Gross Credit Flows*

Giovanni Dell'Ariccia
International Monetary Fund,
CEPR

Pietro Garibaldi
Bocconi University,
CEPR

September 20, 2004

Abstract

The paper estimates gross credit flows for the U.S. banking system between 1979 and 1999 and shows that sizable gross flows coexist at any phase of the cycle, even within narrowly defined loan categories, bank size categories, and regional units. To investigate the macroeconomic dimensions of gross credit flows, the paper studies the cyclical behavior of aggregate credit flows and documents three key cyclical facts. First, excess credit reallocation is countercyclical: for any given rate of change of net credit, gross flows are larger in a recession than in a boom. Second, gross credit flows are highly volatile, with a cyclical volatility which appears more than an order of magnitude larger than GDP volatility. Third, credit contraction is more volatile than credit expansion. Furthermore, the behavior of gross flows over the 1991 recession suggests that persistent and historically high credit contraction is a key feature of the relatively mild cyclical downturn. The results lends some support to aggregate models that emphasize the asymmetric behavior of credit expansion and credit contractions.

Address:
Pietro Garibaldi
Istituto Economia Politica, Università Bocconi
20136 Milan
+39025836–5422, pietro.garibaldi@uni-bocconi.it

Keywords: Credit Flows, Credit Change.
JEL Classification:E4, E5

*Previous versions of this paper were presented at seminars held at the IMF, Bocconi, Ecares-ULB, European University Institute, Louvain, Carlos III, CEPR-ESSIM in Tarragona, Lausanne, Bonn University and the Bank of Italy. We thank the editor and two anonymous referees for helpful comments. Pietro Garibaldi acknowledges the kind hospitality of the IMF Research Department. The views expressed in this paper are those of the authors and do not necessarily reflect those of the International Monetary Fund.

1 Introduction

Net changes in the aggregate level of bank lending are the result of two different gross flows: the extension of new loans and the cancellation of expired and non-performing loans. Banks are active on both margins, screening new applicants to reduce informational asymmetries and investing time and resources to recover non-performing loans. These activities are intrinsically different, implying that for any given change in net credit, its decomposition into credit contraction and credit expansion has economic relevance. For example, to the extent that breaking up bank-client relationships involves loss of information, for any given level of net credit growth, larger gross credit contraction and expansion will be associated with a larger informational cost borne by the banking system. Although a large literature has studied the dynamic adjustment of net credit,[1] little is known about gross credit flows. This paper is an attempt to fill that gap.

We present five new key results about gross credit flows in the U.S. banking system between 1979 and 1999. First, gross flows are much larger than net flows: sizable credit expansion and contraction coexist at any phase of the cycle, within banks of similar size, within particular loan categories, and within each U.S. state. Second, gross flows are highly volatile. Cyclical fluctuations of gross flows are more than an order of magnitude larger than GDP fluctuations. Third, credit contraction is more volatile than credit expansion, and excess credit reallocation, the sum of gross flows in excess of net changes, is negatively correlated to GDP fluctuations. Fourth, the cyclical behavior of the components of aggregate gross flows follows distinctive sectoral patterns, suggesting that important composition effects shape the aggregate outcome. Fifth, the behavior of gross credit flows during the 1991 recession features a high and persistent credit contraction despite a moderate cyclical downturn in economic activity.

These results are novel, but should not be totally surprising. Credit expansion and credit contraction involve inherently different activities, which are often carried out by different bank departments and by people with different expertise. On the one hand, the extension of new loans is likely to be a time-consuming process, especially in markets where asymmetric information is pervasive, screening is costly and time-consuming, and good investment opportunities may be difficult to find. On the other hand, the cost and time associated with credit contractions depend on the liquidity of borrowers and on whether lengthy legal procedures must be pursued. As a result, it is not surprising that credit expansion and

[1] See Friedman and Kuttner (1993) and references therein.

contraction feature different cyclical properties.

We summarize the process of credit expansion and contraction by aggregating positive (negative) quarterly changes in credit across individual banks, using The Report of Condition and Income database (Call Report Files). In constructing these aggregate series, we control for the concentration process experienced by the U.S. banking industry in the period under investigation. This methodology, which to our knowledge has never been applied to the study of aggregate credit, has been extensively employed by Davis and Haltiwanger (1992) and Davis Haltiwanger and Schuh (1996) in studying the aggregate consequences of heterogeneous labor adjustments.

Our finding that sizable gross flows coexist at any phase of the cycle stems from heterogeneous behavior at the bank level. Sizable gross flows coexist even when banks are grouped in terms of regional and/or size characteristics, and heterogeneous adjustments across states and bank size account only partially for the large rates of aggregate credit reallocation. Furthermore, simultaneous expansion and contraction are also pervasive in the gross flows of specific loan categories, such as real estate and commercial loans. This evidence suggests that the heterogeneity in banks' adjustment is not the result of two recent structural phenomena of the U.S. banking system: the aggregate reallocation of credit out of commercial loans and towards real estate loans and the aggregate increase in bank size.

The heterogeneous behavior of banks at the micro level reflects into the cyclical properties of gross flows at the macro level . In our sample, gross flows are more volatile than GDP by an order of magnitude. The volatility of gross flows is also much larger than that of aggregate investment, and it is quantitatively comparable only to the cyclical behavior of inventories. Furthermore, credit contraction appears to be more volatile than credit expansion. This fact, combined with the finding that excess credit reallocation is negatively correlated with GDP fluctuations, suggests that credit contraction increases during cyclical downturns differ from credit expansion increases during cyclical upturns.

From a theoretical perspective, the coexistence of sizable gross flows and their different degrees of volatility lend some support to new matching models of financial intermediation. In these theories, credit expansion involves identifying and selecting profitable borrowers, which requires times and resources; therefore bringing financiers together with cashless households and entrepreneurs can be described by an aggregate matching function.[2] These models can generate a relative volatility of aggregate gross flows consistent with the stylized facts doc-

[2]Den Haan, Ramey, and Watson (2003), Wasmer and Weil (2002), and Dell'Ariccia and Garibaldi (1998) and (2000) apply the theoretical ideas of the matching literature to capital market issues.

umented in this paper, by assuming that, following a positive aggregate shock, banks need time to identify new profitable clients and projects, and that, conversely, following a symmetric negative aggregate shock, banks can recall credit without time delay. Note that the time-consuming nature of credit expansion is also relevant within long-term credit relationships, since a project evaluation also is required in these cases. The asymmetric behavior of credit expansion and contraction can also be rationalized by models of asymmetric information. First, adverse selection problems make fast credit expansion unprofitable.[3] Second, lending standards vary over the cycle, with important consequences for the dynamics of credit expansion and contraction.[4]

The analysis of gross credit flows sheds some new light on the behavior of the economy in relation to macroeconomic shocks and around recessions. For example, Christiano et al. (1996) show that, after a contractionary shock, net funds raised by the business sector first increase and then begin to fall as the recession gains momentum. Standard models cannot explain this behavior, so the authors argue that contractionary shocks reduce firms' cash flow and induce an increase in their short-term demand for funds, which then diminishes once they adjust their productive structure. The behavior of sectoral gross flows over the NBER recessions lends support to this conjecture.

The study of gross credit flows also highlights important facts behind the 1991 recession, when a mild reduction in activity was followed by a relatively slow and "jobless" recovery, a pattern that most macroeconomic models fail to explain.[5] Our findings suggest that the behavior of gross credit flows in 1991 was very different from that of the large 1980 and 1982 recessions. Credit contraction and excess credit reallocation were historically high for about two years, and remained high in the aftermath of the recession. While most scholars, including Hansen and Prescott (1993), discussed the jobless recovery in 1991, the findings of this paper suggest that the recovery was also "creditless"[6] and that a persistent credit contraction and the larger than normal excess credit reallocation may have delayed the recovery.

Craig and Haubrich (1999), following a methodology very close to ours, have constructed similar series for loan creation and contraction. Their work was conducted independently

[3]See Dell'Ariccia, Friedman, and Marquez (1999) for a model in that spirit.

[4]See Rajan (1994).

[5]For example, Hansen and Prescott (1993) and Hall (1993) suggest that it is difficult to explain the slow recovery in the aftermath of the 1991 recession with standard neoclassical models where aggregate shocks are driven by technological shocks.

[6]See Berger et al. (1995) for an analysis of the sources of the net reduction in bank lending in the early 1990s.

from our efforts, and deserves to be fully acknowledged. Relative to the current paper, Craig and Haubrich (1999) focus more on the analysis of the distribution of credit changes across banks, and give less attention to the cyclical analysis of the aggregate series. They find that about 50 percent of loan creation and destruction is accounted for by banks that alter their portfolio only marginally (less than 10 percent in absolute value). In addition, they also find that bank exit plays an important role, explaining 17 percent of total loan contraction.

The paper proceeds as follows. Section 2 describes the empirical methodology and defines credit expansion and contraction. Section 3 presents the descriptive statistics of gross credit flows and analyzes their behaviors in relation to structural changes in the banking system. Section 4 studies the cyclical properties of gross flows, emphasizing the high level of volatility and the different dynamic behaviors of credit expansion and contraction. It, then, studies the 1991 recession and its peculiar behavior of gross flows during the mild cyclical downturn. Section 5 concludes.

2 Empirical Methodology

This section briefly describes the data used in this study and introduces the methodology to construct gross credit flows.

2.1 Data

The Report of Condition and Income database (Call Report Files) contains bank-level balance sheet information for all banks regulated by the Federal Reserve System, Federal Deposit Insurance Corporation, and the Controller of the Currency.[7] Complete balance sheets are available from 1976:1 to 1999:4. We limit our sample to the period 1979:2-1999:2, since foreign loans are included in the data only from the end of 1978.[8]

In our sample period, the U.S. banking industry was subject to important regulatory changes[9] that, together with innovations in information technology, led to a substantial reduction in the number of banks (Table 1) and to an increase in their average size. This

[7] The database is available on-line on the Federal Reserve Bank of Chicago server at address: http://www.chicagofed.org/economicresearchanddata/data/bhcdatabase/index.cfm

[8] Since banks report their lending on a consolidated basis, it is not possible to disentagle foreign and domestic loans after 1978.

[9] Among the regulatory changes were a progressive decline in reserve requirements, an increase in risk-based capital standards, a deregulation of deposit accounts, and a liberalization of geographic expansion rules. A detailed analysis of the evolution of the banking system in the '80s and '90s is in Berger, Kashyap, and Scalise (1995).

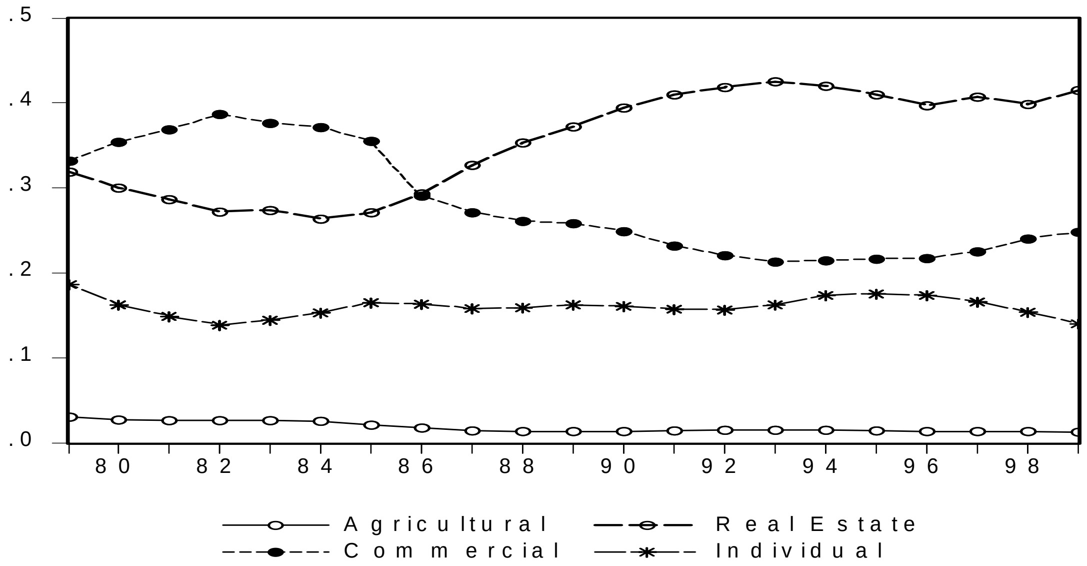

Figure 1: Time Series Evolution of Different Loan Categories as a Share of Total Loans

has resulted in a progressively more concentrated banking industry, as documented by the increase of the Herfindahl index. The Gini coefficient rose steadily over the last twenty years, indicating a mild decrease in the inequality of the bank size distribution. However, an essentially stable coefficient of variation suggests that, despite the dramatic fall in the number of banks, the overall dispersion in the distribution of loans across banks did not change markedly over the sample period.

At the same time, the development of arm's-length financing led to a reallocation of bank credit. Over the sample period the share of commercial loans fell, while the share of real estate loans increased substantially (Figure 1).[10]

2.2 Constructing Gross Credit Flows

We construct gross credit flows adapting the methodology successfully applied by Davis, Haltiwanger, and Schuh (1996) to construct job flows data. The basic logic is as follows. An individual bank expands (contracts) credit in a given period if its credit growth is positive (negative). At the aggregate level, gross credit expansion (contraction) is proxied by the

[10] Figure 1 reports the shares of commercial loans (series RCFD 1600 in the Call Report Files), real estate loans (RCFD 1410), loans to individuals (RCFD 1975), and agricultural loans (RCFD 1590). Cumulatively, these loan categories represent some 85 percent of total loans, the difference being accounted for by minor categories.

sum of the absolute value of all credit changes across banks with positive (negative) credit growth. Finally, dividing the aggregate gross flows by a measure of aggregate credit, we obtain gross rates of expansion and contraction. As we show below, the interpretation of the aggregate series depends on how one measures growth at the bank level. We measure growth alternatively in absolute terms (relatively to zero) and in relation to aggregate trend growth.

2.2.1 Methodological Issues

Our approach faces four main methodological issues. First, it may underestimate gross flows, since there are no data to identify simultaneous expansions and contractions within the smallest unit of observation (the individual bank in this paper). Second, it may overestimate gross flows because of loan trading among financial institutions. Third, it may overestimate gross flows by recording spurious gross credit flows due to merger and acquisitions. Finally, there may be an issue with the interpretation of credit contraction, because of the various reasons for which credit can contract. In this section, we discuss what we can do and cannot do to deal with these issues.

We cannot correct for the simultaneous credit expansion and contraction within banks because of the lack of information on individual loans. Similarly, we cannot control for loan trading among financial institutions. In our data, such trading would show up as simultaneous credit expansion and contraction, even though such transactions are done entirely within the banking system.

The bias introduced by mergers and acquisitions is particularly serious, because of the consolidation process mentioned above. We are able to clean the data from spurious expansions and contractions by using a second database from the Federal Reserve.[11] This "merger file" identifies all bank acquisitions and mergers that occurred between 1976 and 1999. We start from the raw data on gross total loans as defined in the variable RCFD 1400 of the Call Report Files.[12] For each bank i and period t, we consider the change in total loans

[11]This database is available on-line on the Federal Reserve Bank of Chicago server at address: http://www.chicagofed.org/economicresearchanddata/data/bhcdatabase/index.cfm These data can be merged with those from the Call Report files by using the bank identity code variable.

[12]The series RCFD1400 reports the aggregate gross book value of total loans (before deduction of valuation reserves) at the bank level. It includes all of the banks' loans, regardless of the maturity and the borrower type. It includes also commercial paper issued by nonfinancial institutions. Since, in reality, the liquidity of such claims varies across firms, we decided to leave such assets in our definition of total loans. A more detailed description of the series can be found at: http://www.chicagofed.org/economicresearchanddata/data/bhcdatabase/index.cfm

$\Delta l_{it} = l_{i,t} - l_{i,t-1}$, where l_{it} is the value of nominal loans of bank i at time t. Then, we proceed to correct this raw change for the mergers and acquisitions that occurred in the sample.

Consider a merger occurring between time t and time $t-1$, between bank i (surviving bank) and bank j (non-surviving bank).[13] In period t, the total credit of bank j will be zero, while the total credit of bank i will be equal to its own credit in $t-1$ plus the net change in its own credit plus the credit of bank j in period $t-1$ plus the net change in the credit of bank j. Since the first difference of the raw data overestimates both credit expansion and credit contraction, in period t we subtract the credit of bank j in period $t-1$ from the raw difference Δl_{it} for bank i, and add it to the difference for bank j.[14] More formally, we obtain the adjusted difference in credit $\widetilde{\Delta l}_{it}$, whose expression reads

$$\widetilde{\Delta l}_{it} = \Delta l_{it} - \sum_{k=1}^{N} \phi_{ik}(t) l_{k,t-1} - \psi_i(t) \Delta l_{it}. \tag{1}$$

where $\phi_{ik}(t)$ is an indicator function that takes a value of 1 if bank i acquires bank k between t and $t-1$ while $\psi_i(t)$ takes the value of 1 if bank i is acquired between $t-1$ and t. This implies that if a bank is acquired between $t-1$ and t the changing in lending that we ascribe to that bank is zero, and that, instead, all that new credit is ascribed to the acquiring bank. This methodology corrects the effects of most of the mergers and acquisitions in our sample period.[15] We then compute "adjusted credit growth rates" for each individual bank as

$$\widetilde{g}_{it} = \frac{\widetilde{\Delta l}_{it}}{0.5(l_{i,t-1} + l_{i,t})},$$

where we divide $\widetilde{\Delta l}_{it}$ by the average value of loans between t and $t-1$ to better account for entry and exit, since the growth rate $\widetilde{g}_{it}$ varies comfortably between -2 and $+2$. Note that in the numerator of $\widetilde{g}_{it}$ we attribute all the credit change in excess of the merger/acquisition to the surviving bank, while in the denominator it is the surviving bank's credit that appears.[16]

[13] Acquisitions where the charter of the acquired bank was continued, and hence the bank survived as a separate entity, did not need to be corrected for since they do not affect our accounting of credit expansion and contraction.

[14] There are only two exceptions to this methodology. First, when the non-surviving bank was split among numerous surviving banks, we assumed that each surviving bank absorbed an equal share of the credit of the non-surviving institution. Second, when the original bank survived the split, we imputed 0 expansion to the newly formed banks and all the change in credit to the original entity.

[15] For the other mergers and acquisitions, missing data and other mismatches prevented us from doing the correction. We dropped all banks involved in those mergers. The residual sample contains about 97 percent of the existing banks.

[16] It is not straightforward to compute a banks' actual growth rate of credit when a merger occurs. Consider

Before proceeding to the final aggregation, it is useful to stress the nature of a negative value of $\widetilde{g}_{it}$ at the bank level, which represents the key condition for lending contraction. Credit can contract because of loan write-offs associated with borrowers' defaults or simply because a loan is not rolled over at the expiration of its term. Our methodology (and our data) cannot distinguish between these two events. Yet, both events lead to a reduction of credit to the rest of the economy, and they should be included in credit contraction. Note that non-performing loans will contribute to credit contraction only when recognized and partially or totally written off. Similarly, the data include unearned income on loans, which is essentially treated as a further extension of credit. Finally, we do not make any allowance for the fact that the quality of banks' loan portfolios differs. Such corrections, albeit interesting, cannot be implemented with the Call Report Files. The definition of credit expansion is less controversial. In particular, undisbursed loan funds, sometimes referred to as incomplete loans, are excluded unless the borrowers are liable and pay interest.

2.2.2 Aggregation

The final step in obtaining aggregate gross measures requires a simple cross-sectional aggregation of positive and negative changes. The issue here is how to partition the cross-sectional distribution of adjusted growth rates, $\widetilde{g}_{it}$. We partition the distribution in two ways, yielding two definitions of gross flows, which we label "nominal gross flows" and "idiosyncratic gross flows." We start from nominal flows. The idea is simply to partition the distribution of adjusted growth rates around zero, so that the aggregate credit expansion rate between time t and $t-1$ (POS_t) is the weighted sum of the individual banks' adjusted credit growth rates, $\widetilde{g}_{it}$, that were positive (with weights equal to the banks' average market shares between $t-1$

a bank j that is merged with bank i at time τ, where τ is an instant between $t-1$ and t so that $\tau \in (t-1, t)$. There are at least three approaches, and all share the same numerator $\Delta\widetilde{l}_{it}$, but have slightly different denominators. The first option is to treat the "absorbed" bank, j, as if it were operating during the entire period.The second option is to treat bank j as if it were not operating at all between $t-1$ and t, and base bank i's credit growth solely on its own portfolio in t. Finally, one can take an intermediate road, as we do, where the corrected growth rate for bank i is based on bank i's uncorrected portfolio. This means that the "absorbed" bank's credit, $l_{j,t-1}$, enters the denominator through $l_{i,t}$, but does not enter the $t-1$ component. If we indicate with $\widetilde{g}^l_{it}$ and $\widetilde{g}^h_{it}$ the growth rate obtained with the first and second option, one has $\widetilde{g}^l_{it} < \widetilde{g}_{it} < \widetilde{g}^h_{it}$, where $\widetilde{g}_{it}$ is the growth rate used in the text. Note that since the absorbed banks are generally small, the differences between the growth rates are very small. For a bank growing at the average rate of about 2 percent, absorbing a bank about one tenth of its size and growing at a rate of 1 percent, the differences between the corrected growth rates would be below 0.1 percent.

and t). Formally:

$$POS_t = \sum_{i|\tilde{g_{it}} \geq 0}^{N} \tilde{g}_{it} \left(\frac{0.5(l_{i,t-1} + l_{i,t})}{\sum\limits_{i=1}^{N} l_{i,t-1}} \right) = \frac{\sum\limits_{i|\Delta \tilde{l_{it}} \geq 0}^{N} \Delta \tilde{l}_{it}}{\sum\limits_{i=1}^{N} l_{i,t-1}}. \tag{2}$$

Similarly, gross credit contraction is the weighted sum of the absolute values of the adjusted credit growth rates, where the summation is taken over all and only those banks whose rates were negative between t and $t-1$. Thus, its formal expression is

$$NEG_t = \sum_{i|\tilde{g_{it}} < 0}^{N} |\tilde{g}_{it}| \left(\frac{0.5(l_{i,t-1} + l_{i,t})}{\sum_{i=1}^{N} l_{i,t-1}} \right) = \frac{\sum\limits_{i|\Delta \tilde{l_{it}} < 0}^{N} \Delta \tilde{l}_{it}}{\sum\limits_{i=1}^{N} l_{i,t-1}}. \tag{3}$$

In addition to examine positive and negative changes relative to zero, we constructed also idiosyncratic flows, which are the expansion and contraction of bank level credit relative to industry trend, where the latter is defined as the growth rate of the Hodrick-Prescott filtered aggregate credit growth, g_t^{HP}. The idiosyncratic growth rate at the bank level is the difference between our adjusted measures $\tilde{g}_{it}$ and the growth rate of the trend g_t^{HP}:

$$\widehat{g}_{it} = \tilde{g}_{it} - g_t^{HP}. \tag{4}$$

Since we are working with quarterly data, the HP filter is obtained with a standard parameter of 1600. Finally, we aggregate across banks to obtain idiosyncratic expansion and contraction. In the paper, we indicate with $\widehat{POS}_t$ and $\widehat{NEG}_t$ idiosyncratic expansion and contraction, where the only difference with respect to equations (2) and (3) is that we replace $\widehat{g}_{it}$ with $\tilde{g}_{it}$ in $\widehat{POS}_t$ and $|\widehat{g}_{it}|$ with $|\tilde{g}_{it}|$ in $\widehat{NEG}_t$. Note that the two aggregation strategies study different dimensions of the distribution of credit changes. Although it may seem more natural to partition banks' credit changes into positive and negative, there are good reasons for working with idiosyncratic flows. In a banking system growing along a trend, heterogeneity in banks' behavior should be measured relative to such trend. When we study average flows, we rely mainly on the latter definition, while we use nominal flows when we study the cyclical properties.

The difference between gross nominal flows yields the net growth rate of credit, which we label $NET_t = POS_t - NEG_t$. The difference in gross idiosyncratic flows $\widehat{NET} = \widehat{POS} - \widehat{NEG}$, is the growth rate relative to trend, or the cyclical component of net credit growth.

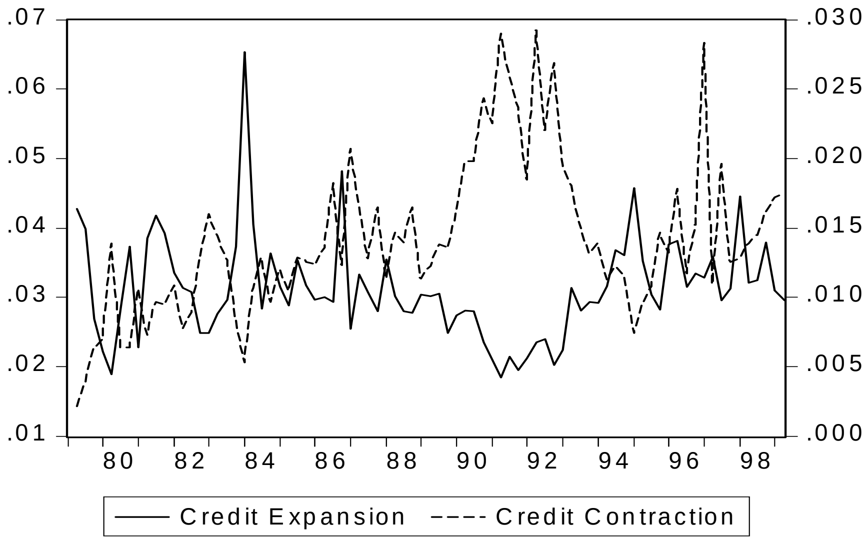

Figure 2: Nominal Gross Credit Flows in the U.S. Banking System, Seasonally Adjusted Quarterly 1979:2-1999:2.

Finally we introduce two measures of credit reallocation. For idiosyncratic flows we use $\widehat{SUM}_t = \widehat{POS} + \widehat{NEG}_t$ to indicate the simple sum of gross credit flows, a measure that accounts for aggregate expansion and contraction relative to trend growth. For nominal flows, we use the reallocation of credit in excess of the net credit change, EXC_t, whose expression reads

$$EXC_t = POS_t + NEG_t - |NET_t|. \tag{5}$$

The next section discusses the aggregate measures introduced here.

3 Descriptive Statistics and Cross-Sectional Decomposition

In this section we show that sizable credit expansion and contraction co-exist at any point in the cycle, and that substantial flows exist also when they are measured as deviations from trend. These flows reflect at the macro level the heterogeneity in bank behavior at the micro level. However, they could also be the result of structural changes in the banking system and of statistical aggregation. To rule out this interpretation, we show that only a small part of aggregate heterogeneity can be explained by composition effects across different types of loans and across banks of different size, and by regional shocks.

The series constructed in the previous section reveal that positive and negative gross credit flows coexist at all phases of the cycle, and that such flows are remarkably larger than net credit.[17] The average quarterly net credit growth of approximately 1.8 percent is the result of a simultaneous quarterly gross expansion of approximately 3.2 percent, and a quarterly gross credit contraction of approximately 1.4 percent (Table 3). Excess credit reallocation, the expansion and contraction in excess of net changes, is about 3 percent per quarter. This implies that in a given quarter 3 percent of the total funds allocated to aggregate credit is reshuffled among individual banks. Of course, this does not necessarily mean that individual loans "move" from one bank to another, but more likely that some banks extend credit to some projects while other banks contract credit to other projects.

Gross flows are sizable also when they are measured in deviation from trend, a better measure for indicating structural flows. Indeed, Table 3 shows that idiosyncratic credit expansion and contraction are approximately equal to 2.1 percent, so that a large number of banks expand and contract credit in excess of trend growth. In a context where relationship banking matters, excess credit reallocation is likely to be costly since it is detrimental to information collection and retention. Models that ignore these effects are likely to underestimate the costs associated with idiosyncratic shocks. Finally, credit contraction is, in relative terms, more volatile than credit expansion. Indeed, the coefficient of variation of credit contraction is 0.42 while that of credit expansion is 0.32. Such asymmetry, already present in the raw data and visible in the nominal data plotted in Figure 2, will figure prominently in the cyclical part.

3.1 Gross Flows and Structural Change in the Banking System

In this section we ask two questions. First, are the large flows due to the structural changes that occured in the U.S. banking system between 1980 and 2000? In other words, are aggregate large flows simply the result of a composition effect, with simultaneous expansion and contraction of loans of different categories? Second, are such flows the other side of the increase in the average size of banks, a phenomenon that we documented in the previous section? To look into these questions, we rely on idiosyncratic flows, since we are mainly interested in understanding the behavior of credit flows around their aggregate trend.

A major bank portfolio reallocation across different loan categories may provide a first

[17] The series are reported in Table 2 and are available on line at www.frdb.org/~pietrogaribaldi/

rationale for aggregate credit reallocation. Since the U.S. banking system went through a sustained asset reallocation, the observed large gross credit flows may simply reflect the expansion of real estate loans and the simultaneous contraction of commercial loans. In other words, $\widehat{SUM}$ at the aggregate level may reflect a portfolio composition effect in a context where banks are specialized by sectors. To assess this conjecture, we construct gross flows for commercial loans, real estate loans, and loans to individuals. The raw data are from the Call Report Files as reported in the variables RCFD 1600, RCFD 1410, and RCFD 1975, respectively.

If the observed large gross flows at the aggregate level reflected mainly a portfolio reallocation, we would find that credit reallocation measured for different categories of loans should not be substantial. Instead, we find that sizable flows exist within each loan category (Table 3). As for aggregate flows, gross flows at the sectoral level are substantially larger than net flows. From this simple observation, we can rule out that aggregate credit reallocation is just the result of a composition effect due to expansion and contraction of different type of loans.

A second explanation for aggregate credit reallocation could be the heterogeneous behavior of banks of different size.[18] To explore the role of banks of different size in generating simultaneous aggregate gross flows, we partition our sample of banks by bank size in deciles, and construct gross credit flows for each decile (for each bank, size is calculated as the average credit across all quarters in which the bank was active). We find that remarkably large gross credit flows coexist within each decile, with values of credit reallocation ($\widehat{SUM}_j$) ranging from 7.4 percent in the first decile to 4.5 percent in the tenth decile (see Table 4).

To measure how much the heterogeneous behavior of banks of different size contributes to aggregate credit reallocation, we decompose the latter into a within and a between component, where banks are divided in groups according to their size decile. If each and every group experienced only credit expansion or contraction, then we could still observe a positive value of $\widehat{SUM}$ at the aggregate level, even though in each group $\widehat{NET}_j$ would be identical to $\widehat{SUM}_j$; thus aggregate credit reallocation would be fully explained by bank size heterogeneity. Conversely, if $\widehat{NET}_j$ were zero in each group, then portfolio reallocation across bank groups would not account for aggregate credit reallocation. Formally, the between

[18] A large literature has showed that banks of different size react heterogeneously to aggregate shocks (see Bernanke and Lown, 1991, Kashyap and Stein, 2000, and references therein).

component of credit reallocation is

$$between = \frac{\sum_j^J |\frac{\sum_{t=1}^T (\widehat{NET}_{jt})}{T}|}{\sum_j^J (\frac{\sum_{t=1}^T (\widehat{SUM}_{jt})}{T})}, \tag{6}$$

where J is the total number of categories (sizes) in the sample. If equation (6) is equal to 1, then aggregate $\widehat{SUM}$ is entirely accounted for by group differences. Confirming our initial intuition, the between index features a value of only 0.05, indicating that only 5 percent of aggregate credit reallocation can be explained by the asymmetric behavior of banks of different size.

Before turning to the cyclical behavior of gross flows, we explore whether the magnitude of credit reallocation at the aggregate level is the result of sizable regional shocks. Indeed, aggregate excess credit reallocation could be explained by heterogeneous credit trends across states. We can also rule out this explanation since, out of 50 states, only 6 experienced an average growth rate different from the aggregate trend by more than one percentage point, and average state credit reallocation is 4.2 percent, identical to the aggregate value (see Table 5). More formally, we construct idiosyncratic measures of credit expansion and contraction within each U.S. state, where the growth rate of each individual bank is measured relative to the aggregate nationwide trend. The relative growth rate of individual bank i in state j is

$$\widehat{g}_{ijt} = \widetilde{g}_{ijt} - g_t^{HP},$$

so that credit expansion (contraction) in state j is simply the cross-sectional sum of positive (negative) $\widehat{g}_{ijt}$. We also decompose aggregate credit reallocation into a within state and between state component. The index between is 0.10, indicating that heterogeneity in the behavior of banks operating in different regions is not quantitatively important and can account for only 10 percent of $\widehat{SUM}$ at the aggregate level.[19]

4 Cyclical Behavior of Gross Credit Flows

Having established the existence of sizable gross credit flows in excess of net credit changes, we turn to examine their dynamic properties. Since bank credit is an important channel for funneling liquidity to new profitable opportunities, it is interesting to study how gross credit flows move relative to aggregate economic activity. In this section, we follow the

[19] Davis and Haltiwanger (1992) used this index to argue that job reallocation takes place mainly within unobservable establishment characteristics.

business cycle literature and look at the dynamic properties of gross credit flows by studying their volatility and the correlations of their cyclical components with respect to the cyclical component of GDP at various leads and lags.[20] In the next section, we further study the dynamic relationships between GDP and credit expansion and contraction using a vector autoregressive specification.

We obtain three important results. First, excess credit reallocation displays countercyclical behavior, suggesting that banks behave more heterogeneously in recessions than in expansions. Second, both credit expansion and credit contraction are much more volatile than GDP, suggesting that their dynamic behavior is not simply the mirror image of GDP dynamics. Third, credit contraction is more volatile than credit expansion, suggesting that the two gross flows may react asymmetrically to macroeconomic shocks.

We start from how gross credit flows move relative to GDP. Predictably, credit expansion is procyclical and credit contraction is countercyclical. The size of both correlations is around 0.35, a value that appears smaller than that of most macroeconomic series. This suggests that there exist specific shocks to gross credit flows that are not correlated with aggregate activity. In terms of leads and lags, the highest correlation is observed between GDP and lagged credit flows. Looking at sectoral flows, the cyclicality of credit expansion is significantly larger than that of credit contraction in all sectors but real estate (Table 6). As we argue in greater detail below, the different cyclical correlation across sectors is consistent with the view that credit expansion and contraction are governed by two different processes.

Our first important finding is that excess reallocation, the measure of credit reshuffling in excess of net changes, is countercyclical, with a correlation with GDP fluctuations equal to -0.30. At the micro level, this aggregate cyclical behavior means that banks behave more heterogeneously during recessions than during expansions. This is consistent with the role assigned to banks by Schumpeter: banks actively reduce lending to unsuccessful sectors while simultaneously reallocating credit toward new profitable investment opportunities. However, at the sectoral level excess reallocation is countercyclical for real estate loans and to a lesser extent for loans to individuals (at lead 2), but not at all countercyclical for commercial credit. This supports an alternative, but to some extent complementary, explanation whereby banks herd in directing their lending toward specific sectors during

[20] The cyclical component of each series is defined as the deviation of its log from its HP-filtered logged values, so as to express it in percentage terms (we used a smoothing parameter of 1600). To be consistent with this approach, here gross credit flows are expressed in levels rather than in rates. This is technically identical to multiplying the nominal flows POS and NEG by the lagged stock of credit. All series were seasonally adjusted using the EViews X11 procedure. See Cooley and Prescott (1995)

booms, and then act idiosyncratically during recessions. In that context, the countercyclical behavior of excess reallocation could be rationalized in a model like that in Rajan (1994), who shows that when banks' managers are interested in short-run earnings and banks' asset allocation is imperfectly observable, banks' policies change with the cycle, with loose lending standards dominating during expansions, followed by a tight standards during recessions.

The countercyclicality of credit reallocation may increase the persistence of aggregate fluctuations. This effect will exist, independent of the underlying microeconomic mechanism, as long as credit contraction involves an information loss. Indeed, since information gathering is costly and time consuming, for any given negative shock with adverse effects on net credit, a larger excess credit reallocation (and consequently a larger gross contraction) is likely to delay the resumption of net credit growth and, hence, to slow down the pace of the recovery. As we argue in the next section, such a mechanism seems to have been particularly important during the 1991 recession.

Turning to overall volatility, we find that gross credit flows feature an average deviation from trend that is more than an order of magnitude larger than GDP volatility. The standard deviation of the cyclical component of gross flows ranges from 18 percent to 28 percent. The volatility of sectoral flows exhibits a comparable absolute magnitude. These numbers are large when compared to those for the cyclical fluctuations of job creation and destruction, which are estimated to be 12 percent (Cole and Rogerson, 1999). In the empirical business cycle literature, only the change in inventories features a volatility similar to that of credit flows, 17 percent over the post-war period (Cooley and Prescott, 1995).[21] This similarity reflects the fact that to some extent bank credit is the financial counterpart of inventories. As firms use inventories to smooth down short-run shocks (Ramey-West, 1999), so they use bank credit to smooth down cash flows shock; this is particular true among large firms, which typically use bank credit as a source of short-term financing. Similarly, individuals use bank credit, in the form consumer loans or mortgage refinancing to absorbs temporary income shocks.

The fact that credit contraction is more volatile than credit expansion is our third key result. The volatility of credit contraction is as high as 28 percent, compared to 18 percent for credit expansion. This suggests that the countercyclical behaviour of excess credit reallocation is driven by the cyclical behavior of credit contraction. In the literature on job flows,

[21] Investement, the most variable component of GDP, has an average volatility over the post-war period of 2.9 percent, far below that of gross credit flows. Not surprisingly, gross credit flows are also much more volatile than the stock of total credit (see Table 6)

a similar difference in volatility has sparked a great deal of research, since it has highlighted an important aggregate dimension behind asymmetric adjustment at the micro level.[22] We believe this finding to be important also in the context of imperfect adjustment in financial markets, and in the next section we review how existing theoretical models can provide a rationale for this new evidence. One dimension to consider is whether asymmetric volatility between credit expansion and contraction reflects asymmetric adjustment at the micro level or asymmetric shocks at the macro level. With respect to the findings in Table 6, we observe that volatility differences are not observed across all loan categories, since credit contraction is more volatile than credit expansion for loans to individuals and real estate loans, but credit contraction and expansion appear equally volatile for commercial loans. While it is always possible that different loan categories are hit by different shocks, this finding gives some support to the view that adjustment is different in different bank departments. In particular, the difference in volatility is largest in loans to individuals.

4.1 The Asymmetric Adjustment Mechanism of Gross Credit Flows

The different cyclical volatility of credit expansion and contraction may be partially connected to banks' inability to adjust the creation margin in response to positive shocks quickly. Theoretically, constraints over the creation margin emerge in models of asymmetric information in the borrower/lender relationship and/or in matching models of the credit market.

A number of papers have argued that asymmetric information between lenders and borrowers, and between different lenders makes fast credit expansion unprofitable.[23] Since lenders acquire private information about their clients, they enjoy an information advantage over their competitors. As a result, banks face an adverse selection problem when they try to expand their loan portfolio faster than the market trend. Asymmetric information plays a less prominent role when banks curtail their loan portfolios, even though banks face the problem of recovering the invested liquidity. The speed of the latter certainly depends on banks' effort, but it is also linked to institutional details such as property rights, the role of collateral, and bankruptcy laws.

Dell'Ariccia and Garibaldi (2000), Wasmer and Weil (2002) and Den-Haan et al. (2003) propose matching models of the credit market, where idiosyncratic shocks interact with aggregate shocks along a creation and a destruction margin. Specifically, they model the problem that banks encounter in expanding credit by assuming the existence of an aggre-

[22] See, for example, Mortensen and Pissarides (1994) and Cole and Rogerson (1999).

[23] See Dell'Ariccia, Friedman, and Marquez (1999) and references therein.

gate matching function, that simply says that it takes time to identify and select profitable clients. In such frameworks, the interaction between symmetric aggregate shocks and idiosyncratic shocks generates a dynamic environment where simultaneous credit expansions and contractions co-exist. Following a positive aggregate shock, credit expansion cannot immediately react, since it takes time to identify a profitable project. Conversely, following a symmetric negative aggregate shock, credit contraction can potentially take place with a substantially smaller delay. In such a framework, credit contraction is more volatile than credit expansion.

Rather than being supply-determined, the differences in volatility may also be demand-determined. Abel and Eberly (1994) show that investment under uncertainty with lumpy adjustment costs is not a smooth process, but rather a "bunched process." While asymmetries on the demand side certainly play a role in shaping our findings, it is not easy to understand why such bunching is relevant only on the contraction margin and less prominent over the expansion margin. Once again, it is always possible that the underlying shocks are asymmetric in nature. We leave it to future research to address this unresolved question.

4.2 Relationship with GDP fluctuations

Having established that gross credit flows exhibit a mild correlation with GDP fluctuations and that they are highly volatile, we now ask how much of the dynamics in gross flows can be rationalized by simple innovations to aggregate activity. To investigate this issue, we study the dynamic relationships between the log values of GDP and the rates of credit expansion and contraction (POS and NEG) using a vector autoregressive (VAR) specification of order two. Figure 3 reports the impulse response functions of credit expansion and contraction to an innovation in the cyclical component of GDP. These impulse response functions are identified through a simple Cholesky decomposition in which contemporaneous innovations to GDP are taken as exogenous. Clearly, these VARs are performed only for describing the dynamic correlation in the data and are not meant to represent structural relations. Nevertheless, the impulse response functions have the shape that one would expect, with credit expansion (contraction) that grows (falls) in response to a GDP innovation. Yet, with the exception of credit expansion at lag two, these impulse responses have large standard deviations and are not statistically significant. In light of the relatively short time series and the large number of parameters to be estimated, this result should not come as a surprise. The variance decomposition (not reported) suggests that innovations to GDP are quantitatively important only for credit expansion.

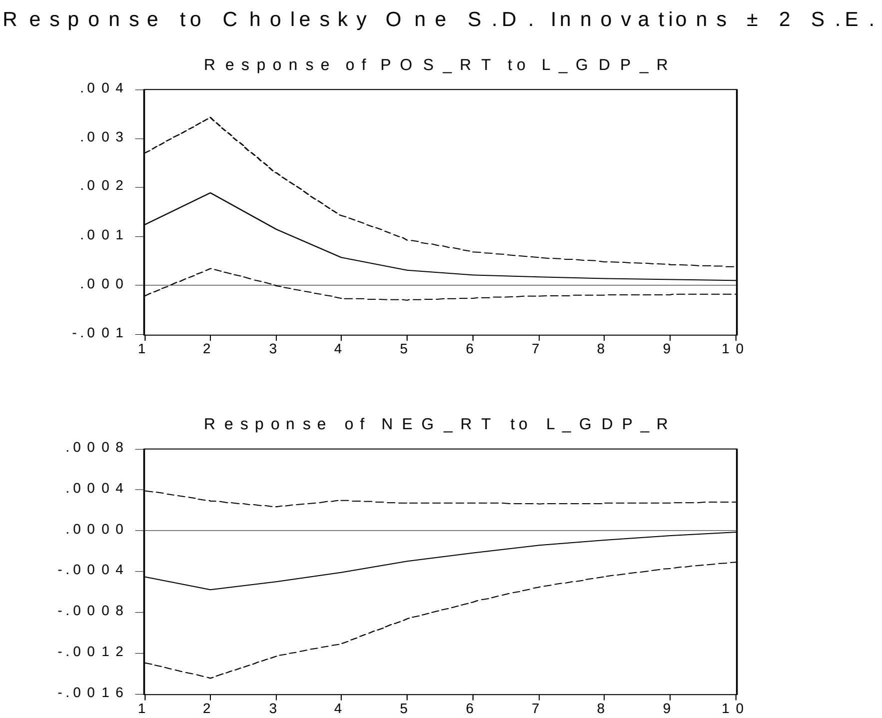

Figure 3: Impulse Response Functions of Nominal Flows (*POS* and *NEG*) to a GDP shock

The VAR exercise confirms the view that fluctuations in real activity alone cannot account for fluctuations in gross credit flows. It is likely that there exist two effects. An innovation to GDP causes a change in demand for investment and consumption, and some of this demand is financed with bank credit. This mechanism induces a positive (negative) link between GDP shocks and credit expansions (contractions). However, GDP shocks are also related to cash flow shocks, which firms and individuals smooth with bank credit. This mechanism works in the opposite direction, leading to a reduction in credit expansion following a positive shock.

4.3 Gross Flows and the 1991 Recession

The 1991 recession has received a great deal of attention in the business cycle literature because of the slow and "jobless" recovery that followed. Standard macroeconomic models have had a hard time in fitting this anomalous recovery, and researchers have experimented, with only partial success, with additional variables and shocks to explain its peculiar pattern.[24] It is well beyond the scope of this paper to participate in that debate. However, the examination of the behavior of gross credit flows around recessions may provide new details on the differences between the 1991 recession and its predecessors and further insights on how gross credit flows interact with the rest of the economy. In this section, we examine the behavior of gross credit flows around the three recessions in our sample period and show that the 1991 recession is "special" also with respect to bank credit (on this point see also Berger et al., 1995).

In the earlier recessions in our sample (1980 and 1982), net credit followed a V-shaped pattern. Credit expansion fell rapidly below its trend level right before and during the recession and rebounded sharply immediately after the trough in economic activity. Credit contraction followed a symmetric and opposite pattern. This pattern is clearly visible in Figure 4, where we report the average value of the cyclical deviation of gross flows over three quarters. In the 1991 recession, in contrast, the decline in credit expansion and the increase in credit contraction were both persistent, and survived for about two years through the recovery, longer than the decline in employment. Hence, the recovery can be characterized not only as "jobless", but even more as "creditless."

In 1991, the increase in credit contraction accounted for about 50 percent of the negative change in net credit, reflecting in part the ongoing effects of the saving and loans crisis.[25] In the previous recessions, instead, credit contraction displayed very little action in absolute terms.[26] Alongside the increase in contraction, the 1991 recession also featured a large and persistent increase in excess credit reallocation. Specifically, excess reallocation was as high as 4.2 percent at the time of the cyclical trough (91:1), remained in the 4 percent range throughout 1991 and 1992, and returned to its average value of 2.7 percent only in 1994. This finding reinforces the idea that a massive sectoral credit reallocation entails a large information loss that may hinder the banking system's ability to resume credit growth and thus may mitigate the strength of the economic recovery.

Regulatory and market structure changes in the banking industry, together with improvements in information technology may have been responsible for the exceptional increase in

[24] Hansen and Prescott (1993) introduces multiple production sectors and population growth. Blanchard (1993) investigates the role of shocks to consumer confidence. Hall (1993) examines several alternative driving forces spanning changes in regulation to fiscal and monetary policy shocks and concludes that established models are unhelpful in understanding the 1991 recession.

[25] See Bernanke and Lown (1991).

[26] The relative deviation from trend in the two episodes is roughly of the same magnitude. However, because of the large persistence of the 1991 episode, similar deviations from trend correspond to very different deviations from the series average.

aggregate excess reallocation in the early 1990s. The introduction of higher capital requirements and more rigorous valuation standards may have induced banks to reposition their portfolios to improve their capital-asset ratios (Hall, 1993). The significant liberalization of geographic restriction on banking led to a reallocation of assets from smaller banks to larger institutions, possibly reducing small business lending; while improvements in information technology reduced the reliance of large firms on bank credit (Berger et al. 1995). The idea that a substantial repositioning of banks' portfolios was behind the increase in excess reallocation of the early 1990s is also supported by the fact that excess reallocation for specific loan categories did not behave differently from the earlier recessions.

The examination of sectoral gross credit flows also helps our understanding of some puzzling features of the behavior of aggregate bank credit around recessions. For the 1980 and 1982 episodes, on the eve of a recession, we witness a sizable drop in the growth of credit to individuals, probably due to a decreased demand for durable goods, as reflected in the sharp contraction in credit expansion. At the same time, commercial credit increases sharply, mainly driven by a larger than average credit expansion, as firms increase their demand for funds. As the recession gains momentum, the expansion of commercial credit diminishes significantly and commercial credit contraction increases, with the growth of credit to individuals remaining well below its average (see Figures 5 and 6). This evidence supports the conjecture in Christiano et al. (1996) which shows that after a contractionary shock, net funds raised by the business sector increase for about a year and then begin to fall as the recession gains momentum. They argue that standard models cannot explain this behavior and argue that if the contractionary shock reduces firms' net cash flow, the demand for funds temporarily increases. Such an increase diminishes once firms manage to adjust their productive structure and reduce their nominal expenses.

Note that the analysis of sectoral flows also highlights an additional difference between the 1980-82 recessions and the 1991 recession. Indeed, on the eve of 1991 recession, commercial credit expansion is completely absent.

5 Conclusions

This paper focused on gross credit flows, the simultaneous process of credit expansion and contraction within the banking industry. Using micro data on the entire U.S. banking system, we constructed new aggregate time series of gross credit expansion and contraction. We showed that simultaneous expansion and contraction is a pervasive phenomenon, even when

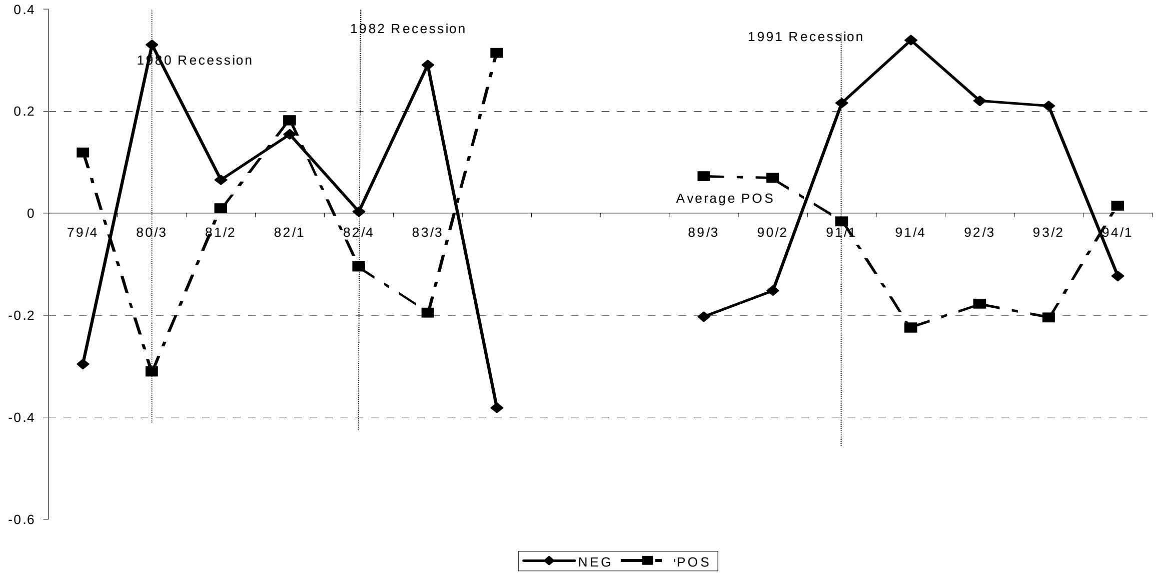

Figure 4: Cyclical Components of Credit Expansion and Contraction around NBER recessions.

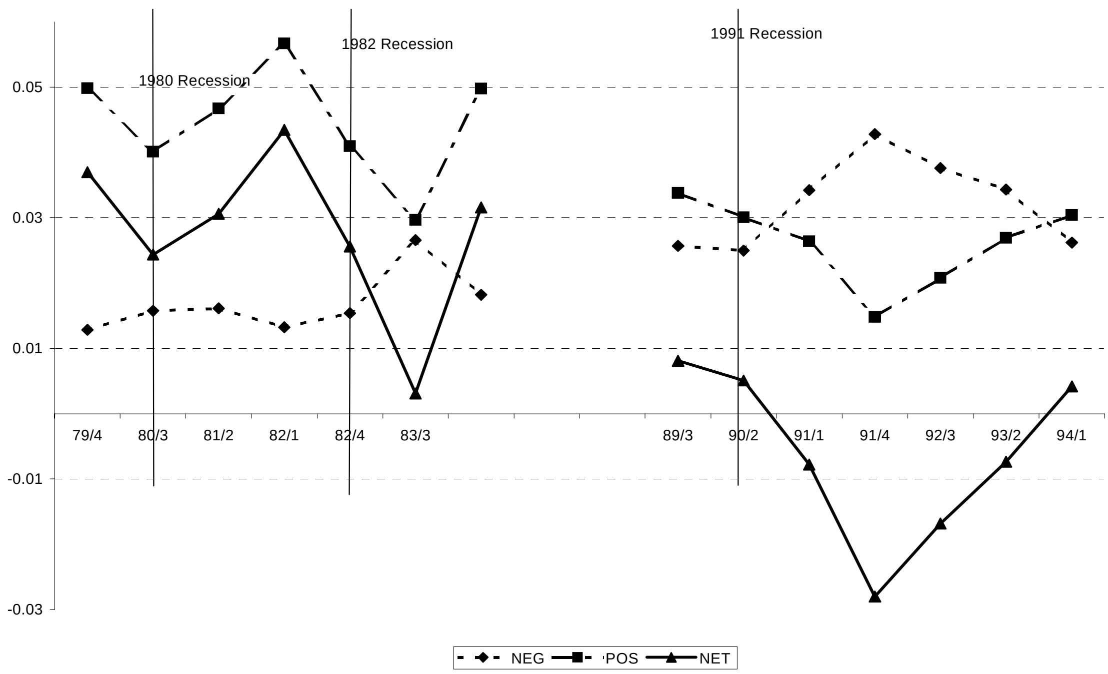

Figure 5: Commercial Nominal Flows Over NBER Recessions

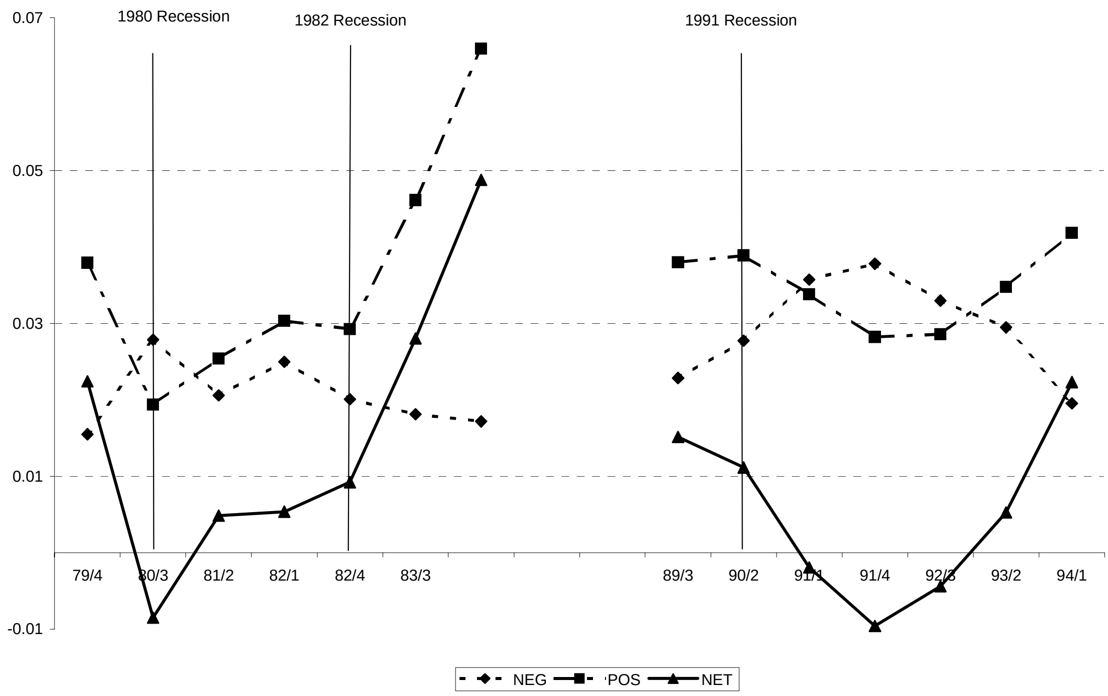

Figure 6: Individual Loans Over NBER Recessions

banks are grouped together in terms of size or regional location, and also when credit is disaggregated by specific loan categories.

In terms of cyclical fluctuations, two key messages emerge from our empirical analysis. First, gross credit flows are highly volatile, with a cyclical volatility that appears to be more than an order of magnitude larger than GDP volatility. Second, credit contraction is more volatile than credit expansion, and excess credit reallocation, the sum of credit expansion and contraction in excess of net credit changes, moves countercyclically. This suggests that there is more reshuffling of credit and larger information loss during downturns than during expansions.

References

Abel, A. and Eberley, J. (1994), "A Unified Model of Investment under Uncertainty," *American Economic Review* 84(5), 1369-84

Berger, A., Kashyap, A., and Scalise, J. (1995), "The Transformation of the US Banking Industry: what a long, strange trip it's been," *Brooking Papers on Economic Activity,* pp. 55-201.

Bernanke, B. and Lown, C. (1991), "The Credit Crunch," *Brookings Papers on Economic Activity,* No. 2, pp. 55-201.

Blanchard, O., (1993), "Consumption and the Recession of 1990-1991," *American Economic Review,* Vol. 83:2 270-75.

Christiano, L., Eichenbaum, M. and Evans, C. (1996) "The Effects of Monetary Policy Shocks: Evidence from the Flow of Funds," *Review of Economics and Statistics* Vol. 78, pp. 16-34.

Cole, H. and Rogerson, R. (1999), "Can the Mortensen Pissarides Matching Model Match the Business Cycle Facts?" *International Economic Review*, 933-960.

Cooley, T. F. and Prescott, E. (1995), "Economic Growth and Business Cycles" in *Frontiers of Business Cycle Research* edited by T. F. Cooley. Princeton: Princeton University Press

Craig. B. and Haubrich, J. (1999) "Gross Loan Flows", *Federal Reserve Bank of Cleveland*, working paper 0014.

Davis, S. and Haltiwanger, J. (1992), "Gross Job Creation, Gross Job Destruction, and Employment Reallocation," *Quarterly Journal of Economics,* Vol. 107, No. 3, pp. 819-63.

Davis, S., Haltiwanger, J. and Schuh, S. (1996), " Job Creation and Destruction," Cambridge: MIT Press.

Dell'Ariccia, G. Friedman, E. and Marquez, R. (1999), 'Adverse Selection as a Barrier to Entry in the Banking Industry", Rand Journal of Economics 30(3).

Dell'Ariccia, G, and Garibaldi, P. (1998), "Bank Lending and Interest Rate Changes in a Dynamic Matching Model", International Monetary Fund Working Paper.

Dell'Ariccia, G, and Garibaldi, P. (2000), "Gross Credit Flows", CEPR Discussion Paper 2569.

Den Haan, W., Ramey, J., and Watson, J. (2003), "Fragility of Business Enterprises," forthcoming *Journal of Monetary Economics.*

Friedman, B. and Kuttner, K. (1993), "Economic Activity and the Short-term Credit Markets: An Analysis of Prices and Quantities," *Brooking Papers on Economic Activity,*

Hall, R., (1993), "Macro-Theory and the Recession of 1990-1991," *American Economic Review,* Vol. 83:2 275-79.

Hansen, G., and Prescott, E. (1993), “Did Technology Shocks Cause the 1990-1991 Recession," *American Economic Review,* Vol. 83:2 280-86.

Kashyap A. and Stein, J. (2000), "What Do A Million Observations on Banks Say About the Transmission of Monetary Policy?", *American Economic Review.*

Mortensen, D. and C. Pissarides,(1994), “Job Creation and Job Destruction in the Theory of Unemployment", *Review of Economic Studies,* Vol. 61 (July) pp. 397-415.

Rajan R., (1994), "Why Bank Credit Policies Fluctuate: A Theory and Some Evidence", *Quarterly Journal of Economics* 400-441.

Ramey, V. and West, K. (1999), "Inventories", in *Handbook of Macroeconomics,* edited by J. Taylor and M. Woodwford, chapter 13 North Holland, Amsterdam.

Wasmer, E, and Weil, P. (2002), “The Macroeconomics of Labor Market and Credit Market Imperfections”, CEPR Discussion Paper 3334.

Table 1: Dynamic Evolution of the U.S. Banking System

Year[a]	Num. [b] Banks	Av. [c] Bank.	Agg. [d] Loan	Coeff. [e] Var.	Herf. [f]	Gini [g]
1979	14946	100.00	100.00	12.42	1.04	0.836
1980	15410	106.72	108.83	14.69	0.99	0.89
1981	15372	118.04	120.07	14.93	1.00	0.894
1982	15412	126.64	129.23	14.68	0.99	0.895
1983	15410	135.12	137.89	13.92	0.89	0.892
1984	15270	151.88	153.55	13.15	0.79	0.895
1985	15270	165.21	166.91	12.39	0.70	0.897
1986	15109	181.17	181.08	11.84	0.64	0.902
1987	14649	197.62	191.39	11.17	0.57	0.908
1988	14086	219.24	204.03	10.74	0.53	0.913
1989	13674	241.16	217.78	10.90	0.54	0.916
1990	13311	253.99	223.08	11.02	0.56	0.917
1991	12887	255.56	217.36	10.98	0.55	0.917
1992	12502	260.28	214.68	11.72	0.63	0.918
1993	12057	282.48	224.89	11.71	0.63	0.921
1994	11541	320.86	244.46	11.74	0.63	0.927
1995	11001	370.21	268.92	12.06	0.67	0.933
1996	10550	416.71	290.66	13.24	0.80	0.939
1997	10090	458.38	306.19	14.56	0.97	0.942
1998	9639	519.24	332.31	12.24	1.18	0.922

[a] Data refer to December.
[b]Number of banks with non-zero value of loans.
[c] Index for the loan value of the average bank.
[d] Index for the aggregate value of loans.
[e] Coefficient of Variation of the value of loans.
[f] Herfindahl index (*100) for the U.S. banking system.
[g] Gini Coefficient for the loan distribution.
Source: Authors' calculations.

Table 2: Quarterly Gross Credit Flows in the U.S. Banking Industry: 1979:2-1999:2

Date	POS^a	NEG^a	$\hat{POS}^b$	$\hat{NEG}^b$	Date	POS^a	NEG^a	$\hat{POS}^b$	$\hat{NEG}^b$
7906	4.627	0.180	2.181	0.591	8906	3.265	1.059	2.591	1.387
7909	3.920	0.357	1.735	1.015	8909	2.968	1.260	2.347	1.562
7912	3.275	0.607	1.494	1.514	8912	3.029	1.323	2.514	1.645
8003	1.582	0.926	0.584	2.522	9003	2.071	2.086	1.689	2.460
8006	1.914	1.215	0.796	2.640	9006	3.033	1.720	2.609	1.988
8009	2.728	0.602	1.211	1.601	9009	2.718	1.813	2.330	2.041
8012	4.454	0.621	2.621	1.250	9012	2.848	2.386	2.568	2.685
8103	1.603	1.367	0.774	2.910	9103	1.586	2.912	1.393	3.259
8106	3.959	0.604	2.309	1.326	9106	2.000	2.511	1.807	2.832
8109	3.941	0.851	2.313	1.557	9109	2.082	2.359	1.842	2.654
8112	4.700	0.885	3.134	1.628	9112	2.373	2.322	2.146	2.645
8203	2.500	1.399	1.547	2.702	9203	1.624	2.408	1.420	2.785
8206	3.413	0.647	1.920	1.406	9206	2.541	2.566	2.249	2.915
8209	3.043	0.790	1.692	1.662	9209	2.316	2.041	1.984	2.420
8212	3.045	1.196	1.795	2.149	9212	2.421	2.652	2.069	3.094
8303	1.809	2.061	1.107	3.539	9303	1.649	2.476	1.321	3.039
8306	2.825	1.200	1.793	2.367	9306	3.336	1.523	2.753	1.946
8309	2.774	1.108	1.763	2.276	9309	2.654	1.319	1.996	1.776
8312	4.522	0.802	2.857	1.321	9312	3.474	1.250	2.723	1.720
8403	4.985	0.723	3.484	1.373	9403	2.189	1.744	1.546	2.398
8406	4.506	0.964	2.879	1.492	9406	3.343	0.948	2.358	1.386
8409	2.878	1.218	1.783	2.245	9409	3.484	1.089	2.401	1.515
8412	4.574	0.954	3.130	1.638	9412	4.317	1.122	3.183	1.588
8503	2.373	1.548	1.459	2.689	9503	3.538	0.976	2.371	1.469
8506	3.090	0.886	1.843	1.685	9506	3.895	0.824	2.616	1.252
8509	3.410	1.160	2.090	1.854	9509	2.992	0.994	1.923	1.658
8512	3.829	1.202	2.656	1.998	9512	3.458	1.448	2.422	2.185
8603	2.135	1.588	1.269	2.651	9603	2.869	1.778	1.953	2.636
8606	3.070	1.191	1.971	1.972	9606	4.127	1.540	2.995	2.202
8609	2.701	1.682	1.794	2.590	9609	3.009	1.048	2.021	1.852
8612	5.782	1.186	4.464	1.660	9612	4.025	1.448	2.896	2.106
8703	1.865	2.627	1.275	3.720	9703	2.497	3.570	1.718	4.554
8706	3.538	1.388	2.540	2.036	9706	3.856	0.802	2.558	1.283
8709	2.955	1.101	2.080	1.800	9709	2.810	1.644	1.898	2.491
8712	3.382	1.556	2.491	2.176	9712	3.761	1.120	2.608	1.711
8803	2.695	1.480	1.920	2.123	9803	3.424	1.666	2.525	2.490
8806	3.281	1.281	2.452	1.797	9806	3.489	1.191	2.401	1.786
8809	2.727	1.284	2.027	1.841	9809	3.129	1.318	2.102	1.953
8812	3.390	1.617	2.581	1.979	9812	4.590	1.562	3.555	2.173
8903	2.303	1.461	1.742	1.982	9903	2.365	2.221	1.583	2.996
					9906	3.183	1.478	2.245	2.125

Numbers are in percent. Flows are not seasonally adjusted
[a] POS and NEG refer to nominal flows.
[b] $\hat{POS}$ and $\hat{NEG}$ refer to idiosyncratic flows.
Source: Authors' calculations.

Table 3: Gross Credit Flows: Summary Statistics 1979:2-1999:2

	NET	POS	NEG	$\hat{SUM}$	EXC
Aggregate Loans					
Nominal Flows					
Average	1.76	3.18	1.42	-	2.69
Standard Deviation	1.46	1.02	0.62	-	0.98
Idiosyncratic Flows [a]					
Average	0.01	2.12	2.08	4.20	-
Standard Deviation	1.12	0.63	0.66	0.06	-
Commercial Loans					
Nominal Flows					
Average	0.68	1.79	1.11	-	1.94
Standard Deviation	0.97	0.57	0.47	-	0.63
Idiosyncratic Flows [a]					
Average	0.01	2.80	2.71	5.52	-
Standard Deviation	1.36	0.87	0.72	0.84	-
Real Estate Loans					
Nominal Flows					
Average	1.04	1.68	0.63	-	1.26
Standard Deviation	0.57	0.46	0.22	-	0.44
Idiosyncratic Flows [a]					
Average	0.01	2.27	2.12	4.39	-
Standard Deviation	0.78	0.53	0.54	0.73	-
Individual Loans					
Nominal Flows					
Average	0.66	1.97	1.30	-	2.11
Standard Deviation	0.11	0.72	0.63	-	0.70
Idiosyncratic Flows [a]					
Average	-0.01	3.28	3.39	6.68	-
Standard Deviation	2.23	1.20	1.43	1.41	-

Numbers are in percent.

[a] Relatively to trend growth of the specific category.

Source: Authors' calculations.

Table 4: Gross Flows Within Size Categories

Decile	$\hat{NET}$	$\hat{POS}$	$\hat{NEG}$	$\hat{SUM}$
1st	-0.05	3.66	3.72	7.39
2nd	0.10	2.90	2.80	5.70
3rd	0.14	2.88	2.74	5.62
4th	0.23	2.79	2.56	5.36
5th	0.29	2.58	2.28	4.86
6th	0.29	2.48	2.18	4.67
7th	0.37	2.52	2.15	4.67
8th	0.34	2.62	2.27	4.90
9th	0.36	2.73	2.37	5.11
10th	-0.02	2.22	2.24	4.46

Numbers are in percent.

between=0.05;

See equation 6.

Source: Authors' calculations.

Table 5: Gross Flows Within States

State	$\hat{NET}$	$P\hat{OS+N}EG$	State	$\hat{NET}$	$P\hat{OS+N}EG$
AK	0.10	4.70	MS	0.22	3.11
AL	0.67	3.16	MT	-0.68	4.44
AR	0.11	4.35	NC	1.09	3.07
AZ	0.20	4.83	ND	-0.04	4.74
CA	-0.41	3.37	NE	-0.07	4.39
CO	-0.03	4.40	NH	1.14	5.46
CT	-0.08	3.98	NJ	0.30	3.83
DC	-0.54	5.01	NM	-0.26	3.78
DE	2.28	8.48	NV	0.38	8.48
FL	1.02	4.40	NY	-0.23	4.83
GA	1.06	4.81	OK	-0.31	4.37
HI	0.50	2.69	OR	0.39	3.94
IA	-0.26	3.95	PA	-0.17	3.37
ID	0.36	3.34	RI	0.36	4.44
IL	-0.17	5.18	SC	1.11	3.08
IN	-0.12	3.31	SD	0.23	6.53
KS	0.08	4.34	TN	0.34	3.48
KY	0.25	3.03	TX	-0.19	5.39
LA	-0.20	3.91	UT	0.42	4.43
MA	0.76	4.43	VA	0.46	3.31
MD	0.17	3.75	VT	-0.12	2.82
ME	0.29	3.62	WA	0.29	3.76
MI	-0.13	2.76	WI	0.05	3.15
MN	0.05	4.18	WV	-0.18	3.29
MO	0.22	3.85	WY	-0.35	4.64

Numbers are in percent.

between=0.10.

See equation 6.

Source: Authors' calculations.

Table 6: Gross Credit Flows: Cyclical Properties

		Cross-Correlation of GDP with:								
	SD	$x(-4)$	$x(-3)$	$x(-2)$	$x(-1)$	x	$x(+1)$	$x(+2)$	$x(+3)$	$x(+4)$
GDP	1.32	0.16	0.40	0.60	0.85	1	0.85	0.64	0.40	0.17
Aggregate										
POS	18.33	-0.07	0.04	0.21	0.37	0.35	0.26	0.16	0.05	-0.15
NEG	28.39	-0.17	-0.28	-0.34	-0.41	-0.32	-0.22	-0.10	-0.00	0.14
EXC	26.92	0.13	0.01	-0.07	-0.18	-0.29	-0.38	-0.31	-0.25	-0.15
Total Credit	2.18	-0.16	-0.12	-0.02	0.12	0.27	0.40	0.49	0.53	0.51
Commercial										
POS	23.03	-0.10	-0.01	0.15	0.27	0.30	0.33	0.23	0.13	-0.09
NEG	23.91	0.08	0.04	-0.07	-0.19	-0.02	-0.18	-0.22	-0.21	-0.15
EXC	22.03	-0.13	-0.13	-0.08	0.02	0.08	0.09	0.18	0.22	0.21
Total Credit	3.48	-0.20	-0.22	-0.18	-0.08	0.08	0.12	0.22	0.27	0.25
Individual										
POS	23.30	0.24	0.32	0.44	0.50	0.43	0.25	0.07	-0.14	-0.30
NEG	28.00	-0.20	-0.20	-0.25	-0.25	-0.14	-0.04	0-09	0.19	0.26
EXC	23.98	0.22	0.14	0.07	-0.06	-0.05	-0.14	-0.22	-0.22	-0.21
Total Credit	4.32	0.12	0.23	0.35	0.47	0.57	0.62	0.62	0.58	0.48
Real Estate										
POS	16.49	0.08	0.14	0.30	0.41	0.44	0.28	0.20	0.07	-0.06
NEG	24.22	-0.03	-0.15	-0.27	-0.39	-0.41	-0.33	-0.26	-0.14	0.01
EXC	25.34	0.01	-0.14	-0.25	-0.33	-0.41	-0.39	-0.27	-0.15	-0.03
Total Credit	2.98	-0.16	-0.12	-0.05	0.03	0.15	0.25	0.34	0.41	0.47

All flows are seasonally adjusted using EViews X-11 procedure.
GDP is the cyclical component of GDP.
All flows are cyclical deviations, defined as the difference
between the log of gross flows in levels and their log hp-filter.
Flows in levels are obtained by multiplying *POS* and *NEG* by $\sum_{i=1}^{N} l_{i,t-1}$
Aggregate is Aggregate loans, *Commercial* is Commercial loans,
Individual is Loans to individual and *RealEstate* is Real estate loans.
Source: Authors' calculations.