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by Ben Craig and Joseph G. Haubrich

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Changes in net lending hide the much larger and more variable gross lending flows. We present a series of stylized facts about gross loan flows and how they vary over time, bank size, and the business cycle. We look at both the intensive (increases and decreases) and extensive (entry and exits) margins. We compare these results with the output from a simple stochastic search model.

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1 Introduction

Economists and policymakers consider aggregate bank lending an important influence on the economy and a key part of the monetary transmission mechanism. This importance has been acknowledged by the Federal Reserve (Greenspan 1997) and explored in a host of academic papers such as Bernanke and Gertler (1995), Friedman and Kuttner (1993), or, more recently, Kashyap and Stein (2000). The change in aggregate loans, however, presents an incomplete and at times misleading picture of the market. An aggregate *net* change masks much larger *gross* changes, as lending increases at some banks and decreases at others. The gross change in fact averages over six times the net change, and is occasionally much higher.

In this paper, we use measures of loan creation, destruction, and gross flows–to further illuminate the banking market. Just as these provide information missed by more popular statistics such as the unemployment rate or employment growth, they similarly uncover the diversity behind traditional measures such as total loans.

Looking at gross, as opposed to net, flows makes sense for a variety of reasons. Underlying factors may affect the creation and destruction of loans differently, in addition to separately affecting the intensive and extensive margins. We explore the extent to which loan creation and destruction differ over time and over the business cycle, and examine how important entry and exit are to loan growth.

Recent theoretical work has suggested that such margins may be important. In Allen and Gale (2000), concentrated difficulties in a few banks can lead to a general contagion, whereas the same losses spread across the entire system have a negligible effect. Freixas, Parigi, and Rochet (2000) have a model with organizational capital where a decrease in loans via a bank failure has a much more severe impact than loan contraction by a surviving bank, and Haubrich (1990) suggests that such effects may explain why Canada's experience of the Great Depression was less severe than that of the U.S.

Furthermore, as in the labor literature, concentrating on gross flows cuts the data in a manner more appropriate for models that emphasize search frictions in the banking market, such as Wasmer and Weil (2004), den Haan, Ramey, and Watson (2003), Dell'Ariccia and Garibaldi (1998), or other models that exploit bank and borrower heterogeneity, such as Monge-Naranjo (2001) or Gorton and He (2005).

Indeed the credit market may have as strong a claim to search frictions as does the labor market. Commercial bank loans are complicated contracts requiring negotiations over the interest rate, fees, and covenants, with firms looking hard for the best deal. Conversely, banks work hard to find profitable borrowers and screen out likely losses. Banks put great effort into both advertising and loan evaluation, and practitioner publications are quite upfront about the search nature of the business (see Wendel (2005) for an example).

Of course the academic literature has noticed this at some level, both in empirical work such as Petersen and Rajan (2002), which looks at the effect of distance on lending relationships, and theoretical work, such as Bizer and DeMarzo (1992), in which borrowers visit a number of lenders. The work on credit scoring (and small business lending in general) certainly seems to depict a market where matches are sought, but not always made. Cole, Goldberg, and White (2004) look at a sample of 4,637 firms, of which 2,011 applied for loans in their sample period. Of those banks applying, 85% where approved.

Heterogeneity across banks matters for a variety of positive and normative questions. Understanding the monetary transmission mechanism requires understanding which banks (if any) are particularly affected by tight money. Policymakers should know if reigning in nationwide inflation will crush the rustbelt or restrain only small banks. Policy designed for a non-existent "average bank" may backfire, particularly if it ends up punishing or rewarding a narrow group.

The proper regulatory response to other problems, such as excessive loan growth (perhaps caused by such subsidies as deposit insurance), depends on how widespread the problem is, a factor that aggregate growth rates cannot determine. If only a handful of banks are responsible, a policy of tightening loan standards would be ineffective if it left the high flyers untouched and positively perverse if it fell upon already contracting banks. Other policies might be designed to target specific sub-groups. For example, the Basle capital standards had a selective goal: changing the portfolio composition of undercapitalized banks (Haubrich and Wachtel 1993).

In this paper, we present a series of stylized facts about gross loan flows and how they vary over time. Though such an exercise provides no definitive conclusions about the transmission of monetary policy or the effectiveness of bank regulations, it adds, we feel, a perspective that offers insights into those problems.

Although some papers such as Kashyap and Stein (2000) have looked at asymmetric responses to macroeconomic shocks, there has been virtually no work on gross loan flows. (This discounts a a much earlier literature that uses the term to mean aggregate changes; see Torrance 1960). The outstanding exception, of course, is recent independent work by Dell'Arricia and Garibaldi (2005) which looks at the "Gross Credit Flows" of U.S. Commercial banks. Despite many similarities, our papers have several substantial differences. We use a longer data series (1959–2004 versus 1979–1999), we track bank entry and exit (the extensive margin), we look at the distribution of changes across banks, and we explicitly compare the gross loan flows with gross job flows. In addition, we present a simple theory to help focus ideas. Conversely, we spend less time documenting business cycle facts and disaggregating across regions, instead building on their excellent analysis.

The remainder of the paper is as follows: section 2 discusses data construction, section 3 presents the basic stylized facts of gross loan flows, section 4 presents a simple model, while section 5 presents more details on the distribution and cyclical properties of the data. Section 6 compares loan and job flows, and section 7 concludes.

2 Data: source and construction

We define *loan creation* as the sum of the change in bank loans at all banks that increased loans since last quarter. *Loan destruction* is similarly defined as the absolute value of the change in loans at all banks that decreased loans. The *gross flow* (akin to what Davis and Haltiwanger (1992) call reallocation) is the sum of creation and destruction.

More formally, letting $L_{i,t}$ denote outstanding loans of bank i in period t, we define:

Loan Creation: $C_t = \sum_{i,t}(L_{i,t} - L_{i,t-1})$for those i s.t.$L_{i,t} - L_{i,t-1} > 0$.

Loan Destruction: $D_t = \sum_{i,t}|L_{i,t} - L_{i,t-1}|$for those i s.t.$L_{i,t} - L_{i,t-1} < 0$.

Gross Flow: $D_t + C_t$.

For loan data, we take quarterly levels of total loans from the *FFIEC Quarterly Reports of Condition and Income* ("Call Reports"). A few small banks were excluded from the sample, such as banks that never made any loans. The data starts in 1959, quarter 4, continuing to 2004:3, and is quarterly on regular basis starting in 1978:2. Because coverage was not uniform, for many calculations we use data starting in 1969:4. Thus for most purposes we have approximately 2 million data points. The loans were adjusted for inflation (using the CPI), converting all amounts into 1982 constant dollars.

For a number of small banks, there are missing call reports. Where this was infrequent, we simply interpolated the loans from the preceding and succeeding calls, using straight line interpolation. On rare dates, when many banks are missing their call reports, entire quarters were discarded before loan creation and destruction figures were calculated.[1]

Four quarters were characterized by an expansion of the coverage in the call report. These were 1959:4, the start of our sample, where many banks "entered," and 1960:4, 1969:2, and 1980:2. In these cases, the quarters were used to make the calculations of flows, and then discarded in the final analysis.[2] For time series calculations, these dates where interpolated. In making this choice, we take the opposite tack from Dell'Arriccia and Garibaldi; as a result, we have a longer, but less consistent series. We adjust for this problem by looking at gross flows in percentage terms, which should reduce the distortion from changes in number of banks reporting. In compensation, we get a significantly longer series containing many more business cycles.

The massive consolidation of the banking industry over this period presents the greatest challenge to using this data. If Bank1 and Bank2 each make $1000 of loans in quarter 1 and quarter 2, there is no creation or destruction. If lending remains constant, but Bank2 merges into Bank1, Bank1 would show creation of $1000 and Bank2 would show destruction of $1000. We solve this by redefining creation and destruction for periods in which there is a merger. Specifically, in this case, we would define creation as $L_{1,t} - (L_{1,t-1} + L_{2,t-1})$. In our time period there were mergers involving 6,889 target banks. Acquisitions, where the original bank kept its charter and thus continued to report, did not cause a problem.

Bank mergers and their timing are taken from the FFIEC file on bank mergers. Further details can be found in Craig and Santos (1999). We used a FORTRAN program to find and identify mergers. Actual mergers often went beyond one bank buying another. In some cases, several banks merged together; in others, the banks merged and then took on a new name. A few small banks were dropped because of difficulty interpreting the merger results, either because no successor bank was found or for other reasons (for example, where A bought B, B bought C, and C bought A). These banks were all tiny and had a negligible impact on our result. The final sample had 6,798 target banks.

[1] These dates clustered around the change from semi-annual to quarterly reports. We dropped 1976:1, 1976:3, 1977:1, 1977:3 and 1978:1.

[2] That is, if coverage expanded in period T, we computed the flows from $T-2$ to $T-1$ and from T to $T+1$, but interpolated the flow from $T-1$ to T.

The date for mergers and exits are defined by the last positive entry in the call, not the official merger date, as many banks fill out call reports one or two quarters after the official date.

Mostly we work with total loans, but we report a few statistics for commercial and industrial (CNI) loans, in cases where their properties differ substantially from total loans. In this case creating a consistent series across the entire sample was not possible. "Acceptances," included in the early definitions of CNI, was split out in 1984 and later dropped from the call report in 2000. As a result, there are two series of CNI loans: an 'old series' from 1959 until 2000, and a 'new' series without Acceptances from 1984 to the present.[3]

3 An Illustrative Model

To help fix ideas and further refine the economic intuition behind the notion of gross loan flows, we explore a simple search-theoretic model of the lending process. Borrowing heavily from the search labor literature, it does not pretend to be a deep theory about intermediation, nor of banking structure, but it does aim to highlight the importance of lending flows. Unlike the labor literature, however, there is virtually no data on the stock variables corresponding to unemployment and vacancies, so the emphasis is even heavier on the flows of creation and destruction.

The model we adopt has many formal similarities to job search models, except that firms search for financing rather than workers. Since we are particularly interested in the effect of aggregate shocks, our model is closest to Shimer (2005), which extends the Pissarides (1985) search model to include aggregate shocks.

The model assumes a continuum of infinitely lived, risk neutral agents called firms, who need financing before they can produce. A continuum of risk neutral and infinitely lived banks, with measure one, can provide this financing, but (unmodelled) credit market frictions mean that banks and firms must expend time and effort to search for each other and find a suitable match.

Banks are endowed with a unit of capital that they may rent to a firm each period, provided they are matched. If not lent to a firm, the capital provides flow utility z (perhaps the bank is investing in government bonds or other non-loan assets). Firms use this capital to produce output, with total output given by the random productivity shock $p(t)$. To find a bank, a firm must search,

[3] In particular, we make no adjustment for loan sales, in part because of the dearth of data post 1998, and in part because treating only those loans on the books remains an important question, even if that number does not match originations. For more on the loan sales market, see Gorton and Haubrich (1990) or Haubrich and Thomson (1996).

paying a flow cost c. As in Shimer (2005) free entry drives the expected present discounted value of search to zero. Holding everything else equal, higher productivity makes firms more willing to pay the search cost and start searching for a loan. Given a match, the bank and firm separate according to a Poisson process with arrival rate $s(t)$.

Productivity and separation rates follow a first order, two-state markov process in continuous time. The rates may take on the two values $\{(p_g, s_g), (p_b, s_b)\}$ Shocks hit the economy with Poisson arrival rate λ, changing the values from (p, s) to (p', s'). Formally, this makes matching a Cox process (see Lando (1998)).

The time spent searching for a loan depends on both the number of firms searching and the number of banks who have money to lend. Let B denote the measure of banks searching for firms (the others are already lending to firms) and let F denote the measure of firms searching for banks. Then $\phi(t) \equiv F(t)/B(t)$ defines the F-B ratio at time t, which Wasmer and Weil (2004) call an index of "credit market tightness." Assuming a constant returns to scale matching technology $m(B(t), F(t))$, a bank finds a firm according to a Cox process with the time-varying arrival rate $f(\phi(t)) \equiv m(1, \phi(t))$. Conversely, firms find banks at rate $q(\phi(t)) \equiv m(\frac{1}{\phi(t)}, 1) = f(\phi(t))/\phi(t)$.

We assume that matches have positive surplus, $p(t) > z$, and that this is split between the parties via Nash bargaining with banks keeping a fraction β. In other words, this bargaining determines the interest rate charged on the loan.

All agents discount the future at rate $r > 0$.

3.1 Equilibrium

We will focus on equilibria in which the F/B ratio depends only on p, s and $\phi_{p,s}$, the F/B ratio in state (p, s). Given this, the measure of banks looking for firms is determined by a differential equation

$$\dot{B}(t) = s(t)(1 - B(t)) - f(\phi_{p(t),s(t)})B(t). \tag{1}$$

A flow $f(\phi(t))$ of the $B(t)$ banks without loans find a firm and lend, while lending stops at $s(t)$ of the $(1 - B(t))$ banks currently lending. An initial condition at the switch date pins down the level of lending. Note that equation 1 is actually two differential equations, one for the good state, (p_g, s_g), and one for the bad state, (p_b, s_b). In the discussion that follows, this is also true for each expression that is subscripted with p, s: the expression actually represents two conditions, one for the good state, when it is the current state, and one for the bad state, when it is current.

The Bellman equations can be combined into a recursive expression for the joint value of a bank-firm match:

$$rV_{p,s} = p - (z + f(\phi_{p,s})\beta V_{p,s}) - sV_{p,s} + \lambda(E_{p,s}V_{p',s'} - V_{p,s}). \tag{2}$$

Here $V_{p,s}$ denotes the value in the current aggregate state, and $E_{p,s}V_{p',s'}$ denotes the expectation of V following the next shock, conditional on the current state (p, s).

The firm's free entry condition provides another set of conditions. The flow search cost c must equal the flow expected return, or the probability of a meeting times the firm's share in the gains, or

$$c = q(\phi_{p,s})(1 - \beta)V_{p',s'}. \tag{3}$$

Using 3 to eliminate $V_{p,s}$ and $V_{p',s'}$ from 2 gives

$$\frac{r + s + \lambda}{q(\phi_{p,s})} + \beta\phi_{p,s} = (1 - \beta)\frac{p - z}{c} + \lambda E_{p,s}\frac{1}{q(\phi_{p',s'})}. \tag{4}$$

Since the parameters (p, s) evolve according to a two-state markov process, 4 further simplifies to

$$\frac{r + s + \lambda}{q(\phi_{p,s})} + \beta\phi_{p,s} = (1 - \beta)\frac{p - z}{c} + \lambda\frac{1}{q(\phi_{p',s'})}. \tag{5}$$

Expression 5 represents two non-linear equations in two unknowns, $\phi_{p_b,s_b}(\equiv \phi_b)$ and $\phi_{p_g,s_g}(\phi_g)$. Solution of these two equations yield equilibrium values for these two parameters, ϕ_b^* and ϕ_g^*, that are constant as long as the state of the economy remains the same. Although in the steady state loan creation equals loan destruction, the presence of aggregate shocks means the market is often far from its steady state. Bank loans then evolve according to the differential equation (1). As a linear first order equation it has the solution

$$B_i = \frac{s}{s + f(\phi_i^*)} + ke^{-(s+f(\phi_i^*))t}. \tag{6}$$

Notice that as $t \to \infty$, B_i approaches its steady state value $\frac{s}{s+f(\phi_i^*)}$, (so long as the state of the economy, (p, s), does not change). The required initial condition comes from the fact that B, the level of banks looking for loans, cannot jump even when the state changes, so $k = B_i(t_0) - \bar{B}_i$ where t_0 is the time that the state changes to state i, and where $\bar{B}_i$ denotes the steady state value of B in state i.

To illustrate, we follow the search literature and make the standard assumption that the matching function takes a Cobb-Douglas form

$$f(\phi) = \phi q(\phi) = \mu \phi^{1-\alpha}. \tag{7}$$

Then

$$\frac{r + s_g + \lambda}{\mu} \phi^{\alpha}_{p_g,s_g} + \beta \phi_{p_g,s_g} = (1-\beta)\frac{p_g - z}{c} + \frac{\lambda}{\mu}\phi^{\alpha}_{p_b,s_b} \tag{8}$$

$$\frac{r + s_b + \lambda}{\mu} \phi^{\alpha}_{p_b,s_b} + \beta \phi_{p_b,s_b} = (1-\beta)\frac{p_b - z}{c} + \frac{\lambda}{\mu}\phi^{\alpha}_{p_g,s_g} \tag{9}$$

This set of two equations has solutions, ϕ^*_b and ϕ^*_g, that are easily found by numerical methods. If we further specialize the matching function 7 setting $\alpha = 1/2$, (this is the number Wasmer and Weil use for bank and firm matching) then the equilibrium credit tightness ratios, emerge as the solution to a pair of simultaneous quadratic equations, where (9) has an analytical solution, although it is quite complicated. For example, if we choose the following values for the parameters:

$$\beta = 0.5, s_g = 0.1, s_b = 0.2, r = 0.01, c = 0.35, \mu = 1, \lambda = 0.075, p_g = 1, p_b = 0.9, z = 0.4 \tag{10}$$

then $\phi_g = 1.426$ and $\phi_b = 1.028$ for the steady-state values of the F/B ratios in the good state and the bad state in the case where $\alpha = 1/2$.

Using (6) along with the parameters (10) allows us to create an artificial series taking as input a particular realization for the shock process. Figure 1 shows one such artificial series for creation, destruction, and gross flows. Although all flows vary over time, note that in the steady state, once the shocks have dissipated, creation equals destruction. This does not hold true during transitions. In the transition to the bad state, creation falls and destruction increases. When the economy moves from the good state to the bad state, destruction increases because the separation rate is higher; loan creation falls because match productivity is lower, leading fewer firms to search for loans, leading to fewer matches. Because the new state changes the equilibrium ϕ, the ratio of firms to banks, creation and destruction may differ in the transition. (Free entry of firms allows the ratio to adjust instantaneously, but loans take longer to adjust.) Eventually, these factors work to decrease the pool of loans and bring creation and destruction back into balance.

By explicitly including finding and separations, this model highlights the simultaneous creation and destruction of loans, a key feature of the data. In contrast to most of the previous literature on aggregate lending, the model attributes changes in lending to changes in finding and separating rates, an interaction between aggregate shocks and search frictions. In a recession, productivity is low, so fewer firms are willing to pay the search cost, so findings fall, and at the same time separations increase. Together, these reduce total loans. Without the search frictions, aggregate lending would be constant (all banks would be making loans) and creation and destruction would always balance. With search frictions, creation and destruction do not always balance, and aggregate lending growth results from an interaction between the flows created by the aggregate shocks and the matching process. We find this a useful framework to organize the data, to which we now turn.

4 Gross Loan Flows: some elementary facts

Two sets of questions organize our exploration of the gross flows data. First, how heterogeneous is the bank loan market? Does a small increase in total loans result from a small increase at most banks or from banks with high creation offsetting those with high destruction? How much of loan growth results from banks entering and leaving the market? Is the growth concentrated in fast growing firms, or spread more evenly across banks?

Second, how do gross flows differ over the business cycle? Is there a difference between recessions and expansions? For example, Davis and Haltiwanger (1992), looking at *job* creation and destruction, emphasize several features. They find a high level of both creation and destruction in all time periods. Good times or bad, many plants are hiring workers and many are laying them off. In recessions, however, destruction dominates, and accounts for much most of the movement in employment. We also find high levels of both loan creation and destruction in all periods, but changes in both creation and destruction contribute to reduced loan growth in recessions.

4.1 The basic time series

Our analysis centers on a time series for six variables: loan growth, creation, destruction, gross flow, entry and exit. The time series starts with data for the fourth quarter of 1959, which, since it has a date of December 30, shows up in plots as 1960. A few simple operations on the series, such as plotting the data and calculating persistence will reveal the main characteristics.

Figure 2 plots the growth of real total loans, loan creation, and loan destruction. At least since the early 1970's, when the data becomes more comprehensive, both loan creation and destruction

Table 1: Loans

	Growth	Creation	Destruction	Entry	Exit	Gross
mean	0.86	3.12	2.25	0.11	0.49	5.37
median	1.08	3.07	2.05	0.06	0.26	5.27
std	1.52	1.17	1.26	0.14	0.68	1.90
min	-4.06	0.66	0.27	0.00	0.00	2.12
max	5.09	7.12	6.20	0.93	4.40	12.99

remain high, though variable. Even when net loan growth was negative, such as the early 1980s or the early 1990s, many banks were increasing the number of loans they made. In 1991:2, the total value of loans fell by $20 billion: this was the difference between creation of $40 billion and destruction of $60 billion. Figure 3, which isolates out gross flows and loan growth, reinforces this point: the gross loan flows far exceed the net loan flows. On average gross flows are over six times aggregate loan growth.

Figures 4 and 5 concentrate on creation and destruction separately. Creation shows a general, if irregular, upward trend, and entry has only a small part in loan creation: most creation comes from existing banks. This is not surprising although it contrasts with Davis and Haltiwanger's result which shows a much larger influence from plant creation. Their data is at the plant level whereas ours is at the bank level. Opening a branch (which might correspond to a plant entry) thus would correspond to an existing bank's increase. Exit plays a larger part in destruction, particularly recently, though most destruction still comes about from surviving banks reducing their loans.

Table 4 expresses this in a somewhat different manner. It lists the mean, median, standard deviation, maximum, and minimum of gross flows, creation, destruction, entry and exit, as a percentage of total loans beginning in 1960:1. Overall, real total loans grow at an average (quarterly) rate of 0.86 percent. This is a balance between a creation rate of 3.12 percent and a destruction rate of 2.25 percent. Thus, in an average *quarter* there is a gross change of 5.37 percent of all bank loans, over six times the net change.

Although the comparison will be imperfect on many levels, a comparison with the Davis and Haltiwanger data on gross job flows can provide a simple benchmark for the loan flows. Table 2 reports their data, which are quarterly numbers from 1972:2 to 1988:4, a somewhat shorter sample than for loans. The reallocation, creation, and destruction rates for jobs all exceed the equivalent numbers for loans. Both markets exhibit large simultaneous creation and destruction, with gross flows exceeding net growth.

Table 2: Davis and Haltiwanger data

	job growth	creation	destruction	gross flow
mean	-0.31	5.2	5.54	10.44
median	0.04	4.93	5.15	10.73
std	2.17	0.89	1.66	2.18
max	2.59	7.32	11.42	14.67
min	-8.17	3.25	3.25	0.94

4.2 Distribution of changes

Not only do banks enter and exit the market, but they also create and destroy loans at very different rates. Figure 6 displays a histogram depicting the distribution of creation rates among banks as a fraction their total loans, beginning in 1970:1. Two features stand out. Modest increases account for most creation: 50 percent of all loan creation occurred in banks that expanded loans between 0 and 10 percent. Large changes are not completely negligible, however. Banks that more than doubled the value of their loans accounted for 8 percent of creation. New entry accounted for another 5 percent. A category we label "strange," comprised of in-sample banks with no loans in the previous period, added 0.6 percent. Thus more than one dollar in eight of new loans is accounted for by banks that either more than doubled the value of their portfolio or did not exist before.

Figure 7 depicts the distribution of destruction rates for the same time period. Again, modest changes dominate: 50 percent of destruction was in banks that decreased loans by between 0 and 10 percent. Large changes are more important than for creation, however. Exits account for 20 percent, and decreases of 95-100 percent account for an additional 1 percent. Thus, slightly more than one-fifth of loan destruction comes from banks that drastically decreased their loans.

In one sense the dominance of banks with smaller growth rates should not be particularly surprising. Most assets are concentrated at the larger banks, which might then be expected to grow slower (see Evans 1987 for a more extensive discussion of this and related issues). Large banks (assets above $5 billion) accounted for 51 percent of the loans in the sample, and 47 percent of the total gross flows. The smallest banks (assets below $50 million) had slightly greater rates of creation and destruction, but with only 6 percent of total loans it made little difference to the aggregates.

Table 3: Total Loans

	Growth	Creation	Destruction	Entry	Exit	Gross
Recessions						
mean	-0.17	2.57	2.74	0.11	0.47	5.30
std	1.55	1.26	1.17	0.14	0.68	1.87
Expansions						
mean	1.06	3.22	2.16	0.11	0.50	5.38
std	1.44	1.13	1.26	0.13	0.69	1.91

5 Gross Loan Flows and Business Cycles

From a macroeconomic perspective the interest in bank lending lies in its interaction with business cycles. An exciting part of the gross job flows literature derived from the prominence of job destruction in recessions. Gross loan flows have the additional possibility of shedding light on the transmission and propagation mechanisms behind business cycles. How do gross flows change over the business cycle, and what accounts for those changes? What has the focus on net changes missed?

5.1 Cyclical patterns

Comparing the summary statistics for gross flows in recessions and expansions gives one set of answers. Table 3 does this,using NBER cycle dates for the period 1969:4 to 2004:3.

The numbers in table 3 show a cyclical pattern, but neither creation nor destruction drives the results. Loan growth slows, on average, by 1.2 percent (quarterly) between expansions and recessions, and this is apportioned between a 0.7 percent drop in creation and a 0.6 percent increase in destruction. Even in recessions, many banks increase lending. Entries stayed even, and more surprisingly, exits, as a percentage of total loans, fell slightly. The stylized facts thus show neither a uniform reduction by all banks nor a reduction concentrated in a few banks. Even in a recession, many banks expand, few fail, and the decline in lending is broad based.

The distribution of creation and destruction does change somewhat across the business cycle, as a look at the histograms in figures 8 and 9 show. There's no obvious pattern to the changes in creation. For destruction, however, recessions show a marked increase in small levels of destruction (at 10% and below) and a marked decrease at larger levels. Exits actually make up a larger fraction of destruction in recoveries than in recessions.

5.2 Model estimation

We can take the business cycle analysis a step further by explicitly estimating the model of section 2. This will provide a notion of how finding and separating rates differ between recessions and recoveries.

Before the model can be taken to data some simple work is needed to allow for the growth of the banking sector over our sample, as the model assumes a constant measure of banks. This requires an adjustment in the fundamental differential equation, 6. If there were no increase in the size of the banking sector, then creation would be given by

$$C = f_i BN$$

where N represents the total size of the banking sector, and C represents total loan creation. Normalizing by N, total loans, creation then evolves according to:

$$\frac{C_t}{N} = \frac{f_i s_i}{s_i + f_i} + f_i k_t e^{-(s_i+f_i)t} + u_{1t} \tag{11}$$

where u_{1t} is the unobserved error term. Similarly, destruction is represented by an equation:

$$\frac{D_t}{N} = \frac{f_i s_i}{s_i + f_i} - s_i k_t e^{-(s_i+f_i)t} + u_{2t}. \tag{12}$$

These equations do not hold if the banking sectors grows over time, however, and in general any adjustment will depend on the growth process. We took a simple approach and assumed a constant secular growth rate for the banking industry, with $N = N_0 e^{ht}$. Then creation and its evolution become

$$C = f_i BN + \Delta N$$

$$\frac{C_t}{N_t} = \frac{f_i s_i}{s_i + f_i} + f_i k_t e^{-(s_i+f_i)t} + h\Delta t + u_{1t} \tag{13}$$

where $h \equiv \frac{\dot{N}}{N}$ is constant. One important difference between this equation and equation (11) above is that N_t is now a function of time, and not constant. For a static model, N can be thought of as simply a normalization that sets the units for loan creation and can thereafter be ignored. Now however, it is a function of time, and the growth rate h becomes another parameter in the two equations we estimate:

$$\frac{C_t}{N_0 e^{ht}} = \frac{f_i s_i}{s_i + f_i} + f_i k_t e^{-(s_i+f_i)t} + h\Delta t + u_{1t} \tag{14}$$

Table 4: Loans

	f_g	s_g	f_b	s_b
estimate	1.10402	0.10896	0.83782	0.11026
standard error	0.0225	0.0238	0.0332	0.0318

and

$$\frac{D_t}{N_0 e^{ht}} = \frac{f_i s_i}{s_i + f_i} - s_i k_t e^{-(s_i+f_i)t} + u_{2t}. \tag{15}$$

These two equations have two initial conditions embedded in them. The first is actually a set of initial conditions that changes with each regime shift. First, because the model does not allow instantaneous jumps in total loans, the first set specifies the the k_t at each regime shift. Once we know the time of each shift, these can be defined recursively once an initial value is chosen, though the recursion is non-trivial.[4] We set the time of the regime shift to coincide with the official NBER definitions of recessions and expansions. We also need to set the value of the initial size of the total loan pool, N_0, which is unobservable. We arbitrarily set the value of k_0, the initial value of B in 1959 to be 0.5 for the estimates reported here, although we also estimated the model with other values. Given the value of B_0, then, we compute the desired loan total to be $\frac{L_0}{B_0}$ where L_0 is the observed total value of loans. Our value for the secular loan growth rate, h, was set at 0.025 per year, about the rate of total loan increase over our sample period.

We estimated equations (14) and (15) using non-linear least squares with technique due to Jorgenson and Laffont (1974) which adjusts for contemporaneous correlation between the error terms u_{1t} and u_{2t}. The estimates are:

The main cyclical pattern that emerges from table 4 is that loan findings decrease during recessions. Separations, increase, although statistically the difference is not significant. This is consistent with the evidence presented above that in recession, creation falls and destruction increases and is consistent with the general tone of our model. However, much work needs to be done before we can say that these parameters are convincing estimates of loan finds and loan separations. The time series properties of the unobserved error terms need to be handled, and the secular growth of the banking sector needs to be modelled more explicitly. The estimates presented here are intended

[4]Thus, k_t is simply B_{t0}, the value of B at the start of the current expansion or recession, which is in turn, a function of the parameters f_g, s_g, f_b, s_b, the total duration of the last recession or expansion, and the value of the initial condition of the previous spell, k_{t-1}. However, k_{t-1} is itself a function of the parameters, f_g, s_g, f_b, s_b, the total duration of the last recession or expansion, and the value of the initial condition of the previous spell, k_{t-2} and so on, recursively back to the first period in the sample, where the initial condition, k_0 must be set. Once k_0 is known, then for each set of parameter values, f_g, s_g, f_b, s_b, the full set of initial conditions, k_t can be recursively computed.

more as an illustration that the model can be estimated in principle in such a way that it yields plausible results. Our illustrative search model of loan generation is broadly consistent with our gross loan flow data.

6 Job Flows and Loan Flows

A raw comparison of job flows and loan flows probably means little, in light of the very different ways the data is organized and constructed, but viewed in percentage terms, some business cycle and time series patterns emerge.

The most notable difference between the two sets of series is the pronounced seasonality of the job creation, destruction, and gross flows. Loan flows show only minor seasonality, at best. This seasonality also lies behind the very different autocorrelation properties of the two data sets. At a one-quarter lag, job flows show insignificant and generally negative autocorrelations. Loan flows show positive and significant, with the first-order autocorrelation of between 0.2 and 0.4. At one year, however, the job flows show a higher autocorrelation, between 0.6 and 0.8, as opposed to the loans, which show coefficient of between 0.2 and 0.4 at the year lag.

Dell'Ariccia and Garibaldi (2005) point out an intriguing connection between job and loan flows. Following the 1990 recession, employment grew extremely slowly, and the time period became known as the "jobless recovery" . The period also witnessed particularly low loan growth (termed 'financial head winds' at the time Greenspan 1997). Is this a robust pattern? The question is particularly interesting because of the small impact loan flows and job flows seem to have on each other, whether measures by cross-correlations or Vector Autoregressions. (not reported here). Figure 10 confirms their point, looking at loan creation, destruction, and net growth around the start of the 1990 recession. Destruction stays high and loan growth is persistently negative. Interestingly, however, the pattern is not repeated after the 2001 recession (figure 11), which saw even more dismal employment patterns (the "job*loss*" recovery). The story is more complicated, however, if we turn to CNI loans. 1990 still looks anomalous, though now because of slow loan growth prior to the recession. In 2001 the slow loan growth appears after the recession, driven by noticeably lower creation.

7 Conclusion

Anyone who has seriously looked at banking data is well aware of the diversity among banks. A focus on gross flows suggests that exploring this diversity yields insights into the causes of underlying trends. And the diversity can at time be shocking, as an anecdote from the southwest shows. One of the largest drops seen in our data came in the third quarter of 1988: in the wake of plunging oil prices, banks in the Dallas Federal Reserve district reduced total loans by five percent in one quarter, a 20% annual rate. The plunge was hardly uniform, however. In that same quarter destruction ran at 24%, with creation a rather astonishing 19%.

Though rarely that extreme, gross flows are large: on average, over five percent of total loans are either created or destroyed, each quarter. This is about six times the net change in loans per quarter. Like loans themselves, total gross flows are concentrated at the large banks, though smaller banks show a greater proportion of creation and destruction than their share of net loan growth would indicate.

At this stage of the investigation, many results raise more questions than they answer. Prominent among this are the distribution of changes across banks. The bulk of creation and destruction occur in banks making a change of less than 10 percent in their loans, but larger changes (either a doubling or better of the loan portfolio or an entry or exit) have a substantial share, accounting for one seventh of new loans and more than one dollar in six of all loans that a bank does not replace. Furthermore, for destruction, smaller changes become more important in recessions. One reason these results are worth noting is because traditional search theory say little about the distribution of changes across firms.

The interaction of gross loan flows with the rest of the economy also seems worthy of further study. The business cycles facts are suggestive but not tightly tied to a model: creation is higher in expansions and lower in recessions, destruction is lower in expansions and higher in recessions, and entry and exit don't show a cyclical pattern. Similarly, the relationship with labor gross flows is suggestive, but needs to be fleshed out. And, given the traditional importance of banks in the transmission of monetary policy, the relation of gross loan flows to monetary shocks deserves scrutiny.

In the labor literature, examination of gross flows helped call attention to the heterogeneity in the employment relation. The banking literature as a whole has been well aware of heterogeneity among banks, but in many cases has lacked the proper perspective to make it manageable and relevant. We think that the gross flows approach can help.

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Figure 1:
GROSS LOAN FLOWS, MODEL

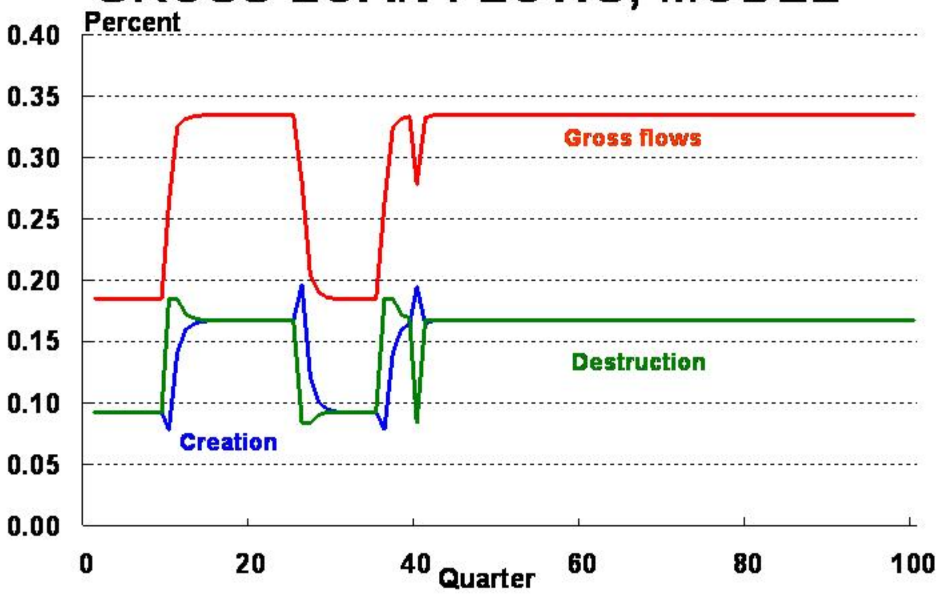


Figure 2: TOTAL LOANS

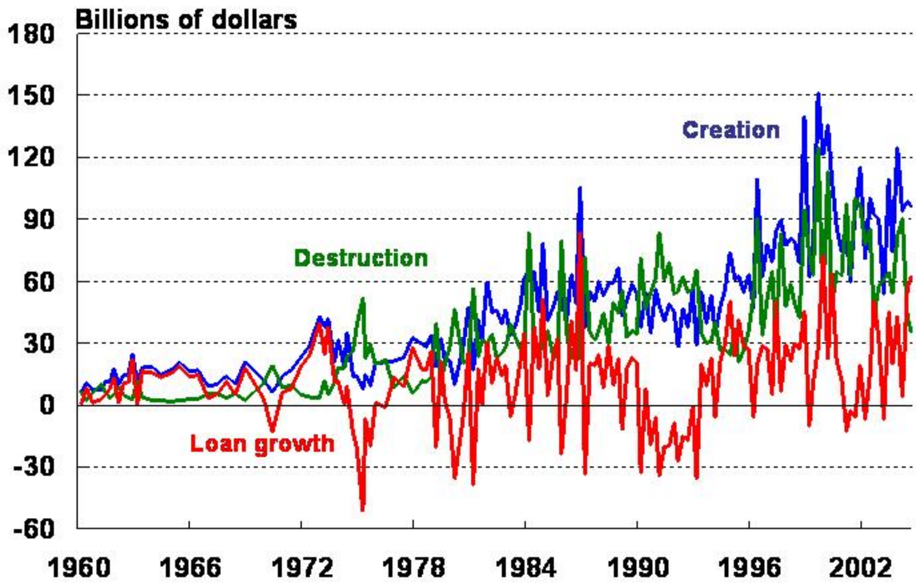


Figure 3: TOTAL LOANS

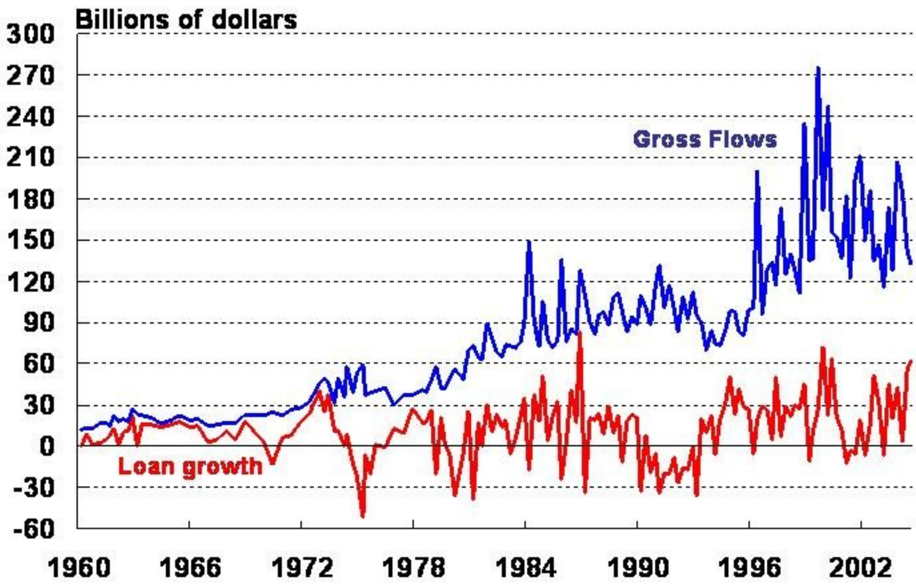


Figure 4: Creation,TOTAL LOANS

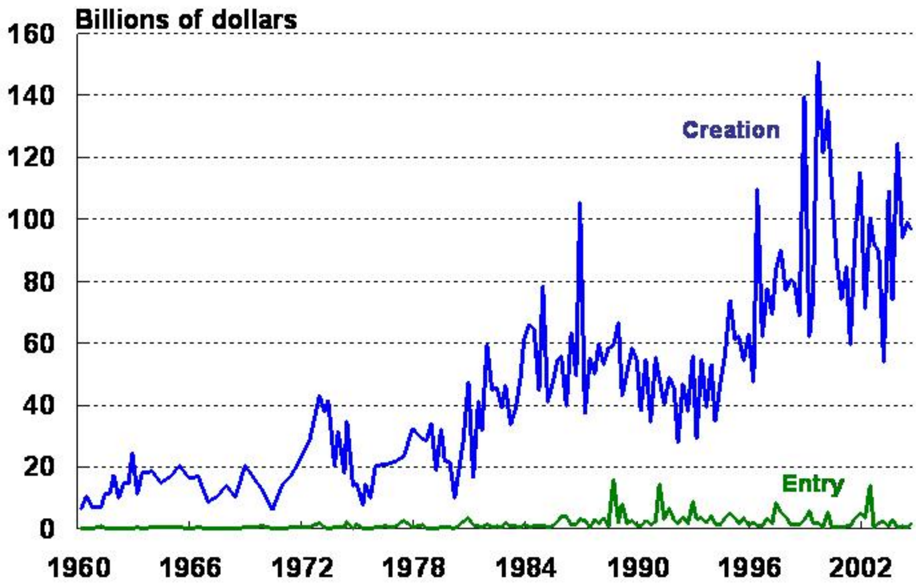


Figure 5: Destruction,TOTAL LOANS

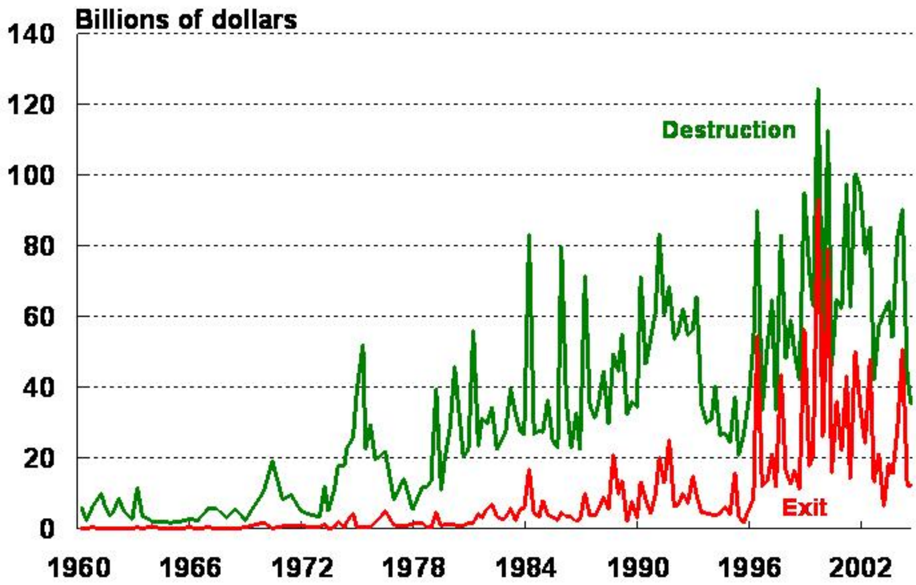


Figure 6:

HISTOGRAM – TOTAL CREATION

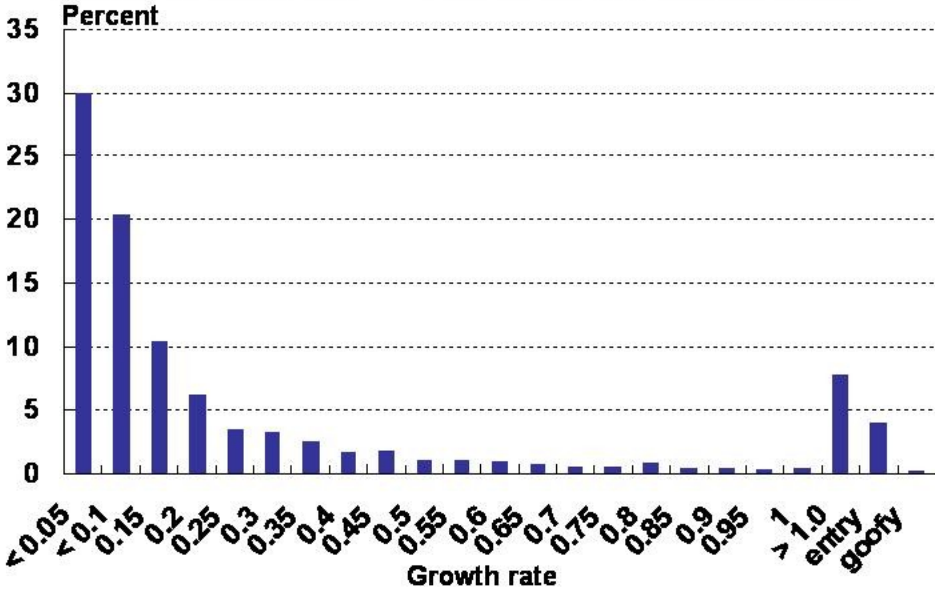


Figure 7:
HISTOGRAM – TOTAL DESTRUCTION

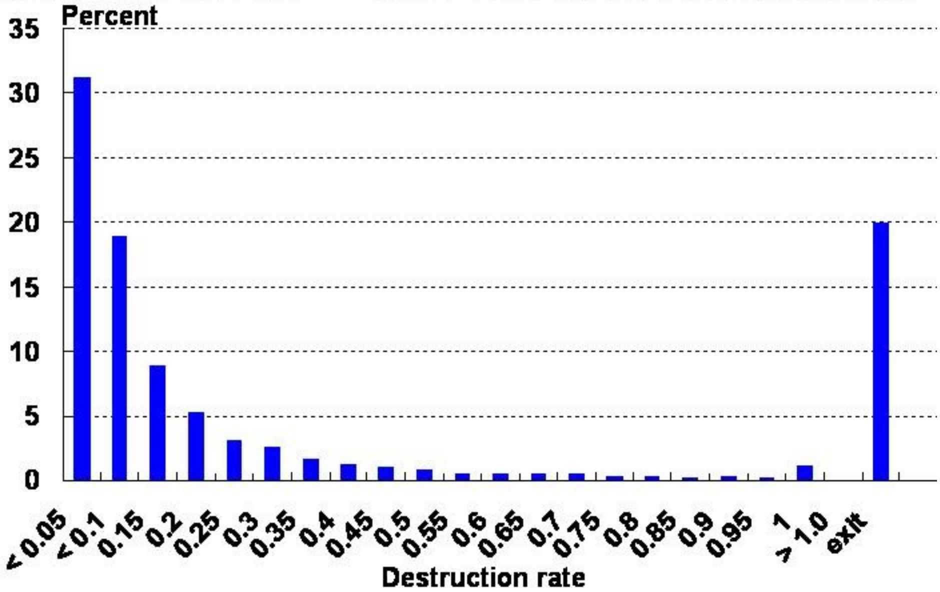


Figure 8:HISTOGRAM – CREATION

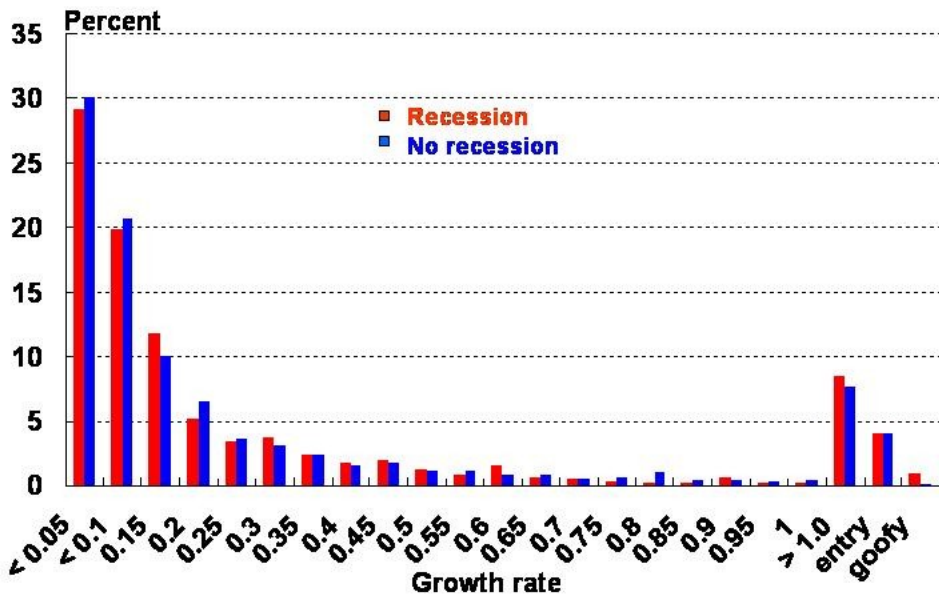


Figure 9:HISTOGRAM – DESTRUCTION

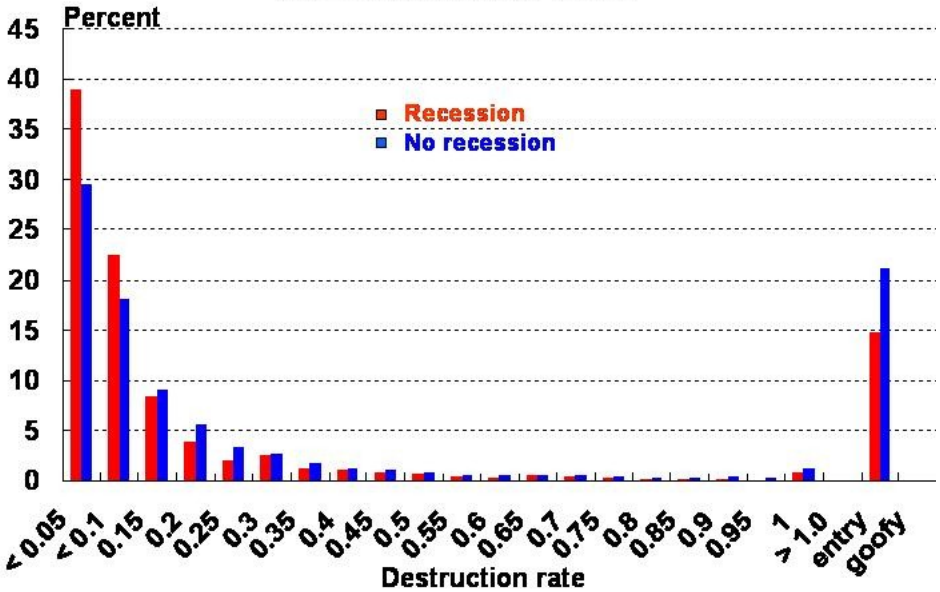


Figure 10: TOTAL LOANS - 1990 RECESSION

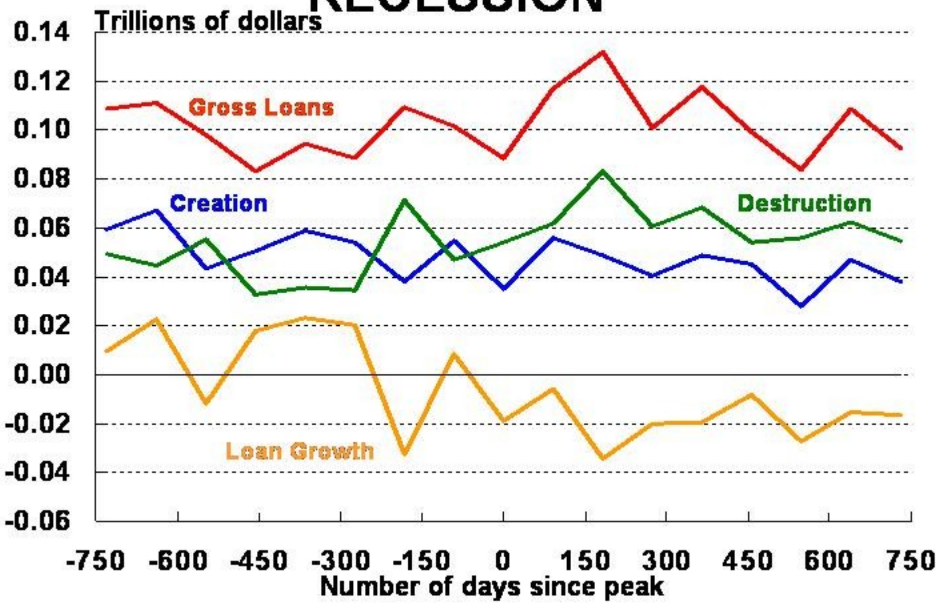
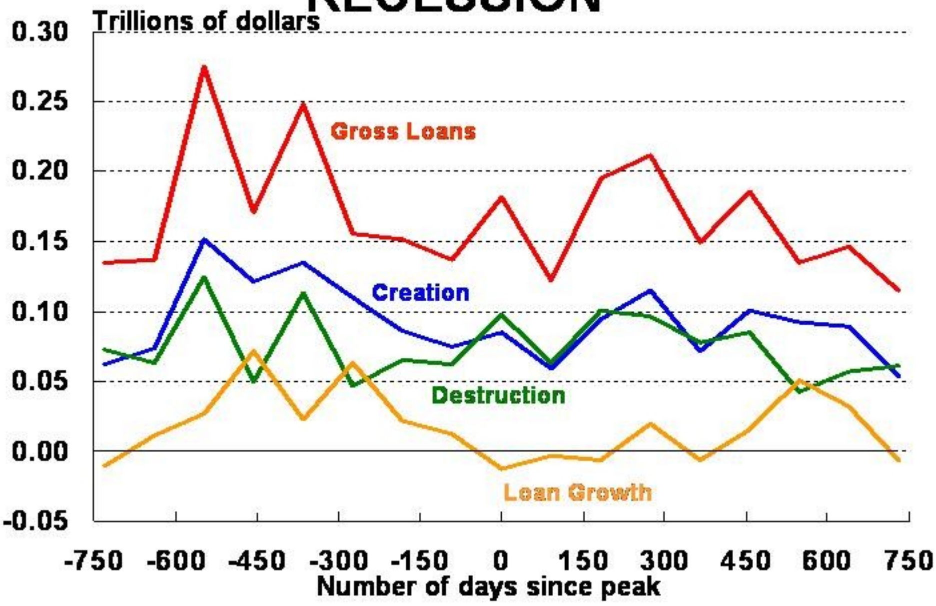


Figure 11: TOTAL LOANS - 2001 RECESSION



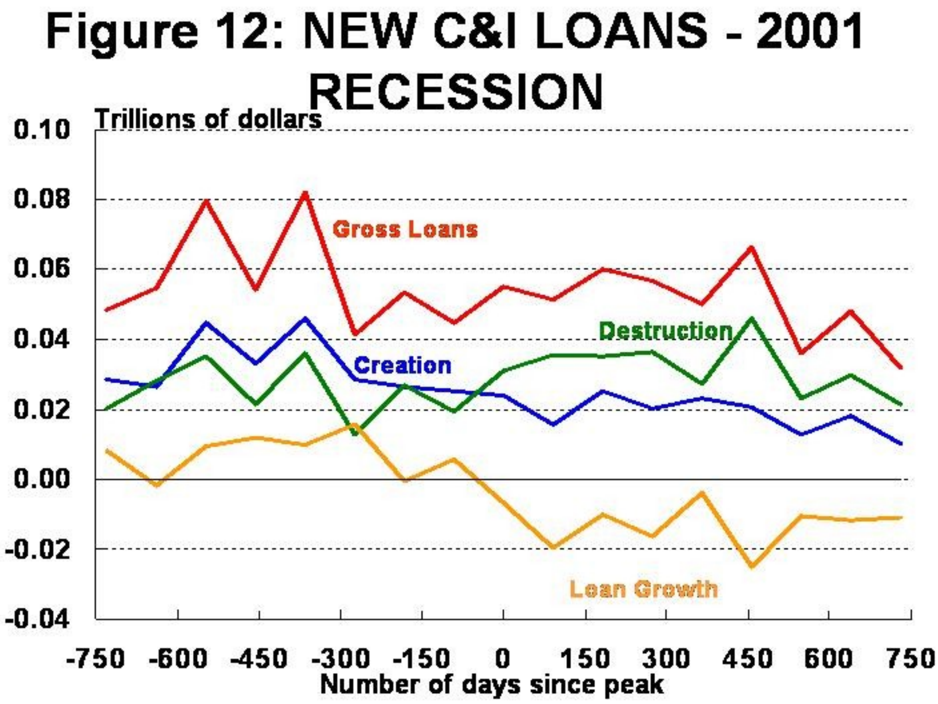


Figure 12: NEW C&I LOANS - 2001 RECESSION
Trillions of dollars
0.10
0.08
0.06
0.04
0.02
0.00
-0.02
-0.04
Gross Loans
Destruction
Creation
Loan Growth
-750 -600 -450 -300 -150 0 150 300 450 600 750
Number of days since peak