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MONETARY POLICY, BUSINESS CYCLES AND THE BEHAVIOR OF SMALL MANUFACTURING FIRMS

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Monetary Policy, Business Cycles and the Behavior of Small Manufacturing Firms[1]

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Abstract

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We present evidence on the cyclical behavior of small versus large manufacturing firms, and on the response of the two classes of firms to monetary policy. Our goal is to take a step toward quantifying the role of credit market imperfections in the business cycle and in the monetary transmission mechanism. Our results indicate that small firms contract substantially relative to large firms after tight money. The difference between small and large firm behavior accounts for a significant portion of both the overall decline in manufacturing sales and the overall decline in manufacturing inventories. An important reason that small firms contribute disproportionately to the decline in inventories is that they maintain a fairly stable inventory/sales ratio. Large firms, on the other hand, let their inventory/sales ratios rise in bad times. Relatedly, short term credit flows to small firms contract sharply after tight money, while they actually rise for large firms. Thus, large firms appear to obtain funds to smooth the impact of declining sales, while small firms do not. Finally, we show that the differential effect of tight money on small firms is asymmetric over the cycle, stronger in bad times than in good times. Overall, the broad array of facts we present is compatible with theories that emphasize financial propagation mechanisms.

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1 Introduction

This paper presents evidence on the cyclical behavior of small versus large manufacturing firms, and on the differential response of the two kinds of firms to several indicators of monetary policy. Our long-term objective is to quantify the importance of financial propagation mechanisms for aggregate behavior.

A number of recent papers have resurrected the view that credit market frictions may help propagate business cycles and, relatedly, that they may play a role in the transmission of monetary policy.[1] Though the underlying theories are diverse, a common prediction is that differences in cyclical behavior should emerge across firms, depending on their respective access to capital markets. This prediction leads us to to compare the behavior of small and large firms at the business cycle frequency.[2]

Practical considerations dictate our using firm size to proxy for capital market access. Doing so enables us to employ a data set that is comprehensive for the manufacturing sector. As a consequence, we can directly assess the quantitative importance of our findings for overall manufacturing fluctuations. The trade off is that some caveats arise in interpreting our results, as we discuss.

In section 2 we develop a simple model designed to illustrate how credit market frictions may help propagate the effects of monetary policy. The goal here is to provide a brief summary of much of the recent theoretical work and also to motivate some of the broad trends we should expect in the data. Impulses other than monetary policy may trigger the financial propagation mechanism we describe. However, we focus on monetary policy because a number of researchers have identified it as an important source of aggregate demand fluctuations in the postwar period [Romer and Romer (1989) and Bernanke and Blinder (1992)]. We borrow the methods of these researchers to identify monetary disturbances. Our empirical strategy then involves tracing out the effect of these disturbances on the time

[1]Bernanke and Gertler (1989), Gertler (1992), Greenwald and Stiglitz (1988) and Williamson (1987) provide recent examples of financial propagation mechanisms. Bernanke and Blinder (1992), Romer and Romer (1990), Kashyap, Stein, and Wilcox (1992) and Fuerst (1991) provide recent discussion of the role of credit market imperfections in the monetary transmission mechanism

[2]Exploiting cross-sectional implications is a theme of firm-level studies of liquidity constraints, beginning with Fazzari, Hubbard, and Peterson (1988). Gertler and Hubbard (1988) discuss the application to aggregate behavior.

series behavior of small firms relative to large firms.

Section 3 describes the data set we use. It consists of quarterly time series variables for all manufacturing firms, disaggregated by size class. We present some justification for using size to proxy for capital market access, but also discuss some of the limitations. The variables we consider include sales, inventories, and short term debt. Our interest in inventories is motivated by Kashyap, Lamont and Stein's (1992) case study of the 1981-82 recession. These authors present evidence that liquidity-constrained firms contributed substantially to the overall inventory decline in the last part of the 1981-82 recession.[3]

Section 4 presents the empirical work. Our most striking results involve the impact of episodes of tight money, as measured by the dummy variables constructed by Romer and Romer (1989). In the wake of a Romer date, small firms contract substantially relative to large firms. The difference between small and large firm growth rates accounts for a significant fraction of the overall decline in manufacturing sales. It accounts for an even larger share of the overall decline in manufacturing inventories. Indeed, small firms play a surprisingly prominent role in the eventual slowdown of aggregate inventory demand. Relatedly, short term lending to small firms contracts sharply after tight money while it actually rises for large firms. A qualitatively similar set of results obtains when we replace the Romer dates with the Federal Funds rate as the indicator of monetary policy. We also show that the response of small firms to the Funds rate is asymmetric over the cycle, stronger in bad times than in good times. Overall, the broad array of facts we present squares neatly with theories emphasizing financial propagation mechanisms. We discuss possible non-financial explanations for our results in section 5.

2 Theory

In this section we motivate how credit market frictions may help propagate the effects of monetary policy. In the model we develop, certain frictions make a firm's input decision sensitive to an endogenously determined credit limit.[4] This limit takes the form of a ceiling

[3]Milne (1991) presents similar evidence. He studies British firm-level inventory data in several recessionary episodes.

[4]The theory we exposit is complementary but distinct from the "credit view" approach to monetary policy, which emphasizes how legal reserve requirements may enable monetary policy to directly regulate

on the ratio of interest costs to expected cash flow. We then use the model to illustrate the following points:

1. A financial mechanism may enhance the impact of interest rates on input demand, via the effect on interest costs per unit of expected cash flow.

2. The mechanism also works indirectly works through the impact of monetary policy on aggregate demand, since shifts in demand alter firms' internal funds (more generally, their collateralizeable assets.) As a consequence, the mechanism may be at work for a considerable time after the initial policy shock.

3. The mechanism varies in strength over the cycle. It is likely most potent when internal funds are low. Hence, evidence of this mechanism is more likely to appear in recessionary periods than in booms.

4. The credit limit implies that constrained firms will maintain a fairly stable ratio of borrowing to expected output. This contrasts with an unconstrained firm, which may borrow heavily to mitigate the impact of declining cash flows.

These points suggest a set of broad patterns to look for in the data.

We first develop the basic framework and then illustrate the impact on input demand of shifts in the interest rate and of shifts in the supply of internal funds.

2.1 A Model of Input Demand with an Endogenous Credit Limit

Our framework is a simple partial equilibrium model of credit rationing. It is based on the costly state verification environments of Townsend (1979), Gale and Hellwig (1985) and Williamson (1987). We interpret the (exogenously given) riskless interest rate as the instrument of monetary policy.

There are two periods: 0 and 1.[5] A risk-neutral firm employs a variable input x in period 0. Think of x as some composite measure of labor and raw materials. To use this

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the flow of bank credit [see, e.g., Bernanke and Blinder (1992), Romer and Romer (1990), and Kashyap, Stein, and Wilcox (1992)]. Our approach emphasizes the general role of liquidity and balance sheet variables on the spending decisions of credit-constrained firms. It permits us to illustrate both the direct and indirect ways financial factors may propagate monetary policy [see points 1 and 2 that follow].

[5]The general kinds of arguments presented here extend to a multi-period environment where borrowers and lenders enter long-term relationships. See Gertler (1992) for an example.

input, it costs the firm a variable expense of $(1/\nu)x^\nu$, where $\nu > 1$, plus a fixed expense of k. The latter reflects the rental price on a fixed factor such as physical capital.

Production in period 0 yields $\tilde{\lambda}x$ intermediate goods. The random variable $\tilde{\lambda}$ is a firm-specific technology shock. It is a non-negative random variable with a continuous cumulative probability distribution function given by $H(\lambda)$ and a probability density function given by $h(\lambda)$. We normalize the mean of $\tilde{\lambda}$ at unity. Finally, we assume that the associated hazard function $h(\lambda)/[1 - H(\lambda)]$ is increasing in λ.

In period 1, just after $\tilde{\lambda}$ is realized, the firm uses the intermediate goods to produce final goods. It transforms each intermediate good into one final good at a cost of $(1 - \alpha)$ per unit, where $0 < \alpha < 1$. Thus, gross output is $\tilde{\lambda}x$ and cash flow (value added in period 1) is $\alpha\tilde{\lambda}x$. Further, expected gross output is simply equal to x, and expected cash flow is simply αx.

The firm finances its expenditures in period 0 partly with internal funds and partly by obtaining a loan from a risk neutral intermediary. The quantity of funds the firm borrows, b, equals the sum of its variable and fixed expenses in period 0, minus its supply of internal funds, s:

$$(1) \quad b = (1/\nu)x^\nu + k - s$$

We assume that the fixed expense exceeds the supply of internal funds:

$$(2) \quad k > s$$

Here we are trying to capture the idea that the firm must rely at least partly on external funds to finance the cost of the fixed factor. As a result, the fixed component of borrowing, $k - s$, is always positive.

Following Townsend (1979), Gale and Hellwig (1985) and Williamson (1987), we introduce an incentive problem between the firm and the intermediary by assuming that the intermediary must pay a cost to observe the firm's cash flow. This monitoring cost may be interpreted more generally as the cost of default, including lawyers fees, liquidation costs, etc. We assume that bankruptcy costs are a fraction γ of the operating size of the firm, as measured by its expected gross output, x.

Under certain assumptions, the optimal financial contract is risky debt.[6] Define d as the non-default payment on the debt. Whenever the ex post cash flow $\alpha\tilde{\lambda}x$ is greater than d, the intermediary receives d and the firm gets to keep the residual. If cash flow falls below d, the firm defaults. The intermediary pays γx, but gets to keep the remaining cash flow. The firm is left with nothing.

Let $z = d/\alpha x$, the non-default debt payment d per unit of expected cash flow, αx. z is thus the value of λ at which cash flow equals d, and H(z) is thus the probability of default. Since the intermediary must receive a competitive return, z has to satisfy

$$(3) \quad z \cdot [1 - H(z)] + \int^{z} \lambda h(\lambda) d\lambda - H(z)(\gamma/\alpha) = rb/\alpha x$$

The left side of equation (3) is the expected return on the risky debt per unit of expected cash flow; while the right side is the opportunity cost of the funds borrowed per unit of expected cash flow.

The firm's expected profits, $V(x, z)$, may be expressed as

$$(4) \quad V(x, z) = max\{\alpha x - r[(1/\nu)x^{\nu} + k - s] - H(z)\gamma x, 0\}$$

The term $H(z)\gamma x$ reflects the expected default costs, which the firm fully internalizes, given equations (1) and (3). In the absence of these costs, the objective simplifies to the case of perfect information.

The firm's investment/contracting problem is to choose x, b and z to maximize (4) subject to (1) and (3). A rationing outcome is possible, where an endogenously determined ceiling on borrowing costs per unit of expected cash flow constrains the firm's input demand. Depending on parameter values, a non-rationing outcome is also possible; however, the expected default costs still distort the choice of x. Further, the qualitative results on how credit market frictions may enhance the potency of monetary policy apply as well in the non-rationing situation. Since the algebra of the rationing optimum is simpler to work

[6] The two required assumptions are: (i) only deterministic auditing schemes are feasible; and, (ii), the intermediary can commit to an auditing policy. [See Williamson, 1987]. Relaxing either of these assumptions does not affect our basic conclusions regarding the impact of the credit market distortions on firm variability. However, we maintain them to preserve tractability.

through, we illustrate the general intuition for our results in the context of this case.[7]

Rationing is possible since the expected default costs are increasing in the promised debt payment per unit of expected cash flow, z. This introduces a limit on the size of z that the intermediary is willing to accept. This limit – call it z^* – is the value of z at which the marginal gain in the expected non-default payment is exactly offset by the marginal increase in expected bankruptcy costs: z^* is thus given by

$$(5) \quad [1 - H(z^*)] - h(z^*)(\gamma/\alpha) = 0$$

where the left side of (5) is the impact of a rise in z on the intermediary's expected return per unit of expected cash flow, evaluated at $z = z^*$.[8] Rationing occurs if equation (5) restricts z, that is, if a non-rationing outcome with z less than z^* is not feasible.

Under the rationing outcome, the intermediary essentially places a ceiling on the firm's relative debt burden, which we define as borrowing costs per unit of expected cash flow, $(rb/\alpha x)$. It follows from (3) and (5) that this ceiling, $q(z^*)$, must equal the intermediary's expected return on the risky debt per unit of expected cash flow, evaluated at $z = z^*$ (i.e., the left side of (3) evaluated at $z = z^*$.) The firm must adjust its choice of x to satisfy this constraint.[9] The optimal input choice is thus the maximum value of x which satisfies

$$(6) \quad q(z^*) = r[(1/\nu)x^{\nu} + (k - s)]/\alpha x$$

where

$q(z^*) \equiv z^* \cdot [1 - H(z^*)] + \int^{z^*} \lambda h(\lambda) d\lambda - H(z^*)(\gamma/\alpha)$

and z^* is given by (5). The right side of equation (6) is borrowing costs per unit of expected cash flow expressed as a function of x, using (1) to eliminate b from the numerator. If there does not exist a value of x that satisfies (6) and that generates non-negative expected

[7] The non-rationing optimum is presented in an earlier version of this paper, Gertler and Gilchrist (1991).

[8] The expression on the left side of (5) is obtained by differentiating the left side of (3) with respect to z. This expression is decreasing in z since the hazard rate is increasing in z by assumption. Therefore, z^* is a unique maximum.

[9] Notice that the relative debt burden is essentially the reciprocal of an interest coverage ratio. Applied macroeconometric frameworks which emphasize financial factors include variables like the interest coverage ratio in aggregate investment equations [see, e.g., Eckstein and Sinai (1986)]. Viewed in this light, our framework provides a loose rationale for this approach.

profits, the firm shuts down.[10]

2.2 The Interest Rate, Internal Funds, and Input Demand

A shift in the interest rate. Equation (6) indicates that, despite rationing, input choice depends on the interest rate. The channel involves the impact of r on borrowing costs per unit of expected cash flow. A rise in r increases this ratio which forces the firm to contract x in order to satisfy the credit ceiling $q(z^*)$. Let η_{xr} denote the elasticity of x with respect to r. From equation (5):

$$(7) \quad \eta_{xr} = -(1+\theta)/[(\nu-1)-\theta)]$$

where

$\theta = (k-s)/[(1/\nu)x^{\nu}]$.

In the rationing optimum θ must be less than $\nu - 1$, which guarantees that η_{xr} is negative; i.e., that x falls when r rises.

In the absence of credit market frictions, η_{xr} equals $-1/(\nu-1)$.[11] Credit rationing increases the sensitivity of x to r since the fixed component of borrowing, $k-s$, is positive. A rise in r, for example, increases the interest expense on the fixed component of borrowing, $r(k-s)$, enhancing the the overall impact on total borrowing costs, rb. This magnifies the drop in input demand x that is required to keep total borrowing costs per unit of expected cash flow (the right side of equation (6)) from rising above the ceiling $q(z^*)$.[12] Equation (7) confirms this intuition; given that k exceeds s, θ is positive, which implies $\eta_{xr} < -1/(\nu-1)$.[13] Further, η_{xr} becomes increasingly negative as $k-s$ rises: The propagation mechanism is thus

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[10]Expected profits will be non-negative if rationing constrains the choice of x below the minimum that enables the firm to cover (in expected terms) its fixed expenses.

[11]In the frictionless case, x satisfies $\alpha - rx^{\nu-1} = 0$ implying $\eta_{xr} = -1/(\nu-1)$.

[12]Farmer (1985) and Gertler (1992) also provide examples where agency problems magnify the effects of interest rates on input demand.

[13]In the benchmark case of $k-s=0$, $\eta_{xr} = -1/(\nu-1)$, the value under perfect markets. In this case, the rationing optimum fixes the average variable cost, $(1/\nu)x^{\nu-1}$ at a constant as (5) suggests. η_{xr} equals its perfect markets benchmark because the elasticity of average variable cost with respect to x equals the elasticity of marginal cost, given the exponential variable cost function. Making average variable cost more elastic than marginal cost raises the value of $k-s$ that is required to make $\eta_{xr} < -1/(\nu-1)$; conversely, making it less elastic reduces the threshhold value of $k-s$ below zero.

stronger, the weaker the cash position of the firm.[14] As the fixed component of borrowing rises, relative debt burdens become increasingly sensitive to interest rate shifts.

A shift in internal funds. The propagation mechanism also works indirectly through the impact of internal funds on relative debt burdens. Suppose that tight monetary policy contracts aggregate demand, and that internal funds decline as consequence. The drop in cash (alone) does not affect the real decisions of a firm with perfect access to capital markets; the firm fully offsets the drop by increasing borrowing. A credit rationed firm, however, is forced to contract input demand in order to satisfy the limit on the ratio of borrowing costs to expected cash flow prescribed by the credit ceiling $q(z^*)$.[15] From (6), the elasticity of x with respect to s, η_{xs} , is given by

$$(8) \quad \eta_{xs} = s/[(\nu - 1) - \theta]$$

where (7) defines θ. Since $\theta < \nu - 1, \eta_{xs} > 0$.[16]

More generally, by altering the supply of internal funds, demand disturbances may also trigger the "financial accelerator" effect on input investment. This suggests, importantly, that the financial propagation mechanism works through the demand side as well as the supply side. In this vein, demand shocks other than shifts in monetary policy may also provide the relevant impulses. However, we emphasize monetary policy in this context, based on the view that it is an important source of aggregate demand disturbances.

Overall, the financial mechanism described here is likely more important when internal

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[14]As we demonstrate, x is increasing in $k - s$, which implies that, overall, θ is increasing in $k - s$.

[15]The impact of internal funds on input demand is an example of the "financial accelerator" emphasized by Bernanke and Gertler (1989), Calomiris and Hubbard (1990), Greenwald and Stiglitz (1988) and others. These theories stress the role of borrower net worth, of which internal funds is a component. There is considerable evidence from panel data for this kind of mechanism [e.g. Fazzari, Hubbard, and Peterson (1988), Gilchrist (1990), and Whited (1992).]

[16]To see that $\nu - 1 > \theta$ in a rationing optimum, first note that borrowing costs per unit of expected cash flow [the right side of (5)] must be decreasing in x in the rationing optimum defined by (5). Otherwise, it would be possible to increase x (and therefore increase expected profits) without violating the credit limit, as equation (5) suggests. This implies that in an optimum with rationing, $(r/\alpha)\{[(\nu-1)/\nu]x^{\nu-2} - F/x^2\} < 0$, or equivalently $\nu - 1 > \theta$.

To see that a rationing optimum that satisfies this condition is feasible, first note that $\nu - 1 > \theta$ in the benchmark case of perfect markets. Expected profits in the perfect markets optimum equal $(\nu-1)(1/\nu)\bar{x}^{\nu} - F$, where $\bar{x}$ is the first best value of x. Thus, $\nu - 1 > \theta$ at $x = \bar{x}$, given that it is profitable to operate in this case. There accordingly exists a region of x below $\bar{x}$, where $\nu - 1 > \theta$, which is larger, the lower the fixed cost F. Thus, a credit rationing optimum at some $x < \bar{x}$ is feasible.

funds are relatively scarce (or, more generally, when collateral assets are low.)[17] In this situation, the credit limit is likely binding across a larger cross-section of firms. Further, debt burdens relative to cash flow are likely larger, and therefore more interest sensitive.

It does not seem controversial to suggest that small firms ought to be more sensitive to the financial mechanisms described here, at least on average. While size itself might not be a direct determinant of this sensitivity, it is likely correlated with the primitive factors that do matter. In the context of our model, factors which reduce the expected default costs relative to the expected cash flow weaken the financial propagation mechanism: The distortions induced by the credit market frictions vanish as the expected default cost become trivial in proportionate terms. Examples of these mitigating factors include: greater collateral (proportionate to loan size); a higher average product; lower idiosyncratic risk; and lower monitoring and bankruptcy costs (proportionate to loan size.)[18] To the extent these factors are positively correlated with firm size, the propagation mechanism is less applicable to large firms, on average, and more applicable to small firms.

3 Data Description

The data set we employ is constructed from the *Quarterly Financial Report for Manufacturing Corporations* (QFR). The QFR reports quarterly time series on a set of real and financial variables for the manufacturing sector. Each aggregate time series is available in disaggregated form, by firm size class. The measure of size is gross nominal assets. There are eight size classes, ranging from under 5 million in gross assets, to over a billion. The data is available from 1958:4 to the present.

The main advantage of the QFR is that the cross-sectional information it provides

[17]Bernanke and Gertler (1989) emphasize that the financial propagation mechanism is likely asymmetric over the cycle. Gertler and Hubbard (1988) find evidence that liquidity effects on investment are stronger in recessions. Oliner and Rudebusch (1992) obtain related results. Finally, Kashyap, Lamont, and Stein (1992) report evidence of asymmetric liquidity effects in inventory data.

[18]While there is little direct evidence on the correlation between size and collateral, there is considerable evidence of a correlation between size and access to financial markets. Smaller firms are less likely to issue publicly traded debt and equity, and more likely to rely on bank loans [see, e.g., Gertler and Hubbard (1988)]. Differences in relative collateralization, broadly defined, is presumably one important factor responsible for this correlation between size and financial structure. Relatedly, there is evidence that average productivity varies positively with size, idiosyncratic risk varies negatively, and proportionate bankruptcy costs vary negatively.

at the business cycle frequency is comprehensive for manufacturing. This permits us to directly infer the quantitative significance of differences in small and large firm behavior for fluctuations in this sector as a whole. Other panel data sets such as Compustat typically restrict attention to publicly traded firms, and therefore under represent small firms.

There are two main limitations to the QFR. The first is that the data are not firm-level. This precludes us from sorting firms by a direct indicator of access to financial markets, such as having a bond rating. Instead, we are constrained to using size as a proxy. We will argue shortly that size is a reasonable proxy for capital market access, based on information from both the QFR and other sources. As we discuss, though, our size control is not ideal since we cannot be certain a priori that it isn't capturing factors in addition to capital market access, as well.

The second drawback to the QFR is that the size classifications are constructed in nominal terms. This introduces measurement bias, since firms may drift from low nominal asset categories to high categories, owing to inflation and trend real growth. Table 1 illustrates the problem. It reports the cumulative percentage of all manufacturing sales accounted for by firms with total assets less than the respective QFR cutoff. Note that all categories of firms, except the largest, shrink in importance over time. For example, the smallest category of firms (assets less than \$5m) accounted for 26% of total manufacturing sales in 1960, but only 12% by 1990. In contrast, the largest category accounted for 15% in 1960 and 56% in 1990.

To adjust for the bias, we reaggregate the size categories into two groups, "small" and "large". We use the thirtieth percentile of sales as the cutoff for small firms. For each period, we construct an approximate (quarterly) growth rate of a variable for small firms by taking a weighted average of the growth rates of the two cumulative asset size classes that straddle the thirtieth percentile of sales at the beginning of each period. The weights are chosen so that the two size classes average thirty percent of sales at t. The growth rate for large firms is similarly constructed, using firms above the thirtieth percentile of sales. We next adjust the growth rates to correct for the bias arising if some firms shifted size classifications between t and $t+1$. [19] This adjustment is based on using the eight

[19] In practice, the bias in the growth rate from t to $t+1$ is likely to be quite small, since the percentage

data points available at t on the cross-sectional relation between sales and asset size to help approximate the entire distribution. An appendix describes this procedure in detail. [20]

We next present some information suggesting that our grouping of small and large firms is reasonable from the standpoint of reflecting capital market access. Table 2 presents information on the composition of debt finance across size classes for 1986Q:4. The size cutoff for the thirtieth percentile of sales (for 1986Q:4) lies somewhere between 100 and 250 million in gross assets, as Table 1 suggests. Given this benchmark, Table 2 suggests that by our definition, small firms rely proportionately more on information-intensive financing. This is true in two main respects: First, they rely heavily on bank finance relative to the mean for manufacturing. Second, for the most part, they do not issue commercial paper. The vast majority of their short term financing is obtained from banks, in contrast to large firms, which rely heavily on the paper market. Overall, these differences in financial structure suggest significant differences in capital market access across our small and large firm categories.

Our use of size to proxy for capital market access also squares with the existing firm level studies of liquidity constraints on investment. Rather than directly sorting firms by size, this literature sorts firms by a more direct indicator of access to financial markets, such as retention behavior or whether the firm has a bond rating. However, in every study thus far, the "likely to be constrained" firms are much smaller on average than the control group. Further, these studies only consider publicly traded companies. Nontraded firms dominate the lower tier of the size distribution in our sample. Thus, we believe that the vast majority of companies in our small firm sample would be considered "likely to be constrained", using one of the conventional financial indicators. [21] Conversely, while some

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of firms near the borders of the cumulative size classes that straddle the thirtieth percentile of sales at any given time t is very low. More generally, "category mixing" has minimal impact on the measured growth rates. In the appendix we show that, on average, more than 98% of the sales in the small firm category is accounted for by firms with assets at least 10% below the cutoff used for small firms. Similarly, more than 98% of the sales in the large firm category is accounted for by firms with assets at least 10% greater than the cutoff for large firms. Thus, firms well within the category borders dominate the respective growth rates.

[20] To provide some cross-validating evidence on our procedure, we obtained data on individual firms from Compustat, and then organized the data into the QFR nominal size class format. We then found that applying the QFR procedure to construct real growth rates from nominal size class data closely approximated the true real growth rates, as the appendix describes.

[21] In Whited's Compustat sample, firms without a bond rating had a median and mean capital stock of \$26 and \$234 million in 1982 dollars, while firms with bond ratings had a median and mean of \$441 and

financially-constrained firms may enter our large firm category, the group as a whole is likely dominated by "unconstrained" firms.

We also have some evidence to suggest that our size control is not simply capturing differences in industry cyclicality. From 1981 on, the QFR has disaggregated the data by industry as well as by size. Table 3 indicates that there are no significant differences in the concentration of small firms across durable and non-durable goods industries, at least based on the evidence from the 1980s.

To summarize, for each QFR variable, we aggregate the eight size class time series into two times series, "small" and "large", using the thirtieth percentile of sales each period as the cutoff for small firms. We then use an approximation of the true cross-sectional distribution between size class and sales (updated each period) to help construct growth rates of the variable for each category of firms. Information from several sources suggests that our size control is strongly correlated with access to financial markets. Whether it may be capturing non-financial factors as well is an issue we take up later.

4 Empirical Results

Our goal is to develop a set of facts on the cyclical behavior of small versus large firms, focusing in particular on the relative responses to monetary policy. We study three sets of variables: sales, inventories and short term debt. We use sales rather than output as an indicator of activity over time because we cannot construct exact output measures – the QFR inventory variable is not disaggregated between finished goods and materials. Inventories are of interest since the firms in our small firm category account for a significant component of total inventory holdings in manufacturing: Table 4 indicates that inventory/sales ratios for small firms, though lower, do not differ widely on average from those of large firms, based on a snapshot of four years over the sample.[22] Finally short term debt is highly

$1775 million. For our small firm category, capital stocks average about one third of gross assets. Therefore, we estimate that, for 1982, our small firms had a median capital stock in the vicinity of $10 million and that the biggest firms in small firm category averaged about $50–$70 million. Thus firms in our small firm category are probably smaller on average than those in Whited's "no bond rating category". This in part reflects the fact that we include non-traded firms.

[22] Later, we calculate the contributions of small firms to the aggregate manufacturing inventory decline after tight money.

relevant because of its role in financing inventories and other working capital needs, which are the components of business spending that are likely most sensitive to macroeconomic disturbances, including shifts in monetary policy.

We begin with an informal descriptive analysis of the data. We then analyze the aggregate behavior of small versus large firms in a sequence of time series models. Using several different methods, we quantify the relative responses of the two classes of firms to shifts in monetary policy.

4.1 Descriptive Analysis of Sales, Inventories, and Short Term Debt

For each of the three variables – sales, inventories and short term debt – we construct a time series of the growth rate for small firms and a time series of the growth rate for large firms, along the lines described in the previous section. We then deseasonalize the data. Figure 1 illustrates the broad trends in each of the three sets of time series. Plotted are smoothed versions of each of the time series.[23] The vertical lines labeled R denote dates of shifts to tight money, using the criteria established by Romer and Romer (1988), and the vertical line labeled CC denotes the 1966 credit crunch. We will refer to all of these points as "Romer dates".

The top panel of Figure 1 plots the growth rates of sales. It appears that small firms decline sharply relative to large firms after episodes of tight money and during recessions. At least based on the smoothed data, this proposition is valid for each of the Romer episodes, the credit crunch, and the last five recessions. Inventory growth exhibits a similar pattern, as the middle panel suggests.[24] If anything, the differences in inventory growth are more pronounced. The growth rate of inventories for large firms picks up slightly just prior to recessions, except in the last recession. Inventory growth for small firms declines steadily over recessionary periods and generally at a faster pace than for large firms.

The bottom panel portrays short term debt, defined as debt with maturity of one year

[23]We smoothed the growth rate series using an Splus program that applies a non-parametric filter to the data. It robustly smooths a time series by means of running medians. The filter is designed to pick up broad trends in the data. The growth rates in the figure are portrayed as deviations from the mean.

[24]The measure of inventories we use are based on book value. As we discuss in the appendix, a correction for FIFO and LIFO accounting procedures is unlikely to affect our results. Nonetheless, we are currently working on making such a correction.

or less. Short term debt for small firms consists mainly of bank loans, as Table 2 indicates. For large firms, it consists mainly of commercial paper and bank loans, with the commercial paper share rising steadily since 1974. The relative patterns of short term debt flows mirror the relative patterns of inventory behavior. Prior to each of the last five recessions, short term debt growth for large firms rises before declining as the recession sets in. For small firms, the decline in short term debt growth begins prior to the recession and is steady throughout. The decline, further, is typically greater in magnitude than for large firms.

We next present some pictures of the raw time series around episodes of tight money. The pictures reenforce the impressions given by the smoothed data. Figure 2 plots the log deviations of small firm and large firm sales from their respective values at Romer dates, relative to trend. The raw data indicates that, after Romer dates, small firms drop substantially more on average than do large firms. Further, there is no single episode where the reverse happens.

Figure 3 illustrates the outcome of the same exercise for inventories and short term debt. For parsimony, however, we report only the average log deviation of each variable from the Romer date. Inventories for large firms rise after a Romer date, on average, before settling back to trend, as the top left panel indicates. For small firms, there is a short surge followed by a large, steady contraction. Further, small firm inventories appear to drag down the total, noticeably. Short term debt exhibits a similar pattern: for large firms, rising after a Romer date, then moving back to trend; for small firms, rising slightly, then contracting sharply. These results, further, hold for each of the major components of short term debt, bank loans and commercial paper. The middle left panel in Figure 3 indicates that short term bank lending across size classes closely mimics the behavior of the short term debt aggregate.[25] Our data also indicates that commercial paper issues, which are concentrated almost entirely among large firms, rise after Romer dates and at about the same general pace as bank loans to large firms.[26]

[25] This differential behavior of bank lending to small and large firms in the wake of tight money is consistent with evidence found elsewhere. Lang and Nakumura (1992) find that the ratio of bank loans made over the prime rate to those made under the prime falls after tight money. Morgan (1992) finds that the ratio of loans not made under commitment to those made under commitment also declines after tight money. Since firms receiving loans made over prime or loans not made under commitment are smaller on average, the results in these papers are complementary to our results.

[26] Kashyap, Stein, and Wilcox (1992) document the surge in commercial paper after Romer dates.

We next examine the inventory/sales ratio. The top panel on the right indicates that this ratio rises initially for both types of firms, but that the rise is sharper and more persistent for large firms. The implication is that after tight money (and as a downturn settles in), large firms exhibit a greater propensity to borrow to carry inventories. Supporting this interpretation is the fact that the relative differences in the short term debt to sales ratios display a pattern similar to the differences in the inventory/sales ratios. The middle panel on the right indicates that the short term debt to sales ratio for small firms remains virtually unchanged after a Romer date while, for large firms, it rises significantly above zero. Similar results hold for the bank loan to sales ratios, as the bottom right panel suggests. Thus, overall, large firms appear to borrow heavily to smooth the impact of declining sales, while small firms do not.

4.2 The Response of Small Versus Large Firms to Monetary Policy

We now supplement the descriptive analysis with a set of formal statistics on the relative response of small versus large firms to episodes of tight money. We first estimate the reactions of both small and large firms to Romer dates, using a variety of econometric specifications. For robustness, we repeat the exercise, using innovations in the Federal Funds rate to capture shifts in monetary policy, as proposed by Bernanke and Blinder (1992). The sample period is 1960Q:1 to 1991Q:4.

Romer dates. To quantify the response of small versus large firms to Romer episodes, we begin by estimating a bivariate VAR which includes four lags of a dependent variable and twelve lags of the dummy variable for tight money. Our choice of twelve lags for the dummy variable follows Romer and Romer's (1990) specification. We augment the original Romer dates with the 1966 credit crunch, as suggested by Kashyap, Wilcox and Stein (1992). However, we also conduct a sensitivity analysis to ensure that any one Romer date is not driving the results. We consider five sets of dependent variables; each set includes a growth rate of a variable for small firms and for large firms. The five variables are sales, inventories, short term debt, the inventory/sales ratio and the short term debt to sales ratio.

The second general type of model is a multivariate VAR in which small and large firm growth rates for a particular variable enter jointly along with a set of macroeconomic variables and the Romer dates. The macro variables include real GNP growth, inflation and the Federal Funds rate.[27] Our goal here is to examine the predictive power of the Romer dates for small versus large firm growth rates after controlling both for the influence of standard indicators of the business cycle and for possible interaction between the two classes of firms. In analogy to the bivariate case, we include four lags each of the quantitative variables and twelve lags of the dummy for tight money.

Table 5 reports a set of summary statistics for the bivariate case. The Romer dates are highly significant predictors of sales, inventories and short term debt for small firms. The sums of coefficients, further, are significantly negative in each case. Dropping any one of the Romer dates does not affect the results, as the table indicates. For large firms, the Romer dates are significant for inventories and short term debt, but not for sales. In addition, the respective sums-of-coefficients do not differ significantly from zero. As with small firms, no particular Romer date drives the outcome.

Table 6 reports the summary statistics for the multivariate case. The results are generally similar to the bivariate case. One interesting difference is that the sum of the coefficients on inventories for large firms is significantly <u>positive</u>. Thus, after controlling for the information contained in the other business cycle indicators, a Romer date predicts a rise in large firm inventories. This outcome is in some ways not surprising, given the surge in large firm inventories that transpires after Romer dates, as portrayed in Figure 3.

To judge the overall impact of a tight money episode on small versus large firms, we now report a set of impulse response functions. We report the results for the multivariate system with the full set of Romer dates, though the outcomes are quite similar across all model specifications. In each case, we simulate the impact of a shift to a Romer date. The results suggest a substantial differential impact. Both small and large firm sales growth decline following a Romer shock; but small firm sales drop more than four percent faster per year than large firms sales for a period of 10 quarters after the disturbance.[28]

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[27] Our results are robust to using the detrended log level of GNP instead of GNP growth.

[28] Dotsey (1992) argues that the predictive power of the Romer dates reflects the impact of oil price increases rather than exogenous shifts to tight money. [See Romer and Romer (1992) for a reply.] The outcome of this debate affects the interpretation that we give to the macro disturbances. However, it need not affect our basic conclusions since oil price shocks may also trigger the financial propagation mechanism that we describe, by reducing cash flows. Indeed, Dotsey cites these types of theories as one way to rationalize

Similar relative behavior arises for inventories. The results indicate that small firms keep inventories roughly in line with sales in periods of declining cash flows. After a slight initial surge, small firm inventories drop at about the same pace as sales. In contrast, large firms appear to permit their inventory/sales ratios to drift up for a considerable period. While their inventories eventually begin to decline, the rate is not as fast on average as it is for small firms. The net effect is that the gap between the small and large firm inventory drop widens appreciably until about ten quarters after the Romer shock. The behavior of short term debt mirrors the differential pattern in inventory behavior: surging for large firms after Romer dates and contracting for small firms.[29] Overall, large firms appear to borrow to smooth the impact of downturn, but small firms do not.[30]

How important is the behavior of small firms for manufacturing as a whole? Here we provide a rough calculation of the fraction that small firms contribute to the total decline in manufacturing that follows a tight money episode. Table 7 reports the percentage change in sales and inventories for small firms, large firms and the total, for four, eight and twelve quarters after the Romer date. It then breaks down the total change between the contribution of small firms and the contribution of large firms. Even though (by our definition) small firms' share of sales each period is thirty percent on average, they account for between fifty-five percent and sixty percent of the drop in total manufacturing sales, four, eight and twelve quarters out. The results for inventories are more startling. Four quarters out, total inventory accumulation is about eighty percent of large firm inventory accumulation, owing to the drop in small firm inventories. Eight quarters out, the percentage drops to fifty, as the small firm inventory decline exerts an even greater impact. Even though large firms begin reducing inventories after eight quarters, small firms continue to drag the total down

the asymmetric effects of oil price shocks that he finds in the data (stronger effects of oil price increases than of decreases.)

[29]It is not the case that small firms are substituting to trade credit. That is, it is not the case that large manufacturing firms are offsetting the contraction of short term loans to small manufacturing firms by supplying them with trade credit. In our 1992 paper we show that trade credit to small manufacturing firms contracts sharply after tight money, similar in behavior to short term loans.

[30]The wide standard error bands for large firm short term debt are in part due to "outlier" behavior after the 1974 Romer date. Short term debt to large firms drops sharply after this Romer date, in contrast to the other episodes (see Figure 1). Note, however, that the 1974 date is the only Romer episode that does not lead the recession; rather it occurs several quarters into the recession. From this perspective, the timing of the drop in large firm short term debt is not unusual (since it occurs after the recession is under way.)

at a faster rate, twelve quarters out.

The Federal Funds Rate. We now explore how the results are affected by using the Federal Funds rate to measure the stance of monetary policy. We first compare the response of small and large firms to shifts in the Funds rate, using a linear framework. We then test for asymmetries: specifically, for whether the response of small firms to monetary policy is stronger in downturns, as the theory in section 2 suggests.

As in the previous case, we estimate two general types of VAR models. The first is a trivariate system which includes the growth rate of a variable for either small or large firms, the Federal Funds rate, and inflation.[31] The second is a multivariate system in which the growth rates of the small and large firm variables enter jointly along with GNP, inflation, and the Funds rate. In both types of models, each variable enters the right hand side with four lags.

Because the Federal Reserve may have significantly reduced its reliance on the funds rate as an intermediate target for a period of time after 1979Q:4, it may not be legitimate to treat this variable as a monetary policy indicator over the entire period, as Bernanke (1991) and Bernanke and Blinder (1992) suggest. Therefore, in addition to estimating each type of system over the entire sample, we also consider the sub-period 1960Q:1 - 1979Q:4.[32]

Table 8 reports summary statistics. Overall the Funds rate appears to Granger cause both small and large firm variables. Based on the t-statistics for the sum-of-coefficients tests, the differential response of small and large firms to the Funds rate appears greater in the pre-1980 period, than over the entire sample. We next present impulse response functions which support this contention.

Figures 5 and 6 plot the cumulative responses of the small versus large firm variables to one standard deviation increases in the funds rate for the 1960Q:1-1991Q:4 and pre-1979Q:4 sample periods, respectively. In each case, the impulse response functions are based on estimation of the multivariate system.[33] Both figures suggest that the funds rate

[31] We include inflation to control for the drift in the nominal funds rate over time, and relatedly to capture the impact of the real funds rate. Leaving inflation out does not alter the results in any significant way.

[32] We also looked at the 1960Q:1 - 1973Q:4 sample split and obtained similar results.

[33] The variables are ordered: GNP, inflation, large firms, small firms, and the funds rate. The funds rate is placed last to capture the idea that monetary policy may adjust to current events, but its effects operate with a one quarter lag. The results, however, are not sensitive to the ordering.

shock has a greater cumulative impact on small firms than on large firms. Sales, inventories and short term debt all drop for small firms relative to large firms. Four to six quarters out, the differences are reasonably significant for inventories and short term debt, though not for sales. The results are generally stronger in both magnitude and significance for the pre-1980 period, however. The difference in the drop in sales is reasonably significant four to ten quarters out, and the same is roughly true for inventories. The difference in short term debt growth is sharpest four quarters out.

The funds rate experiment also produces some additional evidence that large firms borrow to finance an inventory buildup as sales decline, while small firms do not. Both inventories and short term debt for large firms continue to surge as sales decline. For small firms, neither inventories nor short term debt rise significantly, and both begin a steady decline about four quarters after the funds rate increase. However, the dramatic difference in the behavior of the inventory/sales ratios that arose after the Romer dates do not show up in this case.

An important difference between the Romer date and Funds rate experiments is that the former only include tight money episodes. The theory presented in section 2 emphasizes asymmetric behavior, owing to the fact that the credit frictions are more likely to bind in bad times than in good times. Therefore we should expect greater differences between small and large firms during downturns than in a boom. Since the Romer dates restrict attention to periods of tight money (with downturns following) they may capture this asymmetric behavior. We pursue this idea with the Funds rate experiment by allowing for an asymmetric response to monetary policy over the cycle. Specifically, we now allow the coefficients on the Funds rate and the constant term to vary depending on whether or not GNP growth in the prior period was above or below its median value. For parsimony, we consider bivariate regressions of a large or small firm variable on four lags of itself and four lags of the Funds rate.[34]

[34] We thus include an interaction term between the Funds rate and a dummy variable that equals 1 if GNP growth is below its median value over the sample period 1960Q:1-1991Q:4. This effectively allows the Funds rate coefficients to switch between high and low growth rate states, while maintaining an equal number of observations in each state. We also considered regressions that allow the coefficients on the lagged dependent variable to switch as well. We could not reject the constancy of these coefficients, however, so we restricted them to be equal over both high and low growth states to preserve degrees of freedom.

Table 9 reports the regressions for the asymmetric Funds rate experiments. At the bottom, we report the respective p-values of the tests that the coefficients are equal across high and low growth states. We reject this restriction at the 0.02 and 0.00 levels for small firm sales and inventories, but we cannot reject it at the ten percent level for the respective large firm variables. Thus we find strong evidence of asymmetric interest rate effects for small firm variables but not for large firm variables.[35]

Figure 7 plots the dynamic response of small versus large firms to a unit rise in the Funds rate.[36] It clearly illustrates the asymmetric response of small firms over the cycle. Small firm sales and inventories exhibit a sharper decline during low GNP growth periods than during high growth periods. This decline, further, is statistically significant for both small firm variables only in low growth periods. For large firms, the decline is only significant for the sales variable, and even then only in the second quarter after the shock. In addition, the large firm inventory behavior looks fairly similar over both the high and low growth states.

Finally, the dynamic response of the inventory/sales ratio is instructive. For large firms, the asymmetric effect simply pushes the timing of the rise in the inventory/sales ratio forward one period, so that in low growth states it peaks two quarters out rather than three. For small firms, the inventory/sales ratio during high growth states looks strikingly similar to that of large firms, rising by about the same magnitude, and with the same timing. A striking difference emerges in low growth periods, however. In the low growth state, the peak in the inventory/sales ratio for small firms after tight money is less than half the peak for large firms. Small firms thus appear less inclined to borrow to carry inventories as sales decline in bad aggregate times than as sales decline in good aggregate times. Large firms, on the other hand, exhibit no such asymmetry. Overall, the results are compatible

[35]To save space we do not report the regressions using the inventory/sales ratio as the dependent variable. The p-values here were 0.02 and 0.2 for small and large firms respectively.

[36]The dynamic response is the cumulative response of the dependent variable to a one percent increase in the Funds rate that is implied by the coefficients obtained in the low versus high GNP growth states. Because we do not take account of the probability of switching between low and high GNP growth states, the dynamic response is not a true impulse response function. Since the dynamic response is computed as a nonlinear function of the regression coefficients, we compute asymptotic one standard deviation error bands using a Taylor series approximation to the nonlinear function to obtain its distribution (i.e., the so-called delta method.)

with the asymmetric impact of the credit frictions suggested by the theory in section 2.[37] The results also help reconcile the quantitative differences arising between the Romer date and Funds rate experiments.

5 Concluding Remarks

Our results indicate that small firms contract substantially relative to large firms after episodes of tight money. The difference between small and large firm behavior accounts for a significant portion of both the overall decline in manufacturing sales and the overall decline in manufacturing inventories. The results suggest that small firms (by our definition) play an important role in aggregate manufacturing fluctuations.

An important reason that small firms contribute disproportionately to the decline in inventories is that, in periods of declining sales, they maintain a fairly stable inventory/sales ratio. Large firms, on the other hand, let their inventory/sales ratios rise in bad times. Relatedly, the ratio of short term borrowing to sales stays roughly stable for small firms, while it rises sharply for large firms as cash flows decline. An important issue is whether this differential inventory and short term borrowing behavior is due to technological or financial factors (or both). The fact that our evidence suggests that this differential behavior may be asymmetric over the cycle, more distinct in bad times than in good times, is compatible with the financial factors story. As well, the available firm level evidence [Kashyap, Lamont and Stein (1992) and Milne (1991)] suggests that financial factors play an important role. To the extent the proposition is true generally, inventory demand may be an important channel through which liquidity constraints influence aggregate activity.

Another issue is whether small firms are concentrated in industries that are cyclical, so that the relative differences in sales volatility merely capture industry effects. The data required to fully resolve this issue is currently incomplete. Some evidence from recent years indicates that small firms are distributed evenly across durable and non-durable goods industries, as we discussed in Section 3. A related possibility is that technological factors

[37] Oliner and Rudebusch (1992) present related results using the QFR data set. They show that cash flow affects the investment decisions of small firms more after tight money than in normal periods, while cash flow does not matter for large firm investment decisions. See also Gertler and Hubbard (1988) for complementary evidence, using firm-level data.

make small firms more volatile.[38] Mills and Schumann (1985) argue that because small firms are less capital intensive they may face lower costs of adjustment than large firms, and therefore may be more volatile. They present evidence from Compustat that demonstrates a negative correlation between size and volatility, but they do not directly test their hypothesis against an alternative based on financial factors. Gertler and Hubbard (1988) find that when firms are sorted by a financial indicator of access to credit markets, the relation between size and volatility disappears. Instead, volatility is inversely related to financial status. Apparently, in the empirical relation between size and volatility, size proxies for capital market access. We also emphasize that both the "industry effects" story and the "technology" story must explain not only the relative differences in sales volatility across size classes, but also the differences in the behavior of the inventory/sales ratios and of short term borrowing, as well the asymmetries in the behavior of small firms over the cycle. Nonetheless, we agree that more work on this issue is warranted; and we are pursuing this task.

Finally, to assess the overall importance of small firms to the macroeconomy it is also necessary to gather evidence from other cyclically sensitive sectors such as retail and wholesale trade and construction. Small firms are more prominent in these sectors than in manufacturing [see Gertler and Hubbard (1988)].

[38] Our results cannot be explained by the fact that small firms are typically less diversified. This kind of story explains why small firms may have a lot of idiosyncratic volatility, but it does not explain systematic volatility (i.e., co-movement with the cycle). Nor, in the absence of informational frictions, can it explain a greater sensitivity to monetary policy.

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Data Appendix

This appendix contains a brief description of the data source and the methods we use to construct growth rates of various income-statement and balance-sheet variables by size class for the manufacturing sector. All manufacturing data used in this study was obtained from the Quarterly Financial Reports (QFR). The QFR provides aggregate income-statement and balance-sheet data for total manufacturing, and for eight different aggregate size classes of firms within manufacturing. The size classes are based on total assets and are computed using the following nominal cutoffs: $0-5 mil., $5-10 mil. $10-25 mil., $25-50 mil., $50-100 mil., $100-250 mil., $250-1000, and firms with assets greater than $1bil.[39]

The reporting methods used by the QFR lead to three types of biases in the data. First, redefinition of variables and samples results in level shifts in the raw data reported in the QFR. This is relatively easy to correct since the QFR always provides at least one quarter of overlap data to splice together level series. Second, the use of nominal cutoffs means that the real size categories used by the QFR to classify firms contain drift over time. Third, because the QFR reclassifies firms over time, firms may move between size categories. This latter effect could lead to short run biases in the growth rates as firms shift categories. This appendix gives a complete description of the methodology we use to correct for all these factors, and a discussion of results obtained using alternative methods to construct growth rates.

Definition of Variables

We use three variables from the QFR for this study: sales, inventories, and short-term debt. All data are deflated using the GNP deflator, and seasonally adjusted using time dummies. We use a split seasonal dummy, with the split occurring in 1974:Q1 to account for changes in reporting procedures at this time.

The short-term debt variable is constructed using the category short term bank loans for the period 1960-1973:4, and total short-term debt for the period 1974-1991. Prior to 1974, the QFR only provided information on short term bank debt. During this period, short term bank debt accounted for the majority of short-term debt for large firms, and nearly all of the short-term debt of small firms. Furthermore, the dynamics of short term bank debt and total short-term debt are very similar for a given size class of firms as we document in Gertler and Gilchrist (1992) even during the 1974-1991 period when the commercial paper market developed as the preferred form of short term financing for large firms. Thus, we are confident that using these combined series as a measure of short-term debt is reasonable. Nonetheless, as the earlier version of this paper reports, we obtain very similar results by just focusing on short-term bank loans for the entire sample period.

Currently, our inventory measure is the book value of inventories reported by the QFR. Because we are using quarterly data, and the inventory/sales ratio implies complete turnover of inventories within a quarter, correction for FIFO accounting procedures is not likely to affect our results. Correction for LIFO may affect our results for the 1974-1982 period

[39] In early years the QFR provides data on the $0-1 mil. and $1-5 mil. categories separately. We simply reaggregate these into one category.

when LIFO was a widely used accounting procedure, especially for larger firms. As figure A1 shows, an examination of the growth in the inventory/sales ratio for uncorrected Census Bureau Data, BEA adjusted data, and our data around 1982 when the largest adjustments for LIFO-FIFO occurred, as firms shifted back to FIFO from LIFO, shows that our data is much less affected by LIFO-FIFO adjustments than the data collected by the Census Bureau using the M3 survey[40]

The closer correspondence between the QFR unadjusted data and the BEA adjusted data probably reflects the fact that companies who use LIFO are required to report LIFO for the M3 survey over this time period, even on a monthly basis, whereas there is no such reporting requirement for the QFR. Consequently, more firms are likely to report FIFO on a quarterly basis if it is less costly to do so, even if they use LIFO for annual tax-year accounting purposes.

While it may be possible to make crude corrections for these factors, we are confident that our results are not driven by LIFO-FIFO accounting differences across firms. First, as we discussed above, the series in Figure A1 indicate that the LIFO-FIFO issue does not appear to be as important for QFR data as it is for other sources. Second, it is unlikely that the differential response to a Funds rate shock of small- and large-firm sales and inventories is due to LIFO-FIFO issues, since the results are stronger during the 1960-1973 period than either the 1960-1979, or the 1960-1991 periods when LIFO could be a factor. Third, it is equally unlikely that accounting procedures explain the reduced differential response in later sample periods since we observe this phenomenon in both sales and inventories.

Construction of Growth Rates for Small and Large Firms

Correction for Level Shifts

Because the QFR provides overlap data, level shifts in the data are easy to correct, although some care must be taken when aggregating corrected data across size categories. All data for a given year is obtained from the fourth quarter QFR. Since each QFR reports five quarters of data, we also use the fourth quarter QFR data to construct a correction ratio linking one year's data to the prior year. To construct a consistent small-firm level series, we first aggregate across size categories from low to high, before applying the correction. Thus the correction is applied to cumulated size categories.[41] To compute large-firm level series, we first cumulate from the highest asset category to the lowest before applying the correction. This methodology gives fifteen separate corrected level series for each variable: seven level series cumulated from the lowest to the highest asset category, seven level series cumulated from the highest to lowest asset category, and the corrected level series for total manufacturing.

[40] The discrepancy between BEA and the other two series is also due to differential deflators applied to inventories versus sales.

[41] This ensures that in a year when the correction ratio is one, we do not distort growth rates by first applying a correction to each size category, then aggregating across size categories, before computing growth rates. Such a methodology could lead to spurious movements in aggregate growth rates since different subaggregates are not weighted uniformly.

Correction for Short-Run Biases in Growth Rates

Having constructed cumulative level series, we next compute growth rates for each asset size class, correcting for the fact that both inflation over the quarter and differential real growth of firms below a given cutoff relative to firms above the cutoff will lead to biases in the growth rate.

In theory, without such a correction, an increase in the price level leads to a downward bias in our estimate of growth for small firms and an upward bias in our estimate of growth for large firms, since the real cutoff is now lower. If inflation and real differential growth between small and large firms move in the same direction, this bias will dampen the measured differential response of small firms and large firms. If inflation and real differential growth move in opposite directions, this bias will increase the measured differential response. Since differential growth between small and large firms is procyclical, the former is much more likely to be the case, except for the stagflation episodes in the mid-70's and early 80's. Because we observe the inflation rate however, we can precisely determine the adjustment needed based on the interpolation scheme described below, regardless of the direction of bias.

Differential real growth between small and large firms always works in the direction of dampening the measured difference in growth rates, since if small firms grow fast relative to large firms, more firms will be pushed into the higher category. Thus to the extent that the interpolation scheme we use does not entirely correct for differential real growth of firms above and below the chosen cutoff, we are biasing our data towards not finding strong differences between small and large firms.

The actual data correction is best illustrated with an example using total sales. All other variables are corrected in a similar manner. For any given asset cutoff level, we compute the total dollar amount of sales accounted for by firms at or below this cutoff level. Let x be the asset cutoff level chosen. Let $S(x,t)$ be the sales of firms below this cutoff at time t. Ideally, at time $t+1$, we would like to compute the dollar amount of total sales accounted for by all firms at or below x at time t. We call this $S(x_t, t+1)$. We do not observe $S(x_t, t+1)$ however. Instead we observe the eight data cutoff points $S(x, t+1)$ for $x = \$5, \$10, \$25, \$50, \$100, \$250, \$1000$. We therefore use a spline smoothing function provided by the Splus computer package to fit a smooth curve through these eight data points. This in effect fits a cumulative density of sales with respect to asset cutoff levels. We fit this smooth curve after first transforming both the sales data and the asset cutoff levels into logarithmic form.[42] We then create a new series of cutoffs z_t and compute predicted values from the cumulative density of sales using these cutoffs.

The new cutoffs adjusts the nominal cutoffs used by the QFR to account for both inflation and asset growth. They are computed using the formula $z_t = x * (1 + g_{t+1} - \pi_{t+1})$ where π_{t+1} is the quarterly inflation rate between t and $t+1$, and g is the growth rate of total manufacturing assets. Thus we decrease the cutoff to account for higher inflation, and increase the cutoff to account for the fact that firms will move from the lower to the upper

[42]The logarithmic transformation makes the relationship between sales and asset cutoffs much more linear, and gives a better weighting scheme to use in fitting the cumulative density of sales. The spline smoothing function accounts for the remaining curvature in the cumulative density function (if there is no curvature, the methodology essentially uses linear interpolation).

category due to positive real growth in assets over time. We use the same asset growth rate g for all cutoffs.[43]

Given this set of adjusted cutoffs, we predict the value of sales $S(z_t, t+1)$ at the new cutoff level and use this value to compute the growth rate $log(S(z_t, t+1)) - log(S(x,t))$ for each asset cutoff level x. This growth rate thus corrects for biases due to both inflation and real growth in assets. Applying this correction procedure to each cumulated level series gives us fourteen corrected growth rate series for each variable. We then weight these growth rate series to construct growth rates that approximate the growth rate of firms above and below the 30th percentile.

In practice, when using only two size categories, the adjustments to the growth rates are small. The average correction made to sales is less than 0.1 percent of a quarterly growth rate. The maximum correction is around 1 percent. Thus, overall, we find that this short run correction has only a small impact on the computed growth rates, and virtually no impact on our results.

Correction for Long-Term Drift

The more serious problem with the data is the long term drift in the size categories. For example, firms below \$25 mil in assets make up nearly 40 percent of total sales in 1960, and only 20 percent in 1990. Even after correcting for short run biases in the growth rates, such long-run drift means that the small firm category is not constant over time. Accounting for this problem is relatively straightforward if one works in growth rates. Rather than look at the growth rate of firms above and below some absolute size classification, we approximate the growth rate of the 30th percentile of sales, by taking a weighted average of the growth rates of the two nominal categories that straddle the 30th percentile, where the weights depend on how far each nominal category is from the 30th percentile. For example, if firms under \$25 mil. account for $x(x < 30)$ percent of sales and grew at rate g, and firms under \$50 mil. account for $y(y > 30)$ percent of sales in a given quarter and grew at rate s, then we approximate the growth rate of firms below the 30th percentile by $w * g + (1 - w) * s$, where $w = (y - 30)/(y - x)$. In practice, using the growth rates of a variable computed for a given percentile of sales, rather than an absolute size category, do not appear to qualitatively affect our results, since as we show below, firms switching categories cannot account for much in the growth rates.

A Brief Analysis of Potential Biases in the Data

While we believe the methodology used to construct growth rate series for small and large firm variables from the QFR gives very good approximations to the underlying growth rates of a given percentile, we consider a number of ways to evaluate the quality of our data, and the robustness of our results to alternative methods of data construction.

[43] Because this correction is only used to target the 30th percentile, we are implicitly approximating the growth rate of assets of firms at the 30th percentile with the the growth rate of total manufacturing assets (using some other measure for g has negligible effects.)

Data Quality: A Comparison Using Compustat

To examine how the QFR aggregation procedure might bias growth rates, we computed annual sales growth rates for a sample of Compustat firms for the time period 1974-1990, using the aggregation procedure employed by QFR. We then compared these growth rates to growth rates obtained from a procedure which does not induce aggregation bias. Because Compustat principally samples larger, well established, publicly traded firms, the lower tail (firms less than $50 mil. in assets) is relatively sparse, and does not provide meaningful aggregate growth rates. We therefore restrict our attention to a comparison of the growth rates of larger firms.

For a given asset cutoff level, we compute the log-difference in the total value of sales of all firms above a cutoff at time t and t+1. We then compare this procedure to computing the aggregate growth rate of firms above this cutoff at time t only. To be included in the sample in any given year, a firm had to report sales and total assets in that year and the prior year, and have an end-of-calendar fiscal year. Table 1 of the appendix provides a comparison of the growth rates for the $100, and $250 mil. cutoff levels. These are the cutoffs used by our weighting scheme to approximate the growth rates over this sample period. The ratio of the standard error of the bias relative to the standard error of the true growth rate is 0.04 and 0.06 for the $100 mil. and $250 mil. cutoff levels. Overall, the compustat data imply that the QFR method gives very good approximations even on annual data where the drift in categories and biases due to inflation are four times higher than at the quarterly level.

Robustness Exercises

We now turn to a discussion of alternative data construction methods and the effect they have on our results. The first exercise compares our results using weighted and corrected growth rates to those obtained using unweighted, uncorrected growth rates.

If we use unweighted, uncorrected growth rates, as in an earlier version of this paper, where we use the growth rates of firms above and below $25 mil. in assets as a cutoff for all time periods, we obtain very similar results. Although, some of the tests of statistical significance are different, the magnitude and standard error bands of the impulse responses to both the Romer episodes and the Funds rate are very similar. Using a fixed nominal cutoff does not change our results because, over most of the sample period, the movements in firms above and below $25 mil. in assets are dominated by the very small firms and the very large firms, with the intermediary categories contributing very little to changes in the distribution. Because of the relative sparseness of these intermediary categories (e.g., firms between $50m and $100m only account for 6 percent of total sales in 1960, and 4 percent in 1990), we obtained very similar results whether we chose $25mil, $50mil or $100mil as our cutoff. The robustness of this procedure suggests that the growth rates are not influenced by firms near the margin of the chosen cutoff level, and that the choice of cutoff does not greatly influence the growth rates.

All of our results have also been reestimated using weighted growth rates that do not rely on the short-run correction. When we correct for long-term drift but not short-run biases in the data, we find the results to be virtually identical.

Next, we consider the possibility that the correction we use works better for calculating large firm growth rates than small firm growth rates. This might occur for two reasons. First, by definition, large firms make up 70 percent of the distribution. Therefore, an equal number of firms shifting across a cutoff level will have a smaller percentage influence on 70 percent of sales than 30 percent of sales. In addition, the average size of firms moving across a boundary are in the lower tail of the size distribution for large firms, but the upper tail for small firms. This too will lead to a greater influence on the small firm growth rates. If biases in the growth rates are important, we would expect that growth rates calculated using the lower tail will give us different results than growth rates calculated using the upper tail. Specifically, instead of using the small firm data to calculate growth rates we can approximate the growth rates of small firms by taking a weighted difference of the growth rate of total manufacturing and the growth rate of large firms (i.e., small firm growth = (all firm growth - 0.7*large firm growth)/0.3). Using this method for calculating growth rates of the sales variable once again left our results entirely unchanged.

Finally, to demonstate that the bias in the data owing to QFR construction methods is not a problem, we investigate how much of the sales distribution is accounted for by firms with assets that are at least ten percent below a given cutoff. The idea here is to show that firms switching categories have at best a trivial impact on the computed growth rates.

These numbers are reported for select years in table A2 of the appendix. Each column of table A2 gives the ratio of the total sales accounted for by firms with assets less than 10% below a QFR asst cutoff relative to sales of firms with assets less than the cutoff itself. For example, Table 1 shows that firms with assets less than \$100 mil. account for 0.26% of manufacturing sales in 1990. Table A1 shows that firms with assets less than \$90 mil. account for 97% of these sales, in other words, 25% of total manufacturing sales.

Table A2 shows that for the cutoffs that straddle the 30th percentile (bold text), firms with assets at least ten percent below a given cutoff account for 97-98 percent of the total sales of all firms below the cutoff. If we look at firms with assets that are at least 20 percent below a given cutoff, we obtain numbers between 95 percent to 96 percent. Thus, any differential real growth between firms around the 30th percentile will have negligible effects. For example, suppose the true growth rate for firms below the 30th percentile is 3 percent. Also suppose that for whatever reason, we mismeasure the real growth of firms whose assets fall within 10 percent of the cutoff that we use to approximate the 30th percentile, obtaining a growth rate that is twice that of the true value. Under these assumptions, we will obtain a measured growth rate for small firms equal to 3.04 percent. Even if such sizeable mismeasurement extends to firms with assets 20 percent below the cutoff, we would still obtain a growth rate of 3.1 percent for small firms. From these simple calculations, it is easy to see why our results are not likely to be heavily influenced by either the various short-run correction methods we use or by biases that may still remain because of our data construction procedure.

In summary, all evidence so far suggests that our results are immune to alternative data construction methods, and that biases due to the aggregation procedure used by QFR do not distort our results.

Table A1: Bias Estimates for Compustat Sales Growth

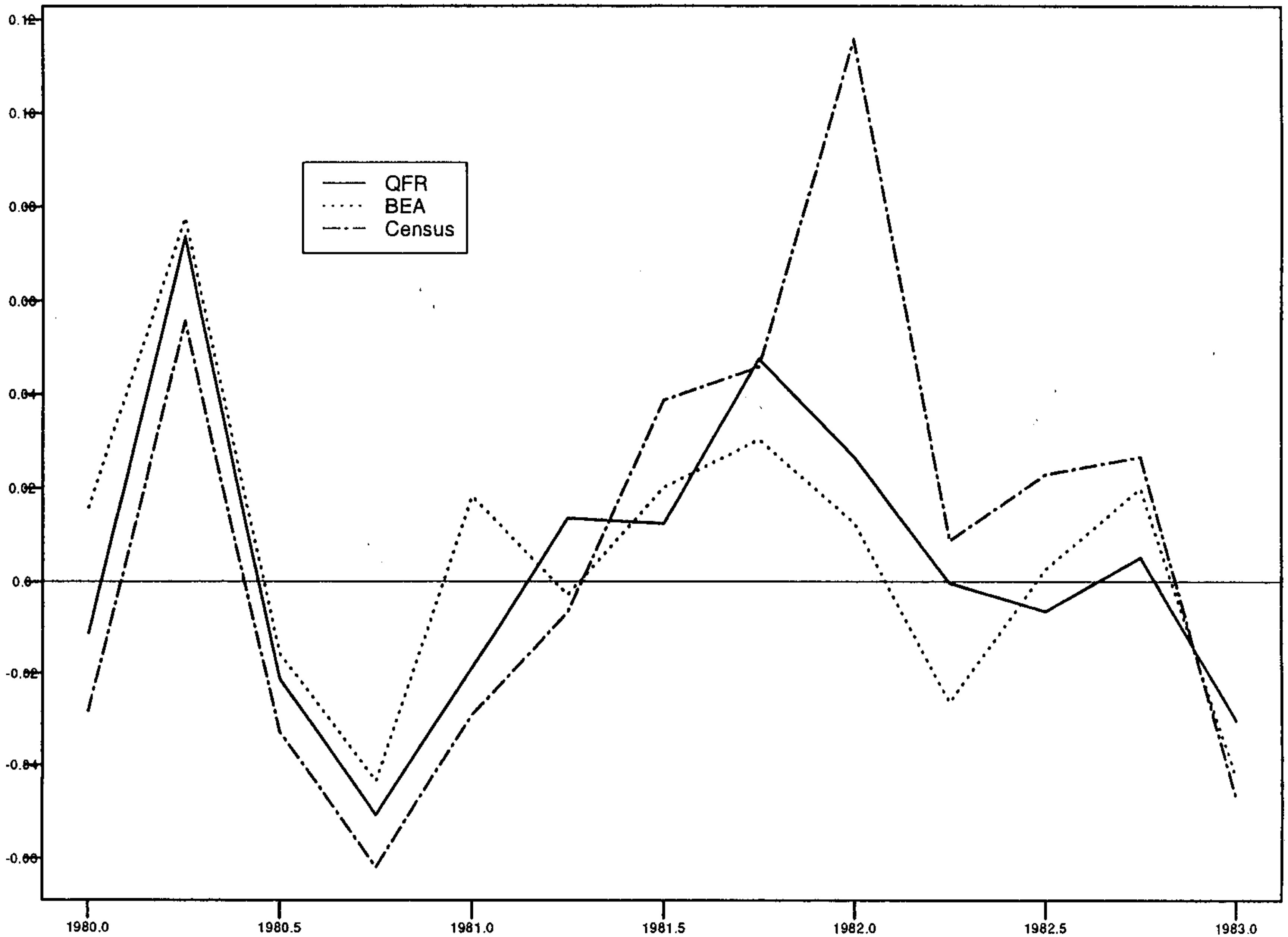
Year	Assets >\$100 mil. Growth Rate	Assets >\$100 mil. Bias	Assets >\$250 mil. Growth Rate	Assets >\$250 mil. Bias
1975	3.49	0.22	3.72	0.62
1976	16.47	0.43	17.21	0.96
1977	13.33	0.36	13.69	0.64
1978	11.16	-0.07	11.57	0.22
1979	17.47	0.20	18.13	0.61
1980	11.98	0.16	12.23	0.26
1981	5.65	0.01	5.70	-0.13
1982	-1.36	0.03	-1.77	-0.63
1983	3.13	0.31	3.14	0.45
1984	5.72	0.02	5.91	0.32
1985	3.91	-0.05	4.16	0.23
1986	-2.43	0.26	-2.47	0.52
1987	12.55	0.28	12.54	0.39
1988	8.59	-0.36	8.84	-0.17
1989	5.05	0.20	5.14	0.07
1990	9.11	-0.42	9.32	-0.41
1991	-3.31	0.05	-3.29	0.06
Avg.	7.09	0.10	7.31	0.24
Std.Dev	6.27	0.23	6.48	0.41

Table A2: Percentage Contributed by Firms 10% Below QFR Cutoff[a]

	Asset Size						
Year	\$5m	\$10m	\$25m	\$50m	\$100m	\$250m	\$1bil.
1960	**0.97**	**0.98**	0.98	0.98	0.97	0.98	0.98
1970	0.98	0.98	**0.98**	**0.97**	0.98	0.97	0.98
1980	0.96	0.98	0.96	0.98	**0.98**	**0.98**	0.98
1990	0.96	0.97	0.97	0.98	**0.97**	**0.98**	0.98

[a]Bold text indicates asset size categories that straddle the 30th percentile of sales.

Figure A1: Growth in Inv/Sales Ratio



R indicates Romer Date, P indicates NBER Business Cycle Peak, CC indicates 1966 credit crunch

Table 1: Percent of Mnfg. Sales by Cumulative Asset Size

Year	Asset Size						
	\$5m	\$10m	\$25m	\$50m	\$100m	\$250m	\$1b
1960	0.26	0.31	0.38	0.44	0.52	0.65	0.85
1970	0.21	0.24	0.29	0.34	0.39	0.49	0.70
1980	0.13	0.16	0.21	0.24	0.28	0.34	0.47
1990	0.12	0.15	0.19	0.22	0.26	0.32	0.44

Table 2: Composition of Debt Finance by Asset Size, 1986:Q4

Type of Debt as Percentage of Total	All	Asset Size (in millions of dollars) <50	50-250	250-1000	>1000
Short-Term Debt	0.16	0.29	0.18	0.14	0.13
Bank Loans	0.08	0.25	0.15	0.09	0.04
Comm. Paper	0.05	0.00	0.00	0.03	0.07
Other	0.02	0.04	0.02	0.02	0.02
Long-Term Debt	0.84	0.71	0.82	0.86	0.87
Bank Loans	0.22	0.43	0.40	0.31	0.14
Other	0.62	0.28	0.42	0.56	0.73
% of Bank Loans	0.30	0.68	0.55	0.40	0.17

Table 3: Percentage of Sales for Durable Manufacturing by Size Class

Year	Cumulative Asset Size Class (in Millions of Dollars)				
	<25	<50	<250	<1000	All Mfg.
1982	0.49	0.49	0.48	0.47	0.44
1986	0.52	0.52	0.52	0.50	0.51
1990	0.54	0.54	0.52	0.51	0.47

Table 4: Inventory/Sales Ratio for Manufacturing by Size Class

Year	Cumulative Asset Size Class (in Millions of Dollars)				
	<25	<50	<250	<1000	All Mfg.
1960	0.58	0.61	0.66	0.66	0.72
1970	0.51	0.54	0.63	0.70	0.74
1980	0.47	0.49	0.53	0.55	0.53
1990	0.47	0.49	0.52	0.54	0.52

Table 5: The Effect of a Romer Episode: The Bivariate Case.

Firms	Variable	Exclusion Tests for Subsets of Episodes[a]					
Small		All	-66:Q2	-68:Q4	-74:Q2	-78:Q3	-79:Q4
	Sales	0.00	0.00	0.02	0.00	0.00	0.07
	Inventories	0.00	0.00	0.00	0.00	0.00	0.00
	Short Debt	0.00	0.00	0.00	0.00	0.00	0.00
	Inv/Sales	0.01	0.01	0.01	0.01	0.00	0.01
	Debt/Sales	0.01	0.00	0.00	0.00	0.00	0.13
Large		All	-66:Q2	-68:Q4	-74:Q2	-78:Q3	-79:Q4
	Sales	0.59	0.26	0.07	0.05	0.34	0.16
	Inventories	0.01	0.00	0.07	0.00	0.02	0.00
	Short Debt	0.00	0.00	0.00	0.00	0.01	0.00
	Inv/Sales	0.65	0.64	0.35	0.23	0.04	0.04
	Debt/Sales	0.00	0.00	0.01	0.00	0.09	0.01

Firms	Variable	T-Stats on Sums of Coefficients for Subsets of Episodes					
Small		All	-66:Q2	-68:Q4	-74:Q2	-78:Q3	-79:Q4
	Sales	-3.36	-2.98	-2.65	-3.14	-3.08	-2.38
	Inventories	-4.19	-3.56	-3.30	-3.57	-3.97	-3.11
	Short Debt	-3.58	-3.64	-2.51	-2.12	-3.39	-3.11
	Inv/Sales	-0.71	-0.32	-0.37	-0.44	-1.21	-0.87
	Debt/Sales	-1.20	-1.63	-0.71	-0.18	-1.24	-1.33
Large		All	-66:Q2	-68:Q4	-74:Q2	-78:Q3	-79:Q4
	Sales	-1.08	-1.27	-0.99	-0.92	-1.51	-0.21
	Inventories	-0.77	-1.45	-0.72	-0.23	-1.21	0.17
	Short Debt	-0.38	-0.76	-0.38	0.95	-1.55	-0.10
	Inv/Sales	0.82	0.35	0.68	1.20	1.09	0.61
	Debt/Sales	0.21	-0.10	0.16	1.58	-0.92	0.12

[a]Regression includes four lags of the dependant variable and twelve lags of the Romer episode indicator. Each column presents results for a given set of Romer episodes, starting with all episodes including the 1966:Q2 Credit Crunch, and subsequently dropping each episode in turn. Sample period: 1960:Q1-1991:Q4. All results based on robust standard errors.

Table 6: The Effect of a Romer Episode: The Multivariate Case

Firms	Variable	Exclusion Tests for Subsets of Episodes[a]					
Small		All	-66:Q2	-68:Q4	-74:Q2	-78:Q3	-79:Q4
	Sales	0.00	0.00	0.00	0.00	0.00	0.00
	Inventories	0.00	0.01	0.00	0.00	0.00	0.00
	Short Debt	0.00	0.00	0.00	0.00	0.00	0.00
	Inv/Sales	0.01	0.04	0.00	0.05	0.00	0.00
	Debt/Sales	0.00	0.00	0.00	0.00	0.00	0.00
Large		All	-66:Q2	-68:Q4	-74:Q2	-78:Q3	-79:Q4
	Sales	0.47	0.02	0.30	0.11	0.24	0.40
	Inventories	0.00	0.05	0.01	0.00	0.00	0.00
	Short Debt	0.03	0.00	0.03	0.00	0.02	0.02
	Inv/Sales	0.59	0.43	0.78	0.84	0.00	0.04
	Debt/Sales	0.37	0.39	0.37	0.01	0.22	0.00

Firms	Variable	T-Stats on Sums of Coefficients for Subsets of Episodes					
Small		All	-66:Q2	-68:Q4	-74:Q2	-78:Q3	-79:Q4
	Sales	-3.16	-1.68	-1.58	-1.57	-4.44	-3.61
	Inventories	-2.81	-1.20	-1.41	-1.94	-3.75	-3.09
	Short Debt	-2.99	-2.93	-2.02	-1.92	-2.58	-3.16
	Inv/Sales	-1.26	-0.63	-0.85	-2.04	-0.87	-0.69
	Debt/Sales	-1.66	-2.45	-1.32	-1.67	-0.23	-1.28
Large		All	-66:Q2	-68:Q4	-74:Q2	-78:Q3	-79:Q4
	Sales	0.18	-0.08	0.33	0.66	-0.48	0.17
	Inventories	2.55	1.62	1.17	1.56	2.87	3.02
	Short Debt	1.50	1.38	0.15	1.50	0.89	2.38
	Inv/Sales	1.33	0.68	0.47	0.48	2.95	2.11
	Debt/Sales	1.41	1.34	0.38	1.34	1.13	2.01

[a]Regression includes four lags of the small and large firm variable, the growth rate of GNP, inflation, the Funds rate, and twelve lags of the Romer episode indicator. Each column presents results for a given set of Romer episodes, starting with all episodes including the 1966:Q2 Credit Crunch, and subsequently dropping each episode in turn. Sample period: 1960:Q1-1991:Q4. All results based on robust standard errors.

Table 7: Contribution of Small vs. Large Firms during Romer Episode

	Change in Log Level[a]			Total Contribution[b]		
Quarter:	4	8	12	4	8	12
Sales						
Large	-1.24	-2.44	-4.39	-0.93	-1.79	-2.97
Small	-4.45	-11.66	-14.93	-1.10	-3.11	-4.82
All	-2.03	-4.90	-7.79	-2.03	-4.90	-7.79
Inventories						
Large	+2.40	+5.12	+3.09	+2.02	+4.15	+2.45
Small	-2.18	-10.75	-17.55	-0.35	-2.02	-3.64
All	+1.67	+2.13	-1.18	+1.67	+2.13	-1.19

[a]Change in log-level for small and large firms is obtained from the impulse response to a Romer episode from a VAR that includes four lags of the small and large firm variable, GNP growth, inflation, and the Funds rate, and twelve lags of the Romer episode. The change in log-level for all firms (total manufacturing) is obtained from a similar VAR, replacing large firms with all firms. Sample period for both VARS: 1960:Q1-1991:Q4

[b]Total contribution for small firms is computed as w(t)*(Change in log-level at t). Total contribution for large firms is computed as (1-w(t))*(Change in log-level at t) where w(t) is chosen to satisfy w(t)*(Small firm change at t) + (1-w(t))*(Large firm change at t) = Change in All Firms at t.

Table 8: The Effect of the Federal Funds Rate

System/Sample	Dependant Variable	P-Value on Exclusion Test		T-Stat on Sum of Coefficients[a]	
		Small	Large	Small	Large
Trivariate[b] 60:Q1-91:Q4					
	Sales	0.00	0.00	-3.59	-4.14
	Inventories	0.00	0.00	-2.59	-2.58
	Short Term Debt	0.00	0.00	-1.12	0.56
	Inventories/Sales	0.01	0.00	2.34	2.14
	Short Debt/Sales	0.00	0.00	2.01	1.92
Trivariate 60:Q1-79:Q4					
	Sales	0.00	0.23	-4.51	-1.60
	Inventories	0.00	0.00	-2.95	-0.16
	Short Term Debt	0.00	0.00	-1.85	-0.66
	Inventories/Sales	0.01	0.04	2.57	2.18
	Short Debt/Sales	0.00	0.00	0.67	0.23
Multivariate[c] 60:Q1-91:Q4					
	Sales	0.06	0.00	-2.73	-4.19
	Inventories	0.14	0.00	-1.77	-0.72
	Short Term Debt	0.11	0.00	0.53	1.74
	Inventories/Sales	0.02	0.00	2.18	2.64
	Short Debt/Sales	0.00	0.00	2.24	3.09
Multivariate 60:Q1-79:Q4					
	Sales	0.15	0.58	-2.47	0.32
	Inventories	0.53	0.00	0.06	3.54
	Short Term Debt	0.15	0.00	-0.77	2.38
	Inventories/Sales	0.08	0.07	2.03	1.92
	Short Debt/Sales	0.00	0.01	0.38	2.05

[a]All tests are based on robust standard errors

[b]System includes four lags of the growth rate of the dependant variable, the inflation rate and the Federal Funds rate.

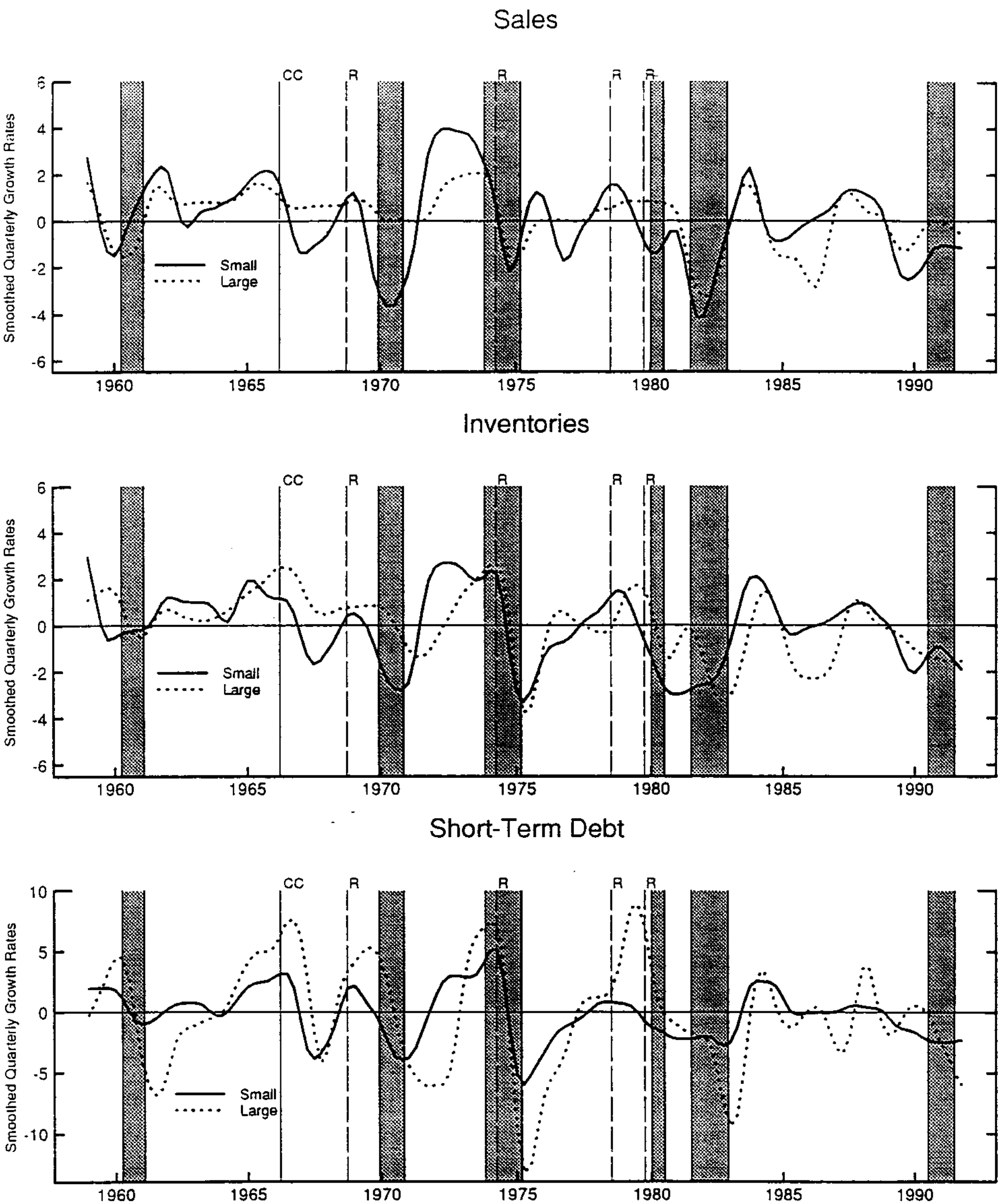
[c]System includes four lags of the growth rate of the small and large firm variable, the growth rate of GNP, the inflation rate, and the Federal Funds rate.

Table 9: Asymmetric Interest Rate Effects

	Small Firms				Large Firms			
	Sales		Inv		Sales		Inv	
C	1.03	1.19	0.45	0.21	1.80	2.15	0.90	0.86
	(0.72)	(0.84)	(0.53)	(0.58)	(0.77)	(0.88)	(0.39)	(0.44)
$Depvar_{t-1}$	0.15	0.11	0.29	0.29	-0.02	-0.06	0.32	0.28
	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)
$Depvar_{t-2}$	0.02	-0.01	0.17	0.14	-0.21	-0.24	0.15	0.11
	(0.10)	(0.10)	(0.01)	(0.09)	(0.11)	(0.11)	(0.10)	(0.11)
$Depvar_{t-3}$	0.04	-0.03	-0.08	-0.11	0.04	-0.01	-0.06	-0.06
	(0.10)	(0.03)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)
$Depvar_{t-4}$	-0.03	-0.03	-0.02	0.00	-0.08	-0.04	-0.03	0.07
	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	(0.10)	(0.09)	(0.09)
FFR_{t-1}	-0.09	0.22	0.17	0.21	0.43	0.36	0.49	0.39
	(0.20)	(0.33)	(0.15)	(0.21)	(0.23)	(0.33)	(0.10)	(0.16)
FFR_{t-2}	-0.33	-0.15	-0.14	0.25	-0.83	-0.31	-0.45	-0.31
	(0.30)	(0.05)	(0.22)	(0.28)	(0.30)	(0.43)	(0.15)	(0.21)
FFR_{t-3}	-0.04	-0.37	-0.25	0.24	0.27	0.05	-0.00	0.38
	(0.31)	(0.56)	(0.22)	(0.38)	(0.31)	(0.59)	(0.15)	(0.30)
FFR_{t-4}	0.07	-0.03	-0.01	-0.78	-0.28	-0.45	-0.15	-0.46
	(0.22)	(0.38)	(0.15)	(0.26)	(0.24)	(0.42)	(0.11)	(0.21)
$D * C$	-	-0.51	-	0.03	-	-0.93	-	-0.09
	-	(1.10)	-	(0.77)	-	(1.12)	-	(0.57)
$D * FFR_{t-1}$	-	-0.37	-	0.05	-	0.27	-	0.17
	-	(0.41)	-	(0.28)	-	(0.41)	-	(0.21)
$D * FFR_{t-2}$	-	-0.54	-	-0.82	-	-1.04	-	-0.18
	-	(0.58)	-	(0.40)	-	(0.60)	-	(0.30)
$D * FFR_{t-3}$	-	0.85	-	-0.26	-	0.65	-	-0.42
	-	(0.67)	-	(0.47)	-	(0.71)	-	(0.36)
$D * FFR_{t-4}$	-	0.00	-	0.91	-	0.10	-	0.37
	-	(0.43)	-	(0.31)	-	(0.45)	-	(0.23)
Rsq.	0.26	0.34	0.37	0.50	0.33	0.38	0.62	0.64
P-Val[a]	-	0.02	-	0.00	-	0.10	-	0.30

[a]P-value for the restriction that the interaction terms $D * C$, and $D * FFR$ do not enter the regression. The interaction dummy $D = 1$ if $DLGNP < Median(DLGNP)$, and 0 otherwise. Sample = 1960Q:1-1991Q:4

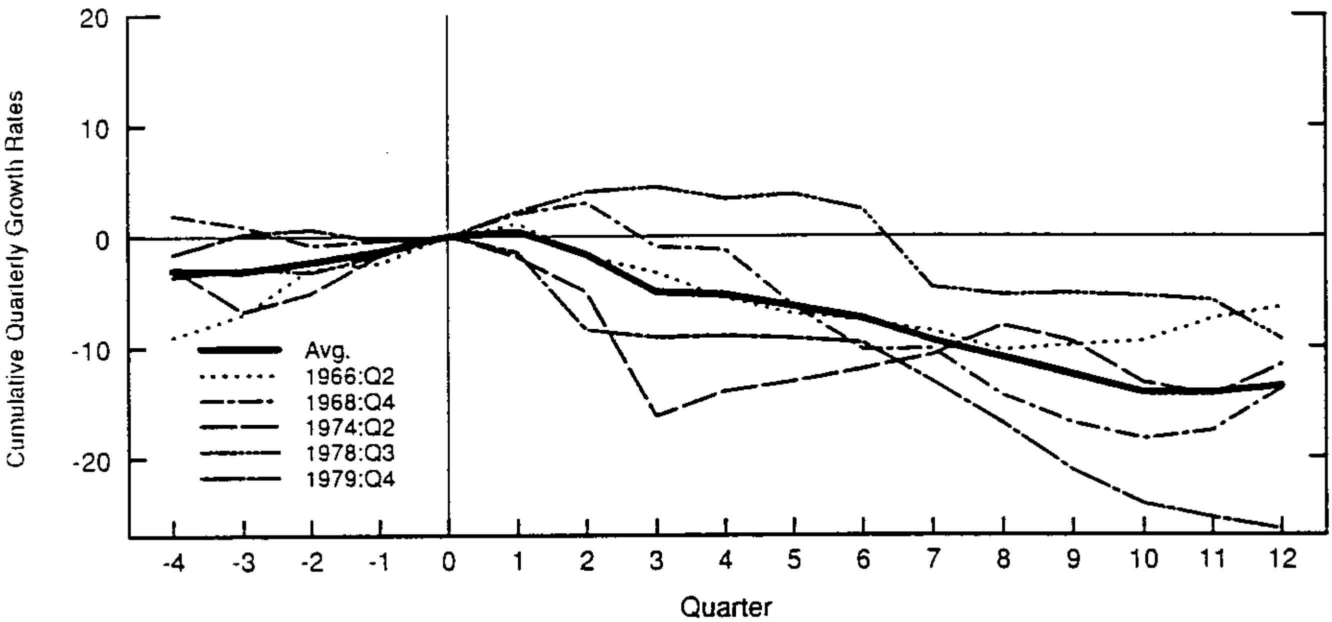
Figure 1



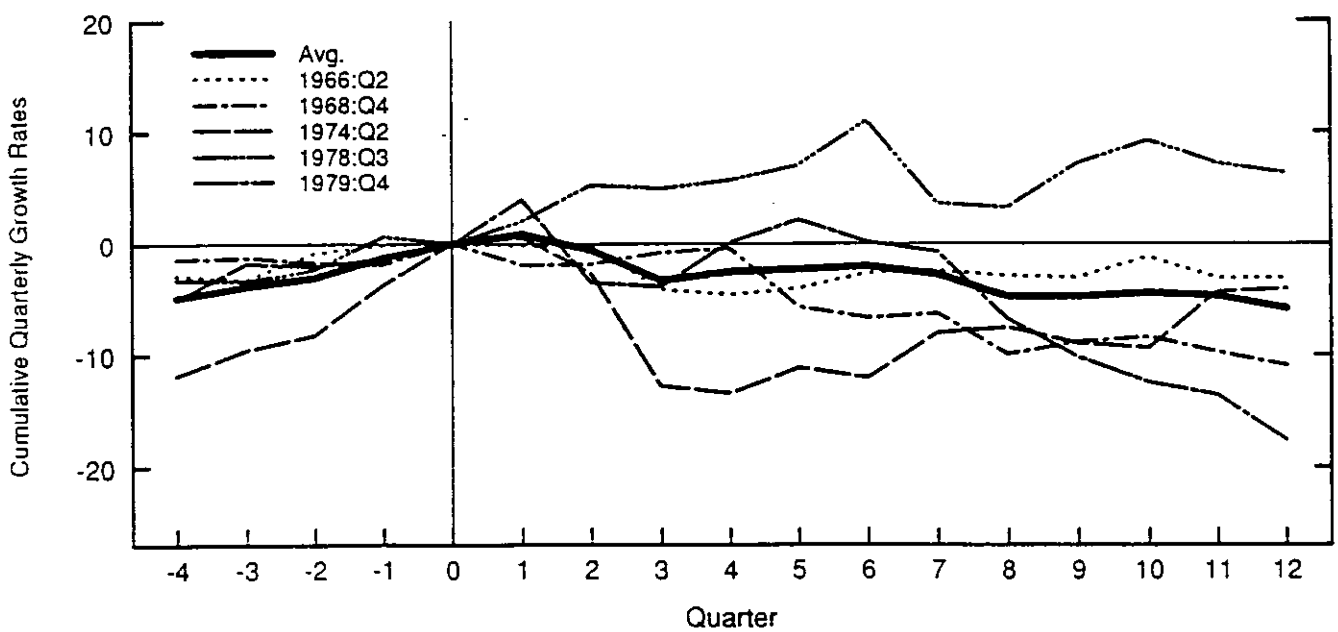
R indicates a Romer date; CC indicates the 1966:Q2 Credit Crunch;
The shaded regions indicate the NBER recessions.

Figure 2

Changes in Sales Around Romer Dates
Small Firms



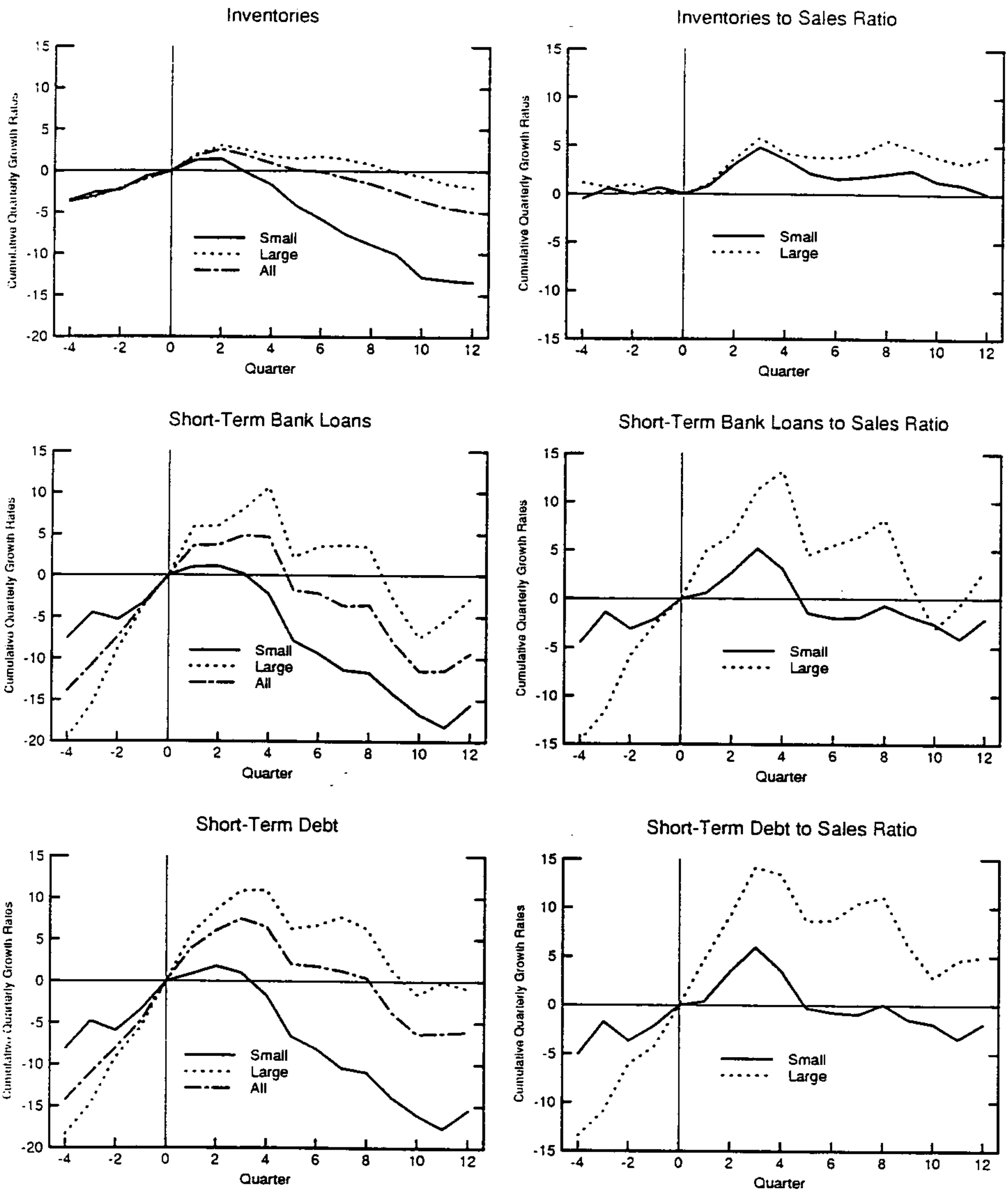
Changes in Sales Around Romer Dates
Large Firms



All series are shown as log deviations from their values at Romer dates.

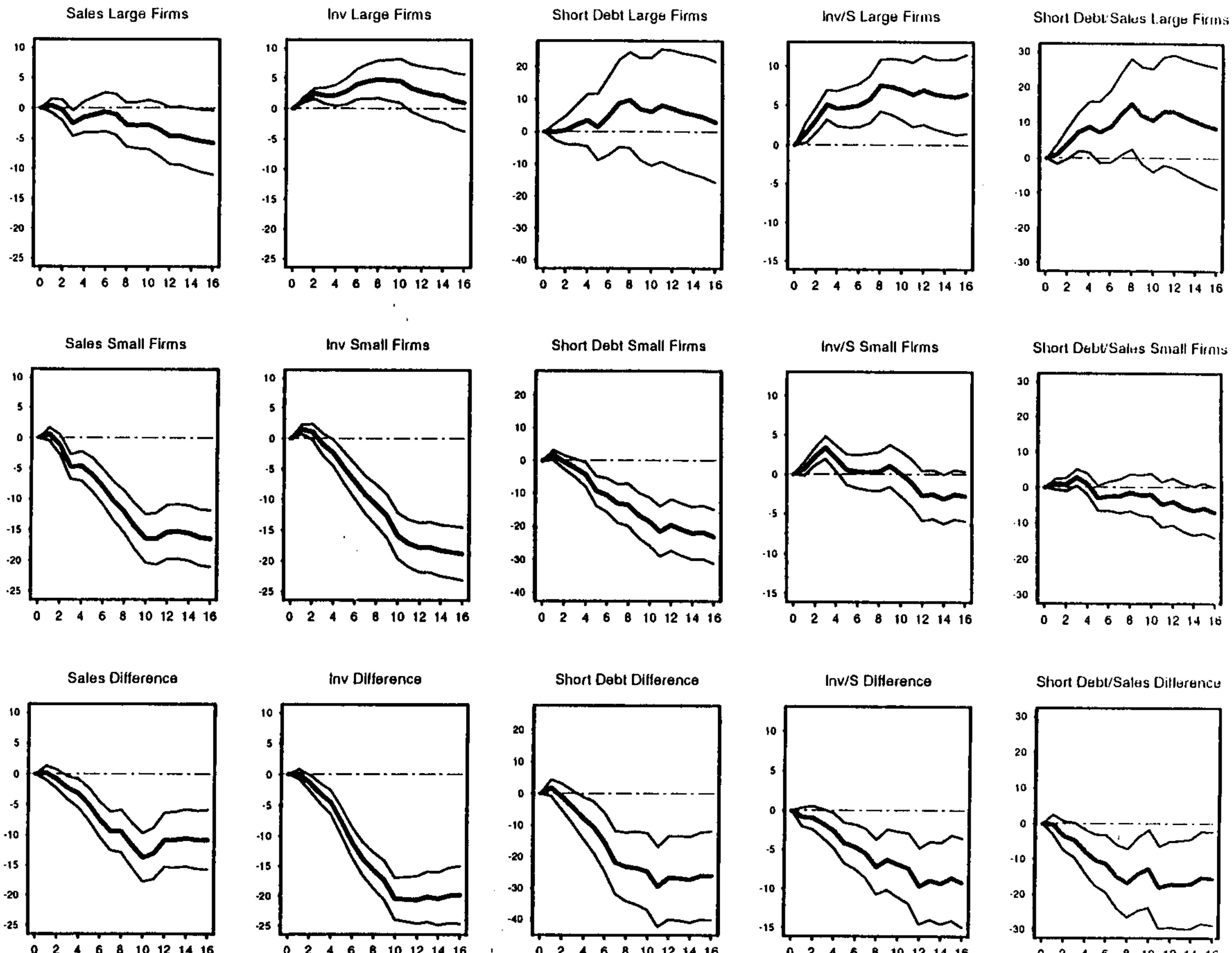
Figure 3

The Average Deviation from Trend Around Romer Dates



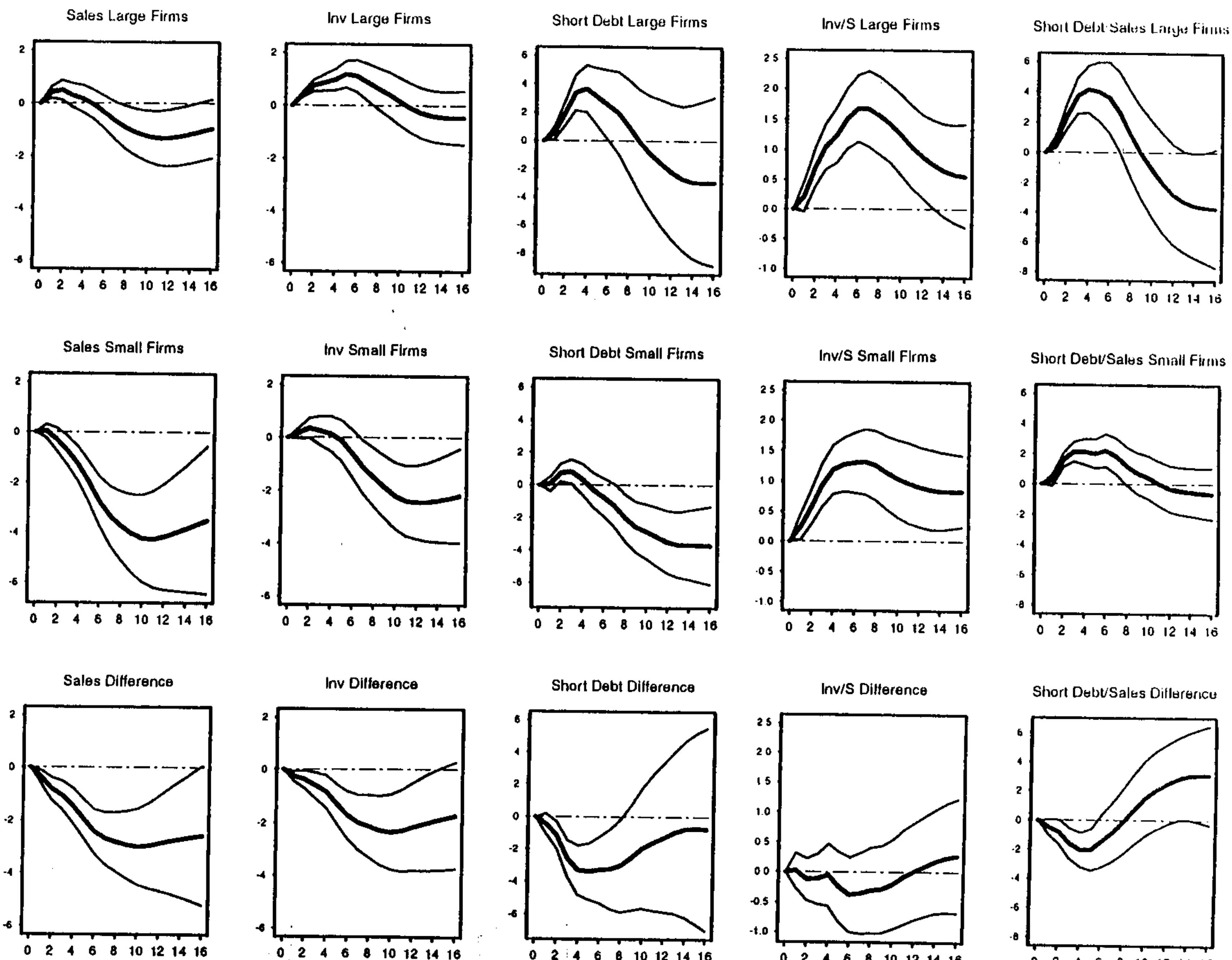
All series are shown as log deviations from their values at Romer dates.

Figure 4: Impulse Response to a Romer Episode



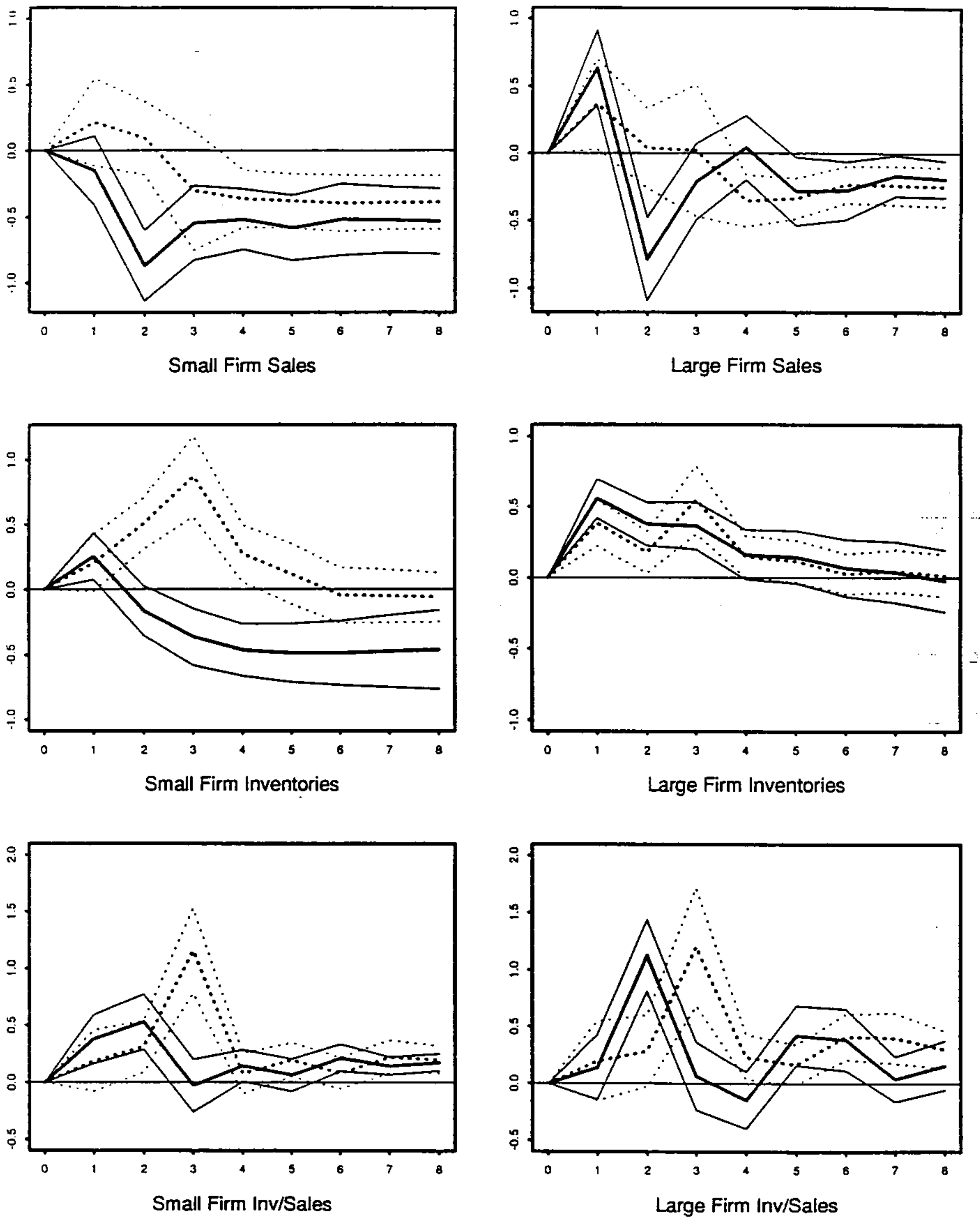
Each column represents a separate Var that includes the growth rate in GNP, Inflation, Large firm variable, Small firm variable, and 12 lags of a Romer episode.
All Figures report the cumulative response of the quarterly growth rate to a one-standard deviation shock to a Romer Episode.
One standard deviation error bands also included. Sample: 1960:Q1 to 1991:Q4

Figure 6: Impulse Response to Funds Rate, Sample:1960:Q1-1979:Q4



Each column represents a separate Var that includes the growth rate in GNP, Inflation, Large firm variable, Small firm variable, and Funds Rate.
All Figures report the cumulative response of the quarterly growth rate to a one-standard deviation shock to Funds Rate.
One standard deviation error bands also included. Sample: 1960:Q1 to 1979:Q4

Figure 7: Asymmetric Interest Rate Effect



Each figure reports the cumulative response of the quarterly growth rate to a rise in the Funds rate.
Solid Line = DLGNP < Median. Dashed Line = DLGNP > Median. One standard error bands also included.