions. To achieve this, we are going to compare BHC-member banks with stand-alone banks in the same size, as done in Campello (2002) and Ashcraft (forthcoming). Using BHC-affiliation as a source of variation in financial constraints across banks has an advantage because it permits a comparison of banks which are identical except for the membership of BHC, possibly eliminating any unobserved differences in loan demand.[23] Since affiliated banks are expected to have better access to uninsured funds through internal capital markets, we take whether a bank is affiliated with BHC as the variation in the ability of tapping uninsured funds, α. That is, BHC-affiliated banks have lower α.[24]

The regression equation takes a form of (11) to estimate the differential responses between two groups:

$$\begin{aligned} R_{it} &= c + \varphi_A \ln(Asset)_{i,t-1} + \varphi_B B_{i,t-1} + \varphi_N NP_{i,t-1} + \varphi_C COM_{i,t-1} + \varphi_E E_{i,t-1} \\ &\quad + \sum_{j=1}^{4} \alpha_j MP_{t-j} + \sum_{j=1}^{4} \beta_j MP_{t-j} COM_{i,t-1} + \sum_{j=1}^{4} \gamma_j MP_{t-j} COM_{i,t-1} BHC_i \\ &\quad + (\text{dummy variables}) + \alpha_i + u_{i,t} \end{aligned} \tag{11}$$

where R_{it} is the ratio of C&I loans to total loans, MP is a measure of monetary policy stance, and COM is defined as 'other loan commitment (RCFD3818)/total loans' as a proxy for

[23] When we make a comparison by size, we are left with unobserved differences of loan demand associated with size. It is because large banks are more frequently matched with large firms while small banks tend to work with small banks. Since small firms are hit harder during recessions, there are uneven loan demands across bank sizes.

[24] One may point out the possibility of endogeneity in banks' becoming BHC-member banks or remaining as stand-alone banks. That is, individual bank characteristics may explain membership in a BHC. To check this possibility, Campello (2002) isolate observations from independent banks that eventually merge into a large BHC during the sample period and compare their lending behavior with that of banks that remain independent. Those comparisons show no indication that premerging and nonmerging small banks respond differently to Fed policies. His finding implies that becoming a target of merger or acquisition would be rather exogenous among small banks.

intensity of using loan commitments in issuing C&I loans. To control for bank size effect, log of bank asset is added. The ratio of security to total assets (B) and the ratio of bank equity to total assets (E) are included in the regression to represent a bank's liquidity position. Also, as a proxy for loan quality, the ratio of non-performing loans to total loans (NP) are included. The dummy variable BHC_i takes 1 if a bank is affiliated with BHC. Other dummy variables included are dummies of time, Federal Reserve district, BHC-affiliation, quarterly effect and credit crunch during the period of 1990:I-1993:IV.

Our interest lies in two sums of coefficients, $\sum \beta_j$ and $\sum \gamma_j$. $\sum \beta_j$ captures the common effect associated with the corresponding explanatory variable while $\sum \gamma_j$ picks up the differential responses between two groups. Our model predicts $\sum \beta_j > 0$ and $\sum \gamma_j < 0$. The first one seems natural if loan take-down from C&I loan commitments increases during high interest periods. For the second one, there can be several explanations for non-zero $\sum \gamma_j$.

The first candidate which explains non-zero $\sum \gamma_j$ is the crowding-out effect of loan commitments, which is our hypothesis. Given the equal size of loan take-down from C&I loan commitments, our model predicts that banks with more limited access to external financing will cut down more of its term loans to deal with increased loan take-down, which will put downward pressure on the denominator of our dependent variable.[25] If this mechanism works, then we expect $\sum \gamma_j$ to be negative. Alternatively, we can interpret the negative $\sum \gamma_j$ as the benefit of internal capital markets in dealing with the pressure of reshuffling between loan take-down and term loans, originated by the increased take-down during recessions. That is, our hypothesis says the response of our dependent variable to loan commitments in bad times would be bigger for stand-alone banks, implying $\sum \beta_j > \sum \beta_j + \sum \gamma_j$.

The second explanation arises from the possibility of firms' endogenous choices of banks. If a firm, whose loan demand is relatively more countercyclical, expects a BHC-member bank to meet its loan demand in bad times better due to a bank's internal capital market and strategically choose it rather than a stand-alone bank, there would be more loan take-down for BHC-member banks given the same shock to both groups. In this case, because BHC-

[25] It is possible to define our depedent variable R as the ratio of C&I loans to non-C&I loans. That is, C&I loans/(total loans$-$C&I loans).

member would experience more loan take-down compared to stand-alone banks, we expect $\sum \gamma_j > 0$.

Invoking MAC (Material Adverse Change) clauses and using covenants on loan commitment contracts also have a potential to explain non-zero $\sum \gamma_j$. It is expected that less liquidity-constrained banks will rely less on these measures given the equal size of loan take-down shock. Thus, BHC-member banks, which have internal capital markets, will provide more funds facing the same amount of loan take-down request, implying again $\sum \gamma_j > 0$.

Among these explanations for non-zero $\sum \gamma_j$, our model predicts $\sum \gamma_j < 0$, which can be an indirect evidence that loan commitments crowd out term loans in bad times. In the following empirical test, the sign of $\sum \gamma_j$ and its statistical significance tell us which factors prevail more.

4.3.2 Results

Table 3 reports our finding. For measures of monetary policy stances (MP), federal funds rate and 6-month paper-bill spread are used. In all specifications, we have $\sum \hat{\beta}_j > 0$ and $\sum \hat{\gamma}_j < 0$ as expected, with very strong statistical significance as shown in p-values. The results in Panel B are based on banks with non-zero loan commitments to check if the results in Panel A are driven by zero loan commitment bank-quarter observations. The bottom of each Panel provides the results with banks with well-capitalized banks, whose equity ratio are in the range of 0.06 and 0.15. Banks with too low or too high equity ratio are dropped since they are not considered as ones with normal operations in the business. Also these results are robust to the variations in the definition of COM, which include 'total unused commitments (RCFD3423)/total loans' and '(total unused commitments−credit card lines (RCFD3815)−securities underwriting (RCFD3817))/total loans,' though 'other loan commitment (RCFD3818)/total loans' seems more appropriate since it is a loan commitment category for C&I loans.

The direct effect of MP on the dependent variable, $\sum \hat{\alpha}_j$, is rather ambiguous. While it is positive when federal funds rate is used for MP, the sign becomes the opposite in case of paper-bill spread. Since our model does not provide any prediction on this and the results are highly significant with the opposite signs, we cannot discuss this result further. One comforting fact is that the magnitude is far smaller than those of our interest, $\sum\hat{\beta}_j$ and $\sum\hat{\gamma}_j$, leaving our main discussion untouched.

One thing noteworthy is high R^2 from the regressions. In our equations, within R^2 is higher than 0.7, which is unusual in micro-level panel data. Indeed, when we replace the dependent variable, the ratio of C&I loans to total loans, with the growth rates of C&I loans or total loans, the value is not higher than 0.2. Whereas R^2 is just one measure of overall fitness, it is encouraging to see more than 70% of total variation in our dependent variable is well explained by the regressors.

As discussed, the reason for using C&I loans is not only that they are being made mostly by loan commitments among loan categories, but also that we have a separate item of "other unused commitments" for C&I loans. As a result, the effect of corresponding loan commitments to C&I loans can be detected more easily. Along with this, they happen to be the loan category which are most closely related with economic activity. Thus, our empirical finding that the ratio of C&I loans to total loans changes with the amount of loan commitments during recessions indicates the possibility that loan commitments may have real effects to the economy. This implication will be tested in the following section.

4.4 Prediction 3: Loan Commitments Stabilize the Economy in Bad Times

4.4.1 Empirical Specification

Empirical studies on economic fluctuations or output volatility have typical measures for them. They are usually variances of demeaned output growth rates (Kim, Piger, and Nelson (forthcoming)), percentage deviations of real GDP from Hodrick-Prescott trend (Taylor (2000)), absolute deviation of conditional growth rates (Morgan, Rime, and Strahan (2004)), and squared terms of demeaned growth rate. In this paper, following Morgan, Rime, and Strahan (2004), the measure of economic fluctuations is the absolute deviation from conditional growth rate of output measures. The conditional growth rate is obtained by regressing growth rate on state dummy and time dummy, in order to get rid of state- and time-specific shocks from growth rate.[26] Output measures include real personal income per capita, real personal income and employment. Also, four lags of the dependent variable are included to control for possible autocorrelations. In particular, the measure of economic fluctuation F_{it} is the absolute value of the estimated residuals from the regression equation (12).

$$(growth)_{it} = c + \sum_{j=1}^{4} \phi_j (growth)_{i,t-j} + \sum_{s=1}^{49} \theta_s D_s + \sum_{t=1}^{62} \delta_t D_t + \varepsilon_{it} \tag{12}$$

Thus, after estimating (12), we define $F_{it} \equiv |\widehat{\varepsilon}_{it}|$ as our dependent variable.[27] Ignoring the autocorrelation part, F_{it} equals the size of the deviation from average growth for the state i during the sample period and from average growth rate for all states in that quarter t.

Call Reports data are aggregated to state level and variables are recalculated accordingly. Thus, we have 50 states over the period of 1984Q2-1999Q4, resulting in total 3200 observations of panel data. Our basic specification to estimate is:

$$\begin{aligned} F_{it} &= c + \varphi_A \ln(Asset)_{i,t-1} + \varphi_B B_{i,t-1} + \varphi_N NP_{i,t-1} + \varphi_C COM_{i,t-1} + \varphi_E E_{i,t-1} \\ &+ \sum_{j=1}^{4} \alpha_j MP_{t-j} + \sum_{j=1}^{4} \beta_j MP_{t-j} COM_{i,t-1} + \sum_{j=1}^{6} \phi_j IS_{i,t}^{j} \\ &+ \sum_{j=1}^{3} \rho_j QUARTER_j + \sum_{j=1}^{8} \varphi_j (Fed\ district)_j + \alpha_i + u_{it} \end{aligned} \tag{13}$$

where IS^j is the j th industry's ratio of sectoral income relative to total nonfarm earnings, as a proxy for industry structure or initial endowment in each state. Industries included are

[26] In case of real personal income and real personal income per capita, their growth rates are defined as differenced terms of log of those variables. Meanwhile, in case of employment, the dependent variable is defined as a differenced terms of level terms. This is because the standard deviation of employment growth rate is too low compared to the other two measures.

[27] Another measure of $F_{it} \equiv \widehat{\varepsilon}_{it}^2$ is also used for estimation and it does not change the main result. Hence, only the result with absolute values will be reported here.

As pointed out in Morgan, Rime, and Strahan (2004), there are two good reasons to use absolute values rather than squared deviations. First, it is easier to interpret the estimated coefficients since the absolute terms keep the same unit of growth rates. Second, we may have very big outliers by using squared terms.

construction, manufacturing, finance, services, government and trading.[28] To control for the seasonal effects and possible effects associated with Fed districts, quarterly dummies and Fed district dummies are added.[29] Four lags of monetary policy index and a lagged COM variable, interacted with four lags of monetary policy variables, are placed in the regression equation, where the variable COM is defined as the ratio of total unused loan commitment to total loans, which measures the intensity of commitment loans in overall loan making activity.

Two models are estimated. Model 1 refers to (13) without bank balance sheet variables. In Model 2, bank balance sheet variables, aggregated to state level, are added to see if the result from model 1 is affected by other bank variables, which might be highly correlated with commitment variable.

Our main prediction is that the states with higher usage of loan commitments will show less volatility in response to changes in monetary policy measures, which implies $\sum_{j=1}^{4} \beta_j < 0$. That is, loan commitments will play a role of dampening shocks during recessions.[30]

For estimation, OLS and fixed effect panel regression are used. Both fixed effect and GLS random effect model produce the similar estimates and Hausman test does not reject the null hypothesis of no fixed effects.[31] Hence, results from GLS random effect model are not reported. In case of OLS, standard errors are clustered by states to allow for correlation across states. Also, considering the possibility that the assumption of strict exogeneity

[28] Other available industry categories are agriculture, mining and transportation. Adding these industries does not affect the results.

[29] Using state/time dummy instead of Fed district/quarter dummy does not change the main results.

[30] Following the model's implication, there exists a possibility of negative effects from terms loans cut down. Though our model predicts the absolute volume of term loans cut down is smaller than the increased loan take-down, whether this negative effect from term loans will dominate the positive effect from loan commitments depends on their marginal importance, possibly associated with when and how both loans are used. Since the model says nothing about which effect prevails more, it would be good to decide after looking at the empirical results.

[31] Note that Hausman test of fixed effect model vs. GLS random effect model is not valid when the assumption of strict exogeneity breaks down. This issue will be discussed in the following section of GMM (Generalized Method of Moments) estimation with instrumental variables.

breaks down, first-differenced GMM (Generalized Methods of Moments) with IV (instrumental variable) is also estimated to deal with endogeneity problem. The results of GMM-type IV estimation follows in the robustness tests below.

4.4.2 Baseline Result

For our baseline result, we estimate Model 1 and Model 2 using OLS and fixed effect estimation, with three kinds of dependent variables. Hence we have total 12 regression equations to estimate. As an indicator of monetary policy stance, the federal funds rate is used. Since Bernanke and Blinder (1992) have strongly advocated the federal funds rate as monetary policy index, it is a prevalent measure in empirical studies of monetary policy. Other measures of monetary policy such as 6-month paper-bill spread and Bernanke-Mihov index are also used for robustness check.

Our main concern is on the sign and statistical significance of $\sum_{j=1}^{4}\widehat{\beta}_j$, sum of the coefficients on $MP_{t-j}COM_{i,t-1}$ $(j = 1, 2, 3, 4)$. We expect this to be negative. Panel A of Table 4 shows our baseline results, in which federal funds rate is used for monetary policy measure. The coefficients of our interest $\sum_{j=1}^{4}\widehat{\beta}_j$ are negative and statistically significant in 10 of 12 specifications, as expected. 7 of 12 estimates are significant at 1 percent level and 3 of 12 are at 10 percent level. Comparing the magnitudes of $\sum\widehat{\beta}_j$ from Model 1 and Model 2, though it seems that other bank balance sheet variables, aggregated to state level, explains a part of the effect we are interested, overall results do not vary considerably in Model 2.[32] F-test also strongly rejects the hypothesis that those coefficients are all zero. Additionally, though the statistical significance is not as strong as the case of $\sum\widehat{\beta}_j$, the direct effect of monetary shocks to economic fluctuations, $\sum\widehat{\alpha}_j$, is positive in all the specifications, which implies the volatility of real economy increases during high interest rate periods. These results seem to support our argument that loan commitment plays a role of moderating economic fluctuations during monetary contractions.

One worry may arise from the possibility that using the absolute values of the estimated

[32] However, other balance sheet variables such as liquid assets and bank equity cannot explain away our empirical findings. This possibility will be discussed in the following robustness tests.

residuals as dependent variable may affect the asymptotic variances of the estimates of our interest, $\sum \alpha_j$ and $\sum \beta_j$, in the second-step regression. If this is the case, our testing based on F statistics above may be invalid or inaccurate. To address this problem, the bootstrap method is used. Figure 4 shows histograms of $\sum \widehat{\alpha}_j$ and $\sum \widehat{\beta}_j$ based on 1,000 replications of non-parametric bootstrap when we use the state real personal income per capita as our output measure.[33] And, they are estimated using fixed effect regression. At a glance, the distribution in panel (c) of Figure 4 does not look like normal distribution while the rest of them seem close to normal distribution. However, it is encouraging that majority of $\sum \widehat{\alpha}_j$'s are in the positive range and most of $\sum \widehat{\beta}_j$'s are in the negative range as we expected. Table 5 reports the 95% confidence intervals of these distributions from bootstrapping. They indicate that $\sum \alpha_j$ are weakly positive and $\sum \beta_j$ are strongly negative, regardless of choices of monetary policy measures and methods of computing confidence intervals. This experiment confirms our previous results based on F-statistics.

Considering the role of loan commitments in our empirical analysis, increased use of loan commitments implies that the economy can better shield itself from external shocks over time. As of 1985:I, the average of COM over 50 states is 0.155 while the average as of 1999:IV amounts to 0.283. This increased use of loan commitments is likely to contribute to the increased macroeconomic stability. One caveat is that, since our measure of COM is the ratio of *unused* commitment loans to total loans, it is just a proxy for the intensity of loan commitment usage, not a accurate measure of how much of commitment loans are actually used at bank or state level.

In the following section, we will perform various robustness tests including the choices of monetary policy measures, GMM-type IV model to deal with endogenous/predetermined variables in a panel data model and others.

[33] Cluster sampling was made by states. Since all the states in our sample are of equal size, the resulting sample sizes by states are the same between replications.

4.4.3 Robustness Tests

Monetary Policy Measures Though the federal funds rate is widely used as monetary policy index, it is not fully free from endogeneity problem with business cycles. Rather than arguing that it is a single best measure, we will use another two measures which are considered to describe the stance of monetary policy: 6-month paper-bill spread and Bernanke-Mihov index.

Panel B of Table 4 reports the estimates with 6-month paper-bill spread. The signs and significances are not much different from Panel A. For the output measures of real personal income and real personal income per capita, all the estimates are negative and they are statistically significant. As to the estimates of $\sum \alpha_j$, 8 of 12 estimates are significant with positive signs.

When we use Bernanke-Mihov index, the results in Panel C of Table 4 are more supporting. 11 estimates of $\sum \beta_j$ among 12 regression equations display statistically significant negative signs. However, the direct effect on the dependent variable $\sum \alpha_j$ is less pronounced with Bernanke-Mihov index.

These results attest the robustness of our result regardless of monetary policy measures.

GMM Estimation with Instrumental Variables In the previous analysis, we use OLS and fixed effect panel regressions. One shortcoming of OLS in our situation is that it may not properly take into account the individual fixed effects (or unobserved heterogeneity) correlated with regressors, which leads to inconsistency of OLS estimator. While fixed effect regression removes those individual fixed effects by demeaning variables within each entity, it is likely to create another problem if the covariates violate the assumption of strict exogeneity. Since fixed effect panel regression is just an OLS of the transformed variables which are demeaned within each entity, fixed effect panel regression with predetermined or endogenous variables induces a non-negligible correlation between the transformed error terms and the transformed independent variables.

As Keane and Runkle (1992) argue that panel data models for testing rational expectations using individual-level data generally do not satisfy the strict exogeneity, any panel data model in which each observation is supposed to respond rationally may not fulfill the assumption of strict exogeneity because any current shocks will affect the future values of independent variables. Specifically, let us consider a linear regression including a fixed effect α_i with N individuals over T time periods:

$$y_{it} = \beta x_{it} + \alpha_i + u_{it} \quad (i = 1, ..., N; t = 1, ..., T) \tag{14}$$

The variable x_{it} is said to be strictly exogenous if it is uncorrelated with past, present and future values of u_{it}:

$$E(u_{it}|x_i^T) = 0 \quad (t = 1, ..., T)$$

where the expectation operator $E(\cdot)$ denotes a linear projection and we use the superscript notation $x_i^T = (x_{i1}, ..., x_{iT})$. We shall say x_{it} is predetermined if:

$$E(u_{it}|x_i^t) = 0 \quad (t = 1, ..., T)$$

When only the future values of dependent variables are affected by the disturbances u_{it}, those regressors are predetermined. In case the current shock u_{it} affects the current value of x_{it} and future values, it is said to be endogenous. When estimating (14) with fixed effect panel regression, the presence of predetermined/endogenous variables will necessarily cause the transformed dependent variable $x_{it} - (x_{i1} + ... + x_{it} + ... + x_{iT})/T$ to be correlated with the transformed error term $u_{it} - (u_{i1} + ... + u_{it} + ... + u_{iT})/T$, which leads to inconsistency of the estimator.[34]

One way to estimate with endogenous covariates is to first-difference and use instrumental variables. Theoretically, any variables which are orthogonal to the first-differenced error term can be instrumental variables. For example, if $E(u_{it}|x_i^{t-1}) = 0$, x_{it-2} and all subsequent ones are orthogonal to $\Delta u_{it} = (u_{it} - u_{it-1})$, like the case of y_{it-2} and its longer lags. In this case,

[34] For more detailed explanation on the panel data estimation with predetermined/endogenous variables, see Arellano and Bond (1998), Arellano and Honore (2001), and Bond (2002).

an instrument matrix takes the form

$$Z_i = \begin{bmatrix} x_{i1} & 0 & 0 & ... & 0 & ... & 0 \\ 0 & x_{i1} & x_{i2} & ... & 0 & ... & 0 \\ . & . & . & ... & . & ... & . \\ 0 & 0 & 0 & ... & x_{i1} & ... & x_{i,T-2} \end{bmatrix}$$

where each row corresponds to the first-differenced equation for period $t = 3, 4, ..., T$ for each state i, and exploits the moment conditions

$$E[Z_i' \Delta u_i] = 0 \quad \text{for} \quad i = 1, 2, ..., N$$

where $\Delta u_i = (\Delta u_{i3}, \Delta u_{i4}, ..., \Delta u_{iT})'$. This is referred to the first-differenced GMM. Also note that the level term u_{it} can be used to construct the moment conditions with Δx_{it-1} for $t = 3, 4, ..., T$ with the assumption that the first-differences Δx_{it} are uncorrelated with α_i. When the first-differenced GMM is combined with these additional level moment conditions, it is called the system GMM. Though we can estimate this system GMM estimation with *all* the possible instruments to enhance efficiency, it will not be attempted. The reasons not to use all the possible instrument variables are: (1) many instruments are dropped due to collinearity in many cases, (2) the number of instruments may be too large relative to the sample size, and (3) it often fails to converge or delivers unreasonably big or small estimates.[35]

To avoid this overfitting bias, we choose the sixth lag of the ratio of nonperforming loans to total loans (NP) as our instrumental variable, without using subsequent lags, and stack the moment conditions together with the level term conditions.[36] As a result, when the federal funds rate is used as our monetary policy measure, the number of instrumental variable is 115. Among them, 57 instruments come from $E[NP_{t-6} \Delta u_{it}]$ for $t = 7, 8, ..., T$ and

[35]Even in the basic specification, the number of instruments used are more than 100. Arellano and Bond (1998) warns that, in models with endogenous regressors, using too many instruments could result in seriously biased estimates.

[36]To check the sensitivity of lags and IVs chosen, five or higher lags of NP_t, the ratio of liquid assets to total assets (B_t) and our dependent variable (F_t) are used and the results do not vary considerably.

the rest of them comes from $E[\Delta NP_{t-5}u_{it}]$ for $t = 7, 8, ..., T$, where T is equal to 63 in our sample.

Table 6 shows the result of GMM estimation with IVs of regression equation (13) when the sixth lags of NP_t variable is used as instrumental variables. Three measures of monetary policy are used for Model 1 and Model 2. Robust standard errors are also provided, which are consistent in the presence of any pattern of heteroskedasticity and autocorrelation within panels. Hansen's J-statistics for overidentifying restrictions show that additional moment conditions are valid. All the estimates of $\sum \beta_j$ in Panel A display the expected signs and all the estimates are statistically significant. In Panel B, where 6-month paper-bill spread is used, all the specifications display the expected signs, $\sum \widehat{\beta}_j < 0$, which are statistically significant. In case of employment in Panel B, we fail to obtain the expected sign. This might be due to a sluggish response of employment, compared to other output measures. The effect of our interest is more pronounced in Panel C, in which Bernanke-Mihov index is used. In Panel C, all the estimates are statistically significant with expected signs. It seems that overall results uphold our predictions.

Consistency of GMM estimator depends on the validity of our instruments. In addition to Hansen's J-statistics, which tests the overall validity of the model, we also look at the serial correlation of first-differenced error terms. In theory, the first-order autocorrelation is expected for $(u_{it} - u_{it-1})$ because $(u_{it} - u_{it-1})$ and $(u_{it-1} - u_{it-2})$ share the term u_{it-1}. In this regard, higher-order autocorrelation in the first-differenced error terms indicates serial correlation in the error term u_{it} itself, which will make some of our instruments invalid. Following this, we test if the differenced error term follows $AR(1)$, but not $AR(2)$. In all the specifications, Arellano-Bond test for autocorrelation confirms our null hypothesis. P-values of these tests are provided in the last two lines of each panel.

Comparing the estimates of $\sum \alpha_j$ and $\sum \beta_j$ from fixed effect estimation and GMM-IV gives a clue on the direction of bias, resulting from endogeneity. Our result shows that $\sum \widehat{\alpha}^{GMM} > \sum \widehat{\alpha}^{FE} > 0$ and $\sum \widehat{\beta}^{GMM} < \sum \widehat{\beta}^{FE} < 0$ in every specification we estimated. One thing we can make an inference from this is that $Cov(MP_{t-j}, u_{it}) < 0$ for $j > 0$ in (13) because this negative covariance will make positive coefficients smaller and negative coefficients larger. Also, as Hausman rejects the null hypothesis that there is no endogeneity, there seems to be a certain level of endogeneity, which makes GMM-IV our preferable choice.

However, this method is not a cure-all for the problem of OLS and fixed effect estimation. One caveat on this estimation method is that it is based on large N and small T situation. Empathetically, our data does not fully fit into this situation. Another problem is the possibility of weak instruments. It is known that large finite sample bias can occur when instrumental variables are weak and this problem carries over into GMM estimation. Unfortunately, most suggestions on detecting weak instruments and robust testing with weak instruments are based on two-stage IV and/or two-stage nonlinear GMM, rather than on the first-differenced GMM context. Bond, Hoeffler, and Temple (2001) is one exception in that they discuss weak instruments problem in the first-differenced GMM with an example of Solow growth model regression. In that paper, their preferred solution is to use the system GMM rather than the first-differenced GMM.[37] In the previous analysis, we used the system GMM and confirmed the validity of moment conditions using the overidentifying restriction test. In this regard, though there is a limitation to use this method in our panel data model and fully trust the result, one thing at least we can say is that the signs and statistical significance of most estimates came up as we expected regardless of specifications and estimation techniques, which adds more validity to our empirical analysis.

Alternative Explanations Our model implication comes from bank level and empirical test is performed at state level. Thus, it is conceivable to check the possibility that our result may be driven by other balance sheet variables, which are likely to comove with loan commitments. Like loan commitments, some other balance sheet variables such as security holdings and bank capital can provide the similar story by playing a role of buffer stock to external shocks, preventing the sudden contraction of bank loans.

As Stein (1998) explains, banks with a low buffer stock of liquid assets should cut back

[37] Another solution proposed in the paper is to strengthen the instrument set used for the equations in first differences by using other variables that are not included in the model, which is not an easy task in most cases.

their lending more in response to a monetary tightening. The reason is that banks with a large amount of liquid securities have an option of selling securities to maintain lendings, rather than incurring the cost of issuing CDs.

Van den Heuvel (2002) discusses the possibility of bank capital channel as monetary policy transmission mechanism. According to his explanation, holding more bank equity can save the cost of issuing equity when its capital level is approaching to regulatory minimum and can be a buffer stock to short-term deterioration of profitability.

Also, the ratio of non-performing loans can be a candidate. If a bank maintains its ratio of non-performing loans to total loans at low level, it can be interpreted that the bank is sound in terms of credit risk management or loan quality. Since credit risk tends to be higher during a recession, a bank with low ratio of non-performing loans possibly faces low credit risk and better protect its loan portfolio.

In addition, the ratio of total loans to assets and the ratio of C&I loans to assets are also tested because their correlation coefficients with our commitment variable are higher compared to those of other balance sheet variables, as shown in Table 7. If our commitment variable is merely a proxy of financial development or active banking activities, these loan ratio variables may explain our finding.

Considering these possibilities, I reestimate the same regression equation of (13) with replacing loan commitment variable with these variables in turn. It is equivalent to check if these variables can explain the empirical pattern found in Table 4 and Table 6. Table 8 shows the results from this experiment. While loan commitment variable is statistically significant with the expected negative sign regardless of estimation methods and output measures, other variables fail to explain the empirical pattern.[38] For example, bank capital ratio, the ratio of security to assets, and the ratio of C&I loans to assets could not produce the expected results in any specifications. While the ratio of nonperforming loans and the ratio of total loans to assets show statistically significant negative signs, these results are not robust to

[38] The regression results using 6 month paper-bill spread and Bernanke-Mihov index as monetary policy measures are not much different from the case of federal funds rate discussed here. They are available on request.

the choices of estimation methods and output measures. It again supports the role of loan commitments in our empirical findings.

Hirtle (1990) suggests that loan commitment is a proxy for the share of corporate borrowers who are not bank-dependent, rather than being the actual sources for funds in bad times. Following her explanation, C&I loans may not respond much to the amount of C&I loan commitments outstanding in bad times, because firms would seek external funds through issuing commercial papers. In this process, loan commitment is just a signal for firms' financial soundness, which enables them to get funds from *non-bank* sources. If this line of reasoning is true, our finding becomes a spurious one. However, our second regression shows that the increasing ratio of C&I loans to total loans in bad times is well explained by the amount of loan commitments outstanding. This is an evidence that loan commitment is an actual source of funds, which becomes more operative during tight periods. More directly, Gatev, Schuermann, and Strahan (2005) show that the observed C&I loan growth during 1998 crisis was concentrated at banks with high levels of undrawn loan commitments prior to the onset of the crisis. If loan commitment is merely a proxy for firms' ability of direct financing, these findings cannot be explained. Thus, though loan commitments can be a proxy for financial market development as Hirtle (1990) suggests, loan commitments have been actual sources of funds to firms in bad times.

Outlier States The reported results are obtained after dropping the states of Delaware and South Dakota.[39] Looking at Table 7, which shows the correlation coefficients of bank balance sheet variables with COM, the influence from Delaware and South Dakota seems strong enough to change the sign of C&I loans/Asset, which is positive at bank level and negative at state level. Hence, it is necessary to check if any particular state may drive our results. The states of our interest are banking-specific states (Delaware, New York), small states (Alaska, Wyoming), oil states (Louisiana, Montana, North Dakota, Oklahoma, Texas,

[39] If we estimate with 50 states after including Delaware and South Dakota, the regression results are still significant with expected signs. However, the effects of our interest are a little bit stronger without these two states.

Wyoming). As a robustness check, I reestimate the model with many kinds of combinations. And, it is found that any particular states does not drive our results.

In our context that loan commitments are likely to bolster economic activity in bad times, it seems that gross state product is a better measure of economic activities compared to state personal income because loan commitments are more relevant to production activity rather than to income or consumption measure. However, gross state product statistics are available only on yearly basis, which is inadequately low frequency for analyzing the effect associated with changes in monetary policy stances. As an alternative route, I calculate the percentage deviations of gross state product from state personal income by each year-state and identify which states are different in terms of this measure. The states of Alaska, Wyoming, Delaware and Louisiana are identified as being distinctively different from other states in terms of discrepancy between gross product and personal income. Hence, I reestimate the regressions with excluding these states in order to minimize the possible bias from incongruency between the two measures. The results are not much different from the ones reported here.

5 Discussion

5.1 Downward Trend in Output Volatility

According to Taylor (2000), cyclical volatility from the early 1980s to the present in the United States has been much lower than during any period of similar length in history. He summarizes possible explanations for the decline in output volatility. To name a few, they include more service-oriented economy, better inventory control, fewer or smaller exogenous shocks, fiscal policy as automatic stabilizers and better managed monetary policy. Any good candidate should satisfy two things, at least. One is its timing. Since we observed the decline in the early 1980s, any potential variable or related trend should display larger changes around the early 1980s. The other is the pervasiveness in volatility reduction, as Kim, Piger, and Nelson (forthcoming) finds the volatility reduction in aggregate GDP is not confined to any one sector or not driven by any intermediate process such production or inventory.

Morgan, Rime, and Strahan (2004) try to explain the increased stability of U.S. economy in the changing environment of commercial banking industry. They find interstate banking appears to have helped stabilize growth fluctuations within states, and to reduce divergence between states. That is, state business cycles have become smaller, but more alike. Their logic is that the increased mobility of capital through bank integration tends to dampen the adverse effect of bank capital/loan supply shocks on state lending and spending. According to them, better finance fits best with the inventory management hypothesis. Firms began smoothing production better in the post-1984 period by building up inventories during periods of low sales growth, and vice versa during periods of high sales growth (Kahn, McConnell, and Perez-Quiros (2002)). These counter-cyclical movements in inventories are only possible if banks are able to provide counter-cyclical credit (Morris and Sellon (1995)). Their conjecture is that interstate banking may contribute in that direction. Our story of how loan commitments work fits well in this argument. By using loan commitments as a safe and stable source of funds when they are in need, firms can smooth their production. This mechanism is reflected in our empirical finding: loan commitments play a role of moderating economic fluctuations during periods of contractionary monetary policy.

Figure 3 indicates that BHC-affiliated banks tend to use more loan commitments. Since loan commitments require a bank to hold some level of liquidity inside to meet unexpected take-down by firms, an BHC-affiliated bank, which can be assisted by their member banks through internal capital markets, has an advantage in using loan commitments over a stand-alone bank. In this regard, an empirical finding by Morgan, Rime, and Strahan (2004) is closely related with our findings. Indeed, combining our findings from Prediction 1 and Prediction 3 gives us a nice interpretation: Interstate banking deregulation allowed more BHC-member banks to operate in the business and the increased use of loan commitments *via* this bank integration may help explain the decline in aggregate U.S. economic volatility.

Broadly interpreting monetary shocks as one kind of external shocks to the economy, the empirical finding in this paper can be interpreted that loan commitments plays a role of dampening such external shocks, contributing to increased stability of U.S. economy.

However, our study has a limitation because the exact mechanism is not identified here. For example, this study does not delve into whether loan commitments contribute more to firms' inventory control or production activity. Also, if the effect of loan commitments is confined only to helping inventory managements, the role of loan commitment becomes weaker because the reduction in volatility is observed not only in inventory, but also in final sales and production, as Kim, Piger, and Nelson (forthcoming) report that the increased stability is observed everywhere. In this regard, more information on how corporate borrowers use loan commitments is necessary to make a clear picture of its mechanism.

5.2 Lending Channel of Monetary Policy

Another issue is on the magnitude of bank lending channel of monetary policy. Driscoll (2004) and Ashcraft (forthcoming) ascertain that bank loan supply is affected by monetary shocks. However, they cast doubt upon its magnitude. Driscoll (2004) estimates the structural equations and concludes that shocks to money demand have large and statistically significant effect on the supply of bank loans, but loans have small and statistically insignificant effect on output. Also, Ashcraft (forthcoming) uses a structural VAR in which he allows the lending channel to be operative and finds that the magnitude of bank lending channel is inconsequential. However, if one tries to match the observed loan changes with the output changes without careful treatment of loan commitments, it is likely to produce inaccurate or even spurious results. It is possible that the observed loan growth change in response to monetary shocks may be smaller due to increased take-down from loan commitments. And even the sign of loan growth response may be inverted when the amount of take-down dominates the contraction of non-commitment loan supply. Hence, more attention should be paid to the behavior of loan commitment and its take-down behavior in studying bank lending channel of monetary policy.

More specifically, counter-cyclical property of *used* loan commitment may be one reason for weak link in loan growth and output measures. Given this, empirical tests which directly relate the changes in loan growth to output measures may find smaller effects on the magnitudes of lending channel since actual impact of monetary shock to banks' loan making activity is not well captured in the data due to existence of commitments and it may wrongly put more weights on other channels of transmission mechanism, underestimating the actual effect from the lending channel.

Morris and Sellon (1995) observe the strength in business lending after the decline in industrial production and make a conjecture that it may be caused by an increased demand for loans to finance an unanticipated rise in unsold inventories. In their view, banks appear to be providing additional liquidity rather than restricting liquidity. This line of reasoning is completely consistent with the patterns of loan commitments observed here. Hence, empirical studies on the lending channel need to address an issue of increased loan take-down during contractionary periods.

5.3 Issues on Risk Exposure and Future of Banks

Another issue is on the risk exposure of banks, stemming from loan commitments. It is well-known that the Basel II Accord strengthens the procyclical property of bank loans, while loans from commitment arrangements are countercyclical as we observe in this paper.[40] In case loans under commitment increase more than the expected level, it would push a bank's capital level closer to its regulatory minimum.[41] In addition, a break in credit conversion factor applied to loan commitments would make things worse due to different credit conversion factors to loan commitments in off-balance sheet and loan take-down to be captured in on-balance sheet.

Though our model abstracts out the distinction between bank capital and external debt financing, we can expect the same implications in the context of bank capital. (15) shows regulatory capital constraint a bank face:

$$k_R \equiv \frac{K}{zC + N + \phi(1-z)C} \geq \gamma \tag{15}$$

where k_R is a bank's risk-based capital ratio, K is bank equity, ϕ is credit conversion factor

[40] See Kashyap and Stein (2004) for cyclical implications of the Basel II Accord.

[41] Using a dynamic model, Van den Heuvel (2002) shows that monetary policy can affect bank lending through bank equity captial.

and γ is a minimum capital ratio.[42]

The Basle Accord states that "commitments with an original maturity of up to one year, or which can be unconditionally cancelled at any time" are eligible for the zero percent credit conversion factor. Otherwise they will be subject to 50 percent credit conversion factor. Here I assume that all the loan commitments are not to be cancelled unconditionally, thus they are subject to 50 percent credit conversion factor. And, when it is taken down, it is regarded as ordinary loans and 100 percent of credit conversion factor is applied. If take-down from loan commitments (zC) increases, it will push a bank's capital level closer to its regulatory minimum. To deal with this situation, a bank has options: (1) to sell its liquid assets, (2) to cut down term loans (N) and (3) to issue new bank equity (K). Again, depending on the relative costs of these options, the amount of term loans to be recalled will be determined.

To understand basic ideas, let us see how a typical bank can deal with deposit outflow and loan take-down, which occurs when there is a negative monetary shock.[43] In the example that follows, we assume that the bank has no reserve requirement and no ability to raise insured/uninsured deposits for the ease of discussion. The bank's balance sheet at the beginning of period t is given below:

Assets	**Liabilities**
Securities = \$30	Deposit = \$95
Loans = \$70	Bank Capital = \$5

[42] It is natural to ask which level of credit conversion factor would be optimal. Boot and Thakor (1991) suggest that capital requirements on loan commitments are counterproductive if their purpose is to reduce risk taking by banks. But zero credit conversion factor on loan commiments may lead myopic banks to issue more loan commitments recklessly in the present, considering not much about liquidity problem it might face in the future. And too high credit conversion factor for loan commitments will deter banks from issuing loan commitments, preventing borrowers from using their reliable source of funds. Another problem is that determining the optimal credit conversion factor in terms of minimizing the credit risk is incomplete. Following Kashyap and Stein (2004), any well-intentioned social planner should care not only minimizing the default cost but also making net present value loans to the economy. For this reason, setting up the objective function of optimal credit conversion factor for loan commitments is not an easy task.

[43] The format of this illustration is heavily borrowed from Mishkin (1997).

Assuming the bank has $60 of unused loan commitments in its off-balance sheet, its risk-based capital ratio (k_R) following equation (15) is $\frac{5}{70+0.5*60} = 5\%$ while its leverage ratio (k_L), the share of capital to assets, is $\frac{5}{30+70} = 5\%$. In this situation, suppose that a Fed-induced policy is expected to cause a shortfall in insured deposit and a rising demand from loan commitment. If a deposit outflow of $5 and loan take-down of $10 occurs, bank's asset amounts to $110 while its liability is $90. Facing increased liquidity demand from both sides of balance sheet, the bank has a problem: It will fall short of bank capital. To eliminate this discrepancy, the bank has three options. One is to sell some of its securities to help cover those outflows. It might sell $15 of its securities, making its risk-based capital ratio lower and leverage ratio higher. Instead, the bank will incur some brokerage and other transaction costs when it sells these securities. The resulting balance sheet would look like:

Assets	**Liabilities**
Securities = $15	Deposit = $90
Loans = $80	Bank Capital = $5

A second alternative is to cut down its term loans by $15, over which the bank has more discretion to control at the current period, compared to loan commitments. That is, the bank can reduce its total amount of loans outstanding by calling in term loans. While it has increased the risk based capital ratio and leverage ratio, reputation effect may bring a very costly consequence for the bank. In this case, the balance sheet would be:

Assets	**Liabilities**
Securities = $30	Deposit = $90
Loans = $65	Bank Capital = $5

A third way that the bank can meet those increased liquidity demands is to acquire new bank capital by issuing new equity. Though equipping the bank with more capital enhances its capital adequacy, it is well-known that raising new capital is very costly.

Considering these options, the real world solution would be to combine all these options. That is, the bank will try to throw out the part of its assets by selling securities, cutting down term loans and going after new capital at the same time. Which option would prevail more will depend on the relative benefits and costs of these options.

One thing obvious is that just holding sufficient buffer stock of liquidity will not solve the capital adequacy problem in the presence of loan commitments and risk-based bank capital regulation, which would have some policy implications for regulators as well. This is because loan take-down tends to increase in bad times and credit conversion factor jumps from 0.5 to 1 when loan commitments are taken down, which imposes additional pressure on its risk-based capital for each dollar of loan commitments taken down. From the example above, just selling securities makes the risk-based capital ratio lower, $\frac{5}{80+0.5*50} = 4.76\%$. This suggests that, though regulators monitor off-balance sheet activity of banks including commitment loan, more information on the patterns of loan commitment take-down along with business cycles is needed for sound monitoring of bank capital requirement. Also, regulators should pay more attention to credit conversion factors related to loan commitments.

Additionally, when a bank issues loan commitments, it accepts the interest and credit risk of the customer. The Basel committee also states "the rapid growth of commitments represents a significant additional risk to banks' funding strategies. ... It is therefore possible that a bank might be faced with large and perhaps unexpected calls under commitments at a time when markets are unreceptive to its needs for additional funds. To the extent that the growth in commitments represents a structural shift in borrowing patters, such that banks move away from direct lending and increasingly towards a "back-stop" function, it may prove difficult to raise large sums at short notice to meet these commitments."[44]

The use of loan commitments mostly by commercial banks has some implication on the future of banks as well. Ergungor (2001) explains why loan commitments are sold by banks alone. The reasons are: (1) it is more costly for an organization not to honor its contractual commitments than it is for an individual (2) only banks have access to the discount window[45] (3) liquidity a bank keeps inside to fund unexpected demand deposit withdrawals can also

[44] "The Management of Banks' Off-Balance-Sheet Exposures," BIS report, March 1986.

[45] Their ability to meet unexpectedly high loan take-down with relatively low-cost funds from the discount facility makes their expected cost of funding commitments lower than that of non-bank competitors (Kanatas 1987).

be used to fund unexpected loan commitment take-down, as shown in Kashyap, Rajan, and Stein (2002). Their argument is that, since both take-down of loan commitments (from asset side) and withdrawal of deposit (from liability side) require a bank to hold a certain amount of liquid assets, both activities can share the cost of the liquid-asset stockpile unless they are perfectly correlated. Due to this synergy effect, banks have comparative advantages in issuing loan commitments.

Recently, some, particularly advocates of "narrow banking," suggest that the main functions of banks (deposit-taking and lending) can be replicated by other financial institutions and there is no more specialness in the role of commercial banks. It appears that these kinds of arguments are made possible by ignoring the exclusive functions being performed by banks. Though the role of commercial banks seems to be in decline, the comparative advantage of banks in providing liquidity will survive due to exclusive functions only banks can perform or functions over which banks have comparative advantages. Though providing liquidity in the form of line of credit is not an exclusive activity performed by commercial banks, loan commitments can be an example of such functions in which banks' functional forms have competitive edge over other financial institutions such as finance/leasing company, insurance company and mortgage banks. Since this comparative advantage comes from the endemic characteristics commercial banks have, it will prevail to the extent the synergy from banks' organizational characteristics are not easily imitated by other financial institutions.[46] In this regard, the future of commercial banking is not doomed as much as the "narrow banking" proponents predict.

[46] Let alone the argument by Kashyap, Rajan, and Stein (2002), the famous Diamond-Dybvig model shows that banks perform a "liquidity transformation" role, in which a synergy between deposit taking and loan making arises out of a desire of agent's to hold liquid (or short-term) asset and the economy's desire to hold illiquid (or long-term) assets.

6 Concluding Remarks

This paper develops a variant of the famous "newsboy problem" in operation research literature. Like a newsboy who needs to order the optimal number of newspapers from his/her supplier in the face of uncertain demand, the amount of liquidity held by a bank is treated as inventory for uncertain liquidity demand. Thus, in the context of optimal inventory management, a bank who seeks to maximize its expected net income should consider the optimal amount of liquidity to be held in preparation for stochastic loan take-down while issuing term loans and loan commitments for profitable investments.

The model's implications are: (1) larger banks and BHC-affiliated banks issue more loan commitments because they have cheaper sources of external financing or internal capital markets, (2) while handling increased take-down from loan commitments, a bank facing more severe adverse selection problem in capital markets tends to cut down more of its term loans, disproportionately affecting the borrowers of loan commitments and term loans, and (3) economic activity with more loan commitments suffers less from external shocks, displaying less economic fluctuations in bad times.

Given the increased use of loan commitments in banking sector and its significance to the macroeconomy, more detailed collection of bank balance sheet information such as *used* amount of loan commitments by industry is necessary to better understand how credit affects the economy.

Appendix

A. Variable Definitions

All bank balance sheet variables are available at the Federal Reserve Bank of Chicago website (http://www.chicagofed.org). Whenever available, I follow the definitions in Kashyap and Stein (2000), Campello (2002) and Ashcraft (forthcoming).

Assets. Total assets are taken from RCFD2170

Total loans. The item RCFD2125 (total loans, net of unearned income) is used for total loans.

Balance. This variable is defined as the ratio of security to total assets. The amount of security a bank holds is defined as RCFD0390 (securities, book value) plus RCFD1350 (federal funds sold) up until 1993:IV. After that, it is the sum of RCFD1754 (held-to-maturity securities, total), RCFD1773 (available-for-sale securities, total), and RCFD1350.

Non-performing loans. Following the definition used in Campello (2002), it equals the ratio of RCFD1407 (loans over 90 days late), plus RCFD1403 (loans not accruing), to total loans.

Commitments. For total unused commitments, the item RCFD3423 is used, which is available for 1983:II-1999:IV. This measure is equal to the sum of RCFD3814 (revolving, open-end lines secured by 1-4 residential properties, e.g. home equity lines), RCFD3815 (credit card lines), RCFD3816 (commitment to fund loans secured by real estate), RCFD3817 (securities underwriting), RCFD3818 (other unused commitments), and RCFD6650 (commitment to fund loans not secured by real estate) from 1991:I.

Industry labor income shares. The data is obtained from the Bureau of Economic Analysis website (http://www.bea.doc.gov). I use the nine industry codes: 100 = agricultural services, forestry, fishing and other, 200 = mining, 300 = construction, 400 = manufacturing, 500 = transportation and public utilities, 610 = wholesale trade, 620 = retail trade, 700 = finance, insurance, and real estate, 800 = services, 900 = government and government enterprises. For trade industry, it is the sum of whole sale and retail trade. To get labor income shares, all industry incomes are divided by non-farm earnings (code = 82).

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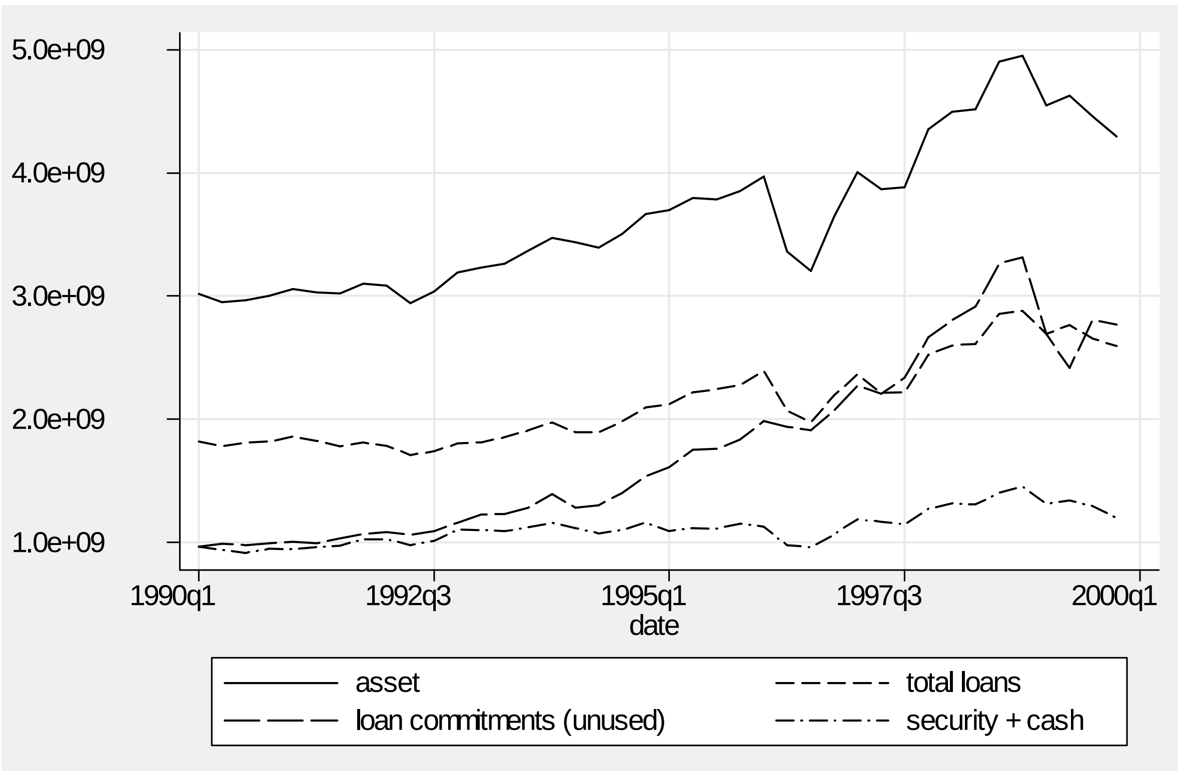

Figure 1: Increased Use of Loan Commitment. Source: author's calculation based on Call Reports.

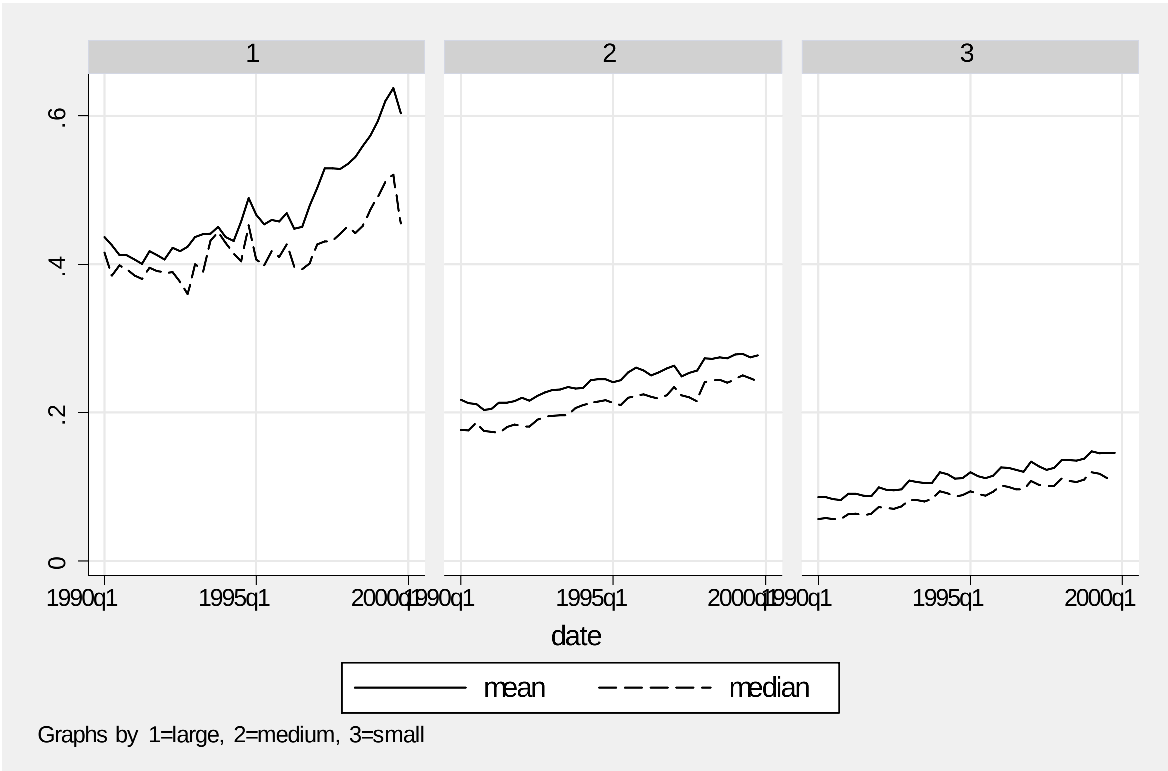

Figure 2: Mean and Median of COM, by Size. The variable COM is defined as "(total unused commitment - credit card lines - securities underwriting)/total loans," as a proxy for intensity of loan commitment in banks' loan making activity. Top 1 percent in terms of average assets during the sample period are categorized into 'large banks.' Banks between below 1 percent and top 5 percent are named as 'medium banks' and below 5 percent are defined as 'small banks.' Source: author's calculation based on Call Reports.

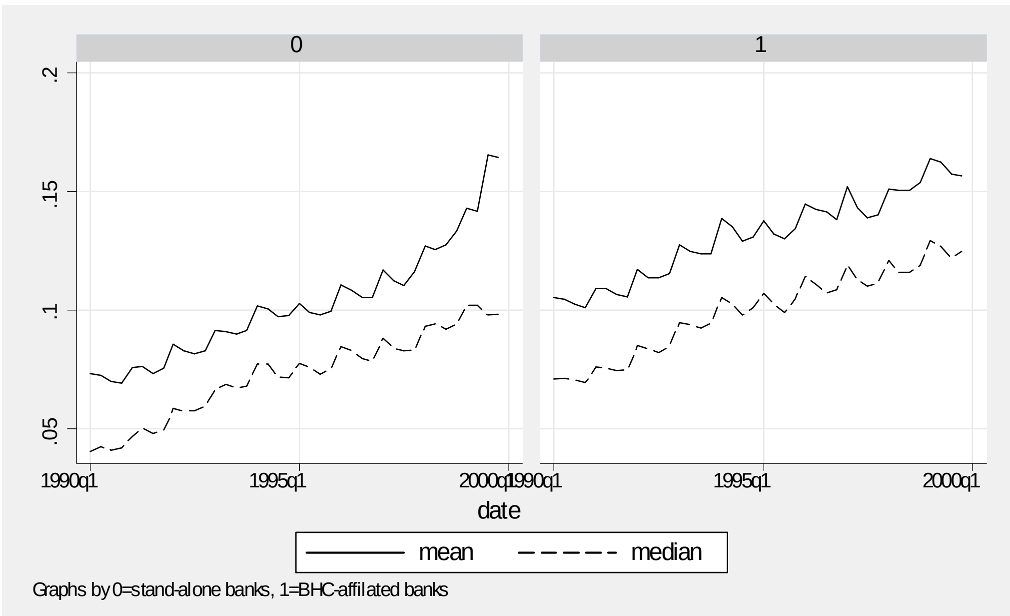

Figure 3: Mean and Median of COM, by BHC (Bank Holding Company)-affiliation. The variable COM is defined as "(total unused commitment - credit card lines - securities underwriting)/total loans," as a proxy for intensity of loan commitment in banks' loan making activity. Source: author's calculation based on Call Reports.

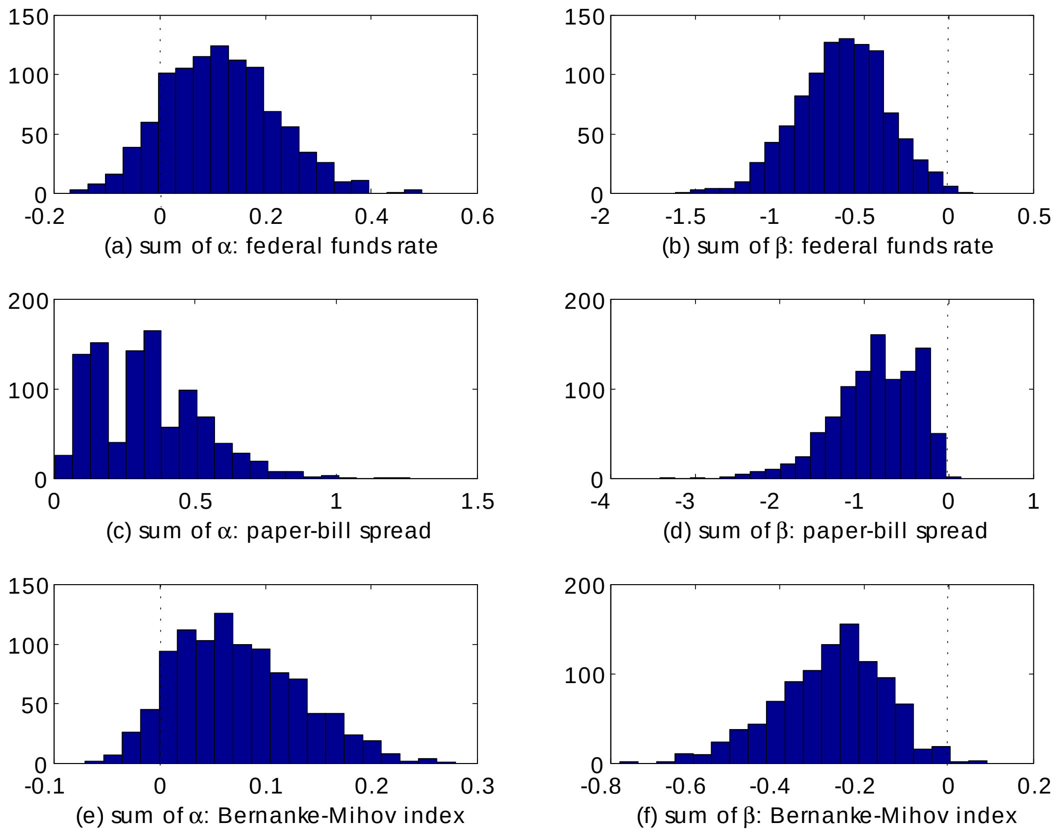

Figure 4: Histograms of $\sum \widehat{\alpha}$ and $\sum \widehat{\beta}$ in regression equation (13) from 1,000 replications of non-parametric bootstrap method.

Table 1 - Descriptive Statistics

All the variables are defined as the ratio to bank total assets, except the number of banks (1), nonperforming loans (7), and commitment/loan (12). Nonperforming loans are defined as the ratio of loans over 90 days late, plus loans not accruing, to total loans. Commitment/loan is defined as the ratio of total unused commitment to total loans. The numbers are median values in each size/BHC (Bank Holding Company)-affiliation categories. Some exclusion criteria, discussed in the text, are applied to remove outliers in the sample. Source: author's calculation based on Call Reports.

year	1985Q1					1999Q4				
size/membership of BHC	large	medium/ BHC	medium/ stand-alone	small/ BHC	small/ stand-alone	large	medium/ BHC	medium/ stand-alone	small/ BHC	small/ stand-alone
1. number of banks	133	500	65	8,453	5,233	71	233	17	6,162	1,623
2. cash	0.136	0.091	0.070	0.063	0.064	0.054	0.038	0.022	0.045	0.050
3. security + cash	0.299	0.348	.0393	0.396	0.448	0.259	0.296	0.351	0.330	0.385
4. total loans	0.627	0.610	0.557	0.556	0.508	0.654	0.656	0.601	0.626	0.575
5. C&I loans	0.229	0.186	0.164	0.130	0.093	0.182	0.118	0.103	0.090	0.079
6. loans to individuals	0.115	0.131	0.133	0.107	0.113	0.077	0.071	0.020	0.067	0.063
7. nonperforming loans	0.022	0.015	0.016	0.021	0.020	0.008	0.006	0.006	0.005	0.005
8. total deposits	0.758	0.854	0.879	0.896	0.888	0.675	0.763	0.794	0.863	0.864
9. transaction deposits	0.214	0.235	0.225	0.219	0.212	0.118	0.129	0.039	0.236	0.237
10. demand deposits	0.164	0.171	0.161	0.131	0.127	0.096	0.097	0.025	0.116	0.125
11. equity	0.057	0.065	0.070	0.079	0.091	0.079	0.076	0.094	0.088	0.108
12. commitment/loan	0.371	0.112	0.059	0.000	0.000	0.509	0.279	0.265	0.130	0.105

Table 2 – Use of Loan Commitments Increases *After* Interstate Banking Deregulation

This table reports the estimates from equation (9) using fixed effect panel regression with IVs and pooled OLS with IVs. Equation (10) is estimated for the first stage. The total number of bank-year observation is 528 with the sample period of 1984-1994. Total numbers of bank-year observations with $D_3 = 1$ and $D_5 = 1$ are 223 and 140 respectively. Robust standard errors are clustered by states. P-values are in parentheses. * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent.

	Dependent Variable: Ratio of Total Unused Loan Commitments to Total Loans					
	Fixed Effect Panel Regression with IV		Pooled OLS with IV		Pooled OLS with IV, Robust Standard Errors	
Three Years after Deregulation ($\alpha_D D_3$)	0.0377** (0.012)	-	0.0404** (0.025)	-	0.0404 (0.153)	-
Five Years after Deregulation ($\alpha_D D_5$)	-	0.0527*** (0.000)	-	0.0414** (0.014)	-	0.0414 (0.120)
Interstate Asset Ratio ($\beta ISAR$)	0.1605* (0.077)	0.2164** (0.015)	0.2148*** (0.001)	0.2440*** (0.000)	0.2148** (0.015)	0.2440*** (0.003)
(within) R^2	0.3916	0.3821	0.4399	0.4351	0.4399	0.4351

Table 3 – Increased Loan Take-Down Crowds Out Term Loans in Bad Times

This table reports the results from fixed effect estimation of equation (11) using the sample of commercial banks, whose average assets are below the 95th percentile of asset size distribution. All regressions include dummy variables for time, region, and quarterly effect. The sample period is 1990:I-1999:IV for federal funds rate and 1990:I-1997:II for 6-month paper-bill spread. Well-capitalized banks refer to banks whose ratio of capital to assets is in the range of 0.06 and 0.15. P-values are in parentheses. * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent.

Panel A: **with Bank-Quarter Observations of Zero Loan Commitments**

Dependent Variable: Ratio of C&I Loans to Total Loans		Monetary Policy Measures	
		Federal Funds Rate	6-Month Paper-Bill Spread
1. Small Banks			
	Monetary Policy Measure ($\sum \alpha_j MP_{t-j}$)	0.0268***	-0.0225**
		(0.0003)	(0.0193)
	Interacted with Loan Commitments ($\sum \beta_j MP_{t-j} COM_{t-1}$)	0.2318***	0.5117***
		(0.0000)	(0.0000)
	With BHC Dummy ($\sum \gamma_j MP_{t-j} COM_{t-1} BHC_i$)	-0.1297***	-0.1466***
		(0.0001)	(0.0081)
	Sample Size (N)	345,326	277,874
	R^2 (within)	0.7993	0.7645
2. Small Banks, Well-Capitalized			
	Monetary Policy Measure ($\sum \alpha_j MP_{t-j}$)	0.0285***	-0.0226**
		(0.0002)	(0.0232)
	Interacted with Loan Commitments ($\sum \beta_j MP_{t-j} COM_{t-1}$)	0.1734***	0.4655***
		(0.0002)	(0.0000)
	With BHC Dummy ($\sum \gamma_j MP_{t-j} COM_{t-1} BHC_i$)	-0.1089***	-0.1894***
		(0.0025)	(0.0017)
	Sample Size (N)	310,702	249,987
	R^2 (within)	0.7944	0.7634

Panel B: without Bank-Quarter Observations of Zero Loan Commitments

Dependent Variable: Ratio of C&I Loans to Total Loans		Monetary Policy Measures	
		Federal Funds Rate	6-Month Paper-Bill Spread
1. Small Banks			
	Monetary Policy Measure ($\sum \alpha_j MP_{t-j}$)	0.0299***	-0.0195*
		(0.0001)	(0.0693)
	Interacted with Loan Commitments ($\sum \beta_j MP_{t-j} COM_{t-1}$)	0.2257***	0.5456***
		(0.0000)	(0.0000)
	With BHC Dummy ($\sum \gamma_j MP_{t-j} COM_{t-1} BHC_i$)	-0.1432***	-0.1605***
		(0.0000)	(0.0065)
	Sample Size (N)	298,836	235,342
	R^2 (within)	0.7940	0.7592
2. Small Banks, Well-Capitalized			
	Monetary Policy Measure ($\sum \alpha_j MP_{t-j}$)	0.0777***	-0.0205*
		(0.0000)	(0.0640)
	Interacted with Loan Commitments ($\sum \beta_j MP_{t-j} COM_{t-1}$)	0.1502***	0.4945***
		(0.0030)	(0.0000)
	With BHC Dummy ($\sum \gamma_j MP_{t-j} COM_{t-1} BHC_i$)	-0.1105***	-0.1899***
		(0.0039)	(0.0031)
	Sample Size (N)	271,325	213,643
	R^2 (within)	0.7944	0.7575

Table 4 – Loan Commitments Help Stabilize the Economy in Bad Times

This table reports the results from estimating equation (13) using OLS and fixed effect panel regression. Three kinds of state-level output measures are used for measuring economic fluctuations: real personal income, real personal income per capita, and employment. Model 1 and 2 in Panel A are estimated over 2,784 observations: 48 states (South Dakota and Delaware excluded) x 1984:II-1999:IV. The sample sizes in Panel B and C are 2,352 and 2,208 respectively. Model 2 includes bank balance sheet variables. In case of OLS, robust standard errors are provided and they are clustered by states. All regressions include quarterly and Fed regional effects. * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent.

Panel A: Monetary Policy Measure – Federal Funds Rates

	Dependent Variables: Fluctuations of Each Output Measure (N=2,784)					
	Real Personal Income		Real Personal Income Per Capita		Employment	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
1. OLS						
Monetary Policy Measure ($\sum \alpha_j MP_{t-j}$)	0.1941**	0.1044	0.1980**	0.1147	0.6848**	0.4936
	(0.0243)	(0.1436)	(0.0272)	(0.1387)	(0.0335)	(0.0951)
Interacted with Loan Commitments ($\sum \beta_j MP_{t-j} COM_{t-1}$)	-0.7439***	-0.6661***	-0.7404***	-0.6542**	-0.3433	-1.4922
	(0.0059)	(0.0098)	(0.0063)	(0.0137)	(0.7813)	(0.1494)
R^2	0.1418	0.1514	0.1351	0.1436	0.2303	0.2672
2. Fixed Effects						
Monetary Policy Measure ($\sum \alpha_j MP_{t-j}$)	0.1096	0.0897	0.1355*	0.1174	0.6080*	0.6418*
	(0.1322)	(0.2245)	(0.0596)	(0.1078)	(0.0592)	(0.0501)
Interacted with Loan Commitments ($\sum \beta_j MP_{t-j} COM_{t-1}$)	-0.6270***	-0.6199***	-0.6447***	-0.6302***	-1.6621*	-1.5852*
	(0.0016)	(0.0019)	(0.0010)	(0.0014)	(0.0589)	(0.0727)
R^2 (within)	0.0964	0.1019	0.0886	0.0938	0.0917	0.0930

Panel B: Monetary Policy Measure – 6-Month Paper-Bill Spread

	Dependent Variables: Fluctuations of Each Output Measure (N=2,352)					
	Real Personal Income		Real Personal Income Per Capita		Employment	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
1. OLS						
Monetary Policy Measure ($\sum \alpha_j MP_{t-j}$)	0.2969**	0.2791*	0.3158**	0.2970**	-0.0383	0.1391
	(0.0494)	(0.0601)	(0.0403)	(0.0499)	(0.8764)	(0.5208)
Interacted with Loan Commitments ($\sum \beta_j MP_{t-j} COM_{t-1}$)	-0.7847*	-0.8191**	-0.8178**	-0.8375**	1.8590	-0.1807
	(0.0641)	(0.0456)	(0.0580)	(0.0455)	(0.1577)	(0.8580)
R^2	0.1402	0.1465	0.1385	0.1444	0.2122	0.2468
2. Fixed Effects						
Monetary Policy Measure ($\sum \alpha_j MP_{t-j}$)	0.2872***	0.2899***	0.3113***	0.3142***	0.0889	0.1054
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.7279)	(0.6810)
Interacted with Loan Commitments ($\sum \beta_j MP_{t-j} COM_{t-1}$)	-0.7692***	-0.7922***	-0.8014***	-0.8167***	0.3197	0.5456
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.7133)	(0.5350)
R^2 (within)	0.0923	0.0962	0.0909	0.0943	0.0704	0.0724

Panel C: Monetary Policy Measure – Bernanke-Mihov Index

	Dependent Variables: Fluctuations of Each Output Measure (N=2,208)					
	Real Personal Income		Real Personal Income Per Capita		Employment	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
1. OLS						
Monetary Policy Measure ($\sum \alpha_j MP_{t-j}$)	0.0455	0.0689	0.0520	0.0753*	0.0500	-0.0595
	(0.3463)	(0.1260)	(0.2654)	(0.0862)	(0.7005)	(0.5715)
Interacted with Loan Commitments ($\sum \beta_j MP_{t-j} COM_{t-1}$)	-0.2320**	-0.2479**	-0.2288**	-0.2476**	-0.8729*	-0.5433
	(0.0447)	(0.0286)	(0.0414)	(0.0255)	(0.0571)	(0.1481)
R^2	0.1362	0.1449	0.1323	0.1412	0.2382	0.2798
2. Fixed Effects						
Monetary Policy Measure ($\sum \alpha_j MP_{t-j}$)	0.0544	0.0652*	0.0601*	0.0710**	0.0666	0.0754
	(0.1128)	(0.0684)	(0.0755)	(0.0442)	(0.6466)	(0.6191)
Interacted with Loan Commitments ($\sum \beta_j MP_{t-j} COM_{t-1}$)	-0.2670***	-0.2678***	-0.2699***	-0.2725***	-0.7637**	-0.7933**
	(0.0024)	(0.0025)	(0.0019)	(0.0018)	(0.0403)	(0.0348)
R^2 (within)	0.0916	0.0943	0.0868	0.0900	0.1273	0.1284

Table 5 – Confidence Intervals from Bootstrapping

The table reports the 95% confidence intervals of two sums of coefficients in equation (13). These are obtained from non-parametric bootstrap method with 1,000 replications. State-level real personal income per capita is used as output measure and fixed effect panel regression is used for estimation.

Dependent Variable: Fluctuation of Real Personal Income Per Capita		95% Confidence Intervals: Sum of Coefficients	
		Monetary Policy Measure	Interacted with Loan Commitments
Monetary Policy Measure	Method of Computing Confidence Intervals	$(\sum \alpha_j MP_{t-j})$	$(\sum \beta_j MP_{t-j} COM_{t-1})$
1. Federal Funds Rate	Normal	(-0.0892, 0.3240)	(-1.1519, -0.1085)
	Percentile	(-0.0740, 0.3305)	(-1.1641, -0.1222)
	Bias-Corrected	(-0.0603, 0.3477)	(-1.1850, -0.1308)
	Bias-Corrected and Accelerated	(-0.0437, 0.3871)	(-1.2843, -0.1855)
2. 6-Month Paper-Bill Spread	Normal	(-0.0632, 0.6915)	(-1.7910, 0.1575)
	Percentile	(0.0653, 0.7563)	(-2.0288, -0.1649)
	Bias-Corrected	(0.0644, 0.7497)	(-2.0260, -0.1644)
	Bias-Corrected and Accelerated	(0.0896, 0.9890)	(-2.6276, -0.2314)
3. Bernanke-Mihov Index	Normal	(-0.0449, 0.1869)	(-0.5285, -0.0165)
	Percentile	(-0.0246, 0.1995)	(-0.5629, -0.0425)
	Bias-Corrected	(-0.0185, 0.02091)	(-0.5833, -0.0614)
	Bias-Corrected and Accelerated	(-0.0050, 0.2497)	(-0.6257, -0.0921)

Table 6 – GMM with Instrumental Variables: Loan Commitments Help Stabilize the Economy in Bad Times

The table reports the results from estimating equation (13) using system GMM with instrumental variables. The dependent variable is the measure of economic fluctuations. Robust standard errors are used, which are consistent in the presence of any pattern of heteroskedasticity and autocorrelation within panels. All regressions include quarterly and Fed regional effects. Model 2 includes bank balance sheet variables. J-statistics from Hansen's overidentifying restrictions, which are χ^2 statistics, are reported with p-values. And, p-values from testing autocorrelation in first-differenced error terms are also reported. P-values are in parentheses. * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent.

Panel A: Monetary Policy Measure – Federal Funds Rate

	Dependent Variables: Fluctuations of Each Output Measure (N=2,784)					
	Real Personal Income		Real Personal Income Per Capita		Employment	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
System GMM with IV, Robust Standard Errors						
Monetary Policy Measure ($\sum \alpha_j MP_{t-j}$)	0.5186	0.4170	0.5308	0.4259	3.7578***	3.2009***
	(0.1274)	(0.2075)	(0.1140)	(0.1755)	(0.0011)	(0.0013)
Interacted with Loan Commitments ($\sum \beta_j MP_{t-j} COM_{t-1}$)	-1.8264**	-1.7473*	-1.7178*	-1.7358*	-9.5590***	-7.5965***
	(0.0464)	(0.0696)	(0.0507)	(0.0630)	(0.0002)	(0.0025)
Hansen's J-statistics for Overidentifying Restrictions Test	29.67	24.44	31.16	27.54	39.83	34.93
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
p-value from Arellano-Bond test for AR(1) in First-Differenced Error Terms	(0.003)	(0.004)	(0.002)	(0.003)	(0.010)	(0.010)
p-value from Arellano-Bond test for AR(2) in First-Differenced Error Terms	(0.351)	(0.351)	(0.276)	(0.264)	(0.362)	(0.305)

Panel B: Monetary Policy Measure – 6-Month Paper-Bill Spread

	Dependent Variables: Fluctuations of Each Output Measure (N=2,352)					
	Real Personal Income		Real Personal Income Per Capita		Employment	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
System GMM with IV, Robust Standard Errors						
Monetary Policy Measure ($\sum \alpha_j MP_{t-j}$)	0.5479**	0.6106*	0.6177**	0.6486**	-0.2259	-1.0722
	(0.0260)	(0.00599)	(0.0167)	(0.0457)	(0.6032)	(0.6560)
Interacted with Loan Commitments ($\sum \beta_j MP_{t-j} COM_{t-1}$)	-1.7732***	-1.7226*	-1.8440***	-1.7741*	2.1095	6.3084
	(0.0046)	(0.0982)	(0.0035)	(0.0870)	(0.2228)	(0.0728)
Hansen's J-statistics for Overidentifying Restrictions Test	33.97	25.58	33.09	33.47	40.59	40.62
	(1.000)	(1.000)	(1.000)	(0.000)	(0.999)	(0.996)
p-value from Arellano-Bond test for AR(1) in First-Differenced Error Terms	(0.002)	(0.003)	(0.002)	(0.002)	(0.011)	(0.010)
p-value from Arellano-Bond test for AR(2) in First-Differenced Error Terms	(0.481)	(0.405)	(0.355)	(0.286)	(0.963)	(0.965)

Panel C: Monetary Policy Measure – Bernanke-Mihov Index

	Dependent Variables: Fluctuations of Each Output Measure (N=2,208)					
	Real Personal Income		Real Personal Income Per Capita		Employment	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
System GMM with IV, Robust Standard Errors						
Monetary Policy Measure ($\sum \alpha_j MP_{t-j}$)	0.4376*	0.4690**	0.4425*	0.4736**	1.1201**	0.7441*
	(0.0875)	(0.0467)	(0.0739)	(0.0339)	(0.0235)	(0.0577)
Interacted with Loan Commitments ($\sum \beta_j MP_{t-j} COM_{t-1}$)	-1.4243**	-1.4907**	-1.4107**	-1.4750**	-3.1778***	-2.2747**
	(0.0337)	(0.0338)	(0.0304)	(0.0281)	(0.0094)	(0.0409)
Hansen's J-statistics for Overidentifying Restrictions Test	29.35	26.95	26.57	24.08	38.89	38.69
	(1.000)	(1.000)	(1.000)	(1.000)	(0.996)	(0.989)
p-value from Arellano-Bond test for AR(1) in First-Differenced Error Terms	(0.002)	(0.002)	(0.001)	(0.001)	(0.010)	(0.009)
p-value from Arellano-Bond test for AR(2) in First-Differenced Error Terms	(0.341)	(0.312)	(0.234)	(0.207)	(0.248)	(0.276)

Table 7 – Correlation Coefficients of Loan Commitment with Other Bank Balance Sheet Variables

The numbers are correlation coefficients of COM (=total unused loan commitments/total loans) with other bank balance sheet variables. Bad loans are defined as loans over 90 days late, plus loans not accruing. N denotes the sample size of the corresponding group. The sample period is 1984:II-1999:IV. Some exclusion criteria, discussed in the text, are applied to remove outliers in the sample. Source: author's calculation based on Call Reports.

		Bank Equity/Assets	Security/Assets	Bad Loans/Total Loans	Total Loans/Assets	C&I Loans/Assets
1. Bank-Level						
	Total (N=684,603)	-0.043	-0.139	-0.093	0.142	0.133
	Large Banks (N=6,889)	0.180	-0.132	-0.033	-0.040	0.163
	Small, BHC-Affiliated (N=455,763)	0.016	-0.067	-0.121	0.095	0.068
	Small, Stand-Alone (N=194,652)	0.015	-0.159	-0.097	0.179	0.164
2. State-Level						
	50 States (N=3,150)	0.137	-0.349	-0.143	0.266	-0.004
	Without DE and SD (N=3,024)	0.008	-0.362	-0.176	0.246	0.135

Table 8 – Other Bank Balance Sheet Variables Fail to Confirm Prediction 3

This table displays the results from estimating equation (13) with other balance bank sheet variables in order to see if the empirical pattern found in Table 4 and Table 6 can be explained by alternative variables. COM is defined as the ratio of total unused loan commitments to total loans and bad loans are defined as loans over 90 days late, plus loans not accruing. Based on our hypothesis, the sign is expected to be negative. Federal funds rate is used as monetary policy measure and three output measures are used. FE refers to fixed effects panel regression while GMM-IV is system GMM estimation with instrumental variables. P-values are in parentheses. † denotes the coefficients which come up with the expected negative sign as well as the statistical significance at 10% level.

		Candidate Variables					
		COM	Bank Equity/Assets	Security/Assets	Bad Loans/Total Loans	Total Loans/Assets	C&I Loans/Assets
1. Real Personal Income							
	FE	-0.6199†	3.6064	0.4509	-4.2199†	0.3172	-0.0546
		(0.0019)	(0.2191)	(0.2610)	(0.0958)	(0.3040)	(0.8933)
	GMM-IV	-1.7473†	-9.4017	-1.7115	12.7507	3.3294	5.5734
		(0.0696)	(0.2259)	(0.4893)	(0.1810)	(0.1460)	(0.0220)
2. Real Personal Income Per Capita							
	FE	-0.6302†	3.6856	0.5299	-3.6852	0.2756	-0.0543
		(0.0014)	(0.2036)	(0.1814)	(0.1407)	(0.3664)	(0.8927)
	GMM-IV	-1.7358†	-7.4945	-1.0997	9.6907	3.2249	5.5263
		(0.0630)	(0.3217)	(0.6590)	(0.3115)	(0.1665)	(0.0208)
3. Employment							
	FE	-1.5852†	-10.5975	-1.1689	19.6577	0.7865	-0.9489
		(0.0727)	(0.4130)	(0.5108)	(0.0792)	(0.5661)	(0.9579)
	GMM-IV	-7.5965†	11.3299	17.4882	-46.6464	-16.4703†	-9.4405
		(0.0025)	(0.8212)	(0.0606)	(0.5017)	0.0352	(0.2150)