RETAIL INVENTORIES, INTERNAL FINANCE, AND AGGREGATE FLUCTUATIONS: EVIDENCE FROM U.S. FIRM-LEVEL DATA

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Retail Inventories, Internal Finance, and Aggregate Fluctuations: Evidence From U.S. Firm-Level Data

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Abstract

We investigate the implications of capital market imperfections for inventory investment in retail trade, using a new new source of firm-level data—the micro data underlying the published Quarterly Financial Reports. An error-correction model that includes internal funds and forward-looking expectations for the stochastic process of sales is not rejected by the data. Both the cross-sectional and timeseries results are consistent with the existence of significant capital market frictions in the retail trade sector: (1) for firms with limited access to capital markets, internal funds are a significant predictor of inventory investment; and (2) the predictive power of internal funds is highly asymmetric over a business cycle, rising considerably in recessions. The quantitative significance of financial factors suggests that a large portion of the observed volatility in aggregate retail inventory investment over a business cycle is due to fluctuations in internal funds.

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1 Introduction

Macro-economists know that inventory movements play a dominant role in business cycle fluctuations—a drop in inventory investment can account for a majority of the decline in output during recessions. For the average U.S. postwar recession, Blinder and Maccini (1991) report that inventory disinvestment accounted for 87% of the total peak-to-trough decline in GDP. Another salient qualitative feature of a postwar business cycle is that business income—and therefore the flow of internal finance—is extremely volatile, pro-cyclical, and tends to lead the cycle (see, for example, Lucas (1977)).

Using a new firm-level data source, this paper links these two stylized facts by appealing to theoretical literature which argues that imperfections in the market for capital—caused by informational asymmetries between borrowers and lenders—may amplify aggregate fluctuations by increasing the sensitivity of current spending to movements in internal funds or net worth.

1.1 The Financial Accelerator

Theoretical research analyzing macroeconomic implications of the interaction between real and financial activity seeks to develop mechanisms by which small, transitory, and exogenous shocks—to either the financial or real side—can be amplified and transmitted through the economy. Termed the "financial accelerator" mechanism by Bernanke, Gertler, and Gilchrist (1996), frictions in financial markets act as a mechanism that amplifies and propagates the initial real or monetary shock to the economy.

The formal development of the financial accelerator mechanism is provided by the theoretical literature which emphasizes the financial aspects of a business cycle—namely, the limited access of many borrowers to external credit markets and the role that balance sheet positions play in determining the terms of credit. A central implication of imperfect capital market access is that internal and external funds are not perfect substitutes. External financing is intrinsically more expensive than internal financing, because it incorporates the "agency premium"—the inevitable dead-weight loss—associated with imperfect information in financial markets.

The agency premium on external finance is inversely related to the strength of a borrower's balance sheet position.¹ Consequently, the relative posi-

¹In other words, a strong balance sheet position indicates that a borrower has more

tions of borrowers' balance sheets determine the spending decisions of certain classes of borrowers. This connection between the net worth used as collateral and the terms of credit leads naturally to the financial accelerator mechanism—that fluctuations in balance sheet positions over the business cycle amplify swings in spending.²

1.2 Inventories and the Financial Accelerator

Empirical research to date analyzing the effects of the financial accelerator mechanism on inventory investment has focused exclusively on inventories held by manufacturing firms. Recent papers by Kashyap, Stein, and Wilcox (1993); Kashyap, Lamont, and Stein (1994); Carpenter, Fazzari, and Petersen (1994, 1997); Gertler and Gilchrist (1994); Calomiris, Orphanides, and Sharpe (1994); Calomiris, Himmelberg, and Wachtel (1995); and Gilchrist and Zakrajšek (1995) offer substantial empirical evidence that financial factors explain and predict the behavior of manufacturers' inventories.

Despite the relative importance of nonmanufacturing inventories as a component of aggregate inventory stocks, current empirical research on the effects of the financial accelerator mechanism on inventory investment does not address inventory investment in the remainder of the economy. Blinder and Maccini (1991) report that in 1989, business inventories accounted for more than 87% of inventory stocks held in the entire U.S. economy. According to Figure I, retail inventories account, on average, for 27% of the total business inventory stocks, making retail inventory investment clearly relevant to aggregate fluctuations.

In addition to the significance of retail trade inventories as a component of aggregate inventory stocks, the analysis of retail inventory investment in this paper is motivated by two findings. First, using the variance of inventory investment as a measure of volatility, inventory investment in retail trade is the most volatile component of aggregate inventory investment. Nearly 25%

resources available to either directly finance a project (for example, inventory or capital accumulation) or to use as collateral in obtaining external finance. A strong balance sheet position, therefore, reduces the borrower's costs of obtaining external funds by lowering the agency premium on external finance.

²Dynamic general equilibrium models that incorporate such a financial accelerator mechanism have been developed by Bernanke and Gertler (1989, 1990); Calomiris and Hubbard (1990); Gertler (1992); Greenwald and Stiglitz (1993); and Kiyotaki and Moore (1997).

of the aggregate variance comes from the movements in retail inventories (see Blinder and Maccini (1991) for full accounting). As shown in Figure II, dynamics of aggregate inventory investment are dominated by fluctuations in retail inventories.³ In their assessment of the state of inventory research, Blinder and Maccini (1990) list the volatility of retail inventories as one of the three basic stylized facts that need to be addressed by the literature.

The second finding motivating this paper centers on the differences in the cross-sectional distribution of firm size between the retail and manufacturing sectors. The cross-sectional distribution of the size of retail trade firms—measured by assets or sales—is skewed toward smaller firms. According to Table 1, firms with assets below \$250 million accounted for slightly more than 16% of all assets and almost 31% of all receipts in the manufacturing sector in 1990. The corresponding class of firms in the retail trade, on the other hand, accounted for nearly 46% of all assets and more than 66% of all receipts.⁴

In their study of small manufacturing firms, Gertler and Gilchrist (1994) found that following a tightening of monetary policy, small firms account for a surprisingly significant share of the decline in inventory investment. To the extent that binding credit constraints associated with capital market imperfections are negatively correlated with size and are felt more acutely by small firms, effects of capital market imperfections may be more prevalent in retail trade than in manufacturing.⁵ Consequently, financial factors are likely to have significant explanatory and predictive power for the aggregate as well as for firm-level inventory dynamics in retail trade.⁶ Because financial

³The growth rates (times 100) are plotted as deviations from the mean and are smoothed by a non-parametric Splus filter; the filter smoothes the data by means of running medians and is designed to pick up broad trends in the data.

⁴See Gertler and Hubbard (1988) for additional evidence.

⁵Using firm-level Compustat data for the retail trade sector, Kwon (1994) finds that for credit constrained firms, financial factors have significant explanatory power for business fixed investment.

⁶The interaction of financial factors with retail inventory investment has, historically, been neglected by econometric investigations. Two exceptions are Irvine (1981a, 1981b). In both studies, Irvine examines the dependence of retail target inventory levels to financial inventory carrying costs, measured as a cost of capital. His analysis proceeds under the assumption of perfect credit markets in which capital costs of financing inventories depend solely on short-term interest rates and the relative price level. Using monthly sectoral (durable and nondurable) aggregate data, Irvine (1981b) found that inventory investment in retail trade responds significantly to variations in cost of capital; similar results were obtained in Irvine (1981a), which utilized monthly data of a single large department store.

factors may exacerbate economic downturns, the differences in the cross-sectional distribution of size and/or capital market access may prove to be an important source of different cyclical variability within the different sectors of the economy.

The remainder of the paper is organized as follows. Section 2 presents a simple linear-quadratic (LQ) model of finished goods inventories and derives the econometric methodology. Section 3 describes the new source of data used in the analysis. Section 4 presents the results, and Section 5 concludes.

2 Econometric Methodology

What is the appropriate structural framework for analyzing retail inventory investment? The widely used production-smoothing/buffer stock model is not appropriate, because it was developed to analyze manufacturers' finished goods inventories. Compelling theoretical arguments, advanced by Blinder (1981) and Blinder and Maccini (1991)—buttressed by some broadly consistent empirical facts—suggest that (S,s) inventory policies are the appropriate structural framework for analyzing retail inventory investment.

Because of the inherent mathematical difficulties in solving (S, s) inventory models, in addition to complex aggregation problems, the current state of inventory research using (S, s) policies avoids the financial considerations that form a primary motivation for this paper. An alternative structural specification is the target-adjustment model (see Lovell (1961) and Schuh (1996)). The target-adjustment model is based on the hypothesis that each firm has a "desired" (optimal) target level of inventories, and that a firm, finding its actual inventory level not equal to its target level, attempts only partial adjustment toward the target level within any one period.

In addition, aggregate and industry-level (2-digit SIC) time-series evidence for the retail trade sector, obtained by Granger and Lee (1989), indi-

⁷The key empirical prediction of the (S, s) inventory strategies that is consistent with the observed data is that the variance of deliveries (i.e., orders) exceeds the variance of sales. This implication follows very naturally from the (S, s) inventory model, while it is fundamentally contradictory to the production-smoothing/buffer stock framework.

Despite the seminal work of Caplin (1985) on the aggregation of (S, s) economies, evidence that aggregate inventory investment in retail trade is consistent with (S, s) inventory rules is mixed. Mosser (1991) obtains indirect empirical evidence that is consistent with the (S, s) model of inventory behavior, while Granger and Lee (1989) reject the (S, s) model in favor of an error-correction framework.

cates that retail inventory levels and sales are cointegrated, indicating that an error-correction framework may adequately capture the dynamics of inventory investment in retail trade. An error-correction specification can be thought of as a generalization of a partial adjustment model and, given its flexibility, can be easily augmented to include financial factors.

2.1 The Model

Let H_{it} denote firm i's log-level of real, end-of-period t inventories, and let H_{it}^* denote firm i's "desired" or optimal log-level of real inventories in period t. Because of adjustment costs, stochastic departures from the optimal inventory policy cannot be reversed without cost. The discounted present value of squared deviations from the optimal path, $(H_{it} - H_{it}^*)^2$, and squared changes in the level of decision instrument (i.e., inventory growth rate), $(H_{it} - H_{it-1})^2$, provide the standard LQ regulator criterion:

$$\min_{\{H_{it+k}\}_{k=0}^{\infty}} E_{it} \left\{ \sum_{k=0}^{\infty} \beta^{k} \left[(H_{it+k} - H_{it+k}^{*})^{2} + \phi(\Delta H_{it+k})^{2} \right] \right\}.$$
 (1)

In equation 1, $0 < \beta < 1$ is a one-period discount factor; $E_{it} \equiv E[\cdot \mid \Omega_{it}]$ is the mathematical expectations operator and Ω_{it} is firm i's information set; Δ is the back-difference operator; and $\phi > 0$ is a constant reflecting inventory holding costs (e.g., storage and handling charges; see West (1986)). As in most applied inventory research, we assume that the stochastic process for H_{it}^* is exogenous, with $H_{it}^* \notin \Omega_{it}$.

The necessary conditions for minimizing the criterion in equation 1 include both the Euler equation

$$E_{it} \{ (1 - \lambda_b L)(\lambda_f - F)H_{it} - (1 - \lambda_b)(\lambda_f - 1)H_{it}^* \} = 0,$$
 (2)

and a transversality condition such as

$$\lim_{k \to \infty} E_{it} \left\{ \beta^k (H_{it+k} - H_{it+k}^* + \phi \Delta H_{it+k}) H_{it+k} \right\} = 0.$$
 (3)

L denotes the lag operator, F denotes the lead operator, and λ_b and λ_f are the characteristic roots of equation 2, given by $\lambda_b + \lambda_f = \frac{(1+\beta+\phi^{-1})}{\beta}$ and $\lambda_b \lambda_f = \frac{1}{\beta}$, which under very general conditions lie on either side of unity,

$$0 < \lambda_f^{-1} < \lambda_b < 1.8$$

The optimal decision rule of firm i confronted with the stochastic inventory target, H_{it}^* , is the solution to the Euler equation 2, which also satisfies the split end-point conditions defined by an initial value, $H_{it-1} \geq 0$, and the transversality condition in equation 3:

$$\Delta H_{it} = (\lambda_b - 1)H_{it-1} + (1 - \lambda_b)(1 - \lambda_f^{-1}) \sum_{k=0}^{\infty} \lambda_f^{-k} E_{it} H_{it+k}^*. \tag{4}$$

Following the inventory literature, we assume that the inventory target is given by

$$H_{it}^* = \omega_i + S_{it+1},\tag{5}$$

where ω_i is an unobservable firm-specific component, which captures the stock-out avoidance motive, as advocated by Kahn (1987), and S_{it+1} is the log-level of real final sales in period t+1.9

If the stochastic process for H_{it}^* is integrated of order one, then the "gap" between inventories and their target path, $H_{it} - (\omega_i + S_{it+1})$, is integrated of order zero.¹⁰ Substituting a univariate time-series representation of the target path, H_{it}^* , into the decision rule given by equation 4, yields the error-correction decision rule of the form:

$$\Delta H_{it} = -\alpha [H_{it-1} - E_{it-1} S_{it}] + \sum_{k=1}^{L_H} \gamma_k \Delta H_{it-k} + \sum_{k=1}^{L_S} \delta_k \Delta S_{it-k} + f_i + u_{it}, \quad (6)$$

where $f_i = -\alpha \omega_i$ is an unobservable composite individual effect, and u_{it} is a white noise expectational error that is, by definition, orthogonal to all variables in the information set Ω_{it} .

⁸The inverse of the unstable root, λ_f^{-1} , is the discount factor of expected future events, while the stable root, λ_b , determines the relative influence of past events (see Tinsley (1970) for detailed discussion).

⁹Note that in *levels*, equation 5 implies that the inventory target in period t is proportional to the expected level of sales in period t+1, based on period t information set, Ω_{it} .

¹⁰Unit root tests for panel data developed by Levin and Lin (1992, 1993) do not reject the null hypothesis of a unit root for both the log-level of inventories and the log-level of sales.

 $^{^{11}{\}rm Error\text{-}correction}$ decision rules for selected time series representations of H_{it}^* are given in Nickell (1985).

The baseline specification for inventory growth estimated in this paper is obtained by augmenting equation 6 with a measure of internal funds from period t-1, Π_{it-1} , to obtain

$$\Delta H_{it} = -\alpha [H_{it-1} - E_{it-1}S_{it}] + \beta \Pi_{it-1} + f_i + d_t + \sum_{k=1}^{L_H} \gamma_k \Delta H_{it-k} + \sum_{k=1}^{L_S} \delta_k \Delta S_{it-k} + \sum_{k=1}^{L_{\Pi}} \theta_k \Delta \Pi_{it-k} + u_{it}.$$
 (7)

Equation 7 captures the basic features of the target-adjustment model. The first two terms imply that firm i's long-run inventory target is a linear function of firm i's expected (based on period t-1 information set) level of sales and firm i's level of internal funds from the previous period. The (composite) fixed firm effect, f_i , captures any time-invariant and firm-specific characteristics that may affect firm i's long-run inventory target. The time effect, d_t , is included to capture aggregate shocks (e.g., movements in prices, interests rates, or seasonal demand shocks) that can similarly affect the inventory target level. Note that, conditional on internal funds and fixed firm and time effects, the long-run inventory-sales ratio is restricted to be constant. 12

The inclusion of lagged differences of each of the variables in equation 7 is consistent with the cointegrating relationship between inventory levels and sales and, consequently, gives equation 7 a general error-correction format. Essentially, the first four terms on the right-hand-side of equation 7 reflect the influence of the long-run target on inventory growth, while lagged differences are included to capture any additional short-run dynamics.

Equation 7 is estimated separately for firms with limited access to capital markets and firms with relatively unimpeded access to sources of external finance. Under the maintained hypothesis, internal funds ought to have predictive power for inventory growth only for firms with limited or non-existent access to external debt markets—that is, credit constrained firms.

A potential problem with this identification strategy lies in the fact that lags of internal funds could contain information about the expected level of current sales, $E_{t-1}S_{it}$. Accordingly, the predictive power of internal funds for inventory growth of credit constrained firms could be due entirely to the predictive power of internal funds for current expected sales.¹³ To control for

¹²Although tests of this restrictions are not reported, the restriction of constant long-run inventory-sales ratio was not rejected for any of the subsequent regressions.

¹³This problem is likely to be amplified because firms that are typically identified as

this spurious correlation, firm i's period t-1 information set, which is used to forecast current sales, includes lagged internal funds.

An extension of this argument would imply that the predictive power of internal funds for inventory growth merely reflects the predictive power of internal funds for the expected future sales. In equation 7, the long-run inventory target depends on the expected level of current sales. It certainly makes plausible an argument that, in addition to current expected sales, the long-run inventory target should also depend on the expected future growth of sales. To test this hypothesis, equation 7 is modified to include the potential forward-looking nature of the long-run inventory target. In particular,

$$\Delta H_{it} = \sum_{k=1}^{F_S} \varphi_k E_{it-1} \Delta S_{it+k} - \alpha [H_{it-1} - E_{it-1} S_{it}] + \beta \Pi_{it-1} + f_i + d_t + \sum_{k=1}^{L_H} \gamma_k \Delta H_{it-k} + \sum_{k=1}^{L_S} \delta_k \Delta S_{it-k} + \sum_{k=1}^{L_{\Pi}} \theta_k \Delta \Pi_{it-k} + u_{it}.$$
 (8)

In equation 8, the long-run inventory target depends on the expected growth of sales in periods $t+1,\ldots,t+F_S$, the expected level of sales in period t, the level of internal funds from period t-1, as well as fixed firm and time effects. As before, firm i's information set, which is used to forecast the current level of expected sales and future growth of sales, includes lags of internal funds.

2.2 Identification

What is an accurate indicator of a firm's ability to mitigate informational asymmetries present in financial markets, an ability that in turn allows a firm

credit constrained are, on average, smaller, younger, and fast-growing. For these firms, lags of internally generated funds are likely to have substantial predictive power for current sales.

¹⁴Equation 8 is an approximation of a general error-correction decision rule that can be derived by adding higher-order polynomial adjustment costs to the LQ regulator criterion. In equation 1, the quadratic penalties are imposed on both the static deviation of the decision instrument from its equilibrium path, $H_{it} - H_{it}^*$, and the dynamic costs of altering the level of the decision instrument, H_{it} . A general polynomial expansion of costs imposes a quadratic penalty not only on the one-period changes in the level of the decision instrument, H_{it} , but also on the growth rate, $(1-L)H_{it}$, or any k-order difference, $(1-L)^k H_{it}$, of the decision instrument; see Tinsley (1993) for an exposition of polynomial adjustment costs and error-correction decision rules.

to enjoy relatively unimpeded access to various sources of external finance? Previous research has used indicators such as firm size, dividend-retention practices, bank-dependency, lack of commercial paper issuance, and the absence of a bond rating to identify firms with limited access to various forms of external credit. Each identification strategy has its advantages and caveats, however, we identify the financial accelerator mechanism through the single most important source of short-term external finance for firms in the United States, namely, trade credit.

2.2.1 Cross-sectional identification

There are many competing theoretical explanations of why nonfinancial firms lend money. Trade credit may be used as capital by firms that are unable to raise it through more traditional channels. Firms that extend trade credit may be more adept than specialized financial institutions in evaluating and monitoring the credit risk of their buyers. Trade credit, consequently, may be a way for firms with better access to capital markets to intermediate finance to firms with little or no access to external credit; see Smith (1987) and Brennan, Maksimovic, and Zechner (1988) for theoretical models of trade credit based on the premise that the seller has information superior to that of formal financial institutions.

In addition, trade credit may allow suppliers to price-discriminate using credit when discrimination through prices directly is illegal. Finally, trade credit may be useful in lowering transaction costs (see Ferris (1981)) or in providing assurances about the quality of the supplier's products.

In a recent paper, Petersen and Rajan (1995) test the most prominent theories of trade credit demand and supply, using a detailed firm-level database compiled by the National Survey of Small Business Finance. Controlling for the supply of trade credit, firms' investment opportunities, asset maturity, liquidity, and access to credit from financial institutions, Petersen and Rajan (1995) reach the following conclusions regarding the use of trade credit:

¹⁵Because the terms of trade credit are typically invariant to the credit quality of the borrower (see Smith (1987) and Petersen and Rajan (1994)), trade credit reduces the effective price of external finance for low-quality borrowers. Since low-quality borrowers form the most elastic segment of the demand curve—because this segment is typically credit rationed—trade credit both lowers the effective price of the good and allows low-quality firms to express its demand; see Brennan, Maksimovic, and Zechner (1988) and Mian and Smith (1992).

- 1. The strength of a relationship between the firm and a financial institution, measured as the firm's longest relationship with a financial lender, correlates negatively with the firm's demand for trade credit. That is, firms that are constrained by their institutional lenders rely mainly on trade credit. 16
- 2. Firms with larger unused lines of credit from banks demand less trade credit, implying that firms treat institutional finance and trade credit as substitutes.
- 3. The firm's ability to generate cash internally reduces its demand for trade credit, implying that firms prefer internal financing to trade credit financing.
- 4. The estimated price elasticity of the demand for trade credit is very small. This result is consistent with the argument that the failure to take advantage of early payment discounts is not driven by the implicit cost of trade credit, but instead by the lack of alternative sources of external credit.¹⁷

The evidence obtained by Petersen and Rajan (1995) and the detailed information on the composition of short-term debt finance in the QFR data provide the basis for the identification strategy used in this paper. We define a firm as credit constrained if a predominant share of its short-term external finance is in the form of trade credit; short-term finance consists of short-term bank loans, commercial paper, trade credit, and other short-term debt.

In particular, for each firm we compute the ratio of trade credit payables to total short-term debt. A firm is classified as credit constrained if its average ratio of trade credit to short-term debt is greater than or equal to the

¹⁶This observation is consistent with an earlier finding by Petersen and Rajan (1994) that relationship between firms and financial institutions relaxes credit rationing.

¹⁷In retail trade, for example, the standard trade credit terms are are known as "2-10 net 30." This means that the firm receives a 2% discount if it pays the bill within 10 days (the discount date), or it must pay the full amount within 30 days (the due date). Thus, for the first 10 days, the firm gets an interest-free loan. If it does not pay by the discount date and pays on the due date, the firm's effective interest rate on trade credit over the next 20 days is almost 44% (annual rate). If it does not pay by the due date, additional sanctions (e.g., eventual cut-off of deliveries) may be imposed, raising the effective interest rate even higher.

median trade credit to short-term debt ratio for all the firms in its QFR industry classification. Otherwise, a firm is classified as credit unconstrained. In addition, we consider a group of firms that are even more likely to be credit constrained by setting the cut-off at the 75th percentile. That is, a firm is classified as credit constrained if its average trade credit to short-term debt ratio is above (or equal to) the industry-specific 75th percentile; otherwise a firm is classified as credit unconstrained. The median and the 75th percentile cut-off values are allowed to vary across industries to control for any industry-specific financing patterns, which may otherwise bias the classification scheme.

The identification strategy based on this cross-sectional concept of "trade credit dependency" is consistent with the stylized facts of firm-level financing patterns. Firms rely relatively more on trade credit financing when trade credit from financial institutions is not available. Although trade credit may be used to minimize transaction costs, substantial discounts for prompt payment and strict penalties for late payment imply that medium- and long-term borrowing against trade credit is clearly a form of financing of last resort. Consequently, inventory investment of a firm that relies heavily on trade credit should be closely tied to fluctuations in its own internal funds.

2.2.2 Time-series identification

Availability of high-frequency firm-level data allows us to add an additional dimension to the identification strategy. As noted in the introduction, the drop in inventory investment accounts for a vast majority of the decline in GDP for the average U.S. postwar recession. The added dimension of the identification strategy in this paper concerns the dynamics of inventory investment during the course of a business cycle.

As business and credit conditions deteriorate in the aggregate, financial accelerator effects on inventory investment should increase disproportionately for firms that are already facing severe agency problems in credit markets. With the onset of a recession, a decline in aggregate spending lowers firms' sales and cash flows, inducing a deterioration of their balance sheet positions, thereby raising the cost of external finance to even higher levels. A firm that relies mainly on trade credit for external financing will find it even more difficult (if not impossible) to take advantage of early payment discounts or

¹⁸The QFR industry classifications correspond closely to the 2-digit SIC categories, although they are not identical; see the Data Appendix for details.

may even find itself unable to pay suppliers by the due date, setting off a "trip wire." Acting on this timely information, suppliers can take additional precautions when granting trade credit (e.g., consignment sales) or may stop extending credit altogether. Onsequently, the deeper the economy falls into recession, the more we expect credit constrained firms to rely on internal funds to finance inventory investment.

2.3 Estimation

We now briefly discuss the econometrics used to estimate equations 7 and 8. It is well known that the standard technique of eliminating individual-specific effects—by transforming all variables to deviations from their respective individual means—is inappropriate in a context of a dynamic model with unobservable individual effects (see Nickell (1981), for example). An OLS or an IV estimator obtained from data that have been transformed in this manner is inconsistent, for finite T, because of the asymptotic correlation that exists between the transformed lagged endogenous variables and the transformed error term. The theoretically correct way to estimate a dynamic model with individual effects is first to difference the data—to eliminate the individual-specific effect—and then to estimate the differenced equation using an instrumental variables procedure like GMM (see Holtz-Eakin, Newey, and Rosen (1988), for example).

An alternative to first differencing that is very useful in the context of dynamic panel data models is the orthogonal deviations transformation proposed by Arellano and Bover (1995). The advantage of the orthogonal deviations transformation is that it gives an equivalent to a within-group estimator while preserving the orthogonality among the transformed errors. That is, individual effects are eliminated by subtracting the mean of all available future observation from the first T-1 observations in the sample:

$$x_{it}^* = w_t \left[x_{it} - \frac{1}{(T-t)} \left(x_{it+1} + \dots + x_{iT} \right) \right]; \quad t = 1, \dots, T-1, \quad (9)$$

¹⁹This scenario is consistent with the findings of Petersen and Rajan (1995), who find that suppliers use this informational advantage in lending to firms of currently suspect credit quality. The lack of any time-series dimension in their data set, however, makes it impossible to trace out the dynamics of trade credit demand and supply over a business cycle.

where x_{it}^* denotes the transformed variable, and $w_t^2 = (T-t)/(T-t+1)$ is the weighting factor that equalizes the variances.²⁰

We use the orthogonal deviations transformation to eliminate the unobservable firm-specific effects from equations 7 and 8. For the transformed equation 7, a valid set of moment restrictions for period t is given by $E[z_{it}u_{it}^*] = 0$, where $z_{it} = (H_{i1}, \ldots, H_{it-2}, S_{i1}, \ldots, S_{it-2}, \Pi_{i1}, \ldots, \Pi_{it-2}, D_t)$ is a vector of valid instruments for period t, u_{it}^* is the transformed error term, and D_t denotes the relevant time dummies. A complete set of moment restrictions for firm i is given by $E[Z_iu_i^*] = 0$, where

$$Z_i = \text{diag}[H_{i1}, \dots, H_{is}, S_{i1}, \dots, S_{is}, \Pi_{i1}, \dots, \Pi_{is}, D_t]; \quad s = 1, \dots, T_i - 2,$$

and diag[·] represents a block-diagonal IV matrix of the type discussed in Arellano and Bond (1991); and u_i^* is a $(T_i \times 1)$ vector of transformed errors for firm i.

Because equation 8 includes the expected growth of sales for periods $t + 1, \ldots, t + F_S$, which are replaced by their realized values, the error term in equation 8 will, by construction, follow an $MA(F_S)$ process, thus invalidating the use of instruments dated $t - F_S$ in the period-t moment restrictions, $E[z_{it}u_{it}^*] = 0$. Accordingly, variables dated $t - F_S$ must be dropped from the vector of instrumental variables, which is used to identify equation 8 in period t. Therefore, a valid IV matrix for firm t is given by

$$Z_i = \text{diag}[H_{i1}, \dots, H_{is}, S_{i1}, \dots, S_{is}, \Pi_{i1}, \dots, \Pi_{is}, D_t]; \qquad s = 1, \dots, T_i - F_s.$$

Because the panel is unbalanced, $\dim(Z_i) = \dim(Z_j)$ if and only if firm i and firm j are in the sample the same number of periods. An IV matrix for the complete transformed system is obtained by stacking up the relevant firmspecific IV matrices, $Z = (Z'_1, \ldots, Z'_N)'$, and adding columns of zeros where necessary to ensure conformability. The resulting transformed equations are estimated with an asymptotically efficient two-step GMM estimator of the type presented in Arellano and Bond (1991).

²⁰This transformation can be regarded as first differencing the equation to eliminate individual-specific effects, followed by a GLS transformation to remove the serial correlation induced by differencing.

 $^{^{21}}$ An asymptotically efficient GMM estimator would exploit all (linear) moment restrictions. In the case of equation 7, this would lead to an IV matrix Z with 3,825 columns (not including time dummies). For computational reasons it is clearly impractical to use

3 Data

Empirical implementation of the above identification strategy requires a data set having the following three characteristics: First, the data set should have a long time-series dimension at the business cycle frequency; second, it should capture a sufficiently rich cross-section of the underlying population; and finally, the data set should include a detailed array of both real and financial variables.

A new data set satisfying the above three specifications is the firm-level data set underlying the published Quarterly Financial Reports (QFR). Collected by the Bureau of the Census, the firm-level QFR data appear promising because of their long time-series dimension at a business cycle frequency and the Bureau of the Census's extensive sampling of smaller and nonpublicly traded firms. These features make the firm-level QFR data more representative of the underlying population than, for example, Compustat. In addition, firm-level income and balance sheets include a great deal of information on real and financial variables that is often unavailable in other commonly used micro-level data sets. Working with the original QFR files through the Center of Economic Studies (CES) at the Bureau of the Census, Mark Gertler, Simon Gilchrist, and I have constructed firm-level data sets for the manufacturing, retail, and wholesale sectors of the U.S. economy, spanning the time period 1977:Q1 to 1991:Q3.²²

all of the available instruments. In addition, given the actual sample size, the finite-sample properties of the estimator are likely to be affected by the use of an excessive number of instruments. Consequently, only lags 2 to 5 were used as instruments in equation 7 and lags 3 to 5 in equation 8. As a robustness check, we extended the lag length to 6 for both equations without affecting any of the results.

The estimation was carried out by DPD.sas—a set of general panel data estimation routines written in SAS by the author—that are based on the GAUSS version of a similar program written by Arellano and Bond (1988).

²²The data for the manufacturing sector are by far the most comprehensive of all the three sectors sampled in the QFR program. The majority of firms in the retail trade sector belong to the certainty components (i.e., firms with assets over \$50 million), although smaller firms are also sampled. The biggest difference is that we can sum up the manufacturing firm-level data to obtain the sectoral aggregates, while for the retail and wholesale trade sectors, we can only obtain consistent aggregates for the firms above \$50 million in total assets.

3.1 Summary Statistics

The data set used in the analysis consists of an unbalanced panel of 782 retail trade firms covering the time period 1977:Q1 to 1991:Q3 (59 quarters); the minimum tenure in the panel is 12 quarters and the longest is 59 quarters, yielding a total of 23,830 observations. The exact selection procedure and the construction of all variables are described in the Data Appendix.

Table 2 provides some summary statistics for the three financial categories of firms used in the analysis.²³ By any measure, firms identified as credit constrained are, on average, smaller that credit unconstrained firms. Similarly, credit constrained firms have a significantly lower inventory-to-sales ratio and maintain a much higher ratio of cash stocks to total assets than their credit unconstrained counterparts.²⁴

Looking at the composition of short-term external finance, we see that trade credit is, on average, still the most important source of external finance for credit unconstrained firms, accounting for 71% of all short-term debt—in fact, for the sample as a whole, trade credit accounts for nearly 84% of all short-term liabilities. For credit unconstrained firms, bank loans are the second most important source of short-term external finance, accounting for 21% of all short-term debt; the remainder of short-term liabilities consists of other debt (6%) and commercial paper (2%).

This picture, however, is starkly different for credit constrained firms. For the firms above the median cutoff, trade credit accounts, on average, for 97% of all short-term debt and for firms above the 75th percentile cutoff, trade payables account for 99% of all short-term external finance. According to Table 2, both categories of credit constrained firms issued no commercial paper or short-term other debt, and bank debt forms a negligible part of their short-term liabilities.

²³The Census Bureau's regulations prohibit the disclosure of all order statistics on raw firm-level data. We use 5%-trimmed means to compute robust summary statistics for the sample; all results are qualitatively similar if medians or simple means are used instead.

²⁴This evidence is consistent with Kashyap, Lamont, and Stein (1994), who find that during the 1982-83 recession, small manufacturing firms with no access to public debt markets financed a significant share of their inventory investment by depleting their buffer stocks of cash and liquid assets.

4 Results

In equations 7 and 8, the dependent variable is the growth rate of inventories. Following a recent study by Carpenter, Fazzari, and Petersen (1997), we use cash flow scaled by a lag of total assets as a measure of internal funds, Π_{it} . We set $L_H = L_S = L_\Pi = 4$ in both equations; that is, we include 4 lags of ΔH_{it} , ΔS_{it} , and $\Delta \Pi_{it}$ in each specification to control for any short-term dynamics. Additional lags were no longer statistically significant. We have also included industry-specific time dummies in place of aggregate time dummies without affecting any of the results.

4.1 Baseline Error-Correction Model

Estimates of equation 7 are presented in Table 3. The results clearly show that period t-1 internal funds, Π_{it-1} , are a highly significant predictor of inventory demand for both categories of firms classified as credit constrained. The point estimate on lagged cash flow is 0.51 for the firms above the median cut-off and nearly three times as much (1.31) for the firms above the 75th percentile cutoff; note that both parameters are precisely estimated with t-statistics exceeding four in both cases.

The sharp increase in the magnitude of the cash flow coefficient across the credit-constrained categories is consistent with our identification strategy, which posits that firms that rely almost exclusively on trade credit for their external financing do so because credit from financial institutions is not available. Given the implicit high cost of trade credit financing, firms prefer to use internal funds to finance their inventory accumulation. For credit unconstrained firms, last period's internal funds have no explanatory power for inventory growth. In fact, the point estimate on period t-1 cash flow is negative (-0.19), although it is not statistically significant at the 5% significance level.

The sum of coefficients on the four lags of $\Delta\Pi_{it}$ is positive and statistically significant for the credit unconstrained firms and for the credit constrained firms above the median cutoff. For the credit constrained firms above the 75th percentile cutoff, the sum of coefficients on the four lags of $\Delta\Pi_{it}$ is negative but imprecisely estimated. The p-values for the joint exclusion test on all cash flow coefficients indicate that the hypothesis that the all cash flow terms are equal to zero is rejected for all categories of firms at, essentially,

100% confidence level.²⁵

These results point to a potential problem in our identification strategy. That is, an alternative hypothesis would ascribe the predictive power of lagged internal funds for current inventory growth to the informational content of past retained earnings for future expected sales. The significant predictive power of lagged growth in internally generated funds for both the credit constrained and credit unconstrained firms is consistent with this hypothesis. Firms with high growth in past retained earnings—which could be due to a strong demand for their goods—may expect strong sales in the future and, accordingly, may want to increase their inventory holdings.

Despite the fact that the over-identifying restrictions imposed by the model are not rejected for all categories of firms and that residuals are free of serial correlation, the results in Table 3 cast doubt on the validity of a simple LQ model. In particular, the estimated adjustment speeds (parameter α), although of the right sign (negative), are not economically plausible. For credit unconstrained firms, for example, the estimated adjustment speed is 0.12, implying that it takes, on average, more than 8 quarters for a firm to adjust its inventory stocks to its optimal target.

4.2 General Error-Correction Model

Estimates of a general error-correction decision rule given in equation 8 are presented in Table 4. We set $F_S = 2$; that is, we include the expected growth of sales for periods t+1 and t+2 in equation 8 to control for the potential predictive power of lagged internal funds for future expected sales. Additional leads of the growth rate of sales were no longer statistically or economically significant. Note that the inclusion of these forward terms induces an MA(2) error structure and, thus, invalidates the use of instruments dated t-2 in the moment restrictions.

²⁵To test this hypothesis, we use the two-step procedure developed by Newey and West (1987). We first estimate the unrestricted version of equation 7, and then use the optimal weighting matrix from the unrestricted specification to estimate the restricted version. The difference in the J-statistics (see Hansen (1982)) is distributed as χ^2 , with degrees of freedom equal to the number of restrictions.

 $^{^{26}}$ The Arellano and Bond (1991) test for the first- and second-order serial correlation indicates that for credit constrained firms above the 75th percentile cutoff, residuals exhibit marginal second-order serial correlation; both the m1 and m2 statistics are distributed as N(0,1).

The results in Table 4 show that lagged internal funds remain a highly significant predictor of inventory demand for both categories of firms classified as credit constrained, even when controlling for the expected future growth of sales. The point estimate on period t-1 level of internal funds is 0.56 for the firms above the median cutoff and 1.50 for the firms above the 75th percentile cutoff, indicating that internal funds are an important determinant of inventory investment for credit constrained firms. For the credit unconstrained firms, the point estimate on lagged internal funds is -0.14, which is statistically, though not economically, significant.

Expectations about the future growth of sales are also an important predictor of current inventory demand. Inventory investment of both credit constrained and credit unconstrained firms is highly sensitive to the expected growth in sales over the immediate future quarter, ΔS_{it+1} . The magnitude of the coefficient on further leads of sales declines rapidly and is no longer quantitatively significant at date t+2. The inclusion of the forward-looking expectations significantly raises the estimated adjustment speeds to somewhat more plausible levels, especially for the credit constrained firms. The significance of the lagged difference coefficients on ΔH_{it} indicates the presence of adjustment costs, although the coefficients do not have much of a structural interpretation in this unrestricted form.

As before, the over-identifying restrictions imposed by the model are not rejected by the data. Combined with the fact that the estimated adjustment speeds are somewhat more plausible, and that sales expectations plays a significant role in determining inventory demand, the data seem to favor the general error-correction decision rule of equation 8 over the baseline specification given in equation 7.

4.3 Business Cycle Asymmetries

The implications of capital market imperfections for inventory investment in retail trade presented in the previous two sections were based solely on the cross-sectional dimension of the identification strategy outlined in Section 2.2.1. The theory, in addition to cross-sectional implications, also provides predictions concerning the dynamics of inventory investment during the course of a business cycle.

To test for the business cycle asymmetry in the use of internal funds for inventory investment, a N.B.E.R. recession indicator variable, R_t , is in-

teracted with the lagged level of internal funds in equation $8.^{27}$ The term $R_t \times \Pi_{it-1}$ measures the increase in the predictive power of internal funds for inventory growth during recessions relative to expansionary times. Under the null hypothesis of imperfect capital markets, we expect that $R_t \times \Pi_{it-1} > 0$.

The results in Table 5 show that the increase in the predictive power of internal funds during recessions is substantial and statistically significant. Firms classified as credit constrained exhibit a sharp and statistically significant asymmetry in their reliance on internal funds to finance inventory accumulation over the course of the business cycle. The point estimate on the predictive power of internal funds during recessions, relative to expansionary times, is 26% higher for firms above the median cutoff and more than 40% higher for the firms above the 75th percentile cutoff. Both estimates are statistically significant with t-statistics exceeding 2.5 in each case.

4.4 Aggregate Implications

The evidence presented so far is consistent with the existence of significant capital market frictions in the retail trade sector. For credit constrained firms, internal funds are an important determinant of inventory investment. Their reliance on internal funds to finance inventory accumulation is highly asymmetric over the course of a business cycle, indicating that the credit constraints become more acute the deeper the economy is in the recession.

For credit constrained firms, shocks to internal funds have an economically significant impact on inventory investment. Estimates from Table 5 imply that for credit constrained firms above the median cutoff, a one standard deviation drop in internal funds during a recession reduces the inventory growth by 9% on an annual basis; for the firms above the 75th percentile, a shock of the same magnitude reduces inventory growth by more than 25%. Given that one standard deviation in the annual growth rate of inventories is approximately 74%, and that the drop in internal funds during a typical recession is of the order of two to three standard deviations, fluctuations in internal funds clearly have a quantitatively important effect on inventory investment.

²⁷Specifically, the recession indicator, R_t , equals one if period t falls in the N.B.E.R. dated recession; otherwise R_t equals zero.

²⁸The standard deviation of internal funds for the credit constrained firms above the median cutoff is 13.2% on the annual basis. This number times 0.68—the point estimate on lagged internal funds during recessions—is approximately 9%.

These results provide strong micro evidence in support of a financial accelerator for inventory investment. An important question remaining, however, is whether these effects matter in the aggregate. Although a complete answer to this question is beyond the scope of this paper, we provide two pieces of evidence suggesting that these effects do matter indeed.

First, during the sample period 1977:Q1-91:Q3, credit constrained firms above the median cutoff accounted, on average, for 30% of all retail inventory stocks in the QFR sample. At the beginning of the sample, these firms account for slightly over 24% of total retail inventory stocks. Consistent with the pronounced upward trend in the overall share of retail inventories (see Figure I), the share of retail inventories held by credit constrained firms nearly doubles over the sample period, accounting for more than 40% of all retail inventories during the latter part of the sample.²⁹

Second, inventories of credit constrained firms are more volatile and procyclical than are inventories of the credit unconstrained firms. Figure IIIa plots the cumulative weighted average growth rate of inventories for the credit constrained firms above the median cutoff and for their credit unconstrained counterparts; figure IIIb plots the cumulative growth rate of sales for the same categories.³⁰

The striking drop in inventory stocks of credit constrained firms following the onset of tight money in 1978:Q3 and the continued inventory disinvestment during the recessions of 1980 and 1981-82 provide strong evidence that credit constrained firms account for a significant share of the decline in aggregate inventory investment during an economic downturn. Also striking is the differentially strong expansions of credit unconstrained firms, which during the 1983-86 recovery—a period of strong sales—quickly accumulated inventories to match their pre-recession levels. For credit constrained firms, on the other hand, sales and inventory levels return to trend much later and never reach their pre-recession levels.

The evidence for the latter part of the sample is not so dramatic. There is no obvious differential pattern following the monetary tightening of 1988:Q4.

²⁹Using the master QFR panel for the retail trade sector, firms are classified as credit constrained or credit unconstrained using the same classification procedure that was used for the subsample of firms described in Section 3.2.

³⁰For each category of firms, we compute, quarter by quarter, the weighted cross-sectional average of the growth rate of inventories and sales, with weights equal to the last period's level of inventories and sales, respectively. The resulting time-series are then cumulated and seasonally adjusted using quarterly dummies and linearly detrended.

Credit unconstrained firms began to experience declining sales in the late 1980s, leading to inventory disinvestment at a pace that continued throughout the 1991 recession. Inventories of credit constrained firms, following the trend-level of sales, remained relatively stable and declined only during the middle and latter part of the 1991 recession.³¹

Based on this evidence, it is easy to see the asymmetric effects of the financial accelerator on inventory investment. As credit and business conditions deteriorate for the economy as a whole, credit constrained firms find it harder and more expensive to obtain external financing. The responsiveness of inventory investment to retained earnings for credit constrained firms increases dramatically throughout the downturn. The amplification effects associated with the financial accelerator mechanism, consequently, become more relevant for aggregate economic activity.

5 Conclusion

Using a new micro-level data source, we present cross-sectional and timeseries evidence in support of a quantitatively significant financial accelerator mechanism for inventory investment in the retail trade sector. Consistent with the existence of credit market imperfections, a significant fraction of firms in retail trade face binding credit constraints by relying almost entirely on trade credit to finance inventory accumulation.

Because of the implicit high cost of trade credit financing, inventory investment of credit constrained firms responds significantly to fluctuations in internal funds. The response of inventory investment to shocks in internal funds is highly asymmetric over the course of a business cycle, increasing considerably in recessions relative to expansionary times. The quantitative significance of financial factors is consistent with the view that a large portion of the observed volatility in aggregate retail inventory investment over a business cycle is due to fluctuations in internal funds.

³¹Note that, according to Figure II, the drop in inventories following the 1988:Q4 Romer episode and the inventory disinvestment in the retail trade sector during the 1991 recessions were not nearly as severe as they were for the remainder of the economy. The fact that the 1991 recession did not hit retail trade as hard as it hit the manufacturing sector could account for the absence of the differential effect during the 1990s.

A Data Appendix

This section describes the construction of variables and the selection rules used to

construct of the data set for our analysis.

A.1 Construction of Variables

- Inventories: The QFR data report the book value of total inventories. In retail trade, inventories consist almost entirely of finished goods inventories (see Blinder and Maccini (1991)). Many retailers are thought to follow first in, first out (FIFO) pricing practices; namely, once a finished good is placed on shelves, it is given a price tag that remains on the item regardless of what subsequently happens to the price of newly produced goods (see Okun (1981), pp. 155-60). Because the firm-level QFR data do not provide any information on the inventory accounting practices, we assumed that all inventory stocks are evaluated using the FIFO method so that the replacement value of inventory stocks equals their book value. To eliminate the inflation bias from the inventory growth rate, inventory stocks were deflated by the implicit inventory deflator for the retail trade sector.
- Sales: To construct a real measure of sales, the reported nominal value of sales was deflated by the industry-specific implicit sales deflator for the retail trade sector.
- Internal Funds: The measure of internal funds is cash flow relative to last period's total assets. Cash flow is defined as income (or loss) from operations plus depreciation, depletion, and amortization of property plant, and equipment. Both cash flow and the book value of total assets are deflated by the implicit GDP price deflator prior to constructing the measure of internal funds; any remaining variables used in the analysis (e.g., all short-term liabilities, cash stocks, etc.) were deflated by the implicit GDP price deflator.

A.2 Selection Rules

From the master panel for the retail trade sector, we selected all firms with at least 12 quarters of data, yielding a sample of 980 firms. To avoid results

that are driven by a small number of extreme observations, three criteria were used to eliminate firms with substantial outliers or obvious errors:

- 1. If a firm's growth rate of (real) inventories was below the 0.50th or above the 99.50th percentile of the distribution at any point during a firm's tenure in the sample, a firm was eliminated in its entirety.
- 2. If a firm's growth rate of (real) sales was below the 0.50th or above the 99.50th percentile of the distribution at any point during a firm's tenure in the sample, a firm was eliminated in its entirety.
- 3. If a firm's ratio of (real) cash flow to last period's (real) total assets (i.e., measure of internal funds) was below the 0.50th or above the 99.50th percentile of the distribution at any point during a firm's tenure in the sample, a firm was eliminated in its entirety.

As a consequence of these selection rules, 198 firms were eliminated, leaving 782 firms in the final data set.³² By industry, 127 firms belong to the QFR industry classification 53 (General Merchandise Stores); 164 belong to the industry classification 54 (Food Stores); 120 to the industry classification 55 (Automotive Dealers & Service Stations); and 371 firms belong QFR the industry classification 59 (Other Retail Industries).³³

A.3 Interpolation

Because the 1978:Q4 original QFR tape has been destroyed (rather than begin the analysis in 1979:Q1), we interpolated the missing quarter where necessary using cubic splines (see de Boor (1981)). In particular, the real log-level of inventories, sales and total assets was interpolated using a cubic spline with the spline knots placed at the start of the first input interval, at the end of the last interval, and at the interval midpoints, except that there are no knots for the first two and the last midpoints. A cubic polynomial curve is then fitted to the input data for each firm, with the restriction that the whole curve and its first and second derivatives are continuous. The

³²Subsequent analysis of firms that were deleted from the sample revealed severe anomalies in their data: quarterly growth rates of sales and inventories in excess of 200%, and abnormal movements in total assets.

³³QFR industry codes 53, 54, and 55 correspond exactly to the 2-digit SIC codes; the industry code 59 includes SIC codes 52 and 56-59.

interpolated 1978:Q4 value is then exponentiated to obtain the missing real value. 34

Unlike the variables from the real side of the balance sheet, short-term credit variables are far more discrete in nature and, therefore, are not suitable for interpolation by cubic splines. The missing quarter for all short-term credit variables was interpolated by fitting a discontinuous piecewise constant curve, with the resulting step function equal to the average value of the variable for the input interval.

³⁴Because they can take on zero or negative values, cash flow and cash stocks were interpolated without the logarithmic transformation.

References

90-104.

Arellano, Manuel and Olympia Bover, "Another Look at the Instrumental Variable Estimation of Error-Components Models," Journal of Econometrics, 1995, 68, 29-51. and Stephen Bond, "Dynamic Panel Data Estimation Using DPD: A Guide for Users," 1988. Unpublished paper, Institute for Fiscal Studies, London. and ____, "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," Review of Economic Studies, 1991, 58, 277-297. Bernanke, Ben and Mark Gertler, "Agency Costs, Net Worth, and Business Fluctuations," American Economic Review, 1989, 79, 14-31. ____ and ____, "Financial Fragility and Economic Performance," Quarterly Journal of Economics, 1990, 105, 97-114. _, __, and Simon Gilchrist, "The Financial Accelerator and the Flight to Quality," Review of Economics and Statistics, 1996, 5, 1-20. Blinder, Alan S., "Retail Inventory Behavior and Business Fluctuations," Brookings Papers on Economic Activity, 1981, 2, 443-505. and Louis J. Maccini, "The Resurgence of Inventory Research: What Have We Learned?," 1990. NBER Working Paper No. 3408. and ____, "Taking Stock: A Critical Assessment of Recent Research on Inventories," Journal of Economic Perspectives, 1991, 5, 73-96. Brennan, Michael J., Vojislav Maksimovic, and Joseph Zechner, "Vendor Financing," Journal of Finance, 1988, 43, 1127-1141. Calomiris, Charles W. and R. Glenn Hubbard, "Firm Heterogeneity, Internal Finance, and Credit Rationing," Economic Journal, 1990, 100,

Investment," 1994. NBER Working Paper No. 4800.

_____, Athanasios Orphanides, and Steve A. Sharpe, "Leverage as a State Variable for Employment, Inventory Accumulation, and Fixed

- , Charles P. Himmelberg, and Paul Wachtel, "Commercial Paper, Corporate Finance, and the Business Cycle: A Microeconomic Perspective," Carnegie-Rochester Conference Series on Public Policy, 1995, 42, 203-250.
- Caplin, Andrew S., "The Variability of Aggregate Demand with (S,s) Inventory Policies," *Econometrica*, 1985, 53, 1395–1409.
- Carpenter, Robert E., Steven M. Fazzari, and Bruce C. Petersen, "Inventory Investment, Internal-Finance Fluctuations, and the Business Cycle," *Brookings Papers on Economic Activity*, 1994, 2, 75–138.
- , <u>— , and , "Financing Constraints and Inventory Investment: A Comparative Study with High-Frequency Panel Data," 1997. Unpublished paper, Dept. of Economics, Washington University.</u>
- de Boor, Carl, A Practical Guide to Splines, New York: Springer-Verlag, 1981.
- Ferris, J. Stephen, "A Transactions Theory of Trade Credit Use," Quarterly Journal of Economics, 1981, 96, 243-270.
- Gertler, Mark, "Financial Capacity and Output Fluctuation in an Economy with Multi-Period Financial Relationship," Review of Economic Studies, 1992, 29, 455–472.
- and R. Glenn Hubbard, "Financial Factors in Business Fluctuations," in "Financial Market Volatility: Causes, Consequences, and Policy Recommendations," Kansas City: Federal Reserve Bank of Kansas City, 1988, pp. 33–71.
- and Simon Gilchrist, "Monetary Policy, Business Cycles and the Behavior of Small Manufacturing Firms," Quarterly Journal of Economics, 1994, 109, 309–340.
- Gilchrist, Simon and Egon Zakrajsek, "The Importance of Credit for Macroeconomic Activity: Identification Through Heterogeneity," in Joe Peek and Eric S. Rosengren, eds., Is Bank Lending Important for the Transmission of Monetary Policy?, Boston: Federal Reserve Bank of Boston, 1995, pp. 129-158.

- Granger, Clive W. J. and Tae H. Lee, "Investigation of Production, Sales and Inventory Relationships Using Multicointegration and Non-Symmetric Error Correction Models," *Journal of Applied Econometrics*, 1989, 4, S145–S159.
- Greenwald, Bruce C. and Joseph E. Stiglitz, "Financial Market Imperfections and Business Cycles," Quarterly Journal of Economics, 1993, 108, 77-114.
- Hansen, Lars P., "Large Sample Properties of Generalized Method of Moment Estimators," *Econometrica*, 1982, 50, 1029–1054.
- Holtz-Eakin, Douglas, Whitney Newey, and H. Sherwin Rosen, "Estimating Vector Autoregression With Panel Data," *Econometrica*, 1988, 56, 1371–1395.
- Irvine, F. Owen, "The Influence of Capital Costs on Inventory Investment: Time-series Evidence for a Department Store," Quarterly Review of Economics and Business, 1981, 21, 25-44.
- , "Retail Inventory Investment and the Cost of Capital," American Economic Review, 1981, 71, 633-648.
- Kahn, James A., "Inventories and the Volatility of Production," American Economic Review, 1987, 77, 667–679.
- Kashyap, Anil, Jeremy C. Stein, and David W. Wilcox, "The Monetary Transmission Mechanism: Evidence from the Composition of External Finance," *American Economic Review*, 1993, 83, 78–98.
- , Owen Lamont, and Jeremy C. Stein, "Credit Conditions and the Cyclical Behavior of Inventories," Quarterly Journal of Economics, 1994, 109, 565-592.
- Kiyotaki, Nobuhiro and John Moore, "Credit Cycles," Journal of Political Economy, 1997, 105, 211-248.
- Kwon, Eunkyung, "Role of Financing Constraints on Firms' Investment: Evidence from the Retail Trade Sector," 1994. Unpublished paper, Dept. of Economics, New York University.

- Levin, Andrew and Chien-Fu Lin, "Unit Root Tests in Panel Data: Asymptotic and Finite Sample Properties," 1992. Unpublished paper, Dept. of Economics, University of California, San Diego.
- and , "Unit Root Tests in Panel Data: New Results," 1993.
 Unpublished paper, Dept. of Economics, University of California, San Diego.
- Lovell, Michael, "Manufacturers Inventories, Sales Expectations, and the Acceleration Principle," *Econometrica*, 1961, 39, 293–314.
- Lucas, Robert E., "Understanding Business Cycles," in Karl Brunner and Alan Meltzer, eds., Stabilization of the Domestic and International Economy, Carnegie-Rochester Series in Public Policy, 1977, pp. 7–29.
- Mian, S. and Cliff W. Smith, "Accounts Receivable Management Policy: Theory and Evidence," *Journal of Finance*, 1992, 47, 169–200.
- Mosser, Patricia C., "Trade Inventories and (S,s)," Quarterly Journal of Economics, 1991, 106, 1267–1286.
- Newey, Whitney K. and Ken D. West, "Hypothesis Testing With Efficient Method of Moments Estimation," *International Economic Review*, 1987, 28, 777-787.
- Nickell, Stephen, "Biases in Dynamic Models with Fixed Effects," Econometrica, 1981, 49, 1417–1426.
- , "Error Correction, Partial Adjustment and All That: An Expository Note," Oxford Bulletin of Economics and Statistics, 1985, 47, 119-129.
- Okun, Arthur M., Prices and Quantities: A Macroeconomic Analysis, Washington, D.C.: The Brookings Institution, 1981.
- Petersen, Mitchell A. and Raghuram G. Rajan, "The Benefits of Lending Relationships: Evidence from Small Business Data," *Journal of Finance*, 1994, 49, 3–37.
- and _____, "Trade Credit: Theories and Evidence," 1995. Unpublished paper, Graduate School of Business, University of Chicago.

- Schuh, Scott, "Evidence on the Link Between Firm-Level and Aggregate Inventory Behavior," 1996. Unpublished paper, Board of Governors of the Federal Reserve System.
- Smith, Janet K., "Trade Credit and Information Asymmetry," Journal of Finance, 1987, 42, 863–869.
- Tinsley, Peter A., "On Ramps, Turnpikes, and Distributed Lag Approximations of Optimal Intertemporal Adjustment," Western Economic Journal, 1970, pp. 397-411.
- ——, "Fitting Both Data and Theories: Polynomial Adjustment Costs and Error-Correction Decision Rules," 1993. Unpublished paper, Board of Governors of the Federal Reserve System.
- West, Kenneth D., "A Variance Bound Test of the Linear Quadratic Inventory Model," Journal of Political Economy, 1986, 94, 374-401.

Table 1
Percent of Assets and Receipts by Firm Size (1990)

Cumulative	Manufacturing		Retail Trade	
Asset Size	Assets	Receipts	Assets	Receipts
< \$1M	1.30	4.30	13.1	21.9
< \$5M	3.70	10.2	25.4	40.9
< \$10M	5.20	13.4	29.9	48.2
< \$25M	7.50	18.2	34.5	54.6
< \$50M	9.40	21.5	37.3	58.0
< \$100M	11.6	25.0	40.1	61.1
< \$250M	16.1	30.9	45.3	66.1

Source: Statistics of Income, 1990.

Table 2
Summary Statistics

TCDEP < 50P: Firms with the average ratio of trade payables to total short-term debt below their industry-specific median.

TCDEP ≥ 50P: Firms with the average ratio of trade payables to total short-term debt above (or equal to) their industry-specific median.

TCDEP ≥ 75P: Firms with the average ratio of trade payables to total short-term debt above (or equal to) their industry-specific 75th percentile.

Trimmed Means	TCDEP < 50P	TCDEP ≥ 50P	TCDEP ≥ 75P
Inventories	139.8	116.4	80.1
Net Sales	276.8	251.0	199.0
Total Assets	526.8	431.8	375.5
Inv/Sales	0.61	0.42	0.34
Cash Stocks/Assets	0.05	0.09	0.11
Trade Payables/S-T Debt	0.71	0.97	0.99
Bank Loans/S-T Debt	0.21	0.03	0.01
Other Debt/S-T Debt	0.06	0.00	0.00
Comm. Paper/S-T Debt	0.02	0.00	0.00
No. of Firms	390.0	392.0	197.0
Avg. Tenure	39.9	38.8	36.2
Observations	12,037	11,793	5,374

Notes: Trimmed means exclude observations below the 2.5 percentile and above the 99.75 percentile. Sample period: 77:Q1-91:Q3. All variables are in millions of real (1992) dollars.

 Table 3

 Baseline Error-Correction Specification

TCDEP < 50P: Firms with the average ratio of trade payables to total short-term debt below their industry-specific median.

TCDEP ≥ 50P: Firms with the average ratio of trade payables to total short-term debt above (or equal to) their industry-specific median.

TCDEP ≥ 75P: Firms with the average ratio of trade payables to total short-term debt above (or equal to) their industry-specific 75th percentile.

Parameter	Full Sample	TCDEP < 50P	TCDEP ≥ 50P	TCDEP ≥ 75P
$H_{it-1} - S_{it}$	-0.083	-0.118	-0.127	-0.147
	(0.003)	(0.007)	(0.008)	(0.003)
ΔH	-0.042	-0.013	-0.089	-0.453
	(0.009)	(0.027)	(0.062)	(0.092)
ΔS	0.181	0.152	0.146	0.347
	(0.008)	(0.031)	(0.033)	(0.108)
ΔΠ	1.051	0.748	0.725	-1.009
	(0.089)	(0.305)	(0.360)	(1.032)
		·	, ,	(====)
Π_{it-1}	0.180	-0.187	0.509	1.311
	(0.027)	(0.102)	(0.104)	(0.321)
Excl. Test ^a	0.000	0.000	`0.000	0.000
7.0			·	
J-Statistic ^b	651.15	336.48	331.16	149.90
d.f.	648.00	648.00	648.00	648.00
m1 ^c	0.370	0.793	-0.146	1.527
m2	0.848	1.704	0.400	1.973
	i		İ	
No. of Firms	782.00	390.00	392.00	197.00
Observations	18,356	9,307	9,049	3,995

Notes: Estimation period: 78:Q4-91:Q3. ΔX denotes the sum of four coefficients on the lagged differences of X. Asymptotic standard errors reported in parenthesis. All regressions include fixed time effects (not reported) and are estimated with GMM using $S_{it-2}, \ldots, S_{it-5}; H_{it-2}, \ldots, H_{it-5};$ and $\Pi_{it-2}, \ldots, \Pi_{it-5}$ as instruments.

^aP-value for the exclusion test on internal finance variables (see Newey and West (1987)).

^bTest of the over-identifying restrictions (see Hansen (1982)).

^cRobust test for the first-order (m1) and second-order (m2) residual serial correlation (see Arellano and Bond (1991)).

Table 4
General Error-Correction Specification

 $extbf{TCDEP} < 50P$: Firms with the average ratio of trade payables to total short-term debt below their industry-specific median.

TCDEP ≥ 50P: Firms with the average ratio of trade payables to total short-term debt above (or equal to) their industry-specific median.

TCDEP ≥ 75P: Firms with the average ratio of trade payables to total short-term debt above (or equal to) their industry-specific 75th percentile.

Parameter	Full Sample	TCDEP < 50P	TCDEP ≥ 50P	$TCDEP \ge 75P$
ΔS_{it+2}	0.026	0.009	0.088	0.059
	(0.007)	(0.006)	(0.005)	(0.023)
ΔS_{it+1}	0.301	0.264	0.398	0.448
	(0.010)	(0.007)	(0.007)	(0.026)
$H_{it-1} - S_{it}$	-0.125	-0.160	-0.221	-0.294
	(0.008)	(0.006)	(0.006)	(0.036)
ΔH	-0.412	-0.280	-0.248	-0.419
	(0.025)	(0.020)	(0.023)	(0.087)
ΔS	0.412	0.255	0.335	0.205
	(0.027)	(0.023)	(0.027)	(0.088)
ΔΠ	-0.553	0.783	-0.148	-1.940
	(0.221)	(0.204)	(0.233)	(0.930)
			(5.220)	(0.550)
Π_{it-1}	0.344	-0.135	0.555	1.500
	(0.058)	(0.056)	(0.052)	(0.295)
Excl. Test ^a	0.000	0.000	0.000	0.000
				0.000
J-Statistic ^b	486.75	335.58	333.27	146.70
d.f.	476.00	476.00	476.00	476.00
m1 ^c	3.322	1.909	2.885	2.726
m2	1.457	1.659	1.698	2.273
Ì			2.000	2.210
No. of Firms	782.00	390.00	392.00	197.00
Observations	16,792	8,527	8,265	3,601

Notes: Estimation period: 78:Q4-91:Q1. ΔX denotes the sum of four coefficients on the lagged differences of X. Asymptotic standard errors reported in parenthesis. All regressions include fixed time effects (not reported) and are estimated with GMM using $S_{it-3}, \ldots, S_{it-5}; H_{it-3}, \ldots, H_{it-5};$ and $\Pi_{it-3}, \ldots, \Pi_{it-5}$ as instruments.

^aP-value for the exclusion test on internal finance variables (see Newey and West (1987)).

^bTest of the over-identifying restrictions (see Hansen (1982)).

^cRobust test for the first-order (m1) and second-order (m2) residual serial correlation (see Arellano and Bond (1991)).

Table 5
General Error-Correction Specification

TCDEP < 50P: Firms with the average ratio of trade payables to total short-term debt below their industry-specific median.

TCDEP ≥ 50P: Firms with the average ratio of trade payables to total short-term debt above (or equal to) their industry-specific median.

TCDEP ≥ 75P: Firms with the average ratio of trade payables to total short-term debt above (or equal to) their industry-specific 75th percentile.

Parameter	Full Sample	TCDEP < 50P	TCDEP ≥ 50P	TCDEP ≥ 75P
ΔS_{it+2}	0.025	0.008	0.087	0.061
	(0.007)	(0.006)	(0.005)	(0.023)
ΔS_{it+1}	0.301	0.264	0.398	0.457
	(0.010)	(0.007)	(0.008)	(0.027)
$H_{it-1} - S_{it}$	-0.125	-0.160	-0.224	-0.306
	(0.008)	(0.006)	(0.006)	(0.037)
ΔH	-0.405	-0.276	-0.243	-0.407
	(0.025)	(0.021)	(0.024)	(0.092)
ΔS	0.411	0.258	0.336	0.176
	(0.027)	(0.023)	(0.026)	(0.088)
ΔΠ	-0.477	0.836	-0.140	-1.683
	(0.222)	(0.207)	(0.229)	(0.982)
			` ′	(******)
Π_{it-1}	0.309	-0.179	0.536	1.419
	(0.062)	(0.057)	(0.055)	(0.296)
$R_t imes \Pi_{it-1}$	0.153	0.134	0.141	0.576
	(0.049)	(0.044)	(0.055)	(0.189)
Excl. Test ^a	0.000	0.000	0.000	0.000
_				
J-Statistic ^b	486.14	335.39	333.01	142.39
d.f.	476.00	476.00	476.00	476.00
m1 ^c	3.296	1.909	2.912	2.952
m2	1.424	1.634	1.740	2.337
				•
No. of Firms	782.00	390.00	392.00	197.00
Observations	16,792	8,527	8,265	3,601

Notes: Estimation period: 78:Q4-91:Q1. ΔX denotes the sum of four coefficients on the lagged differences of X. Asymptotic standard errors reported in parenthesis. All regressions include fixed time effects (not reported) and are estimated with GMM using $R_t, S_{it-3}, \ldots, S_{it-5}; H_{it-3}, \ldots, H_{it-5}$; and $\Pi_{it-3}, \ldots, \Pi_{it-5}$ as instruments.

^aP-value for the exclusion test on internal finance variables (see Newey and West (1987)).

^bTest of the over-identifying restrictions (see Hansen (1982)).

^cRobust test for the first-order (m1) and second-order (m2) residual serial correlation (see Arellano and Bond (1991)).

Figure I
Share of Retail Inventories

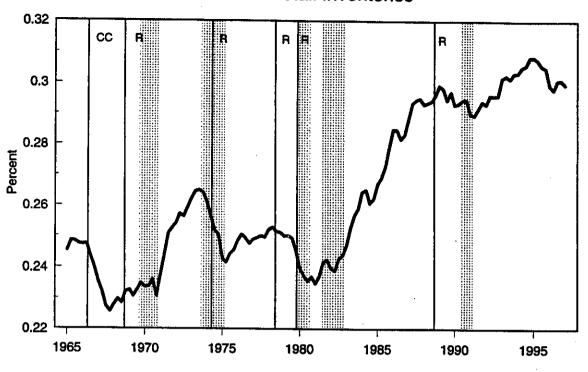
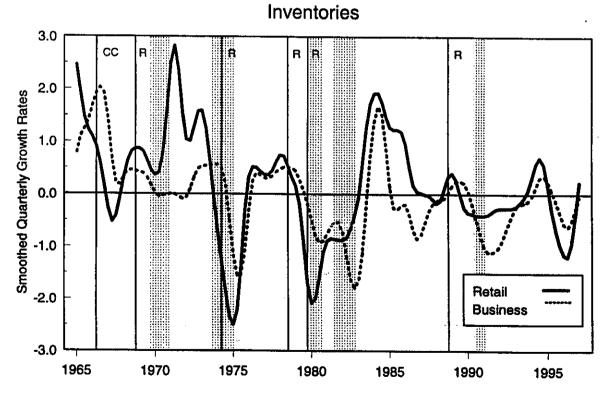


Figure II



Notes: The shaded regions represent N.B.E.R. recessions; R denotes a Romer date; and CC denotes the 1966: Q2 credit crunch.

Figure IIIa
Cumulative Growth Rate of Inventories

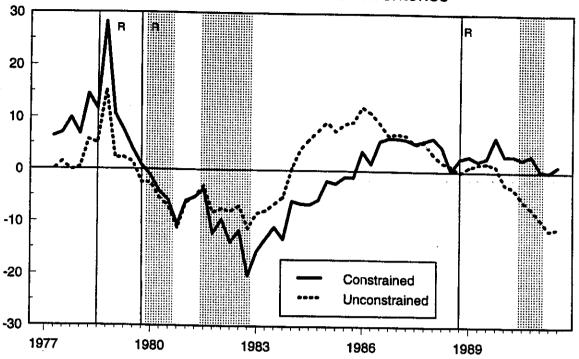
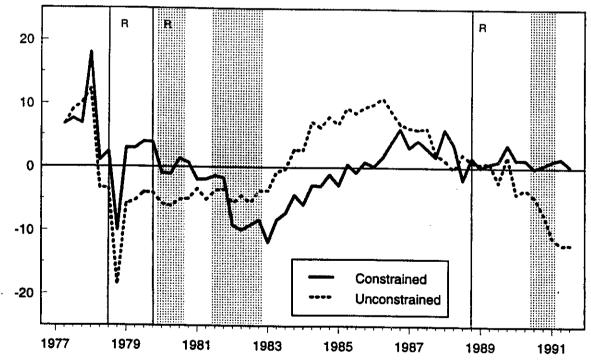


Figure IIIb
Cumulative Growth Rate of Sales



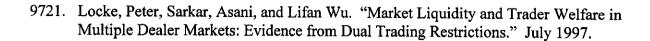
Notes: The shaded regions represent N.B.E.R. recessions; R denotes a Romer date.

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