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 allocation of loanable funds. To provide a road–map for our empirical investigation, we present a simple framework which demonstrates that an increase in macroeconomic uncertainty will lead to more homogeneous behavior among banks. We test this prediction on a comprehensive U.S. commercial bank data set, and find that as macroeconomic uncertainty increases the cross–sectional dispersion of banks' loan–to–asset ratios narrows, supporting our basic hypothesis. Our results are broadly similar across total loans and three major categories of bank loans, and robust to the inclusion of macroeconomic factors.

JEL: C22, C23, D81, E51.

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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 ratio evolve over time. Such an analysis would be very valuable as commercial banks are considered to be the main source of intermediated credit.[1] 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.[2] Hence, a reduction in private sector spending due to a reduction

[1]It is generally accepted that commercial banks play a special role in the macroeconomy. See Gatev and Strahan (2003) and the references therein.

[2]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 (2003).

in the supply of credit should not be surprising to anyone. In particular, firms that are small, non–rated or those with poor credit ratings—in short, those firms that suffer from asymmetric information problems—will be severely affected by any change in bank lending behavior.[3]

There are various reasons why banks' loan supply would change over time.[4] 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. 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).[5] 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 loans) causing them to rebalance their portfolios. Contrarily, when uncertainty is lower, returns will be more predictable leading to a wider dispersion of loan–to–asset ratios and an efficient allocation of funds in comparison with the high uncertainty case.

[3]See Schiantarelli (1996) for a survey on the role of financial constraints on firm' investment behavior. Also, see Myers and Majluf (1984) who investigate the investment behavior of firms under asymmetric information.

[4]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.

[5]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.

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 guide our empirical investigation, 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.

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. Our extract of this data set 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 1,264,185 bank–quarters.

Our empirical investigation yields the following observations. There is a clear negative association between proxies for macroeconomic uncertainty 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 as well—real estate loans, commercial and industrial loans, and loans to households—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 certainty equivalent framework, one need only consider the key indicators of macroeconomic performance and model the central bank's reaction function to evaluate the outcome of a stimulus to the supply of credit. However, since banks may rarely exhaust their lending capacity—i.e. become "fully loaned up"—it is crucial to evaluate the degree to which macroeconomic uncertainty—over and above the levels of macroeconomic aggregates—will affect the banking sector's willingness to utilize available funds. 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) will matter. As our empirical analysis clearly demonstrates the effects of second–moment variables on bank lending behavior, we believe that this message—the second moments matter—should be of key relevance to economic policymakers.

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. Even for larger firms, Kashyap et al. (1996) find that there is a significant substitution away from bank loans during episodes of tight monetary policy. 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 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 this behavior could

[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.

[7]Although banks' expected returns from their loan portfolio are much higher than

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]

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 some stochastic return 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

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.

[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.

$Var(premium_{i,t}) = \sigma^2_{\epsilon,t}$.[11] 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 $\epsilon_{i,t} \sim N(0, \sigma^2_{\epsilon,t})$.[12] Variations in $\sigma^2_{\epsilon,t}$ may be considered 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 be interested in maximizing the expected returns on loans only. However, banks would not exist in such a world.[13] Due to financial market failures, such as moral hazard and adverse selection problems, banks invest in private information.[14] Hence, we assume that the bank manager, prior to allocating bank assets between the risky and risk free alternatives, observes a noisy signal on $\epsilon_{i,t}$ in the form of $S_{i,t} = \epsilon_{i,t} + \nu_t$, where 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.[15] The noise in this sense is taken as a proxy for the degree of macroeconomic uncertainty and it affects all banks similarly.[16] In times

[11]Note that the actual risk premium is not fixed, as it varies over time as $\epsilon_{i,t}$ changes.

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

[13]See Cebenoyan and Strahan (2004) on risk management and bank lending.

[14]For example, the literature on the bank lending channel rests on asymmetric information between banks and purchasers of time deposits.

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

[16]If all banks were to reveal their signal to a private agent, the law of large numbers would allow ν_t to be observed, fully eliminating the uncertainty. However, this strategy

of greater turmoil in the economy, 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 behaving more predictably, 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. However, we must emphasize that without the additional information contained in $S_{i,t}$, it would 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 $\lambda_t = Cov(\epsilon_{i,t}, S_t)/Var(S_{i,t}) = \frac{\sigma^2_{\epsilon,t}}{\sigma^2_{\epsilon,t}+\sigma^2_{\nu,t}}$.[17] 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

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)).

[17] Simple application of a linear regression allows the manager in an uncertain environment to predict the "unobserved variable in a manner that is optimal, in a certain sense." (Sargent (1987), p. 223).

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

$$E(\tilde{U}_{i,t}|S_{i,t}) = E(\tilde{Y}_{i,t}|S_{i,t}) - \frac{1}{2}\alpha Var(\tilde{Y}_{i,t}|S_{i,t}), \tag{3}$$

where α is the coefficient of risk aversion.[18] Given equations (**??**) and (**??**), we can easily derive the i^{th} bank's optimal loan–to–asset (LTA) ratio as:

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

Equation (**??**) indicates that each bank's optimal loan–to–asset ratio is stochastic, as it is positively related to the signal observed by the manager, as well as to both $\sigma^2_{\epsilon,t}$ and $\sigma^2_{\nu,t}$. Unfortunately, we cannot use this equation to empirically investigate how the level of the loan–to–asset ratio changes in response to macroeconomic uncertainty since it contains the unobservable and idiosyncratic signal $S_{i,t}$. Nevertheless, this equation leads to a clear–cut link between macroeconomic uncertainty (as captured through the variance of the noise in the signal) and variations in the cross–sectional distribution of banks' LTA ratios. Computing the variance of the cross–sectional distribution of the loan–to–asset ratio

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

[18]Although the introduction of risk aversion may seem stringent, we consider it as a reasonable stylized approximation to 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) desire to avoid risk of ruin, an assumption of risk aversion on their part is a reasonable one.

we observe that it is related to both $\sigma^2_{\epsilon,t}$ and $\sigma^2_{\nu,t}$.[19] As equation (**??**) shows, 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. This will lead to more heterogeneous behavior on the part of bank managers, and a widening of the cross–sectional distribution. Conversely, as shown in equation (**??**) below, 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:

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

This arises because when the true returns are harder to predict, banks behave more similarly, leading to a narrowing in the cross–sectional distribution and implying a homogeneous behavior among banks. In contrast, when the signal becomes more informative (i.e., when $\sigma^2_{\nu,t}$ becomes smaller) the predictability of loan returns improves and leads to a widening of the cross–sectional distribution of the loan–to–asset ratio, which corresponds to more heterogeneous behavior as each manager responds more accurately to differences in the profitability of loans to potential borrowers.

To provide support for our hypothesis as depicted by equation (**??**), 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

[19] Recall that ν_t does not vary across banks. Hence, (**??**) follows.

macroeconomic uncertainty at time t and e_t is an *i.i.d.* error term. We expect to find the spread of the distribution of LTA ratios—the heterogeneity exhibited by commercial banks' diverse behavior—will be negatively related to a measure of macroeconomic uncertainty, and that these effects may systematically vary across classes of banks. 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.

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.[20] Therefore, we rewrite equation (**??**) 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.[21]

Our proxies for macroeconomic uncertainty are derived from monthly industrial production (International Financial Statistics series $66IZF$) and

[20] 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.

[21] Although $\hat{h}_t$ is a generated regressor, the coefficient estimates for equation (2) are consistent; see Pagan (1984, 1986).

from consumer price inflation (IFS series $64XZF$).[22] 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).[23] 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 ($\hat{h}_t$).

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.[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

[22] 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.

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

[24] 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.

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 available, 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_t 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)

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

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 (**??**), 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.

From these figures, the presence of a statistically negative effect between these variables should not be surprising. Our model predicts that a reduc-

[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.

tion in macroeconomic uncertainty (as evidenced, in broad terms, by the movements of either proxy in Figures 2 and 3) will coincide with an increase in the heterogeneity of banks' behavior. That is, we would expect that the dispersion of banks' LTA ratios will increase as macroeconomic uncertainty wanes.

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 those tables, we present OLS regression results (with heteroskedasticity– and autocorrelation-consistent standard errors) for each of the proxy series. 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. Along with the contemporaneous uncertainty measures, we consider 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 the tables 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 Ba-

[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.

sic 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 C&I loans, we included a dummy variable for 1984 to capture the effects of the redefinition of C&I loans between 1984Q2–1984Q3.

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 over a 20+ 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.[29] 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

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

[29] For the sample period under consideration, the mean conditional variance (at a quarterly frequency) for IP is 0.0400, with values ranging from 0.0207 to 0.1256. Similar figures for the conditional variance of the CPI inflation rate are 0.0859, 0.0248 and 0.2403. Hence, it should be no surprise to see a doubling of uncertainty in some periods as well as its halving in some others.

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 1% level for IP variance and at the 10% level of significance when the variance of inflation is used. A similar exercise as 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 investigate 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.

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. The empirical results 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 example, one strand of literature discusses the idea that uncertainty leads to distortion in the efficient allocation of capital investment while another investigates whether small macroeconomic shocks could lead to large effects: the 'small shocks large cycles' puzzle. When we consider the first strand, 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. Studies in the second strand—for example, 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 overall economic significance of reducing macroeconomic uncertainty would be quite substantial. We believe that this message may be key relevance to economic policymakers, and that further research along these lines would be useful.

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) $\log(IP)$	(2) $\log(\dot{P})$
$\log(IP)_{t-1}$	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%

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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. These statistics are based on 1,260,093 bank–quarters: 758,672 bank–quarters prior to 1992 and 482,534 bank–quarters thereafter.

Table 2. Results for total loans

	(1)	(2)	(3)	(4)	(5)	(6)
	Tot_Sigma	Tot_Sigma	Tot_Sigma	Tot_Sigma	Tot_Sigma	Tot_Sigma
d_BA	-0.017	-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

Robust standard errors in brackets

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

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

Table 3. Results for real estate loans

	(1) RE_Sigma	(2) RE_Sigma	(3) RE_Sigma	(4) RE_Sigma	(5) RE_Sigma	(6) 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

Robust standard errors in brackets

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

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

Table 4. Results for loans to households

	(1)	(2)	(3)	(4)	(5)	(6)
	HH_Sigma	HH_Sigma	HH_Sigma	HH_Sigma	HH_Sigma	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

Robust standard errors in brackets

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

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

Table 5. 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

Robust standard errors in brackets

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

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

Figure 1. Loan-to-asset ratios

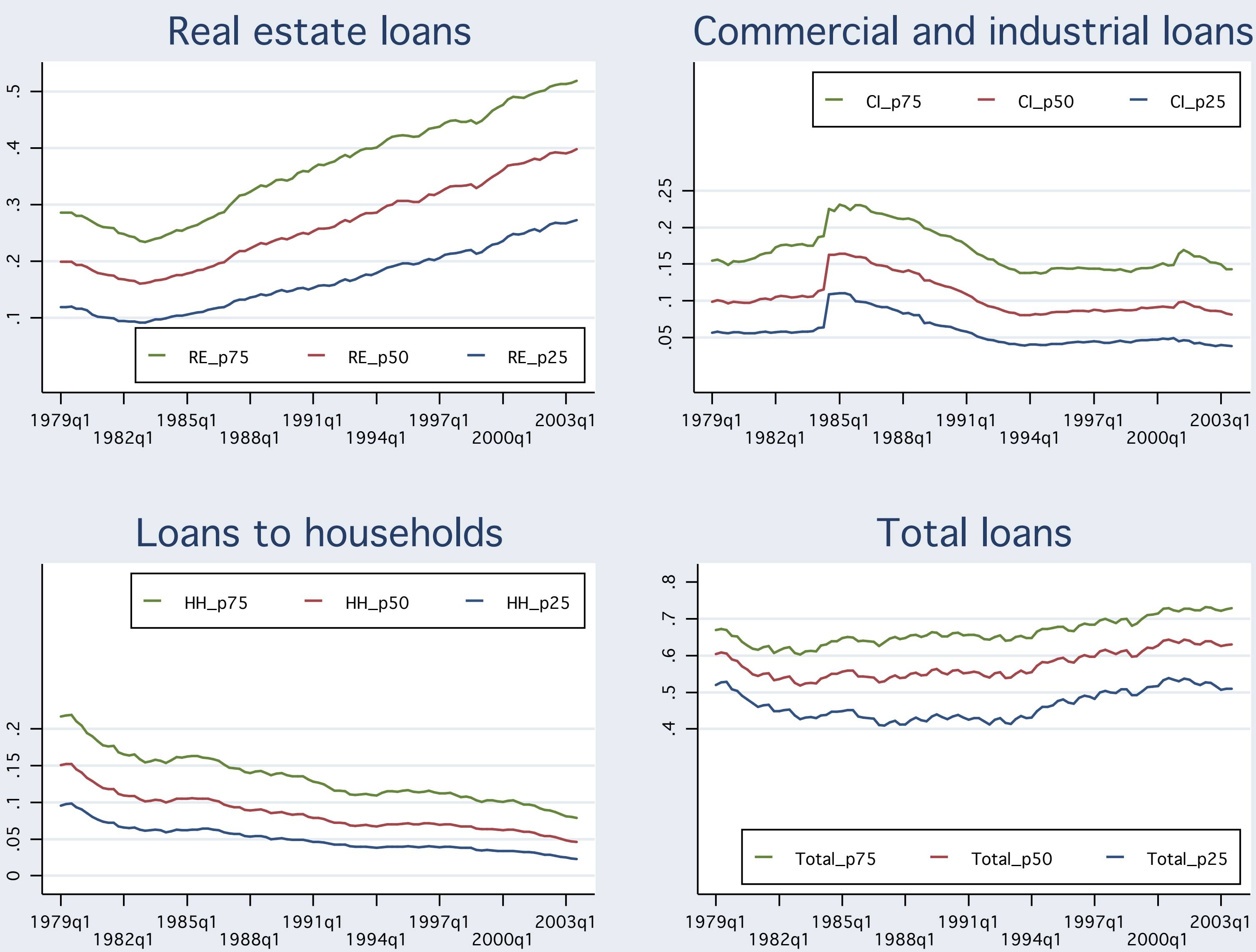

Figure 2. ln LTA Sigma vs ln conditional variance of IP

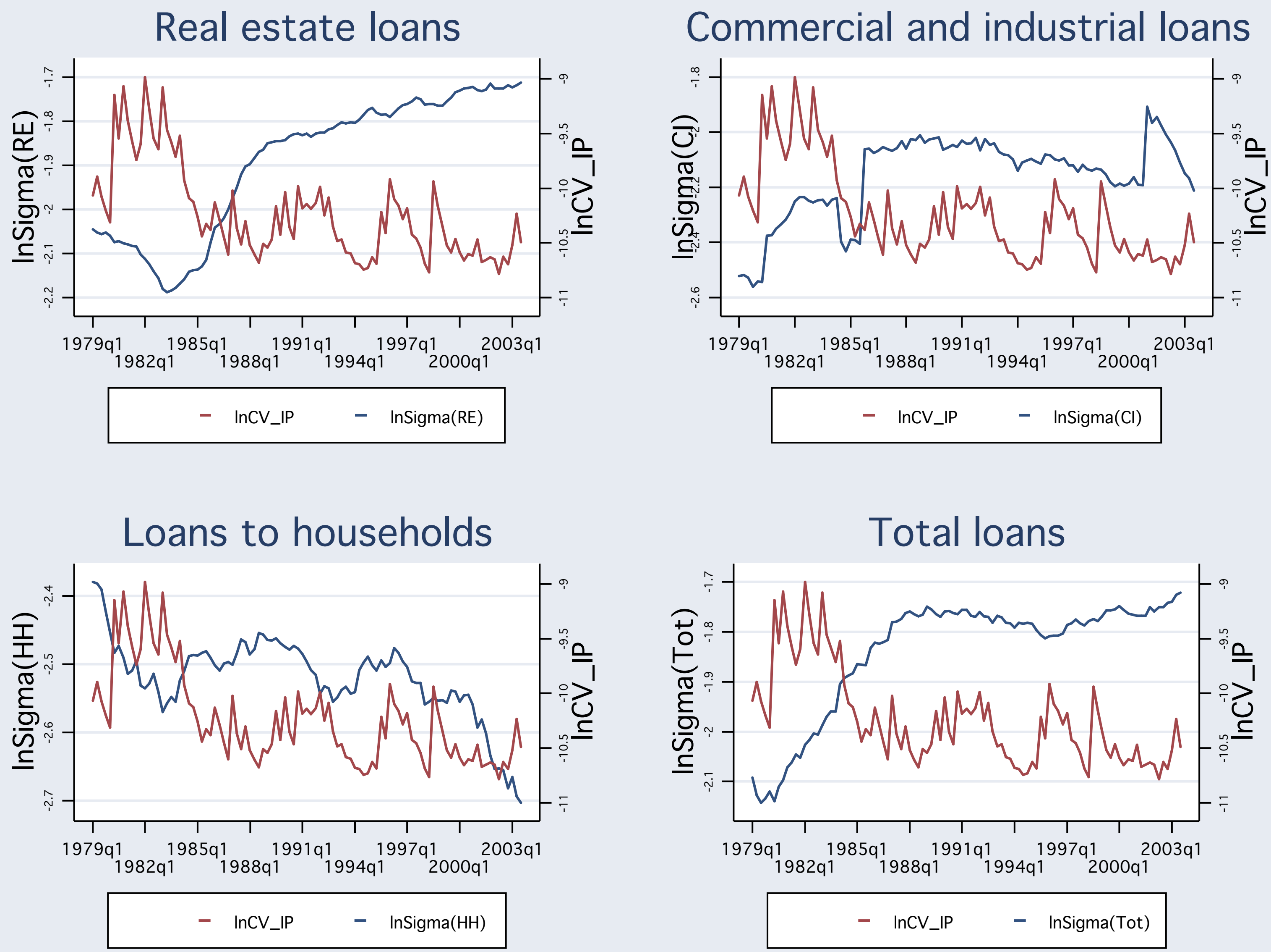

Figure 3. ln LTA Sigma vs ln cond. var. of inflation