The second moments matter: The response of bank lending behavior to macroeconomic uncertainty

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December 25, 2005

*We thank Evren Ors, Richard Arnott, participants at the Eighth International Conference of the Society for Computational Economics; the 2003 European Meetings of the Econometric Society; the Macro, Finance and Understanding the Evolving Macroeconomy Programme Conference, University of Warwick; and the Middle East Technical University VI International Economics Symposium, as well as seminar participants at the University of Zaragoza, University of Oklahoma, University of Bristol, University of Liverpool, Brandeis University, Boston College, Queen Mary-University of London, Bilkent University, Koç University and Sabanci University for their comments on earlier drafts. We are grateful to Oleksandr Talavera for excellent research assistance. The standard disclaimer applies. Corresponding author: Christopher F. Baum, Department of Economics, Boston College, Chestnut Hill, MA 02467 USA, Tel: 617-552-3673, fax 617-552-2308, e-mail: baum@bc.edu.

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Abstract

This paper investigates whether variations in macroeconomic uncertainty distort banks' allocation of loanable funds by affecting the predictability of banks' returns from lending. Low levels of macroeconomic uncertainty will allow bankers to base their lending decisions on more accurate evaluations of different lending opportunities, leading to a more unequal distribution of lending across banks. Contrarily, increased macroeconomic uncertainty will hinder bankers' ability to identify and channel funds towards the best opportunities, inducing more similar lending behavior across banks. Our empirical analysis provides support for the hypothesis that macroeconomic uncertainty adversely affects the efficient allocation of loanable funds.

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), and 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 variation in bank lending behavior may have a serious impact on these disadvantaged borrowers.[2]

There are various reasons why banks' lending behavior would change over time. 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 would tend to distort the efficient allocation of loanable funds. In particular, we claim that higher uncertainty will hinder the ability of the bank manager to accurately predict returns from available lending opportunities. Contrarily, when the macroeconomic environment is more tranquil, returns from each potential project will be more easily predictable allowing the bank manager to lend to the projects with higher expected returns. This 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. In this view, stability of the macroeconomic environment will favor more efficient allocation of loanable funds.

To test these claims, we investigate whether changes in macroeconomic uncertainty explain the time variation in the *cross-sectional dispersion* of

[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.

loan-to-asset ratios of banks. We expect to find that the cross-sectional dispersion of loan-to-asset ratios narrows as greater economic uncertainty hinders managers' ability to accurately evaluate the expected returns from lending. Furthermore, we investigate whether a reduction in macroeconomic uncertainty leads to a more unequal distribution of lending across banks as managers take advantage of more accurate information about different lending opportunities. In that case, macroeconomic tranquility would lead to a widening of the cross-sectional distribution of banks' loan-to-asset ratios.

Answers to these questions will not only complement the investigation carried by McEvoy (1956), but also will give us another reason to promote macroeconomic stability to stimulate the efficient allocation of resources. Beaudry, Caglayan and Schiantarelli (2001) put this claim into close empirical scrutiny by investigating the impact of aggregate price uncertainty on the time-variation in the cross-sectional distribution of investment at the aggregate and the industry level. Using UK firm level data, they show that the cross-sectional distribution of firm investment narrows—implying more homogeneous investment behavior across firms during times of uncertainty—whereas a reduction in inflation uncertainty leads to a widening of the dispersion as higher-quality information allows firms to invest in projects with differing expected returns. Their findings provide evidence that inflation uncertainty hinders the efficient allocation of resources. The empirical approach we follow here is closely related to that of Beaudry et al. as we test for the effects of macroeconomic uncertainty on commercial banks' allocation of loans.[3]

[3]A related paper by Baum, Caglayan, Ozkan and Talavera (2006) investigates the relationship between firms' cash holdings and uncertainty. They show that an increase in uncertainty induces similar movements in firms' cash-to-asset ratios whereas economic tranquility promotes more idiosyncratic behavior across firms.

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 uncertainty and the cross-sectional variability of banks' loan-to-asset ratios: that is, banks' lending behavior becomes more homogeneous in times of increased uncertainty. This association strongly holds for total bank loans and for two major loan components—real estate loans and loans to households—showing that our results are not driven by aggregation but are genuine. However, we obtain mixed results for the commercial and industrial loans category, which might be due to the presence of firm–specific characteristics such as existence of credit lines between banks and firms during times of uncertainty. Finally, 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.

Our approach to investigating the bank lending behavior across banks, to our knowledge, is unique in the banking literature as we concentrate on the *distribution* of bank lending and analyze the behavioral impact of uncertainty on all banks in the US. However, similar to Beaudry et al. (2001), our main purpose is to evaluate the consequences of uncertainty on the allocation of resources, in this case loanable funds. The rest of the paper is constructed as follows. Section 2 discusses how macroeconomic uncertainty may affect the lending behavior of banks. 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 fully loan available funds.[4] 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 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 pa-

[4] 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.

per 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, 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.[5] 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 often be correlated with macroeconomic conditions, as well as with financial-market outcomes such as changes in the cost of short-term funds.[6]

[5]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.

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

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.[7] This implies that banks readjust their exposure to risky loans in the face of changes in perceived uncertainty about macroeconomic factors, and the resulting likelihood of borrowers' default, leading to variations in the cross-sectional distribution of loan-to-asset ratios over time.

In the next section, we lay out the reduced form relationship that links macroeconomic uncertainty to time variation in the cross-sectional distribution of banks' loan-to-asset (LTA) ratios. We stress that our main concern in this paper is not to test a specific model but to document and verify the presence of an empirical relationship.[8] We should also note that we do not investigate the impact of uncertainty on the representative bank's lending behavior, nor the changes in banks' levels of deposits. These questions are beyond the scope of the paper. However, both questions are interesting and important, and have been investigated by various researchers including Baum, Caglayan and Ozkan (2004) and Gatev and Strachan (2003). Considering these papers along with the current study should lead to a better understanding of bank lending behavior under uncertainty.

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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).

[7]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.

[8]Appendix C presents a simple framework that provides a mechanism showing how the empirical model could arise.

2.1 The reduced form model

The negative relationship between macroeconomic uncertainty and the cross-sectional variation of banks' LTA ratios can be intuitively explained as follows. During tranquil periods, each bank responds 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, 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.

To provide support for our hypothesis, we consider the following reduced form relationship:

$$Disp_t(L_{it}/TA_{it}) = \beta_0 + \beta_1 \sigma^2_{\nu,t} + e_t, \tag{1}$$

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.

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.[9] Therefore, we rewrite equation (1) in the following form:

$$Disp_t(L_{it}/TA_{it}) = \beta_0 + \beta_1 \hat{h}_t + e_t, \tag{2}$$

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.[10]

Our proxies for macroeconomic uncertainty are derived from monthly industrial production (International Financial Statistics series $66IZF$) and from consumer price inflation (IFS series $64XZF$).[11] 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).[12] 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 ($\hat{h}_t$). In some of the estimated models, we use a weighted average of the current and last three quarters' conditional variances.

[9]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.

[10]Although $\hat{h}_t$ is a generated regressor, the coefficient estimates for equation (2) are consistent; see Pagan (1984, 1986). We employ instrumental variables estimation to mitigate any problems of measurement error in the construction of these proxies.

[11]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.

[12]Details of the GARCH models for CPI and IP are given in Appendix B.

We tested each of these constructed proxies for stationarity via DF-GLS and Clemente–Montañés–Reyes (CMR) unit root tests. The DF-GLS test is an improved version of the Augmented Dickey–Fuller test, while the CMR tests examine the series allowing for the presence of one or two innovational outlier (IO) structural breaks.[13] Although the DF-GLS tests were unable to reject the null of $I(1)$ for the conditional variance of industrial production or its weighted average, the CMR tests were able to reject the unit root null for either one or two structural breaks for those series. Both the DF-GLS and CMR tests handily rejected their $I(1)$ null for the conditional variance of inflation. Detailed results are available on request.

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 covers 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.[14] 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

[13] For more details on the CMR test, please see [1].

[14] 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.

US over the 1980–2002 period.[15]

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.[16]

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 55% 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.

[15] 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.

[16] Details of the construction of these measures from the BHC database are presented in Appendix A.

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. We also may note the general decline in the importance of C&I lending through 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).[17] The visible increase in loan-to-asset ratios over the sample period appears to be driven by real estate loans, which are displacing the traditional C&I loans as a larger fraction of banks' loan portfolios.

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 (2), we use the standard deviation of the loan-to-asset ratio (LTA_Sigma) as a measure of the cross-sectional dispersion of bank loans.[18]

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 three

[17] A redefinition of C&I loans in 2001Q1 created a break in this series. Consequently, our empirical work uses data through 2000Q4 for this category of loans.

[18] 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.

loan categories. In Table 2–7, we present instrumental variables–generalized method of moments (IV-GMM) regression results with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors for each of the proxy series.[19] 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.[20] 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. 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.[21]

[19] Instruments used include several lagged values of both conditional variance series. The J statistic in these tables is Hansen's test of overidentifying restrictions, with their p-values given below.

[20] 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.

[21] 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. All estimated models include the Federal funds rate to capture the stance of monetary policy, d_BA to capture the possible effects of the Basel Accord and a time trend to reflect secular movements in bank lending behavior and the level of macroeconomic uncertainty. The 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 IP and CPI inflation. We find that, at the end of one year, the dispersion of the LTA ratio for total loans declines by 9.2% and 5.7%, respectively, each significantly different from zero.

Next, in Tables 3–5 we examine the same relationship for three major components of loans: real estate loans, household loans and commercial and industrial loans. Results for the real estate loan category (Table 3) are quite strong, with each model's uncertainty coefficients negative and significant at the 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 11.2% and 6.3% 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 10.4% and 6.6% 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 results for the commercial and industrial loans category. Contrary to results presented earlier, the effect of macro uncertainty exhibits a significant positive sign in all models. The one-year cumulative effect of a 100 per cent increase in uncertainty as captured by the conditional variance of IP causes a 12.0% widening in the dispersion of C&I loans, while that of CPI inflation rate leads to a widening of 8.3%, both of which are distinguishable from zero. This observation contrasts with our hypothesis that increases in macroeconomic uncertainty are expected to lead to a narrowing of the dispersion. However, one can rationalize this finding by recalling that U.S. banks make over 80 percent of all commercial and industrial loans via loan commitments (Shockley and Thakor (1997)). It has been argued that loan commitments—whereby banks sell promises to extend future credit to their customers at partially predetermined terms—have been widely used as an essential element of relationship banking. Relationship banking can partially overcome capital market frictions and lower firms' cost of external finance. Thus, during times of uncertainty firms can benefit from relationship banking and have access to C&I loans, which tend to be based on "soft information" (Berger and Udell, 2004). In that case, given banks' prior commitments, we would not necessarily expect homogenous behavior in banks' C&I lending in response to increased macro uncertainty.

3.2.3 Summary of BHC results

While commercial and industrial loans yield contrasting results to our proposition, 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 9–11% (5–7%) reduction in the dispersion of banks' loan-to-asset ratios for total loans, real estate loans and household loans. These findings support the view that uncertainty distorts the efficient allocation of funds across potential borrowers. However, we also note that our measures of macroeconomic uncertainty appears to cause an expansion in the dispersion of banks' C&I loan-to-asset ratios. As mentioned above, this finding is in line with the fact that the preponderance of C&I loans are made via loan commitments as a part of relationship banking, which could help firms have access to loans during times of uncertainty.

3.2.4 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 (2) 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. The models including the conditional variance of inflation all have negative and statistically significant coefficients for that variable, even when controlling for the level effects of interest rates, inflation and the leading indicators. Those including the conditional variance of industrial production lack statistical significance, but have the expected negative sign in two of three cases. 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 household loans, and to a lesser degree for real estate loans. The COMPUSTAT results for C&I loans echo the positive association with uncertainty for the IP-based measure, while lacking significance for the inflation-based measure. This weakness of the model for C&I loans may reflect the presence of other significant factors, such as firm-specific evaluation of borrowers' prospects (based on "soft information") or extensive use of loan commitments (lines of credit) by borrowers.

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 similar in magnitude to that estimated from the universe of commercial banks in the BHC database, despite the size and presumed market power of the banks in the COMPUSTAT sample. The effect of a 100 per cent increase in uncertainty proxied by IP (CPI inflation) is a 6.4% (11.4%) reduction in the dispersion of banks' total 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 should have clear effects on banks' lending strategies over and above the movements of macroeconomic aggregates or the constraints posed by monetary policymakers' actions so as to distort the efficient allocation of loanable funds. In particular, we evaluate the role of macroeconomic uncertainty in explaining the time variation in the cross-sectional dispersion of loan-to-asset ratios of banks. We investigate whether the presence of greater macroeconomic uncertainty leads to a narrowing of that dispersion, and conversely, whether economic tranquility would provide banks with the latitude to behave more idiosyncratically, leading to a widening of the cross-sectional dispersion of banks' LTA ratios.

To test this claim, 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 macroeconomic uncertainty leads to a narrowing of the dispersion of banks' loan-to-asset ratios, disrupting the efficient allocation of loanable funds. Our findings hold for total loans and its two major components—real estate loans and household loans—showing that the results are not driven by aggregation. However, our analysis yield mixed results when we investigate commercial and industrial loans which could reflect the importance of relationship lending and loan commitments in that lending sector. Finally, 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) document 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. A recent paper by Baum, Caglayan, Ozkan and Talavera (2006) shows that increased uncertainty induces similar movements in non-financial firms' cash-to-asset ratios while economic tranquility promotes more idiosyncratic behavior across firms. In this study, we provide evidence 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 6% to 12% in banks' loan-to-asset ratios' dispersion in response to a doubling of macroeconomic uncertainty. Although we do not provide an analysis regarding welfare consequences, we conjecture that the overall impact of reducing macroeconomic uncertainty would be quite substantial and 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 (2000). 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, 1979Q1–2000Q4

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%

Appendix C: A simple analytical framework

The analytical framework we present here is a variant of the island model used by Lucas (1973).

Each period, the bank manager allocates x per cent of total assets as loans to the private sector and $(100-x)$ per cent to securities to maximize bank profits. The securities provide the risk free return $(r_{f,t})$. The risky loans yield a stochastic return based on a time-varying risk premium denoted by $\tilde{r}_{i,t} = r_{f,t} + premium_{i,t}$. 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 $\epsilon_{i,t} \sim N(0, \sigma^2_{\epsilon,t})$. Variations in $\sigma^2_{\epsilon,t}$ are observable, but a bank manager does not know what her draw from this distribution will be at a point in time. Also assume that $\epsilon_{i,t}$ is orthogonal to $\epsilon_{j,t}$: each bank has a specific set of borrowers with different risk structures.

Although the bank manager, prior to allocating bank assets between the risky and risk free alternatives, cannot observe the risk premium, 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 normally distributed as $\nu_t \sim N(0, \sigma^2_{\nu,t})$ and independent of $\epsilon_{i,t}$. (Though the bank manager cannot observe $\sigma^2_{\nu,t}$, she may form an optimal forecast of that quantity.) Each bank manager observes a different signal and the noise component of the observed signal in all cases is identical, which proxies for the degree of macroeconomic uncertainty. 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, and vice versa.

Within this framework, 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. 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 $\lambda_t = \frac{\sigma^2_{\epsilon,t}}{\sigma^2_{\epsilon,t}+\sigma^2_{\nu,t}}$. Therefore, at each point in time, total expected returns conditional on the signal takes the form

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

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

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

Modeling 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

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

where α is the coefficient of risk aversion, we can easily derive the i^{th} bank's optimal loan-to-asset (LTA) ratio as:

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

Next, we compute the variance of the cross-sectional distribution of the loan-to-asset ratio

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

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.[1] An increase in macroeconomic uncertainty, as captured by an increase in $\sigma^2_{\nu,t}$, leads to a decrease in the cross-sectional variance of the LTA ratio:

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

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

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

	μ	σ	p_{25}	p_{50}	p_{75}
Full sample					
RE	0.260	0.164	0.139	0.237	0.356
CI	0.111	0.090	0.049	0.090	0.150
HH	0.106	0.085	0.049	0.087	0.142
Total	0.548	0.162	0.457	0.568	0.660
Pre-1992					
RE	0.215	0.139	0.116	0.197	0.289
CI	0.121	0.096	0.055	0.099	0.164
HH	0.121	0.085	0.061	0.103	0.162
Total	0.534	0.153	0.446	0.551	0.641
1992-2003Q3					
RE	0.330	0.174	0.206	0.325	0.446
CI	0.092	0.074	0.042	0.076	0.122
HH	0.083	0.079	0.036	0.065	0.106
Total	0.569	0.172	0.480	0.597	0.689

Note: RE, CI, HH refer to loan-to-asset ratios for real estate loans, commercial and industrial loans, and loans to households, respectively. CI statistics cover the period 1979q1–2000q4. 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, 1980q4–2003q3

	(1)	(2)	(3)	(4)	(5)	(6)
CV_IP	-0.420***					
	(0.050)					
CV_IP_03			-0.430***		-0.384***	
			(0.042)		(0.042)	
CV_Infl		-0.134***				
		(0.018)				
CV_Infl_03				-0.117***		-0.111***
				(0.019)		(0.018)
Inflation					0.002**	0.002**
					(0.001)	(0.001)
LeadIndic					0.001*	0.001**
					(0.000)	(0.000)
FedFunds	-0.115***	-0.181***	-0.124***	-0.189***	-0.211***	-0.296***
	(0.032)	(0.038)	(0.030)	(0.035)	(0.049)	(0.055)
d_BA	-0.009**	-0.021***	-0.009**	-0.018***	-0.007	-0.014**
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
t	0.210*	0.413***	0.172*	0.378***	0.135	0.234*
	(0.091)	(0.101)	(0.087)	(0.105)	(0.091)	(0.109)
Constant	0.181***	0.175***	0.184***	0.175***	0.184***	0.181***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
Quarters	92	92	92	92	92	92
$\hat{\eta}$	-0.100	-0.069	-0.103	-0.060	-0.092	-0.057
s.e.	0.012	0.009	0.010	0.010	0.010	0.009
J	6.985	7.804	5.884	10.364	7.313	10.649
J pvalue	0.430	0.350	0.553	0.169	0.397	0.155

HAC IV-GMM estimates, based on 1241206 bank-quarter obs.

$*$ <10%, **<5%, ***< 1%

Table 3: BHC results for real estate loans, 1980q4–2003q3

	(1)	(2)	(3)	(4)	(5)	(6)
CV_IP	-0.354***					
	(0.078)					
CV_IP_03			-0.400***		-0.443***	
			(0.071)		(0.076)	
CV_Infl		-0.097***				
		(0.020)				
CV_Infl_03				-0.098***		-0.115***
				(0.025)		(0.022)
Inflation					0.003***	0.003***
					(0.000)	(0.001)
LeadIndic					-0.001**	-0.001
					(0.000)	(0.000)
FedFunds	0.094	0.030	0.101	0.028	-0.081	-0.159**
	(0.055)	(0.052)	(0.057)	(0.057)	(0.059)	(0.056)
d_BA	0.008	-0.003	0.007	-0.002	0.002	-0.006
	(0.005)	(0.006)	(0.006)	(0.006)	(0.003)	(0.004)
t	0.563***	0.748***	0.538***	0.723***	0.614***	0.822***
	(0.120)	(0.122)	(0.123)	(0.126)	(0.093)	(0.090)
Constant	0.128***	0.123***	0.131***	0.125***	0.132***	0.121***
	(0.009)	(0.008)	(0.009)	(0.009)	(0.006)	(0.006)
Quarters	92	92	92	92	92	92
$\hat{\eta}$	-0.089	-0.052	-0.102	-0.053	-0.112	-0.063
s.e.	0.020	0.011	0.018	0.014	0.019	0.012
J	8.155	7.543	8.418	7.362	9.010	7.783
J pvalue	0.319	0.375	0.297	0.392	0.252	0.352

HAC IV-GMM estimates, based on 1245923 bank-quarter obs.

$*$ <10%, **<5%, ***< 1%

Table 4: BHC results for household loans, 1980q4–2003q3

	(1)	(2)	(3)	(4)	(5)	(6)
CV_IP	-0.212***					
	(0.035)					
CV_IP_03			-0.214***		-0.211***	
			(0.024)		(0.027)	
CV_Infl		-0.067***				
		(0.009)				
CV_Infl_03				-0.065***		-0.062***
				(0.009)		(0.010)
Inflation					0.000	0.000
					(0.000)	(0.000)
LeadIndic					-0.000	-0.000
					(0.000)	(0.000)
FedFunds	0.085***	0.039*	0.080***	0.026	0.072**	0.009
	(0.020)	(0.019)	(0.015)	(0.018)	(0.024)	(0.024)
d_BA	0.001	-0.001	0.002	-0.001	0.001	-0.003
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
t	-0.131**	-0.088**	-0.157***	-0.092**	-0.124**	-0.071
	(0.046)	(0.033)	(0.040)	(0.035)	(0.044)	(0.040)
Constant	0.089***	0.088***	0.090***	0.089***	0.089***	0.089***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Quarters	92	92	92	92	92	92
$\hat{\eta}$	-0.103	-0.070	-0.106	-0.068	-0.104	-0.066
s.e.	0.017	0.010	0.012	0.009	0.013	0.010
J	6.347	8.220	6.452	8.357	5.991	8.853
J pvalue	0.500	0.314	0.488	0.302	0.541	0.263

HAC IV-GMM estimates, based on 1205914 bank-quarter obs.
$*$ <10%, **<5%, ***< 1%

Table 5: BHC results for C&I loans, 1980q4–2000q4

	(1)	(2)	(3)	(4)	(5)	(6)
CV_IP	0.145***					
	(0.034)					
CV_IP_03			0.204**		0.249***	
			(0.068)		(0.058)	
CV_Infl		0.045**				
		(0.014)				
CV_Infl_03				0.080**		0.087***
				(0.027)		(0.022)
Inflation					-0.002***	-0.003***
					(0.001)	(0.000)
LeadIndic					0.001***	0.001**
					(0.000)	(0.000)
FedFunds	0.013	0.059	0.000	0.071	0.137***	0.196***
	(0.039)	(0.042)	(0.055)	(0.039)	(0.025)	(0.021)
d_BA	-0.008	-0.005	-0.012*	-0.008	-0.005*	-0.004*
	(0.005)	(0.005)	(0.006)	(0.005)	(0.002)	(0.002)
t	-0.246*	-0.269*	-0.141	-0.112	-0.278***	-0.250***
	(0.105)	(0.104)	(0.127)	(0.146)	(0.054)	(0.062)
Constant	0.093***	0.092***	0.089***	0.082***	0.089***	0.089***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.005)	(0.005)
Quarters	81	81	81	81	81	81
$\hat{\eta}$	0.069	0.043	0.099	0.077	0.120	0.083
s.e.	0.016	0.013	0.033	0.026	0.028	0.021
J	5.885	6.870	6.894	6.253	7.248	5.845
J pvalue	0.553	0.442	0.440	0.511	0.404	0.558

HAC IV-GMM estimates, based on 1218180 bank-quarter obs.

$*$ <10%, **<5%, ***< 1%

Table 6: Bank COMPUSTAT results for total loans, 1981–2002

	(1)	(2)	(3)	(4)	(5)	(6)
CV_IP	0.409					
	(0.624)					
CV_IP_01			-0.373		-0.249	
			(0.359)		(0.152)	
CV_Infl		-0.428**				
		(0.165)				
CV_Infl_01				-0.282**		-0.211***
				(0.086)		(0.041)
Inflation					0.005**	0.007***
					(0.002)	(0.001)
LeadIndic					-0.003***	-0.001***
					(0.000)	(0.000)
FedFunds	-0.198	-0.372*	-0.069	-0.293*	-0.130	-0.319***
	(0.161)	(0.156)	(0.166)	(0.127)	(0.093)	(0.080)
d_BA	0.020	-0.012	0.025*	-0.002	0.009*	0.004
	(0.011)	(0.018)	(0.011)	(0.011)	(0.004)	(0.002)
t	0.650	2.247	0.064	1.276	2.037***	1.941***
	(0.916)	(1.161)	(0.876)	(0.710)	(0.375)	(0.267)
Constant	-1.181	-4.294	0.000	-2.376	-3.937***	-3.732***
	(1.828)	(2.296)	(1.745)	(1.411)	(0.746)	(0.533)
N	19	19	19	19	19	19
$\hat{\eta}$	0.102	-0.224	-0.096	-0.151	-0.064	-0.114
s.e.	0.156	0.085	0.092	0.045	0.039	0.022
J	4.903	2.922	4.722	3.257	4.222	2.451
J pvalue	0.179	0.404	0.193	0.354	0.239	0.484

HAC IV-GMM estimates, based on 10497 bank-year obs.

$*$ <10%, **<5%, ***< 1%

Table 7: Bank COMPUSTAT results for loan categories, 1981–2002

	Real Est	Real Est	Household	Household	C & I	C & I
CV_IP_01	-0.170		-0.215***		0.316*	
	(0.196)		(0.056)		(0.127)	
CV_Infl_01		-0.223***		-0.082***		0.036
		(0.035)		(0.012)		(0.029)
Inflation	0.008***	0.009***	-0.001	0.001	0.002	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
LeadIndic	-0.000	0.001	-0.002***	-0.002***	0.001	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
FedFunds	-0.252	-0.396***	0.071	-0.031	0.035	0.164*
	(0.130)	(0.102)	(0.042)	(0.042)	(0.092)	(0.067)
d_BA	-0.000	-0.010	-0.002	-0.004	0.002	0.004
	(0.005)	(0.006)	(0.002)	(0.002)	(0.003)	(0.003)
t	4.132***	4.385***	1.429***	1.486***	1.315***	1.163**
	(0.571)	(0.544)	(0.238)	(0.206)	(0.312)	(0.363)
Constant	-8.120***	-8.602***	-2.760***	-2.873***	-2.548***	-2.241**
	(1.136)	(1.081)	(0.474)	(0.409)	(0.620)	(0.722)
N	19	19	19	19	19	19
$\hat{\eta}$	-0.046	-0.127	-0.088	-0.071	0.110	0.026
s.e.	0.053	0.020	0.023	0.010	0.045	0.021
J	5.790	3.039	5.241	2.991	5.586	4.847
J pvalue	0.122	0.386	0.155	0.393	0.134	0.183

HAC IV-GMM estimates, based on 2934–2993 bank-year obs. $*$ <10%, **<5%, ***< 1%

Figure 1. Loan-to-asset ratios