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THE SECOND MOMENTS MATTER: THE RESPONSE OF BANK LENDING BEHAVIOR TO MACROECONOMIC UNCERTAINTY

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Abstract

In this paper we investigate whether macroeconomic uncertainty could distort banks' allocation of loanable funds. To provide a road–map for our empirical investigation, we present a simple framework which demonstrates that lower uncertainty about the return from lending should lead to a more unequal distribution of lending across banks as managers take advantage of more precise knowledge of different lending opportunities. When bank–specific differences in lending opportunities are harder to predict, we should observe less cross–sectional variation in loan–to–asset ratios. Using a comprehensive U.S. commercial bank data set, we receive support for our hypothesis.

JEL: C22, C23, D81, E51.

Keywords: Bank lending, financial intermediation, credit, macroeconomic uncertainty, panel data, ARCH.

1 Introduction

In a pathbreaking 1956 study, McEvoy presents a snapshot of the U.S. banking industry by analyzing banks' asset and liability reports as a whole, and by various classifications including bank size. His study covers all data available in June 1953, a total of 13,435 banks, and presents information on the 'bank–to–bank variation of total loans–to–asset ratio' as well as commercial and industrial loans, real estate loans and loans to individuals among other ratios. Finding significant differences among individual banks, he claims that '[I]t is in the details of *portfolio policy* that individual banks adjust their operations to lending and *investing opportunities* in their particular communities, ...' (emphasis added). He continues to state '[T]he value of the present study lies not, therefore, in discovery of the completely unknown, but rather in confirming and quantifying a highly plausible *a priori* idea' (McEvoy (1956), p. 469).

McEvoy provides us with a unique portrayal of banks' total loan–to–asset ratio dispersion including other major loan components. However, since that time, no one else has provided similar statistical information which could have helped us understand how the dispersion of loan–to–asset ratios changes over time as the state of the macroeconomy evolves. Such an analysis would be very valuable as commercial banks are considered to be an important source of intermediated credit. They specialize in overcoming frictions in the credit market by acquiring costly information on borrowers, and extend credit based on that information along with market conditions.[1] Firms that

[1] It is generally accepted that commercial banks play a special role in the macroeconomy. See Gatev and Strahan (2003) and the references therein. Also note that banks may overcome informational problems by monitoring and screening, establishing long term relationships with firms, and utilizing other loan management principles. See, for example, Mishkin (2000), Hadlock and James (2002).

are small, non–rated or those with poor credit ratings—in short, those firms that suffer from asymmetric information problems—are likely to rely heavily on bank loans given their inability to access the public securities markets on attractive terms (or at all). Thus, any change in the supply of bank loans may have a serious impact on these disadvantaged borrowers.[2]

There are various reasons why banks' loan supply would change over time.[3] We argue that since banks must acquire costly information on borrowers before extending loans to new or existing customers, uncertainty about economic conditions (and the likelihood of loan default) would have clear effects on their lending strategies over and above the movements of macroeconomic aggregates or the constraints posed by monetary policymakers' actions, and distort the efficient allocation of available funds. We hypothesize that as uncertainty increases, the cross–sectional dispersion of loan–to–asset ratios should narrow as greater economic uncertainty hinders banks' ability to foresee the *investment opportunities* (returns from lending). Contrarily, when uncertainty is lower, returns will be more predictable leading to a more unequal distribution of lending across banks as managers take advantage of more precise information about different lending opportunities. Thus, as macroeconomic uncertainty declines, banks will rebalance their portfolios, causing the cross–sectional distribution of banks' loan–to–asset ratios to widen, and allowing for a more efficient allocation of loanable funds in

[2]See Houston and James (2001) and Schiantarelli (1996) for surveys of the role of financial constraints in firm' investment behavior; Myers and Majluf (1984) who investigate the financing behavior of firms under asymmetric information; Hadlock and James (2002), who discuss banks' provision of "financial slack"; and Petersen and Rajan (1994), who consider the importance of relationship lending.

[3]For example, several researchers have investigated the transmission of monetary policy through banks and shown that monetary policy will have effects on the macroeconomy over and above those predicted by a simple model of the multiple expansion of credit. See Kashyap and Stein (2000) and the references therein.

comparison with the high uncertainty case.

The above argument implies that during times of higher macroeconomic uncertainty banks behave more homogeneously, and that during times of low uncertainty banks will have more latitude to behave idiosyncratically. To provide support for our claims, we investigate the behavior of the cross–sectional distribution of banks' loan–to–asset ratios in the spirit of Beaudry, Caglayan and Schiantarelli (2001).[4] We use a simple application of portfolio theory to demonstrate that variations in macroeconomic uncertainty will affect banks' asset allocation between loans and securities. The model provides an unambiguous negative link between the cross–sectional dispersion of banks' loan–to–asset ratios and macroeconomic uncertainty: a hypothesis that may be empirically tested.

Our investigation utilizes U.S. bank–level data from the Federal Reserve System's Commercial Bank and Bank Holding Company database, which contains all banks regulated by the Federal Reserve System, the Federal Deposit Insurance Corporation, and the Comptroller of the Currency. The extract of this data set employed here covers essentially all banks in the U.S. on a quarterly basis from 1979–2003Q3, with 8,600–15,500 observations per calendar quarter, and a total of 1,241,206 bank–quarters. We also validate our empirical findings using a separate, annual sample of several hundred large banks from Standard and Poor's Bank COMPUSTAT data set, which yields qualitatively similar findings.

Empirical investigation of these data yields the following observations. There is a clear negative association between proxies for macroeconomic un-

[4]Beaudry et al. (2001), using a panel of U.K. firms, investigate the effect of uncertainty on the efficient allocation of investment. They provide evidence that changes in macroeconomic stability, captured by the volatility of inflation, would lead to a reduction in the cross–sectional variation of firms' investment rates.

certainty and the cross–sectional variability of banks' loan–to–asset ratios: that is, banks' behavior becomes more homogeneous in times of increased uncertainty. This association not only holds for total bank loans but for three major loan components—real estate loans, loans to households and (to a lesser degree) commercial and industrial loans—showing that our results are not driven by aggregation but are genuine. Furthermore, our results are robust to the introduction of several other variables controlling for changes in monetary policy such as the Federal funds rate, inflation rate, the index of leading indicators, and an indicator of regulatory changes.

The rest of the paper is constructed as follows. Section 2 presents a simple model illustrating how macroeconomic uncertainty may affect the lending behavior of banks, and discusses the methodology we employ in our investigation. Section 3 documents our empirical findings, while Section 4 concludes and draws implications for future theoretical and empirical research.

2 Assessing bank lending under uncertainty

In a world with perfect information one need only consider the key indicators of macroeconomic performance to evaluate the outcome of a stimulus to the supply of credit. However, given that banks rarely exhaust their lending capacity, asymmetric information problems induced by macroeconomic volatility render it crucial to evaluate the degree to which macroeconomic uncertainty will affect the banking sector's willingness to utilize available funds.[5] In the presence of uncertainty, it is likely that not only the first moments (such as the rate of GDP growth, the level of interest rates, or the level of inflation) but also the second moments (measures of uncertainty

[5]For example, Stiglitz and Weiss (1981) show that in equilibrium a loan market may be characterized by credit rationing. This result is driven by imperfect information, present in loan markets after banks have evaluated loan applications.

about those magnitudes) will matter.

We must point out that any partial–equilibrium investigation of banks' behavior in extending credit must ensure that variations in the volume of credit reflect the supply side of the market for loanable funds. The literature contains a variety of evidence suggesting that in periods of monetary tightening, firms may substitute non–bank finance for bank loans; for instance, Kashyap, Stein and Wilcox (1993) find that the issuance of commercial paper increases during these periods, while Calomiris, Himmelberg and Wachtel (1995) show that the volume of trade credit granted by larger firms to their smaller counterparts also increases. Despite this documented substitution, there is still a significant reduction in firm spending, particularly due to small firms' inability to tap alternative sources of finance (see, for example, Gertler and Gilchrist (1994)). Kashyap, Lamont and Stein (1994) document that during recessionary periods, inventory movements of non–rated companies were much more sensitive to their cash holdings than those of rated companies. Notwithstanding these demonstrated effects, our premise—that bank lending behavior will vary with macroeconomic uncertainty—requires only that banks face an excess supply of potential borrowers. Apart from conditions approximating the depths of the Great Depression, it is difficult to imagine that this condition will not hold, for each bank and time period, in our sample.

In a nutshell, we assume that the manager of a commercial bank operates in a risky environment and chooses the appropriate allocation of assets over two asset classes: third–party securities and loans.[6] Securities (even if free

[6]Two earlier papers of interest are Freixas, Parigi and Rochet (2000) which investigates whether insolvency of one bank due to consumer spending uncertainty would generate a chain reaction in the banking system, and Thakor and Udell (1984) which considers bank loan commitments when the value of borrowers' assets are uncertain.

of default risk) bear market risk, or price risk, but the market value of this component of the bank's asset portfolio has a predictable and manageable response to both financial–market and macroeconomic shocks. In contrast, loans to private borrowers exhibit both market risk and default risk: and the latter risk will be correlated, in many cases, with macroeconomic conditions, as well as with financial–market outcomes such as movements in the cost of short–term funds.[7] One potential impetus for the choice between securities and loans can be motivated by a simple portfolio optimization model in which managers must rebalance their asset portfolios to maintain an appropriate level of risk and expected return.[8] Such a model implies that banks would readjust their exposure to risky loans in the face of greater perceived uncertainty about macroeconomic factors, and the resulting likelihood of borrowers' default.

In the next section, we present a simple intuitive mechanism borrowed from the portfolio theory literature to demonstrate how the empirical results could arise. For reasons of tractability and simplicity, we consider a one–period problem.[9]

[7] Although banks' expected returns from their loan portfolio are much higher than those from "safe" third–party investments, they may find these attractive expected returns simply too risky; as *The Economist* recently stated, "... the percentage of American banks' assets made up of securities, notably safe government bonds, has grown from 34% at the beginning of 2001 to more than 40% today...with loans falling as a proportion." (October 26th 2002, p. 91).

[8] The idea of treating bank asset allocation as a portfolio problem is not unique to us. See, for example, Lucas and McDonald (1992) and the references therein.

[9] We recognize that in reality banks will make both short–term and long–term loans. To the extent that banks attach covenants to their loans, loans may be considered as renewable each period at the bank's discretion based on their reevaluation of the borrower's credit status. Hence, one can assume that a mix of loan tenors could be considered in a one–period framework.

2.1 The model

We assume that the bank manager, to maximize bank profits, each period allocates x per cent of total assets as loans to the private sector and $(100-x)$ per cent to securities. The securities provide the risk free return $(r_{f,t})$ set by the central bank at the beginning of each period and the risky loans yield a stochastic return based on a time–varying risk premium denoted by $\tilde{r}_{i,t} = r_{f,t} + premium_{i,t}$.[10] We assume that the expected risk premium is $E(premium_{i,t}) = \rho$ and its variance is $Var(premium_{i,t}) = \sigma^2_{\epsilon,t}$. Hence, the true return on risky loans takes the form $\tilde{r}_{i,t} = r_{f,t}+\rho+\epsilon_{i,t}$ where the random component $\epsilon_{i,t}$ is distributed as $\epsilon_{i,t} \sim N(0, \sigma^2_{\epsilon,t})$.[11] Variations in $\sigma^2_{\epsilon,t}$ are observable, in the sense that the overall risk of participating in the banking business may be gauged, but a bank manager does not know what her draw from this distribution will be at a point in time. Furthermore, one may consider variations in $\sigma^2_{\epsilon,t}$ as reflections of the uncertain rate of technological change in the economy, which may lead to periods of "irrational exuberance" (such as the recent "dot-com" boom and bust) in which the return to lending is much more uncertain. We also assume that $\epsilon_{i,t}$ is orthogonal to $\epsilon_{j,t}$: each bank has a specific set of borrowers with different risk structures, and hence, the random component of returns across banks are not correlated.

In a Modigliani–Miller world with no financial frictions, the manager of a bank would only be interested in maximizing the expected returns on loans. However, banks would not exist in such a world. Due to financial market failures induced by uncertainty, such as moral hazard and adverse

[10]Note that $r_{f,t}$ changes over time as the central bank adjusts interest rates in response to macroeconomic shocks. Given our objectives, we do not attempt to model this aspect of the problem. In our empirical analysis we introduce several variables, including the Fed funds rate, to evaluate the robustness of our findings.

[11]The normality assumption simply captures the idea that the probability of observing small shocks to risky returns is higher than large ones.

selection problems, banks invest in private information.[12] Hence, we assume that although the bank manager, prior to allocating bank assets between the risky and risk free alternatives, cannot observe the risk premium nor $\epsilon_{i,t}$ directly, she does observe a noisy signal on $\epsilon_{i,t}$ in the form of $S_{i,t} = \epsilon_{i,t} + \nu_t$. The random variable ν_t denotes the noise, which is assumed to be normally distributed as $\nu_t \sim N(0, \sigma^2_{\nu,t})$ and independent of $\epsilon_{i,t}$. Note that although each bank manager observes a different signal, the noise component of the observed signal in all cases is identical.[13] The noise in this sense is taken as a proxy for the degree of macroeconomic uncertainty and it affects all banks similarly.[14] In times of greater turmoil in the economy, a higher variance of ν_t will render bank managers' estimates of the true returns on risky loans less accurate. In contrast, when the macroeconomy is more tranquil, the return from bank lending will be concomitantly more predictable.

By employing this framework, we capture the notion that a bank manager takes all available information into consideration before making any decision, yet can still inadvertently pursue suboptimal decisions since the information content of the signal tends to change over time.[15] However, we must emphasize that without the additional information contained in $S_{i,t}$, it would

[12]For example, the literature on the bank lending channel rests on asymmetric information between banks and purchasers of time deposits. Also see Cebenoyan and Strahan (2004) and the references therein on risk management and bank lending.

[13]It is possible to assume that each bank observes a private signal with a different noise level. This assumption would lead to a more complicated analysis with little added insight.

[14]If all banks were to reveal their signal to a private agent, ν_t could be observed, fully eliminating the uncertainty. However, this strategy is not feasible for some banks would put more resources to observe the signal than some others allowing for some to free ride on others. Furthermore, knowledge of ν_t implies that the agency will have full information on the true return of each bank, which may lead to substantial changes in the fortunes of the banking sector. Hence, information revelation (or sharing) seems unlikely. (See, for example, Goenka (2003), Perotti and von Thadden (2003), Caglayan and Usman (2000)).

[15]The analytical framework we present here is a variant of the island model used by Lucas (1973) that highlights the manager's optimal lending decision as a signal extraction problem.

not be possible to improve upon the naïve prediction of a zero value for $\epsilon_{i,t}$. Conditioning upon the signal $S_{i,t}$, the manager can form an optimal forecast of the return from risky loans as $E_t(\epsilon_{i,t}|S_{i,t}) = \lambda_t S_{i,t}$, where $\lambda_t = \frac{\sigma^2_{\epsilon,t}}{\sigma^2_{\epsilon,t}+\sigma^2_{\nu,t}}$. We assume that the bank manager cannot observe $\sigma^2_{\nu,t}$, but rather that she may form an optimal forecast of that quantity. For instance, although we have not specified a law of motion for $\sigma^2_{\nu,t}$, it is plausible to model its variation over time as a low–order GARCH process. Therefore, at each point in time, total expected returns conditional on the signal will take the form

$$E(\tilde{Y}_{i,t}|S_{i,t}) = x_{i,t}(r_{f,t} + \rho + \lambda_t S_{i,t}) + (1 - x_{i,t})r_{f,t}, \tag{1}$$

where $\tilde{Y}_{i,t}$ denotes total returns, and the conditional variance of returns will be

$$Var(\tilde{Y}_{i,t}|S_{i,t}) = \lambda_t \sigma^2_{\nu,t} x^2_{i,t}. \tag{2}$$

As noted earlier, because of financial market frictions (i.e. failure of the Modigliani and Miller assumptions) we model the bank manager's objective function using a simple expected utility framework, $E(\tilde{U}_{i,t}|S_{i,t})$, which is increasing in the expected returns and decreasing in the variance of returns conditional on the signal $S_{i,t}$ in the form

$$E(\tilde{U}_{i,t}|S_{i,t}) = E(\tilde{Y}_{i,t}|S_{i,t}) - \frac{\alpha}{2} Var(\tilde{Y}_{i,t}|S_{i,t}), \tag{3}$$

where α is the coefficient of risk aversion.[16] Given equations (1) and (2), we can easily derive the i^{th} bank's optimal loan–to–asset (LTA) ratio as:

[16] We utilize risk aversion in order to capture banks' practices of relationship lending (extending credit to favored customers) and monitoring (via audits, compensating balance requirements, and the like). Since banks' managers (acting for their shareholders, or in their own self–interest) are operating in an uncertain environment with the desire to avoid risk of ruin, an assumption of risk aversion on their part is a reasonable one.

$$x_{i,t} = \frac{\rho + \lambda_t S_{i,t}}{\alpha \lambda_t \sigma^2_{\nu,t}}. \tag{4}$$

Equation (4) indicates that each bank's optimal loan–to–asset ratio depends on the signal observed by the manager, as well as to both $\sigma^2_{\epsilon,t}$ and $\sigma^2_{\nu,t}$. As intuition would suggest, although any change in macroeconomic uncertainty (as captured through the variance of the noise in the signal σ^2_ν) will have an impact on this ratio, we cannot pin down the overall effect since the sign of the signal is not known. Nevertheless, using equation (4), we can compute the variance of the cross–sectional distribution of the loan–to–asset ratio

$$Var(x_{i,t}) = \frac{\sigma^2_{\epsilon,t}}{\alpha^2 \sigma^4_{\nu,t}}, \tag{5}$$

to investigate the effects of the time variation in the variance of macroeconomic uncertainty σ^2_ν as it is this variance that reflects bank managers' ability to forecast the returns from loans and hence banks' lending behavior.[17]

As shown in equation (6) below, equation (5) provides us a clear–cut link between macroeconomic uncertainty σ^2_ν and variations in the cross–sectional distribution of banks' LTA ratios. An increase in macroeconomic uncertainty, as captured by an increase in $\sigma^2_{\nu,t}$, will lead to a decrease in the cross–sectional variance of the LTA ratio:

$$\frac{\partial Var(x_{i,t})}{\partial \sigma^2_{\nu,t}} = -\frac{2\sigma^2_{\epsilon,t}}{\alpha^2 \sigma^6_{\nu,t}} < 0. \tag{6}$$

The negative relationship between macroeconomic uncertainty and the cross–sectional variation of banks' LTA ratios can be intuitively explained as follows. During tranquil periods (i.e., when $\sigma^2_{\nu,t}$ is low), each bank responds

[17]Recall that ν_t does not vary across banks. Hence, (5) follows.

more accurately to loan demand as bank managers take advantage of the perceived lending (*investment*) opportunities which may be more clearly identified in this environment in comparison to more turbulent times. Hence, as banks behave more idiosyncratically, the cross–sectional distribution of LTA ratios should widen. Contrarily, during times of uncertainty (i.e., when $\sigma^2_{\nu,t}$ is high), the actual returns to lending will be harder to predict. Under these conditions, as bank managers would have greater difficulty identifying profitable lending opportunities, they will behave more homogeneously leading to a narrowing of the cross–sectional distribution of LTA ratios.[18]

To provide support for our hypothesis as depicted by equation (6), we consider the following reduced form relationship:

$$Disp_t(L_{it}/TA_{it}) = \beta_0 + \beta_1 \sigma^2_{\nu,t} + e_t, \tag{7}$$

where $Disp_t(L_{it}/TA_{it})$ is a measure (the standard deviation) of the cross–sectional dispersion of banks' loan–to–asset ratio at time t, $\sigma^2_{\nu,t}$ denotes the macroeconomic uncertainty at time t and e_t is an *i.i.d.* error term. Our claim is that the spread of the distribution of LTA ratios—the heterogeneity exhibited by commercial banks' diverse behavior—is negatively related to a measure of macroeconomic uncertainty. Hence, we would expect to find a negative sign on β_1 if greater macroeconomic uncertainty was associated with a smaller dispersion of banks' loan–to–asset ratios.

[18] One should note (per equation (5)) that an increase in $\sigma^2_{\epsilon,t}$ will quite reasonably lead to a widening of the dispersion of the LTA ratio. Given a certain signal, an increase in the variance of returns allows bank managers to predict future economic activity more accurately, for the information content of the signal has increased relative to the noise. In other words, accuracy in predicting the bank's true returns from lending depend on changes in the idiosyncratic component in returns (the local shocks) relative to the macroeconomic (global) shocks. In our empirical analysis, we introduce several variables to control for the effects of time variation in $\sigma^2_{\epsilon,t}$.

2.2 Identifying macroeconomic uncertainty

To provide an appropriate proxy for macroeconomic uncertainty as perceived by banks' managers, we make use of the conditional variance of industrial production, a measure of the economy's health available at a higher (monthly) frequency than that of the national income aggregates. As an alternate measure focusing on the financial sector, we use the conditional variance of CPI inflation.[19] Therefore, we rewrite equation (7) in the following form:

$$Disp_t(L_{it}/TA_{it}) = \beta_0 + \beta_1 \hat{h}_t + e_t, \tag{8}$$

where $\hat{h}_t$ represents macroeconomic uncertainty, captured by the conditional variance of industrial production or CPI inflation evaluated at time t. The advantage of this approach is that we can relate the behavior of bank loans directly to a measurable variable for economic uncertainty.[20]

Our proxies for macroeconomic uncertainty are derived from monthly industrial production (International Financial Statistics series $66IZF$) and from consumer price inflation (IFS series $64XZF$).[21] In each case, we fit a generalized ARCH (GARCH) model to the series, where the mean equation is an autoregression (AR(1) for industrial production, AR(2) for inflation).[22] The conditional variance derived from this GARCH model for each proxy, averaged to annual or quarterly frequency, is then used as our measure of macroeconomic uncertainty ($\hat{h}_t$).

[19] The conditional variances of industrial production or inflation are better suited for our purposes than that of any monetary aggregate, for any signs of weakness or overheating in the economy will show up initially in the behavior of production and inflation.

[20] Although $\hat{h}_t$ is a generated regressor, the coefficient estimates for equation (8) are consistent; see Pagan (1984, 1986).

[21] We also tested measures of uncertainty derived from quarterly GDP and its growth rate; since the results were broadly similar we preferred the monthly series.

[22] Details of the GARCH models for CPI and IP are given in the appendix.

3 Empirical findings

3.1 Data

The main data set we exploit in our empirical analysis is a comprehensive data set for U.S. commercial banks; the Federal Reserve System's Commercial Bank and Bank Holding Company (BHC) database which cover essentially all banks in the U.S. on a quarterly basis from 1979–2003Q3. The degree of concentration in the U.S. banking industry (which increased considerably over our period of analysis) implies that a very large fraction of the observations in the data set are associated with quite small, local institutions.[23] We also use Standard and Poor's Bank COMPUSTAT database to confirm the results obtained from the BHC database. This database is an unbalanced panel of annual observations for the largest and the strongest banks in the US over the 1981–2002 period.[24]

In our empirical investigation, we analyze total loans as well as its three major components (real estate loans, loans to households, and commercial and industrial loans) to ensure that our findings are not a result of aggregation but they are robust. The BHC data set provides us with measures of loans to the private sector: three loan categories (real estate loans, loans to households, and commercial and industrial loans), total loans and total assets.[25] Many fewer observations are available for the commercial and industrial loan category (567,615 bank–quarters) than for the other two categories of loans (which have 1,149,367 (RE) and 1,112,574 (HH) bank–quarters avail-

[23]There were over 15,500 banks required to file condition reports in the early 1980s. By 2003Q4, the number of reporting banks fell to 8,661.

[24]Real estate loans, loans to households, commercial and industrial loans, total loans and total assets are COMPUSTAT items *data14*, *data20*, *data21*, *data23* and *data36*, respectively.

[25]Details of the construction of these measures from the BHC database are included in the appendix.

able, respectively).

Descriptive statistics on the loan–to–asset ratios that we obtain from the BHC data set are presented in Table 1. From the means of the annual sample over the entire period, we see that bank loans constituted about 56% of total assets, with household and commercial/industrial (C&I) loans having similar importance. Splitting the sample at 1991–1992, when Basel Accord risk–based capital standards fully came to bear, we observe a considerable increase in the importance of real estate loans, and a somewhat lesser decline in the importance of household loans after that period. A similar pattern for the loan categories' changes is visible in their median (*p50*) values. Banks' reliance on loans increased by several percentage points, in terms of mean or median values, between the early 1990s and the later period.

In the following subsections, we present our results, first considering the dynamics of the loan–to–asset ratios themselves, without reference to macroeconomic uncertainty. Then we proceed with presenting the estimates of our models linking the dispersion of the LTA ratios' distribution to measures of macroeconomic uncertainty.

3.2 The link between lending and uncertainty

Figure 1 displays the quartiles of the LTA distribution for total loans and the three major categories. There is a sizable increase in the importance of real estate loans over these decades, while loans to households show some decline in importance over the period. The commercial and industrial (C&I) loan series shows a break in 1984, which is an artifact of the composition of the data. Also note the general decline in the importance of C&I lending as of the mid–1980s. Lown and Peristiani suggest that a shift away from C&I lending over the last several decades reflected "a declining trend in the intermediation role of banks" (1996, p.1678), and that banks maintained a constant presence in consumer lending; these features appear to be present in Figure 1.

However, we do not focus upon these measures of central tendency, but rather upon the dispersion of banks' LTA ratios around their mean values. To formally test our hypothesis, as presented in equation (8), we use the standard deviation of the loan–to–asset ratio (LTA_Sigma) as a measure of the cross–sectional dispersion of bank loans.[26] Figure 2 juxtaposes the log LTA_Sigma ratio for total loans and the three components with our first proxy for macroeconomic uncertainty: the log conditional variance of industrial production (CV_IP), while the panels of Figure 3 present this juxtaposition for total loans and the loan categories for the second proxy, the log conditional variance of CPI inflation (CV_Infl). The CV_IP proxy exhibits a stronger declining trend over these two decades, while CV_Infl exhibits some cyclical behavior as well as an increase in the late 1990s. Nevertheless, the overall reduction in both measures over the period is striking: in clear contrast to the general trends in the LTA_Sigma ratios over the period, which (with the exception of loans to households) are increasing.

3.2.1 Model specification

The relation between the dispersion of banks' LTA ratios and macroeconomic uncertainty is statistically tested in Tables 2–5 for total loans and for the three loan categories, exploiting the BHC database. In Tables 6 and 7 we depict results obtained from the Bank COMPUSTAT database: Table 6 portrays results for total loans and Table 7 summarizes our results for the

[26] The inter–quartile range (LTA_IQR) or the range between 90th and 10th percentiles (LTA_90_10) could also be examined in order to consider the behavior of the outlying firms. Results from these measures are broadly similar to those derived from LTA_Sigma, and are not reported here.

three loan categories. In Table 2–7, we present OLS regression results (with heteroskedasticity– and autocorrelation-consistent standard errors) for each of the proxy series. The dependent variable measures the standard deviation of the LTA ratio for each category of loans; e.g. *Tot_Sigma* for total loans, *RE_Sigma* for real estate loans, etc. In these models, we enter an indicator, (d_BA) for 1992Q1 and beyond to capture the effect of the full implementation of Basel Accord risk–based capital standards on banks' lending behavior. In the quarterly estimates from the BHC database, we consider both the contemporaneous uncertainty measures and three quarters' lagged effects of the proxies for macroeconomic uncertainty: CV_IP_03 and CV_Infl_03, with arithmetic lags over the current and prior three quarters' values.[27] Since banks may already have extended irrevocable commitments to provide credit, the observed change in the LTA ratio may only reflect desired alterations in the supply of loans with a lag. We also include the Federal funds rate as a factor influencing the supply of credit, and a time trend to deal with long–term movements. Columns (5) and (6) of each panel of Tables 2–5 present results of regressions including two additional control variables: the rate of CPI inflation and the detrended index of leading indicators (computed from DRI-McGraw Hill Basic Economics series $DLEAD$) to judge the robustness of our results in the presence of these macroeconomic factors.[28] Also note that when we investigate the behavior of quarterly C&I loans, we included a dummy variable for 1984 to capture the effects of the redefinition of C&I loans between 1984Q2–1984Q3.

[27]We imposed an arithmetic lag structure on the values of the proxy variables with weights 0.4, 0.3, 0.2, 0.1. Results based on once–lagged proxies for uncertainty were similar.

[28]We also investigated the explanatory power of other macroeconomic factors, such as the GDP gap and the Bernanke–Mihov index (1998) of the impact of monetary policy. Neither factor had a significant effect on the relationship across the loan categories.

3.2.2 Estimation results for the BHC data

We present our results obtained from regressing the variance of LTA ratios for total loans on the conditional variances of IP and inflation in Table 2. Columns 1 and 2 provide estimates of our baseline regressions; coefficients on both measures of uncertainty are negative and significant at the 1% level, as are the measures in columns 3 and 4 based on distributed lags of the conditional variances.

Since we are investigating this relationship over a 24–year period, one may question if our findings are driven by other macroeconomic events. To see if this is the case, columns 5 and 6 report regression results when we introduce inflation and the index of leading indicators. Observe that these additional regressors do not change our conclusion that uncertainty has a negative impact on the dispersion of the LTA ratio for total loans. Finally, to gain more insight, we compute the effect of a 100 per cent increase in uncertainty as captured by the conditional variances of industrial production and CPI inflation. We find that, at the end of one year, the dispersion of the LTA ratio for total loans declines by 8% and 5%, respectively, each significantly different from zero.

Next, in Tables 3-5 we look at the same relationship for other major components of loans, namely real estate loans, household loans and commercial and industrial loans, respectively, to demonstrate that our findings above is not driven by aggregation and the link is genuine.

Results for the real estate loan category (Table 3) are quite strong, with each model's uncertainty coefficients negative, significant at the 5% or 1% level for the weighted average measures of the variances of industrial production and inflation. A similar exercise to that above shows that the one–year cumulative effect of a 100 per cent increase in uncertainty as captured by the conditional variance of IP and CPI inflation is a 9% and 6% reduction in the dispersion of real estate loans, respectively, each of which is significantly different from zero.

For the household loans category, reported in Table 4, each of the six models contains a highly negative significant coefficient (at the 1% level for all cases) on the macroeconomic uncertainty measure. In this category of loans, the one–year cumulative effect of a 100 per cent increase in uncertainty, as captured by the conditional variances of IP and CPI inflation, is a 10% and 7% reduction in the dispersion of household loans, respectively, both of which differ from zero at any conventional level of significance.

Finally in Table 5, we present the results for the commercial and industrial loans category—the weakest of the set. The effect of macro uncertainty exhibits the expected sign in all models, but it is not distinguishable from zero. We do find that the Federal funds rate may play an important role in the dispersion of C&I loans. The one–year cumulative effect of a 100 per cent increase in uncertainty as captured by the conditional variance of IP causes a 8% reduction in the dispersion of C&I loans, while that of CPI inflation rate leads to a reduction of 2%, neither of which are distinguishable from zero.

While the commercial and industrial loans yield only weak support, overall our empirical results derived from the BHC database provide strong support for the hypothesis that fluctuations in macroeconomic uncertainty are associated with sizable alterations in the heterogeneity of banks' lending behavior. We also document that the one–year cumulative effect of a 100 per cent increase in uncertainty, as captured by the conditional variance of IP (CPI inflation) leads to somewhere between a 10% (8%) and 7% (4%) reduction in the dispersion of banks' loan–to-asset ratios, where both differ from zero at any conventional level of significance. These findings support the view that uncertainty distorts the efficient allocation of funds across potential borrowers. We note that our measures of macroeconomic uncertainty do not appear to explain movements in the dispersion of banks' C&I loan–to–asset ratios, which appear to be more sensitive to movements in the Federal funds rate. This finding deserves a closer examination in future work.

3.2.3 Validation using the Bank COMPUSTAT database

To validate our findings, we applied the same model to a set of bank–level data drawn from Standard and Poor's Bank COMPUSTAT database over 1981–2002. Unlike the BHC data (which essentially encompass the universe of commercial banks), Bank COMPUSTAT covers no more than 1,350 large, traded banks, but the concentration of the commercial banking sector implies that these banks control a very sizable share of the banking system's total assets. Their lines of business differ somewhat from those of the universe of commercial banks, with real estate and commercial/industrial (C&I) loans having similar importance among large banks.

Table 6 displays results for total loans based on the estimation of equation (8) using the conditional variances of industrial production and inflation along with several macroeconomic variables as controls. We consider both the contemporaneous conditional variances and a weighted average of current and lagged conditional variances (*CV_IP_01* and *CV_Infl_01*), with declining arithmetic weights. These results are very strong, with all but the first model exhibiting a negative and statistically significant coefficient on the uncertainty measure, and the weighted average measures of uncertainty significant at the 1% level even when controlling for the level effects of interest rates, inflation and the leading indicators in columns 5 and 6. In Table 7, for brevity, we only display the results for these latter two specifications by category of loan: real estate, household, and commercial & industrial (C&I). These results are reasonably strong, with the most satisfactory findings for real estate loans, and to a lesser degree for household loans. Even for the C&I category, the point estimates are negative for both measures of uncertainty, although not distinguishable from zero. As in the BHC results, the weakness of the model for C&I loans may reflect the presence of other significant factors, such as an industry–specific evaluation of borrowers' prospects.

Finally, to gain some insight on these results from the annual data, we compute the effect of a 100 per cent increase in uncertainty as captured by the conditional variances of industrial production (IP) and CPI inflation. The overall effect is perhaps even stronger for the sample of large banks included in Bank COMPUSTAT than for the universe of commercial banks in the BHC database. The effect of a 100 per cent increase in uncertainty proxied by IP (CPI inflation) is between a 16% (12%) and 11% (4%) and reduction in the dispersion of banks' loan–to–asset ratios. These figures substantiate our findings from the BHC database and confirm the view that macroeconomic uncertainty significantly distorts the efficient allocation of funds among potential borrowers.

4 Conclusions

In this paper, we argue that uncertainty about economic conditions would have clear effects on banks' lending strategies over and above the movements of macroeconomic aggregates or the constraints posed by monetary policymakers' actions and distort the efficient allocation of funds. Based on an application of portfolio theory, we demonstrate that variations in macroeconomic uncertainty over the business cycle would affect banks' portfolio allocation decisions, and in the aggregate will have clear effects on the degree of heterogeneity of banks' loan–to–asset ratios. In particular we use the model to guide us in our empirical test: that in the presence of greater macroeconomic uncertainty, banks' concerted actions lead to a narrowing of the cross–sectional distribution of banks' loan–to–asset (LTA) ratios. Conversely, when the economic environment is more tranquil, banks will have more latitude to behave idiosyncratically, leading to a broadening of the cross–sectional dispersion of banks' LTA ratios.

To test this hypothesis, we estimate a simple reduced–form equation using the BHC database which provides comprehensive information on all U.S. banks. These results are validated by reestimating the model on a sample of large banks from the Bank COMPUSTAT database. The empirical results from both datasets strongly support our hypothesis that increased uncertainty leads to a narrowing of the dispersion of banks' loan–to–asset ratios, disrupting the efficient allocation of loanable funds. Our findings hold not only for total loans but also its three major components showing that results are not driven by aggregation. Furthermore, we provide evidence that our model is robust to the inclusion of macroeconomic factors that capture the state of the economy.

It could be useful to evaluate our findings in the light of some earlier work. For instance, Beaudry, Caglayan and Schiantarelli (2001) present a novel analysis which documents that an increase in macroeconomic uncertainty could lead to a significant reduction in the cross–sectional dispersion of the investment rate and meaningful resource allocation problems. Gertler and Gilchrist (1996) suggest that changes in credit market conditions may amplify the impact of initial shocks, impairing firms' and households' access to credit although the need for finance may be increasing at the time. Given our empirical findings, it is apparent that macroeconomic uncertainty significantly distorts the allocation of loanable funds, and that the magnitude of effects that we find in this paper is qualitatively important: a change of 4% to 16% in banks' loan–to–asset ratios' dispersion in response to a doubling of macroeconomic uncertainty. As our empirical analysis clearly demonstrates, there should be no doubt that the overall economic significance of reducing macroeconomic uncertainty would be quite substantial. We believe that this message—"the second moments matter"—should be of key relevance to economic policymakers.

Appendix A: Construction of bank lending measures from the Fed BHC database

The following variables from the on–line BHC database were used in the quarterly empirical study. Many of the definitions correspond to those provided by on–line documentation of Kashyap and Stein. We are grateful to the research staff of the Federal Reserve Bank of Chicago for assistance with recent releases of the data.

RCFD2170: Average total assets

RCON1400: Total loans

RCON1410: Real estate loans

RCON1975: Loans to households

RCON1600: C&I loans, 1979Q1–1984Q2

RCON1763 + RCON1764: C&I loans, 1984Q3–2003Q3

Appendix B: Proxies for macroeconomic uncertainty

Table B1. GARCH models proxying macroeconomic uncertainty

	(1)	(2)
	$\log(IP)$	$\log(\dot{P})$
$\log(IP)_{t-1}$	0.979	
	[0.012]***	
$\log(\dot{P})_{t-1}$		1.246
		[0.053]***
$\log(\dot{P})_{t-2}$		-0.253
		[0.052]***
Constant	0.000	0.022
	[0.001]	[0.020]
$AR(1)$	0.851	-0.841
	[0.056]***	[0.036]***
$AR(2)$		-0.790
		[0.036]***
$MA(1)$	-0.605	0.952
	[0.079]***	[0.007]***
$MA(2)$		0.980
		[0.008]***
$ARCH(1)$	0.249	0.164
	[0.057]***	[0.030]***
$ARCH(2)$	-0.184	
	[0.054]***	
$GARCH(1)$	0.916	0.799
	[0.022]***	[0.036]***
Constant	0.000	0.004
	[0.000]**	[0.001]***
Observations	561	559

Standard errors in brackets

Models are fit to detrended $\log(IP)$ and $\log \dot{P}$.

* significant at 10%; ** significant at 5%; *** significant at 1%

References

[1] Beaudry, Paul, Mustafa Caglayan and Fabio Schiantarelli, 2001. Monetary instability, the predictability of prices, and the allocation of investment: An empirical investigation using U.K. panel data. *American Economic Review*, 91, 648–62.

[2] Bernanke, Ben and Ilian Mihov, 1998. Measuring Monetary Policy. *Quarterly Journal of Economics*, 113, 869–902.

[3] Caglayan, Mustafa and Murat Usman, 2000. Costly signal extraction and profit differentials in oligopolistic markets, *Economics Letters*, 69(3), 359–63.

[4] Calomiris, Charles W., Charles P. Himmelberg, and Paul Wachtel, 1995. Commercial paper, corporate finance, and the business cycle: A microeconomic perspective. *Carnegie Rochester Conference Series on Public Policy*, 42, 203–50.

[5] Cebenoyan, A. Sinan and Philip E. Strahan, 2004. Risk management, capital structure and lending at banks. *Journal of Banking and Finance*, 28(1), p. 19-43.

[6] Freixas, Xavier, Bruno M. Parigi and Jean-Charles Rochet, 2000. Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank. *Journal of Money, Credit and Banking*, 32(3), 611-38.

[7] Gatev, Evan and Philip E. Strahan, 2003. Banks' Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market. Unpublished working paper, Boston College.

[8] Gertler, Mark, and Simon Gilchrist, 1994. Monetary policy, business cycles, and the behavior of small manufacturing firms. *Quarterly Journal of Economics*, 109, 309–40.

[9] Gertler, Mark, and Simon Gilchrist, 1996. The Financial Accelerator and the Flight to Quality. *Review of Economics and Statistics*, 78(1), 1-15.

[10] Goenka, Aditya, 2003. Informed trading and the leakage of information, *Journal of Economic Theory*,109(2) 360–377.

[11] Hadlock, Charles J. and Christopher M. James, 2002. Do banks provide financial slack? *Journal of Finance*, 57(3), 1383–1419.

[12] Houston, Joel F.. and Christopher M. James, 2001. Do Relationships Have Limits? Banking Relationships, Financial Constraints, and Investment, *Journal of Finance*, 74(3) 347–374.

[13] Kashyap, Anil K., Owen A. Lamont, and Jeremy C. Stein, 1994. Credit conditions and the cyclical behavior of inventories. *Quarterly Journal of Economics*, 109, 565–92.

[14] Kashyap, Anil K. and Jeremy C. Stein, 2000. What Do a Million Observations on Banks Say about the Transmission of Monetary Policy? *American Economic Review*, 90, 407–28.

[15] Kashyap, Anil K., Jeremy C. Stein, and David W. Wilcox, 1993. Monetary policy and credit conditions: Evidence from the composition of external finance. *American Economic Review*, 83, 78–98.

[16] Lown, Cara and Stavros Peristiani, 1996. The behavior of consumer loan rates during the 1990 credit slowdown. *Journal of Banking and Finance*, 20, 1673–94.

[17] Lucas, Deborah J. and Robert L. McDonald, 1992. Bank Financing and Investment Decisions with Asymmetric Information about Loan Quality. *RAND Journal of Economics*, 23(1), p. 86-105.

[18] Lucas, Robert E., Jr., 1973. Some International Evidence on Output–Inflation Tradeoffs. *American Economic Review*, 63(3), 326–34.

[19] McEvoy, Raymond H. 1956. Variation in bank asset portfolios. *Journal of Finance*, 11(4), 463–73.

[20] Mishkin, Frederic S., 2000. *The economics of money, banking, and financial markets*, 6th ed. Boston: Addison Wesley Longman.

[21] Myers, Stewart C. and Nicholas S. Majluf, 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2), 187–221.

[22] Pagan, Adrian R., 1984. Econometric issues in the analysis of regressions with generated regressors. *International Economic Review*, 25, 221–47.

[23] Pagan, Adrian R., 1986. Two stage and related estimators and their applications. *Review of Economic Studies*, 53, 517–38.

[24] Perotti, Enrico C. and Ernst-Ludwig von Thadden, 2003. Strategic transparency and informed trading: will capital market integration force convergence of corporate governance? *Journal of Financial & Quantitative Analysis*, 38(1), p61–86.

[25] Petersen, Mitchell A. and Raghuram G. Rajan, 1994. The Benefits of Lending Relationships: Evidence from Small Business Data, *Journal of Finance*, 49(1), 3–37.

[26] Schiantarelli, Fabio, 1996. Financial Constraints and Investment: Methodological Issues and International Evidence. *Oxford Review of Economic Policy*, 12(2), pp. 70-89.

[27] Stiglitz, Joseph E. and Andrew Weiss, 1981. Credit Rationing in Markets with Imperfect Information. *American Economic Review*, 71(3), 393–410.

[28] Thakor, Anjan V. and Gregory F. Udell, 1984. Bank forward lending under asymmetric information. New York University, Salomon Brothers Center, Working Paper No. 319.

[29] The Economist, 2002. Doors now closing. October 26th 2002: pp. 91–92.

Table 1: Loan-to-asset ratios: Descriptive statistics

	μ	σ	p_{25}	p_{50}	p_{75}
Full sample					
RE	0.252	0.161	0.134	0.226	0.340
CI	0.120	0.090	0.057	0.102	0.163
HH	0.120	0.090	0.056	0.102	0.163
Total	0.564	0.141	0.482	0.579	0.661
Pre-1992					
RE	0.208	0.132	0.114	0.191	0.277
CI	0.127	0.093	0.062	0.109	0.172
HH	0.131	0.085	0.070	0.116	0.176
Total	0.552	0.134	0.472	0.565	0.644
1992-2003Q3					
RE	0.384	0.167	0.271	0.382	0.495
CI	0.100	0.079	0.046	0.085	0.136
HH	0.086	0.094	0.028	0.063	0.111
Total	0.602	0.154	0.525	0.627	0.707

Note: RE, CI, HH refer to loan–to–asset ratios for real estate loans, commercial and industrial loans, and loans to households, respectively. p_{25}, p_{50} and p_{75} represent the quartiles of the distribution, while μ and σ represent its mean and standard deviation, respectively. The statistics for total loans are based on 1,241,206 bank–quarters: 758,672 bank–quarters prior to 1992 and 482,534 bank–quarters thereafter.

Table 2. BHC results for total loans

	(1) Tot_Sigma	(2) Tot_Sigma	(3) Tot_Sigma	(4) Tot_Sigma	(5) Tot_Sigma	(6) Tot_Sigma
d_BA	-0.017	-0.021	-0.016	-0.021	-0.014	-0.017
	[0.006]***	[0.006]***	[0.006]***	[0.006]***	[0.006]**	[0.006]***
FedFunds	-0.196	-0.208	-0.180	-0.213	-0.064	-0.133
	[0.048]***	[0.052]***	[0.058]***	[0.053]***	[0.067]	[0.075]*
t	0.393	0.484	0.359	0.468	0.318	0.400
	[0.142]***	[0.133]***	[0.155]**	[0.134]***	[0.139]**	[0.146]***
CV_IP	-0.216					
	[0.063]***					
CV_Infl		-0.085				
		[0.022]***				
CV_IP_03			-0.290		-0.316	
			[0.098]***		[0.083]***	
CV_Infl_03				-0.097		-0.086
				[0.023]***		[0.026]***
Inflation					-0.002	-0.001
					[0.001]**	[0.001]
LeadIndic					-0.000	0.000
					[0.000]	[0.000]
Constant	0.172	0.168	0.175	0.171	0.176	0.171
	[0.007]***	[0.008]***	[0.008]***	[0.008]***	[0.008]***	[0.008]***
Observations	96	96	96	96	96	96
R^2	0.85	0.86	0.86	0.87	0.89	0.89
$\hat{\eta}_{CV}$	-0.05	-0.04	-0.07	-0.05	-0.08	-0.05
s.e.	0.02	0.01	0.02	0.01	0.02	0.01

* significant at 10%; ** significant at 5%; *** significant at 1%

HAC standard errors shown. SD based on 1241206 bank-quarter obs.

Table 3. BHC results for real estate loans

	(1)	(2)	(3)	(4)	(5)	(6)
	RE_Sigma	RE_Sigma	RE_Sigma	RE_Sigma	RE_Sigma	RE_Sigma
d_BA	0.003	-0.000	0.005	-0.000	-0.002	-0.006
	[0.007]	[0.007]	[0.006]	[0.006]	[0.005]	[0.005]
FedFunds	0.065	0.056	0.100	0.059	-0.007	-0.081
	[0.056]	[0.055]	[0.057]*	[0.056]	[0.064]	[0.065]
t	0.710	0.774	0.644	0.760	0.764	0.856
	[0.144]***	[0.137]***	[0.135]***	[0.130]***	[0.135]***	[0.127]***
CV_IP	-0.152					
	[0.084]*					
CV_Infl		-0.058				
		[0.038]				
CV_IP_03			-0.300		-0.343	
			[0.100]***		[0.097]***	
CV_Infl_03				-0.083		-0.099
				[0.041]**		[0.033]***
Inflation					0.001	0.002
					[0.001]**	[0.001]***
LeadIndic					-0.001	-0.000
					[0.000]**	[0.000]
Constant	0.117	0.115	0.123	0.117	0.122	0.117
	[0.011]***	[0.010]***	[0.011]***	[0.011]***	[0.010]***	[0.009]***
Observations	96	96	96	96	96	96
R^2	0.89	0.89	0.90	0.90	0.93	0.93
$\hat{\eta}_{CV}$	-0.04	-0.03	-0.08	-0.05	-0.09	-0.06
s.e.	0.02	0.02	0.03	0.02	0.02	0.02

* significant at 10%; ** significant at 5%; *** significant at 1%

HAC standard errors shown. SD based on 1245923 bank-quarter obs.

Table 4. BHC results for loans to households

	(1) HH_Sigma	(2) HH_Sigma	(3) HH_Sigma	(4) HH_Sigma	(5) HH_Sigma	(6) HH_Sigma
d_BA	0.001	-0.001	0.002	-0.001	0.001	-0.002
	[0.002]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]
FedFunds	0.041	0.038	0.055	0.037	0.071	0.032
	[0.025]*	[0.021]*	[0.020]***	[0.019]*	[0.031]**	[0.026]
t	-0.122	-0.075	-0.150	-0.085	-0.137	-0.083
	[0.048]**	[0.039]*	[0.046]***	[0.036]**	[0.052]***	[0.043]*
CV_IP	-0.114					
	[0.029]***					
CV_Infl		-0.049				
		[0.011]***				
CV_IP_03			-0.174		-0.192	
			[0.032]***		[0.036]***	
CV_Infl_03				-0.062		-0.062
				[0.011]***		[0.012]***
Inflation					-0.000	0.000
					[0.000]	[0.000]
LeadIndic					-0.000	-0.000
					[0.000]	[0.000]
Constant	0.088	0.086	0.090	0.088	0.091	0.088
	[0.002]***	[0.003]***	[0.002]***	[0.003]***	[0.002]***	[0.003]***
Observations	96	96	96	96	96	96
R^2	0.58	0.66	0.66	0.74	0.68	0.74
$\hat{\eta}_{CV}$	-0.06	-0.05	-0.09	-0.07	-0.10	-0.07
s.e.	0.01	0.01	0.02	0.01	0.02	0.01

* significant at 10%; ** significant at 5%; *** significant at 1%

HAC standard errors shown. SD based on 1205914 bank-quarter obs.

Table 5. BHC results for commercial and industrial loans

	(1) CI_Sigma	(2) CI_Sigma	(3) CI_Sigma	(4) CI_Sigma	(5) CI_Sigma	(6) CI_Sigma
d_BA	-0.017	-0.018	-0.017	-0.018	-0.020	-0.021
	[0.007]**	[0.007]**	[0.008]**	[0.007]**	[0.007]***	[0.008]***
d_84	-0.014	-0.015	-0.013	-0.014	-0.015	-0.016
	[0.004]***	[0.004]***	[0.004]***	[0.004]***	[0.005]***	[0.005]***
FedFunds	-0.205	-0.210	-0.200	-0.219	-0.070	-0.127
	[0.077]***	[0.076]***	[0.086]**	[0.077]***	[0.099]	[0.099]
t	0.254	0.288	0.243	0.286	0.305	0.343
	[0.195]	[0.179]	[0.212]	[0.184]	[0.198]	[0.197]*
CV_IP	-0.083					
	[0.098]					
CV_Infl		-0.031				
		[0.043]				
CV_IP_03			-0.107		-0.223	
			[0.150]		[0.148]	
CV_Infl_03				-0.018		-0.023
				[0.050]		[0.051]
Inflation					-0.002	-0.002
					[0.001]**	[0.001]*
LeadIndic					-0.001	-0.001
					[0.001]**	[0.001]
Constant	0.131	0.130	0.132	0.129	0.135	0.129
	[0.013]***	[0.012]***	[0.014]***	[0.013]***	[0.014]***	[0.013]***
Observations	96	96	96	96	96	96
R^2	0.51	0.51	0.51	0.50	0.56	0.54
$\hat{\eta}_{CV}$	-0.03	-0.02	-0.04	-0.01	-0.08	-0.02
s.e.	0.03	0.03	0.05	0.04	0.05	0.04

* significant at 10%; ** significant at 5%; *** significant at 1%

HAC standard errors shown. SD based on 585552 bank-quarter obs.

Table 6. COMPUSTAT annual results for total loans

	(1)	(2)	(3)	(4)	(5)	(6)
	Tot_Sigma	Tot_Sigma	Tot_Sigma	Tot_Sigma	Tot_Sigma	Tot_Sigma
d_BA	0.013	0.009	0.015	0.007	0.010	0.004
	[0.012]	[0.010]	[0.012]	[0.010]	[0.007]	[0.004]
FedFunds	-0.090	-0.071	-0.069	-0.139	-0.183	-0.339
	[0.111]	[0.098]	[0.172]	[0.134]	[0.132]	[0.074]***
t	1.260	1.708	0.970	1.525	1.487	1.929
	[1.020]	[0.779]**	[1.022]	[0.722]**	[0.676]**	[0.397]***
CV_IP	-0.255					
	[0.168]					
CV_Infl		-0.124				
		[0.038]***				
CV_IP_01			-0.362		-0.515	
			[0.186]*		[0.127]***	
CV_Infl_01				-0.146		-0.180
				[0.041]***		[0.032]***
Inflation					0.004	0.006
					[0.003]	[0.001]***
LeadIndic					-0.002	-0.001
					[0.001]***	[0.000]***
Constant	-2.378	-3.271	-1.799	-2.899	-2.826	-3.706
	[2.031]	[1.551]**	[2.035]	[1.439]**	[1.346]**	[0.791]***
Observations	22	22	21	21	21	21
R^2	0.84	0.87	0.83	0.86	0.91	0.95
$\hat{\eta}_{CV}$	-0.08	-0.08	-0.11	-0.09	-0.16	-0.12
s.e.	0.05	0.03	0.06	0.03	0.04	0.02

* significant at 10%; ** significant at 5%; *** significant at 1%

HAC standard errors shown. SD based on 10497 bank-year obs.

Table 7. COMPUSTAT annual results for loan categories

	(1) Real Est	(2) Real Est	(3) Househld	(4) Househld	(5) C & I	(6) C & I
d_BA	-0.002	-0.007	-0.002	-0.003	0.004	0.003
	[0.006]	[0.006]	[0.004]	[0.003]	[0.004]	[0.004]
FedFunds	-0.291	-0.399	-0.005	-0.040	0.163	0.148
	[0.152]*	[0.101]***	[0.060]	[0.042]	[0.132]	[0.093]
t	3.821	4.150	1.193	1.293	1.453	1.512
	[0.665]***	[0.572]***	[0.288]***	[0.260]***	[0.403]***	[0.414]***
Inflation	0.007	0.008	-0.001	-0.000	0.003	0.003
	[0.003]***	[0.002]***	[0.001]	[0.001]	[0.002]	[0.002]
LeadIndic	0.000	0.001	-0.002	-0.001	0.000	0.000
	[0.001]	[0.000]	[0.000]***	[0.000]***	[0.001]	[0.001]
CV_IP_01	-0.372		-0.116		-0.061	
	[0.126]***		[0.080]		[0.193]	
CV_Infl_01		-0.143		-0.041		-0.030
		[0.032]***		[0.019]**		[0.038]
Constant	-7.486	-8.141	-2.289	-2.488	-2.822	-2.939
	[1.324]***	[1.139]***	[0.572]***	[0.516]***	[0.803]***	[0.825]***
Observations	21	21	21	21	21	21
R^2	0.96	0.97	0.89	0.90	0.67	0.68
$\hat{\eta}_{CV}$	-0.12	-0.10	-0.05	-0.04	-0.02	-0.03
s.e.	0.04	0.02	0.04	0.02	0.08	0.03

* significant at 10%; ** significant at 5%; *** significant at 1%

HAC standard errors shown. SD based on 2934–2993 bank-year obs.

Figure 1. Loan-to-asset ratios

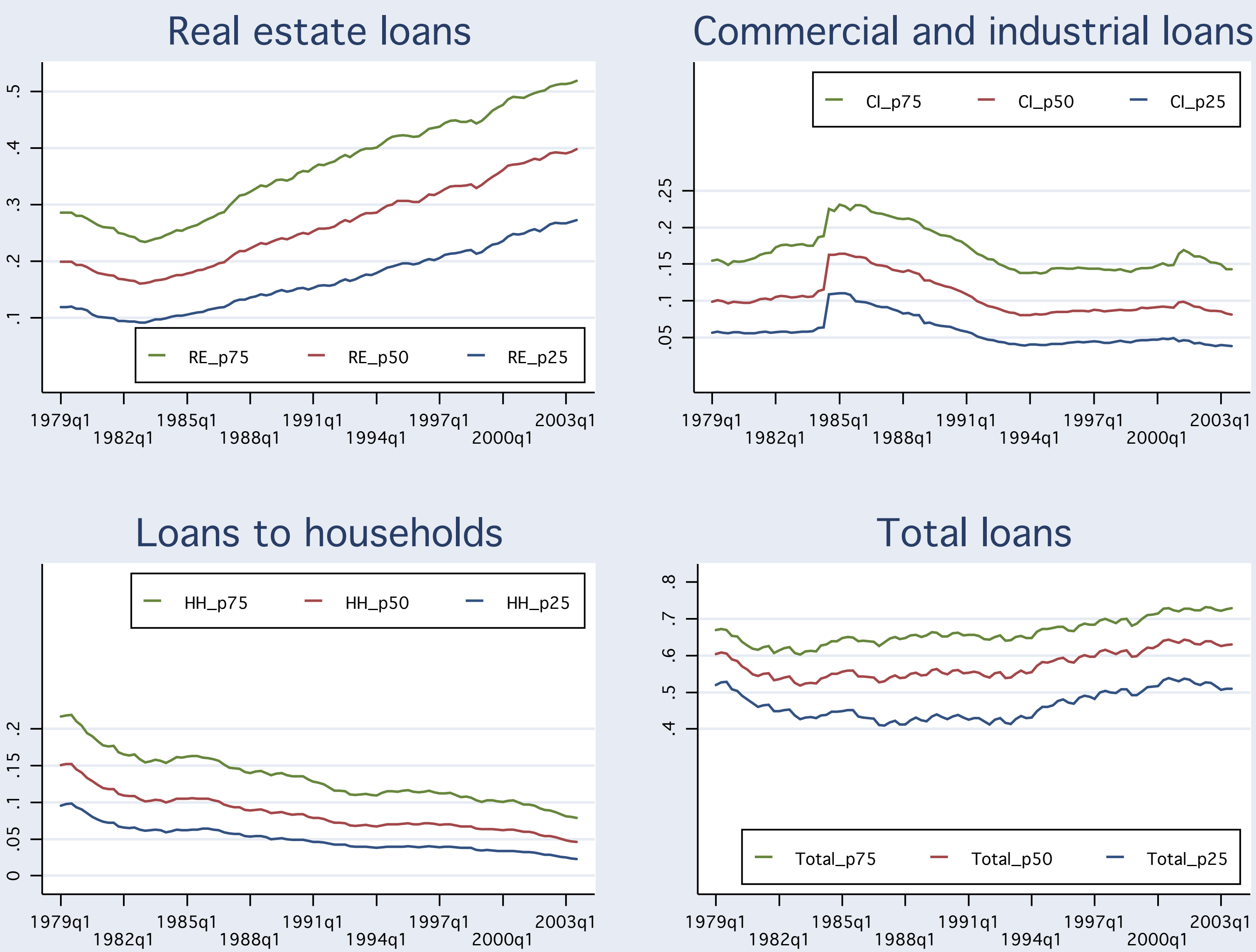
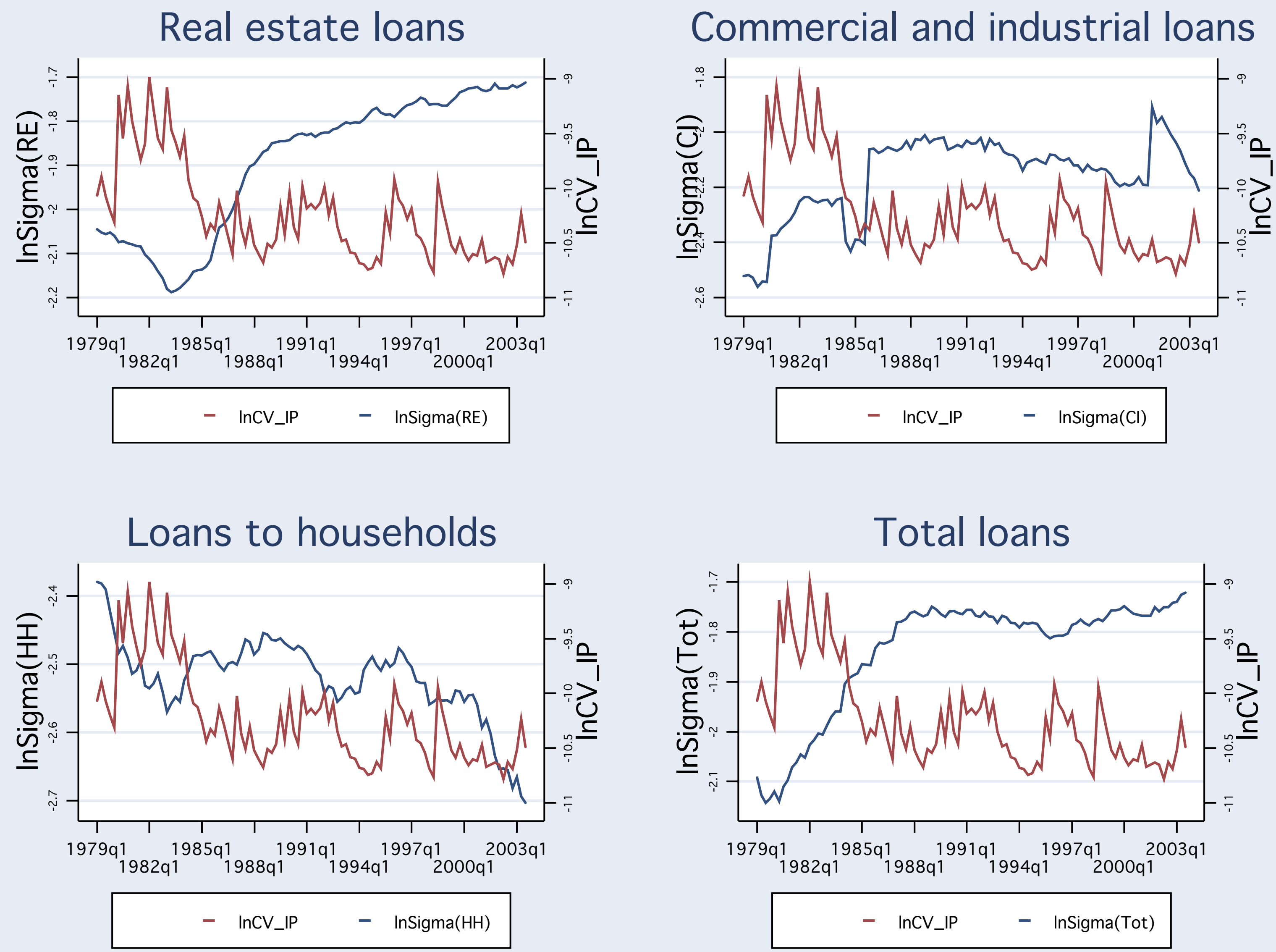


Figure 2. ln LTA Sigma vs ln conditional variance of IP



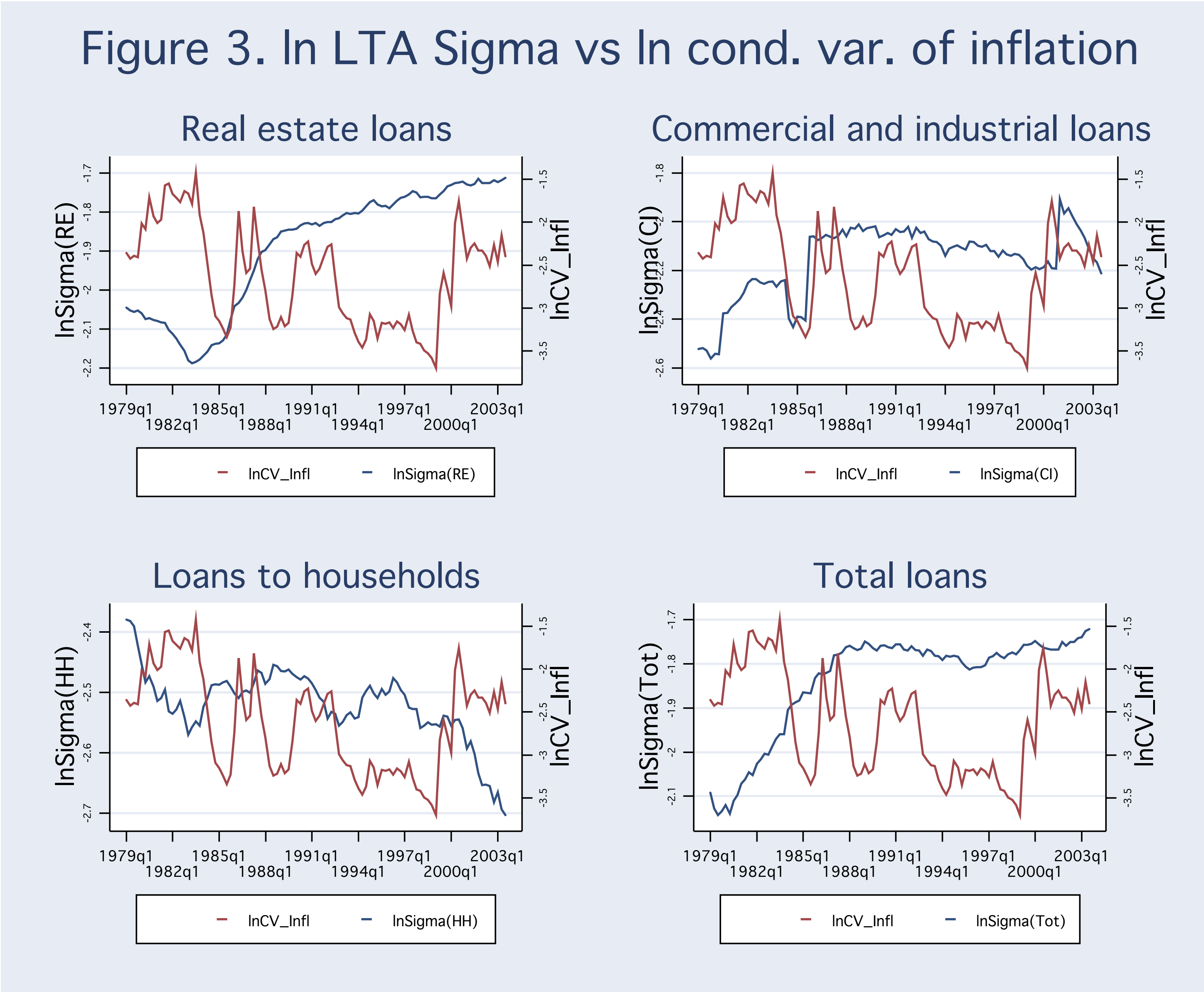


Figure 3. ln LTA Sigma vs ln cond. var. of inflation
Real estate loans
lnSigma(RE)
lnCV_Infl
lnCV_Infl
lnSigma(RE)
Commercial and industrial loans
lnSigma(CI)
lnCV_Infl
lnCV_Infl
lnSigma(CI)
Loans to households
lnSigma(HH)
lnCV_Infl
lnCV_Infl
lnSigma(HH)
Total loans
lnSigma(Tot)
lnCV_Infl
lnCV_Infl
lnSigma(Tot)
1979q1
1982q1
1985q1
1988q1
1991q1
1994q1
1997q1
2000q1
2003q1