The Impact of Macroeconomic Uncertainty on Cash Holdings for Non–Financial Firms

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Abstract

This paper investigates the effects of macroeconomic volatility on non–financial firms' cash holding behavior. Using an augmented cash buffer–stock model, we demonstrate that an increase in macroeconomic volatility will cause the cross–sectional distribution of firms' cash–to–asset ratios to narrow. We test this prediction on a panel of non–financial firms drawn from the annual COMPUSTAT database covering the period 1970–2000, and find that as macroeconomic uncertainty increases, firms behave more homogeneously. Our results are shown to be robust to the inclusion of the levels of several macroeconomic factors.

Keywords: Cash holdings, macroeconomic uncertainty, panel data, time series, ARCH, non–financial firms.

1 Introduction

Some recent quotations indicate that non–financial firms maintain very large cash holdings. For example, Apple Computer reported in October, 2002: "For the year, the Company reported net earnings of $65 million on revenues of $5.74 billion, compared to a net loss of $25 million on revenues of $5.36 billion in 2001... We were extremely pleased with our ability to achieve our revenue target for the fourth quarter while reducing channel inventory to a normal level... Continued strong asset management enabled us to maintain a solid balance sheet with over *$4.3 billion in cash...*"[1]

Kester (1986), studying a sample of 452 US firms in 1983, reported that their average ratio of cash plus marketable securities to total assets is 8.6%; later Kim et al. (1998) reported an average of 8.1% for a sample of 915 US industrial firms over 1975–1994. Harford (1999) indicated that the largest 25 percent of US nonfinancial corporations held an average of eight percent of their assets in cash reserves, citing that "cash represents 20 percent or more of the equity values of many well–known companies, such as IBM and Chrysler" (1999, p. 1971). In our sample of COMPUSTAT firms, the average cash–to–asset ratio for all non–financial firms over the last 31 years is 10.5% with a significant difference between large and small firms' ratios: 7.0% versus 13.5%, respectively.

Why do firms hold these sizable levels of liquid assets? Over the years, many researchers have asked similar questions and provided various explanations. One potential explanation is that cash provides low–cost, assured finance in a world with financial market imperfections and failures. Therefore, firms would want to hold cash far in excess of their transactions needs

[1] Citation (emphasis added): Fred Anderson, CFO, in Apple Computer Inc. press release, 16 October 2002, http://www.apple.com/pr/library/2002/oct/16earnings.html

to mitigate the effects of unfavorable changes in interest rates or restrictions on their access to credit. In essence, these high levels of liquid assets may be viewed as options purchased by the firms' managers that may be exercised in adverse times (via drawdowns) to ensure the long–term survival of the firm as a going concern.

In search of an answer to the question of firms' apparent "excess liquidity", research carried out by Opler, Pinkowitz, Stulz and Williamson (1999), Faulkender (2002) and Ozkan and Ozkan (2004) has focused on the role of firm–specific characteristics such as leverage, growth opportunities, cash flow, and cash flow uncertainty.[2] They found that small, non–rated firms and firms with strong investment opportunities and riskier cash flows hold more cash. One can interpret these findings to suggest that firms facing a high degree of asymmetric information are likely to hold more cash because of potential difficulties in their access to external financing.

In addition to firm–specific variables, macroeconomic aggregates could be an important determinant of firms' cash–holding behavior and one that has received little attention in previous research.[3] In this paper, we aim to contribute to the literature on corporate cash holdings by arguing that *volatility* in macroeconomic conditions would affect managers' determination of the appropriate level of liquid asset holdings. Hence, a firm facing higher uncertainty in its cash flows may find it optimal to augment its liquid assets, in the form of cash, in order to offset the adverse effects of negative cash

[2]Other related papers include Almeida, Campello and Weisbach, (2004) and Dittmar, Mahrt-Smith and Servaes (2003). Also see Mikkelson and Partch (2003) who investigate linkages between sizable cash holdings and firm performance.

[3]One exception is the work of Almeida et al. (2004), which examined firms' cash flow sensitivity of cash holdings over the business cycle. Additionally, views of a broad "credit channel" have considered the sensitivity of firms' net worth and creditworthiness to macroeconomic factors.

flow shocks.[4] We expect that changes in macroeconomic stability will trigger adjustments in firms' liquid asset holdings as managers react to changes in economic conditions. Naturally, this would in turn generate variations in the *cross–sectional distribution* of corporate cash holdings.

To explore the effects of macroeconomic uncertainty on firms' cash holding behavior, we construct a simple cash–buffer model augmented with a signal extraction framework. The model generates a testable hypothesis: one should observe a negative link between a measure of macroeconomic uncertainty and variation in the cross sectional distribution of firms' cash–to–asset ratios. Increasing macroeconomic uncertainty will hinder managers' ability to accurately forecast future cash flows. Given that all managers are faced with a similar problem, they will react homogeneously, causing the dispersion of the cross–sectional cash–to–asset ratio to fall. Conversely, in times of greater macroeconomic stability, managers will be able to produce more accurate forecasts of cash flows, allowing them to have more latitude to behave idiosyncratically, leading to a broadening of the cross–sectional dispersion of firms' cash–to–asset ratios.

Our modeling and empirical strategy differ from the prevalent approach that links the level (or the changes) of firms' cash holdings to various firm–specific characteristics in order to explain the cash holding behavior for the representative firm. Our analytical model does not yield a signable prediction of the effect of macroeconomic uncertainty on the *level* of a firm's cash holdings. However, it allows one to understand the cash holding behavior of the entire *group* of firms under scrutiny rather than that of the representative firm. Although they differ, these two methodologies are not contradictory; rather, they are complementary analyses. Our strategy also differs from that

[4]We use the terms macroeconomic volatility and macroeconomic uncertainty interchangeably in this paper.

of much of the literature by allowing us to study the much–debated (but never properly tested) hypothesis that macroeconomic uncertainty affects firms' cash holding behavior. To ascertain the impact of macroeconomic uncertainty on the cross–sectional distribution of firms' cash–to–asset ratios, we utilize a panel of non–financial firms obtained from the COMPUSTAT database over the 1970–2000 period. Our data set contains over 125,000 firm–years, with an average of 4,125 firms per annum.[5]

We can summarize our results as follows. The data yield a clear negative relationship between the variance of the cross–sectional distribution of non–financial firms' cash–to–asset ratios and a proxy for macroeconomic uncertainty: the conditional variance of real gross domestic product. In our regression analysis, we incorporate several additional variables to gauge the robustness of our findings and guard against potential misspecification of the model. Our analysis provides evidence that macroeconomic uncertainty is a determinant of corporate cash holding behavior, and that this relationship is robust to inclusion of these variables.

The rest of the paper is constructed as follows. Section 2 presents a simple model of the influence of macroeconomic uncertainty on the optimal cash holdings of non–financial firms. Section 3 describes the data and discusses our results. Finally, Section 4 concludes and gives suggestions for further research.

[5] Considering the fact that the COMPUSTAT database covers the strongest and the largest firms in the US economy, generalizing our observations as typical of corporate behavior might be considered reasonable.

2 Cash holdings under uncertainty

It is well known that some non–financial corporations hold significant amounts of cash equaling a considerable fraction of their annual turnover.[6] Recent research (for instance, Ozkan and Ozkan (2004) and the references therein) has emphasized the importance of firm–specific characteristics as a determinant of firms' cash–holding behavior. However, the macroeconomic environment within which firms operate could be an equally important determinant. For instance, in March, 2001, *Business Week* reported: "So with the economy stalling and fears of recession rising, executives are becoming more concerned about protecting the cash they've got. 'People are more conservative than they were a year ago,' says Charles G. Ward III, co-head of investment banking at Credit Suisse First Boston. 'CEOs and CFOs are making sure they have bank lines and cash, and they want to make sure capital expenditures don't outstrip their cash-raising capability.' Adds Richard H. Brown, CEO of technology–services giant Electronic Data Systems Corp.: 'Cash is king now.' "[7] This quotation suggests that managers, finding it difficult to gauge their firm's future cash flows in a context of increasing macroeconomic uncertainty, may decide to augment their firms' cash holdings as a precaution. Conversely, macroeconomic stability provides managers with the ability to more accurately forecast their firms' future cash flows and will give them the latitude to behave more idiosyncratically.

One recent study evaluates the effects of macroeconomic conditions on cash holdings. Almeida et al. (2004) investigate how macroeconomic shocks

[6] One may recall a well publicized dispute in 1996 between Robert J. Eason, the Chairman of Chrysler Corporation, and the investor Kirk Kerkorian over the latter's proposal for the distribution of cash and marketable securities in excess of $7.5 billion to shareholders in the form of share repurchases and dividends.

[7] Citation: *Business Week*, 12 March 2001. "In Today's Corporate America, Cash Is King." http://www.businessweek.com/magazine/content/01_11/b3723021.htm.

affect firms' cash flow sensitivity of cash holdings. They find that financially constrained firms' cash flow sensitivity increases during recessions, while financially unconstrained firms' cash flow sensitivity is unaffected by the business cycle. But to our knowledge, there is no study which explicitly considers the influence of macroeconomic *uncertainty* on firms' demand for liquidity.[8]

In this paper, we argue that a firm facing higher uncertainty in its cash flows may find it optimal to augment its cash holdings for precautionary reasons.[9,10] Given that all managers are faced with a similar problem, adjustments in liquid assets in response to variations in the macroeconomic environment will in turn generate predictable variations in the cross–sectional distribution of corporate cash holdings. To provide a basis for our hypothesis and our empirical work, we present a basic cash buffer–stock model augmented with a signal extraction framework. For tractability, our model only contains the basic building blocks required to link the dispersion of firms' cash–to–total assets ratio to macroeconomic variability. In our empirical work, we incorporate several additional variables to gauge the robustness of our findings and guard against potential misspecification of the model.

2.1 The model

A straightforward cash buffer–stock model augmented with a signal extraction framework, where a non–financial firm's manager adjusts her cash hold-

[8]In a related context, Beaudry, Caglayan and Schiantarelli (2001) investigated the effects of monetary uncertainty on firms' fixed investment behavior, while Baum, Caglayan and Ozkan (2004) considered the effects of macroeconomic uncertainty on commercial banks' lending activity.

[9]The precautionary motive requires that a firm will accumulate cash to meet unanticipated contingencies that may arise.

[10]Some authors have also suggested that "excess liquidity" may reflect a speculative motive, allowing firms to take advantage of profitable future investment opportunities. If firms face higher costs of external finance, positive "excess liquidity" may also reflect this motive (Kim, Mauer and Sherman (1998, p. 336); Harford (1999, p. 1969)).

ings to minimize the expected costs of cash management, implies that the manager will alter her cash holdings in anticipation of variations in macroeconomic shocks.[11] Initially, we assume that the firm's cash flow is uniformly distributed, while the upper and lower bound of the distribution are known to the manager and are identical across all firms. We show that the optimal amount of cash holdings will crucially depend on the bounds of the distribution, as well as the opportunity cost of holding cash and the cost of borrowing. Next, we allow these bounds to be subjected to a random shock.[12] Augmenting the basic model with a signal extraction framework, we then show that the manager's ability to accurately predict future cash flow is important.[13] Using this aspect of the model, we link the variance of the cross–sectional distribution of firms' cash–to–asset ratios to macroeconomic uncertainty leading us to an unambiguous negative link between the two variables: a hypothesis that may be empirically tested.

2.1.1 The basic cash buffer–stock model

Assume that in each period, firm i receives an uncertain amount of net cash flow between time t and $t+1$, drawn from a uniform distribution with an upper bound H, and a lower bound, $L = -H$. The manager of the firm, seeking to continue its operations, would want to hold an optimal amount of cash buffer for precautionary reasons, which involves an opportunity cost of r_1 percent. If there is a negative cash flow shock that exceeds current cash holdings, the firm has to borrow from an external source to meet its

[11] Models developed by Whalen (1966), Schnure (1998), and Frenkel and Jovanovic (1980) motivate our analytical approach.

[12] This assumption provides that cash holdings across firms are no longer identical.

[13] Our approach is a variant of the island model used by Lucas (1973) highlighting the manager's cash holding decision as a signal extraction problem, seeking to separate local from global shocks.

obligations at a higher interest rate of r_2 percent. We assume that $r_2 > r_1$, and possibly $r_2 >> r_1$ due to financial frictions. Here, a firm holding a cash buffer of C_i faces the following three possible outcomes.

First, the net cash flow of the firm could be positive, so that the firm merely faces the opportunity cost of holding C_i[14]

$$COST_1 = C_i r_1, \tag{1}$$

with probability $P_1 = \frac{H}{2H} = \frac{1}{2}$.

Second, the firm could face a negative cash shock (CF_i) of a magnitude up to C_i. The cost now includes the opportunity cost of holding the cash buffer as well as the cost of replenishing it:

$$COST_2 = C_i r_1 - E(CF_i| - C_i < CF_i < 0) = C_i r_1 - \frac{-C_i}{2}, \tag{2}$$

which occurs with a probability of $P_2 = \frac{C_i}{2H}$.

Finally, as the third case, the firm may not have enough cash to cover the negative shock and has to borrow from external sources at a higher interest rate to remain solvent:[15]

$$\begin{aligned} COST_3 &= C_i r_1 + C_i - (E(CF_i| - H < CF_i < -C_i) + C_i)(1 + r_2) = \\ &= C_i r_1 + C_i + \left(\frac{H - C_i}{2}\right)(1 + r_2). \end{aligned} \tag{3}$$

In this case, the firm bears the full opportunity cost $C_i r_1$ and must fully replenish its cash buffer to the optimal level C_i. Furthermore, the firm borrows an additional amount from an external source at the gross interest rate $(1 + r_2)$, with a probability of $P_3 = \frac{H - C_i}{2H}$.

[14] Any unused cash is assumed to be distributed back to the shareholders in the form of dividends or share repurchases.

[15] To simplify the argument, we do not consider the likelihood of liquidation and assume that the firm can always borrow from an external source. Since in the empirical implementation we work with large, publicly traded firms, this should be generally reasonable.

Therefore, given all possible costs associated with holding cash as expressed in equations 1–3, the manager of the firm would want to minimize its total expected cost, $ECOST = COST_1P_1 + COST_2P_2 + COST_3P_3$, which takes the following form after some manipulation:

$$\begin{aligned} ECOST \;\; = \;\; & \frac{1}{2}C_ir_1 + \left(C_ir_1 - \frac{-C_i}{2}\right)\frac{C_i}{2H} + \\ & \left(C_ir_1 + C_i + \left(\frac{H - C_i}{2}\right)(1 + r_2)\right)\frac{H - C_i}{2H}. \end{aligned} \tag{4}$$

The first order conditions imply that the optimal cash buffer will be[16]

$$C_i = \frac{H}{r_2}(r_2 - 2r_1). \tag{5}$$

Observe that the optimal cash buffer for each firm depends positively on the fixed bound, H, of the distribution from which cash flow is drawn and the interest rate for external funds, r_2 and negatively on the opportunity cost of holding funds captured by r_1. Note that the firm is guaranteed to have positive cash holdings if $r_2 > 2r_1$. Also note that when the managers have full information on the bounds of the cash flow distribution, each firm holds an identical amount of cash. However, in real life, this is hardly the case.[17]

2.1.2 The augmented cash buffer–stock model

Let us now assume that each firm experiences a random shock to their cash flow of the size $\epsilon_{i,t}$. In this context, $\epsilon_{i,t}$ represents the level of uncertainty of net disbursements that is faced by each firm, implying that the bounds of the cash flow distribution will now be random. We assume that $\epsilon_{i,t}$ is distributed

[16]The second order condition, $\frac{\partial^2 ECOST}{\partial C_i^2} = \frac{r_2}{2H} > 0$, confirms that we have a minimum.

[17]One can argue that in reality interest rates faced by each firm will differ across firms leading to differences across firms with respect to their cash buffer. In the next section we will provide another rationale for this heterogeneity without resorting to (generally unobservable) firm–specific costs of borrowing.

normally with mean 0 and variance $\sigma^2_{\epsilon,t}$ across all firms.[18] We should point out that variations in $\sigma^2_{\epsilon,t}$ are observable, as the overall risk of production and marketing in the industry may be gauged, but a firm manager does not know what her draw from this distribution will be at a point in time. We also assume that $\epsilon_{i,t}$ is orthogonal to $\epsilon_{j,t}$: each firm has a specific output line with different risk structures, and the random components of cash flow across firms are not correlated. Hence, the upper bound of the cash flow for each firm i will be equal to $H_{i,t} = H + \epsilon_{i,t}$.

In a world with no financial frictions, the manager of the firm would be interested in minimizing the cost of expected cash holdings as finding new funds when required would not constitute any problem. However, due to financial market failures induced by uncertainty, such as moral hazard and adverse selection problems, firms invest in private information to achieve an optimal cash buffer.[19] We assume that the manager of each firm observes a noisy signal in the form of $S_{i,t} = \epsilon_{i,t} + \nu_t$ on $\epsilon_{i,t}$, where ν_t denotes noise, which is normally distributed as $\nu_t \sim N(0, \sigma^2_{\nu,t})$ and independent of $\epsilon_{i,t}$. Note that although each firm manager observes a different signal, the noise component of the observed signal in all cases is identical.[20] The noise in the signal is assumed to reflect macroeconomic uncertainty, in the sense that a larger variance of ν_t makes the manager unable to accurately predict the bounds of the distribution, as would higher uncertainty in the economy. Contrarily, greater stability of macroeconomic conditions would allow one to make accurate predictions of the bounds of the distribution.

[18]This approach captures the idea that probability of observing small shocks is higher than that of larger ones.

[19]During times of high uncertainty, firms generally face a rising cost of external finance due to capital market imperfections and depend more heavily on internally generated funds.

[20]It is possible to assume that each firm observes a private signal with a different noise level. This assumption would lead to a more complicated analysis with little added insight.

By employing the above framework, we assume that the manager takes all available information into consideration before making any decision to minimize the cost of holding a cash buffer–stock. Although the manager can still make suboptimal decisions (as the information content of the signal tends to change over time), the presence of the additional information contained in $S_{i,t}$ makes it possible to improve upon the naïve prediction of a zero value for $\epsilon_{i,t}$. After conditioning upon the signal $S_{i,t}$, the manager forms an optimal forecast of the range of net disbursements as $E_t(\epsilon_{i,t}|S_{i,t}) = \lambda_t S_{i,t}$, where $\lambda_t = \frac{\sigma^2_{\epsilon,t}}{\sigma^2_{\epsilon,t}+\sigma^2_{\nu,t}}$. We assume that the firm manager cannot observe $\sigma^2_{\nu,t}$, but rather that she may form an optimal forecast of that quantity. For instance, although we have not specified a law of motion for $\sigma^2_{\nu,t}$, it is plausible to model its variation over time as a low–order GARCH process. Therefore, substituting for $E_t(H_{i,t}|S_{i,t}) = H + \lambda_t S_{i,t}$, we can modify equation (5) as:

$$E(C_{i,t}|S_{i,t}) = (H + \lambda_t S_{i,t})(\frac{r_2 - 2r_1}{r_2}) = kH + k\lambda_t S_{i,t}, \tag{6}$$

where $k = (\frac{r_2-2r_1}{r_2}) > 0$, so that optimal cash holdings $C_{i,t}$ are positive as long as $r_2 > 2r_1$. The difference of this new optimal cash level and that given in equation (5) is in the addition of the second term: $k\lambda_t S_{i,t}$. As macroeconomic uncertainty increases, λ_t will diminish so that there will be no difference between the two equations. However, if the economic environment is stable, then the manager will be better off using equation (6).

As intuition would suggest, although any change in macroeconomic uncertainty (as captured through the variance of the noise in the signal σ^2_ν) will have an impact on the optimal cash buffer, we cannot sign the overall effect on the firm's level of cash holdings as it contains the idiosyncratic signal $S_{i,t}$. Nevertheless, using equation (6), we may examine the cross–sectional distribution of cash holdings for each period,

$$Var(C_{i,t}|S_{i,t}) = \frac{k^2\sigma^6_{\epsilon,t}}{\sigma^4_{\epsilon,t} + \sigma^4_{\nu,t}}, \tag{7}$$

to investigate the effects of the time variation in the variance of macroeconomic uncertainty σ^2_ν for it is this variance that reflects firm managers' ability to forecast the optimal cash buffer.[21] As shown in equation (8) below, when the macroeconomic environment becomes less predictable or "noisier" (i.e., when $\sigma^2_{\nu,t}$ becomes large), the cross–sectional distribution of the optimal cash buffer narrows:

$$\frac{\partial Var(C_{i,t}|S_{i,t})}{\partial \sigma^2_{\nu,t}} = -2\frac{k^2\sigma^6_{\epsilon,t}\sigma^2_{\nu,t}}{(\sigma^4_{\epsilon,t} + \sigma^4_{\nu,t})^2} < 0 \tag{8}$$

The negative relationship between macroeconomic uncertainty and the cross–sectional variation of firms' cash–to–asset ratios can be explained as follows. During tranquil periods (when $\sigma^2_{\nu,t}$ is low), each firm responds more accurately to shocks hitting the cash flows $(H + \epsilon_{i,t})$ as managers can be more clearly identify the necessary amount of cash buffer in this environment in comparison to more turbulent times. Hence, as firms behave more idiosyncratically, the cross–sectional distribution of cash buffer should widen. Contrarily, during times of uncertainty (when $\sigma^2_{\nu,t}$ is high), the actual shocks to the cash flow of each firm will be harder to predict. Under these conditions, as firm managers would have greater difficulty identifying the true cash flows, they will behave more homogeneously leading to a narrowing of the cross–sectional distribution of cash buffer.

To provide support for our hypothesis as displayed in equation (8), we investigate the link between macroeconomic uncertainty and changes in the cross–sectional distribution of the cash–to–asset ratio for U.S. non–financial

[21] Recall that ν_t does not vary across firms. Hence, (7) follows.

firms considering the following reduced form relationship

$$Disp_t(C_{it}/TA_{it}) = \beta_0 + \beta_1 \tau_t^2 + \epsilon_t, \tag{9}$$

where $Disp_t(C_{it}/TA_{it})$ is a measure of the cross–sectional dispersion of firms' cash–to–asset ratio at time t, and τ_t^2 stands for the measure of macroeconomic uncertainty at time t. We claim that the heterogeneity exhibited by non–financial firms' behavior will be negatively related to macroeconomic uncertainty. Hence, we would expect to find a negative sign on β_1 if greater macroeconomic uncertainty was associated with a smaller dispersion of firms' cash–to–asset ratio.

In the model we derive heterogeneous behavior across non-financial firms from purely stochastic elements. However, in reality we might expect that different classes of firms respond differently to shocks. In our empirical analysis, we consider subgroups of firms with various defining characteristics (size, growth rate, financial constraints, factor intensity) to verify this expectation in a panel data context.

2.2 Identifying macroeconomic uncertainty

In order to test our hypothesis of a negative relationship between the cross–sectional variance of firms' cash–to–asset ratio and macroeconomic uncertainty, we must provide a proxy that captures the state of the macroeconomy. To provide such a proxy we compute the conditional variance of a monthly measure of real gross domestic product as a measure of overall macroeconomic activity.[22] The conditional variance of real GDP is well suited for

[22]Alternatively, some researchers suggest using a moving standard deviation of the macroeconomic series while others propose using survey–based measures based on the dispersion of forecasts. The former approach suffers from substantial serial correlation problems in the constructed series while the latter potentially contains sizable measurement errors.

our purposes to measure the stability of the macroeconomy.[23] Therefore, we rewrite equation (9) in the following form:

$$Disp_t(C_{it}/TA_{it}) = \beta_0 + \beta_1 \hat{h}_t + \epsilon_t, \tag{10}$$

where $\hat{h}_t$ denotes the measure of macroeconomic uncertainty, captured by the conditional variance of real GDP evaluated at time t. The advantage of this approach is that we can relate the behavior of cash holdings directly to a measurable variable for economic uncertainty.

Our proxy for macroeconomic uncertainty is derived from quarterly real GDP (International Financial Statistics series $99BRZF$). We generated the monthly GDP series via the proportional Denton procedure *dentonmq* using the index of industrial production (which is available at a monthly frequency) as an interpolating variable (see Baum, 2001). We fit a generalized ARCH (GARCH(2,2)) model to the deviations of the imputed monthly GDP series from an exponential trend, where the mean equation is an AR(1) model with ARMA(1,1) errors.[24] The conditional variance derived from this GARCH model, averaged to annual frequency, is then used as our measure of macroeconomic uncertainty ($\hat{h}_t$).[25]

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[23] In our analysis, we also use the conditional variance of industrial production as a proxy for uncertainty. Since the real GDP measure captures overall economic activity, we present only those results.

[24] Details of the estimated GARCH model are provided in Appendix B.

[25] Since $\hat{h}_t$ is a generated regressor, potentially measured with error, we employ a generalized method of moments (GMM) instrumental variables estimation technique. Tests of the orthogonality of the generated regressor to the error (the "difference in Hansen J" or "C" statistic: see Baum, Schaffer and Stillman (2003, pp. 20–24)) reject their null hypothesis in almost every case. In contrast, the overidentifying restrictions are generally accepted following the GMM–IV estimation.

3 Empirical findings

3.1 The data

The COMPUSTAT Industrial Annual database of U.S. non–financial firms is used for testing our hypothesis. It covers on average 4,125 firms' annual characteristics from 1970 to 2000. The firms are classified by four-digit Standard Industrial Classification (SIC) code. We consider all firms outside of one–digit codes 6 (finance, insurance and real estate) and 9 (government enterprises), and two–digit code 49 (utilities). We utilize COMPUSTAT data items Cash (*data1*) and Total Assets (*data6*) to construct the Cash–to–Asset ratio.[26] In order to evaluate the severity of firms' financial constraints, we compute the dividend payout ratio as $\frac{data21}{data13 - data15 - data16}$, where those data items are defined in the Appendix. Our analysis is carried out in a panel data context, where the unit of observation is taken to be the one–digit SIC category, observed annually. Thus, the dispersion in the cash–to–asset ratio is computed from the firms within each one–digit SIC category each year, generating a maximum of 196 industry–year observations.

We apply a number of sample selection criteria on our original sample of 173,592 firm–years. First, we marked non–positive values of cash and total assets as missing. Second, we considered that values of the cash–to–asset ratio beyond three standard deviations from the mean were implausible; this only affected 5,352 firm-years, placing an effective upper bound on the cash–to–asset ratio of 0.72. Third, our model should be applied to firms who have not undergone substantial changes in their composition during the sample period (e.g., participation in a merger, acquisition or substantial divestment should be disqualifying). Since we do not directly observe these phenomena,

[26]Empirical results obtained using an alternative measure, the Cash–to–Non–Cash–Asset ratio, are qualitatively similar and available upon request.

we calculate the growth rate of each firm's real total assets, and trim the annual distribution of this growth rate by the 10th and 90th percentiles to remove firms exhibiting substantial changes in their scale. Fourth, we wish to exclude firms in clear financial distress or those facing substantial liquidity constraints. We consider two consecutive years of negative cash flows as an indicator of these conditions. Where these appear, we remove them as well as the prior and subsequent cash flows from the sample. These screens collectively reduced the sample to 127,929 firm–years.[27] Descriptive statistics for the annual means of cash–to–asset ratios are presented in Table 1. From the means of the sample we see that firms hold over 10 percent of their total assets in cash.

In our analysis of subsamples of firms, we focus on the applicability of the general model to a group of like firms rather than testing for differences between groups of firms, which would necessitate the imposition of constraints across those groups. Furthermore, our groupings are not mutually exhaustive, but designed to identify firms which are strongly classified as, e.g., large or high–growth firms. Thus, a strategy based on category indicators would not be appropriate, since many firms will not fall in the group defined by either extreme.

In our analysis, we first investigate the behavior of large and small firms. A firm is considered to be LARGE if its total assets are above the 90th percentile by year, and SMALL if its total assets are below the 25th percentile for that year.[28] There are significant differences in behavior between large

[27]Empirical results drawn from the full sample yielded qualitatively similar findings; we prefer to use the screened data to reduce the potential impact of outliers upon the parameter estimates. We also carried out the analysis using a longer data set covering the period between 1950–2000. Obtained results were qualitatively similar to those we report in this paper and are available from the authors.

[28]These asymmetric bounds have been chosen, given the highly skewed distribution of firms' assets, in order to roughly equalize the number of firm–years in each category.

and small firms, with large firms' average cash–to–asset ratio 6.5 percentage points lower than that of small firms. This can be explained by the fact that large firms have easier access to external financing, and they may face economies of scale in cash management.[29]

We categorize firms into high–growth and low–growth categories, defining firms as above the 75th percentile and below the 25th percentile of the annual distribution of the growth in real total assets, respectively. We find that high–growth firms hold, on average, 3.6 percentage points more cash relative to total assets than do low–growth firms.

We also analysed the distinction between firms that might be considered financially constrained and those that might be considered financially unconstrained. Following the literature, we used the dividend payout ratio as a measure of financial stringency, defining those firms which lay below the 25th percentile of the annual distribution—or those firms paying zero dividends—to be financially constrained.[30] We defined those firms above the 75th percentile of the annual distribution of the dividend payout ratio to be financially unconstrained. We find that the average cash–to–asset ratios of financially constrained and unconstrained firms differ by 1.3 percentage points, with the latter firms holding more cash.

We classify our manufacturing firms' ($sic2x$ and $sic3x$) factor utilization

[29]Some researchers, for example Almeida et al. (2004), classify large firms as financially unconstrained, following Gilchrist and Himmelberg (1995). However, our categorization does not necessarily imply that firms in the large category are free from financial constraints. For our dataset, using the dividend payout ratio as the criterion, only 9,322 of 127,302 firm–years appear as both large and unconstrained (see below).

[30]It is possible to use alternative criteria to measure financial constraints along the lines of Almeida et al. (2004). Due to space constraints we specifically concentrate on the dividend payout ratio. As those authors note, the distinction that financially constrained firms have significantly lower payout ratios follows from Fazzari et al. (1988), among others. However, there is a notable trend toward lower dividend payout ratios during the period of analysis, so that even the median firm in our sample had a zero payout ratio after 1985.

as capital intensive, labor intensive or neutral. Using the NBER and U.S. Census Bureau's Center for Economic Studies (CES) database[31] we classify a four–digit SIC industry CAPITAL intensive if it has an average capital–to–labor ratio above the 75th percentile and LABOR intensive if its average capital–to–labor ratio is below the 25th percentile. Industries within the interquartile range are considered NEUTRAL, and not further considered here. The LABOR and CAPITAL categories of firms hold similar amounts of cash relative to total assets, whether measured by mean or median with little variation between each group.

3.2 The link between cash holdings and uncertainty

Tables 2–10 present our regression results obtained for equation (10) for all firms and four category splits (large/small, low and high growth firms, financially constrained/unconstrained firms, and capital intensive/labor intensive firms, respectively) in a one–digit SIC panel data context over the period between 1970–2000. In those tables, we present GMM (instrumental variables–generalized method of moments) estimation results,[32] where the macroeconomic uncertainty proxy *Lwcvgdp* is a weighted average of lagged effects.[33,34] Column (2) of each table presents results of regressions adding the detrended index of leading indicators (computed from DRI–McGraw Hill

[31]NBER-CES Manufacturing Industry Database, http://www.nber.org/nberces/, June 2000.

[32]The rationale for this approach is discussed above in section 2.2. Instruments employed include the conditional variances of inflation, industrial production, short–term interest rates and money growth as well as a linear time trend.

[33]We imposed an arithmetic lag on the values of the proxy variable for periods $t-1$, $t-2$ and $t-3$, with weights 0.48, 0.34, 0.18 respectively, to capture the combined effect of contemporaneous and lagged uncertainty on cash holding behavior. Analysis based on contemporaneous and once–lagged uncertainty yielded similar results.

[34]Use of similar measures based on the conditional variance of industrial production as a regressor yielded qualitatively similar results. These are available from the authors upon request.

Basic Economics series *DLEAD*) as a control variable to check for stability of our results while incorporating level effects from the macroeconomic environment in the basic relationship. We consider the potential impact of interest rates on cash–holding behavior in columns (3) and (4), which include the three–month LIBOR rate (*LIBOR3mo*) and the three–month Treasury bill rate (*TB3mo*) as proxies for the private cost of funds. Column (5) presents results with *LIBOR3mo*, the more successful interest rate variable, and the inflation rate added to the basic specification. The last two rows of each table report $\hat{\eta}$, the estimated elasticities of the dispersion of the cash/asset ratio with respect to *Lwcvgdp*, and their estimated standard errors, labelled "*s.e.*". All models contain dummies for six of the seven included one–digit SIC categories (*sicIx*) to allow for differential baseline effects of macroeconomic volatility across industry groups.[35]

3.2.1 Results for all firms

Table 2 presents the relationship between the cross–sectional distribution of non–financial firms' cash–to–asset ratio and a proxy for macroeconomic uncertainty for the full sample. In all cases the coefficient on the proxy for macroeconomic uncertainty is significantly negative at the 1% level. The sign of the coefficient and its significance is robust to inclusion of additional regressors which one may consider to have an impact on managers' decision making process. To provide a better insight, we compute the elasticities with respect to the macroeconomic uncertainty measures for each model. We find that for each specification the elasticity has a significant magnitude: a 100% increase in uncertainty will lead to a significant decline in the dispersion of

[35]Recall that we investigate the behavior of the cross–sectional dispersion of the cash–to–asset ratio in an industry–year panel context. Thus, our methodology does not allow for firm–specific characteristics in the estimated equation.

the cash–to–asset ratio, in a range between 18% and 57%. These results bear out that firms will behave much more homogeneously, in terms of their demand for liquid assets, in times of greater uncertainty.

3.2.2 Results for subsamples of firms

Having established the negative impact of uncertainty on the cross–sectional dispersion of the cash–to–asset ratio for the full sample, we next investigate if the predictions of the model hold for different firm classifications. We start our investigation by comparing the effect of uncertainty between large and small firms, as presented in Tables 3 and 4, respectively. The common finding is that uncertainty will reduce the dispersion of cash–to–asset ratios for both small and large firms, although uncertainty appears to have a more substantial effect on larger firms. The coefficient for macroeconomic uncertainty is negative and significant at the 1% level for large firms and the corresponding elasticity estimate is similar across the first four specifications. The elasticities for large firms have substantially higher values than those for all firms: about 50% higher than the latter point estimates. In contrast, the elasticities for small firms, in comparison to large firms, exhibit considerably lower levels of sensitivity to macroeconomic uncertainty: close to one–third of the corresponding estimates for large firms. Specifically, a 100% increase in uncertainty would lead to about a 70% reduction in the dispersion of the cash–to–asset ratio for large firms, while the effect for the small firms is in the vicinity of 25%. This difference may reflect the fact that small firms hold significantly larger amounts of cash than their larger counterparts, and are thus able to make proportionally smaller adjustments to their cash holdings when faced with shocks to their cash flow.[36] One may interpret these results

[36]In a relevant context, Kim et al. (1998, pp. 349–353) find a negative relation between a measure of liquidity (roughly our cash–to–asset ratio) and firm size as measured by the

as suggesting that small firms find more room to maneuver during turbulent periods in comparison to larger firms.

Low–growth firms (reported in Table 5) are likely to be more mature firms, perhaps those in declining industries. They exhibit significant negative effects, with estimated elasticities of a similar magnitude to those for all firms. In contrast, the impact of macroeconomic uncertainty on high–growth firms (as reported in Table 6) is uniformly significant and larger than that of low growth firms (and that for all firms as well). The effect of a doubling of uncertainty on the cross–sectional dispersion of the cash–to–asset ratio will be a reduction of approximately 35% and 55% for low– and high–growth firms, respectively. These findings suggest that high–growth firms—likely to be younger firms with substantial uncertainty about their near–term prospects, and facing a high degree of asymmetric information—are more sensitive to macroeconomic factors. Furthermore, one would expect that their access to external finance may be limited, requiring them to behave more cautiously, particularly in times of higher macroeconomic uncertainty. These results are broadly in line with the previous literature: e.g., Harford (1999), who finds a positive relation between industry–level market–to–book (MB) ratios and firms' cash–to–asset ratios. He states that MB ratios are proxies for information asymmetry, with high values observed in firms which derive much of their market value from firm growth opportunities and intangibles (p. 1973).

In Tables 7 and 8, we investigate the effects of uncertainty on financially constrained and unconstrained firms. For the financially constrained firms, the effects of macroeconomic uncertainty are substantial, with significant and sizable estimated elasticities, whereas for the unconstrained firms

market value of assets.

macroeconomic uncertainty does not appear to have as large an effect. A 100% increase in uncertainty leads to a reduction in the cross–sectional cash–to–asset ratio dispersion for the financially constrained firms ranging from 15% to 60%, whereas the equivalent point estimates for the unconstrained firms lie between 8% and 20%. This result is also quite intuitive. As uncertainty in the macroeconomic environment increases, financially constrained firms would want to augment their cash buffers substantially to weather the storm, while the unconstrained firms can be expected to have more latitude to behave idiosyncratically (including altering their dividend policy). This result is broadly consistent with those of Almeida et al. (2004). They find that financially constrained firms' cash flow sensitivity of cash holdings increases during recessions, while unconstrained firms' sensitivity is unaffected by macroeconomic innovations.

Finally, we report how capital–intensive *versus* labor–intensive firms' cash–to–asset ratio dispersion responds to macroeconomic uncertainty in Tables 9 and 10, respectively.[37] Similar to the previous set of results, we obtain significant and negative effects for both firm classifications. For each specification reported in Table 9, the computed elasticities for capital–intensive firms are substantially larger than those of labor–intensive firms. While a 100% increase in uncertainty leads to an average 65% reduction in the dispersion of the cash–to–asset ratio for capital–intensive firms, it only causes a 50% decline in dispersion for labor–intensive firms. This finding may indicate that capital–intensive firms may not be as flexible as labor–intensive firms due to costs of adjustment of their capital stock. Contrarily, it may be easier for labor–intensive firms to adjust their operating costs in response to a cash flow shock.

[37] Recall that the data employed for this classification utilize manufacturing firms (*sic2x* and *sic3x*) only, for a total of 56 industry–year observations.

3.2.3 Summary findings

In summary, these results support for the model's predictions that there is a clear negative relationship between the variance of the cross–sectional distribution of non–financial firms' cash–to–asset ratios and macroeconomic uncertainty. We find that the effects of macroeconomic uncertainty on corporate cash holdings are more pronounced for some categories of firms than for others. Large firms with substantial exposure to macro demand conditions exhibit greater sensitivity. Firms experiencing rapid growth, firms that might be considered financially constrained and capital–intensive firms are also found to be quite sensitive to macroeconomic uncertainty. Firms that are paying sizable dividends exhibit a lower sensitivity to these macro effects, while capital–intensive firms' sensitivity is somewhat greater than that of labor–intensive firms. The overall message of our analysis is that macroeconomic uncertainty is an important determinant of corporate cash holding behavior, and the strength of those effects systematically differ with respect to firm–specific characteristics.

4 Conclusions

In this paper we focus on the link between the dispersion of firms' cash–to–asset ratios and macroeconomic uncertainty using a panel of U.S. non–financial firms drawn from the COMPUSTAT database over the period 1970–2000. Based on an augmented cash buffer–stock model, we demonstrate that firms become more homogeneous in their cash–holding behavior in response to an increase in macroeconomic uncertainty. Conversely, when the macroeconomic environment is more stable, firms have more latitude to behave idiosyncratically, leading to a broadening of the cross–sectional dispersion of firms' cash–to–asset ratios. To test the predictions of our model, we estimate a simple reduced–form equation using an annual data set describing individual firms' behavior and a proxy for macroeconomic uncertainty derived from monthly estimates of real GDP. On the basis of our empirical findings, we suggest that the cash holdings of large firms, high–growth firms, financially constrained firms and capital–intensive firms are more sensitive to variations in macroeconomic volatility than are those of smaller or more slowly growing firms, those which are labor–intensive or those which do not face financial constraints. These results are shown to be robust to the inclusion of the levels of macroeconomic factors such as the index of leading indicators, the rate of inflation, and short–term Treasury and LIBOR interest rates. Overall, our findings verify and support the hypothesis that macroeconomic uncertainty is a significant determinant of firms' cash holding behavior, with the size of its impact differing substantially across firm classifications.

Appendix A

Construction of cash holdings and uncertainty measures

The following variables are used in the empirical study.

From Standard and Poor's COMPUSTAT database:
DNUM: Industry Classification Code
DATA1: Cash Holdings
DATA6: Total Assets
DATA13: Operating Income before Depreciation
DATA15: Interest Expense
DATA16: Income Taxes–Total
DATA21: Dividends–Common

From the IMF's International Financial Statistics:
66IZF: Industrial Production monthly
64XZF: Consumer Price Inflation
99BRZF: GDP at 1996 prices

From the DRI-McGraw Hill Basic Economics database:
DLEAD: index of leading indicators

Appendix B

GARCH(2,2) proxy for macroeconomic uncertainty

	log(*Real GDP*)
$\log(Real\ GDP)_{t-1}$	0.986
	(0.01)***
Constant	0.000
	(0.00)
AR(1)	-0.981
	(0.01)***
MA(1)	1.001
	(0.00)***
ARCH(1)	0.123
	(0.03)***
ARCH(2)	0.126
	(0.03)***
GARCH(1)	-0.187
	(0.05)***
GARCH(2)	0.814
	(0.05)***
Constant	0.000
	(0.00)***
Observations	535

OPG standard errors in parentheses
Model is fit to detrended log(Real GDP).
** significant at 5%; *** significant at 1%

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Table 1: Mean of Annual Cash/Asset ratios: Descriptive statistics, 1970–2000

	μ	σ	$p25$	$p50$	$p75$	N
All firms	0.105	0.014	0.091	0.107	0.117	127,302
Small firms	0.135	0.014	0.121	0.139	0.147	18,592
Large firms	0.070	0.006	0.067	0.070	0.074	16,582
Low–growth firms	0.085	0.008	0.078	0.084	0.090	25,923
High–growth firms	0.121	0.025	0.099	0.125	0.147	25,871
Financially constrained firms	0.107	0.018	0.088	0.112	0.122	64,546
Unconstrained firms	0.094	0.008	0.089	0.093	0.101	29,869
Capital–intensive firms	0.102	0.110	0.026	0.062	0.138	38,113
Labor–intensive firms	0.102	0.115	0.025	0.059	0.138	32,428

Note: $p25$, $p50$ and $p75$ represent the quartiles of the distribution, while μ and σ represent its mean and standard deviation. N refers to the number of firm–years of data in each category which have been collapsed into 196 observations, identified by year and one–digit SIC category (56 observations for capital– and labor–intensive categories).

Table 2. Dispersion of Cash/Asset ratio for all firms 1970–2000

	(1) RAT1_Sig	(2) RAT1_Sig	(3) RAT1_Sig	(4) RAT1_Sig	(5) RAT1_Sig
Lwcvgdp	-99.811	-91.653	-132.705	-135.272	-42.253
	[15.832]***	[15.097]***	[20.638]***	[21.783]***	[13.165]***
sic1x	-0.027	-0.027	-0.021	-0.021	-0.028
	[0.009]***	[0.009]***	[0.009]**	[0.009]**	[0.006]***
sic2x	-0.032	-0.032	-0.030	-0.030	-0.032
	[0.009]***	[0.009]***	[0.009]***	[0.010]***	[0.005]***
sic3x	-0.009	-0.007	-0.008	-0.008	-0.009
	[0.010]	[0.010]	[0.010]	[0.010]	[0.006]
sic4x	-0.035	-0.034	-0.031	-0.031	-0.034
	[0.008]***	[0.008]***	[0.008]***	[0.009]***	[0.005]***
sic5x	-0.042	-0.041	-0.039	-0.039	-0.042
	[0.009]***	[0.009]***	[0.009]***	[0.010]***	[0.005]***
sic7x	0.025	0.026	0.027	0.027	0.024
	[0.009]***	[0.009]***	[0.010]***	[0.010]***	[0.006]***
LeadIndic		-0.000			
		[0.000]			
TB3mo			0.245		
			[0.088]***		
LIBOR3mo				0.173	0.303
				[0.067]***	[0.073]***
Inflation					-0.005
					[0.001]***
Constant	0.191	0.185	0.187	0.191	0.162
	[0.010]***	[0.009]***	[0.009]***	[0.010]***	[0.006]***
Observations	196	196	196	196	196
$\hat{\eta}$	-0.42	-0.39	-0.56	-0.57	-0.18
s.e.	0.07	0.07	0.09	0.09	0.06

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Estimation by HAC IV–GMM. SD based on 127302 firm-year obs.

Table 3. Dispersion of Cash/Asset ratio for large firms 1970–2000

	(1) RAT1_Sig	(2) RAT1_Sig	(3) RAT1_Sig	(4) RAT1_Sig	(5) RAT1_Sig
Lwcvgdp	-109.217	-108.538	-111.583	-108.467	-59.384
	[16.578]***	[16.608]***	[18.394]***	[17.979]***	[13.593]***
sic1x	0.028	0.029	0.027	0.027	0.032
	[0.010]***	[0.009]***	[0.009]***	[0.009]***	[0.008]***
sic2x	0.022	0.022	0.023	0.023	0.026
	[0.008]***	[0.007]***	[0.008]***	[0.008]***	[0.007]***
sic3x	0.037	0.037	0.038	0.038	0.041
	[0.008]***	[0.007]***	[0.008]***	[0.008]***	[0.007]***
sic4x	0.025	0.025	0.025	0.025	0.028
	[0.008]***	[0.008]***	[0.008]***	[0.008]***	[0.007]***
sic5x	0.012	0.013	0.013	0.013	0.016
	[0.008]	[0.008]*	[0.008]*	[0.008]*	[0.007]**
sic7x	0.054	0.052	0.056	0.054	0.052
	[0.010]***	[0.010]***	[0.010]***	[0.010]***	[0.009]***
LeadIndic		0.001			
		[0.001]			
TB3mo			0.030		
			[0.088]		
LIBOR3mo				-0.023	0.039
				[0.065]	[0.065]
Inflation					-0.003
					[0.001]***
Constant	0.104	0.104	0.102	0.105	0.089
	[0.011]***	[0.011]***	[0.011]***	[0.011]***	[0.010]***
Observations	195	195	195	195	195
$\hat{\eta}$	-0.75	-0.75	-0.78	-0.76	-0.41
s.e.	0.11	0.12	0.13	0.12	0.09

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Estimation by HAC IV–GMM. SD based on 16582 firm-year obs.

Table 4. Dispersion of Cash/Asset ratio for small firms 1970–2000

	(1)	(2)	(3)	(4)	(5)
	RAT1_Sig	RAT1_Sig	RAT1_Sig	RAT1_Sig	RAT1_Sig
Lwcvgdp	-62.080	-56.067	-110.258	-115.591	-36.314
	[18.153]***	[17.531]***	[21.104]***	[22.312]***	[17.040]**
sic1x	-0.011	-0.007	-0.002	-0.001	-0.005
	[0.011]	[0.011]	[0.010]	[0.011]	[0.009]
sic2x	-0.014	-0.013	-0.012	-0.011	-0.014
	[0.011]	[0.011]	[0.011]	[0.012]	[0.009]
sic3x	-0.020	-0.020	-0.017	-0.016	-0.019
	[0.010]*	[0.010]**	[0.010]*	[0.010]	[0.007]***
sic4x	-0.004	-0.001	0.002	0.003	-0.000
	[0.011]	[0.011]	[0.010]	[0.011]	[0.011]
sic5x	-0.037	-0.035	-0.029	-0.028	-0.034
	[0.010]***	[0.010]***	[0.010]***	[0.010]***	[0.008]***
sic7x	0.012	0.012	0.015	0.015	0.013
	[0.011]	[0.011]	[0.011]	[0.012]	[0.008]*
LeadIndic		-0.001			
		[0.001]			
TB3mo			0.434		
			[0.104]***		
LIBOR3mo				0.326	0.442
				[0.081]***	[0.091]***
Inflation					-0.004
					[0.001]***
Constant	0.192	0.188	0.182	0.188	0.165
	[0.013]***	[0.013]***	[0.012]***	[0.012]***	[0.010]***
Observations	196	196	196	196	196
$\hat{\eta}$	-0.21	-0.19	-0.38	-0.40	-0.12
s.e.	0.06	0.06	0.07	0.08	0.06

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Estimation by HAC IV–GMM. SD based on 18592 firm-year obs.

Table 5. Dispersion of Cash/Asset ratio for low–growth firms 1970–2000

	(1) RAT1_Sig	(2) RAT1_Sig	(3) RAT1_Sig	(4) RAT1_Sig	(5) RAT1_Sig
Lwcvgdp	-77.636	-75.057	-72.834	-72.145	-22.851
	[15.516]***	[16.052]***	[21.337]***	[23.390]***	[17.870]
sic1x	-0.006	-0.002	-0.001	-0.001	-0.007
	[0.011]	[0.010]	[0.010]	[0.010]	[0.009]
sic2x	-0.022	-0.020	-0.019	-0.019	-0.023
	[0.010]**	[0.010]**	[0.010]*	[0.010]*	[0.008]***
sic3x	-0.008	-0.007	-0.004	-0.004	-0.009
	[0.011]	[0.010]	[0.011]	[0.010]	[0.008]
sic4x	-0.027	-0.023	-0.024	-0.024	-0.028
	[0.010]**	[0.010]**	[0.010]**	[0.010]**	[0.008]***
sic5x	-0.031	-0.028	-0.028	-0.028	-0.032
	[0.011]***	[0.010]***	[0.010]***	[0.010]***	[0.008]***
sic7x	0.021	0.024	0.026	0.026	0.021
	[0.012]*	[0.012]**	[0.012]**	[0.012]**	[0.009]**
LeadIndic		0.001			
		[0.001]			
TB3mo			0.021		
			[0.111]		
LIBOR3mo				0.004	0.159
				[0.089]	[0.099]
Inflation					-0.004
					[0.001]***
Constant	0.154	0.150	0.146	0.147	0.134
	[0.012]***	[0.011]***	[0.010]***	[0.011]***	[0.008]***
Observations	196	196	196	196	196
$\hat{\eta}$	-0.38	-0.37	-0.36	-0.36	-0.11
s.e.	0.08	0.08	0.11	0.12	0.09

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Estimation by HAC IV–GMM. SD based on 25923 firm-year obs.

Table 6. Dispersion of Cash/Asset ratio for high–growth firms 1970–2000

	(1) RAT1_Sig	(2) RAT1_Sig	(3) RAT1_Sig	(4) RAT1_Sig	(5) RAT1_Sig
Lwcvgdp	-133.811	-128.052	-161.531	-156.886	-53.126
	[21.223]***	[20.496]***	[24.202]***	[24.343]***	[16.753]***
sic1x	-0.016	-0.020	-0.016	-0.015	-0.020
	[0.012]	[0.012]*	[0.012]	[0.012]	[0.008]**
sic2x	-0.010	-0.011	-0.011	-0.010	-0.012
	[0.011]	[0.011]	[0.011]	[0.012]	[0.006]*
sic3x	0.005	0.004	0.004	0.004	0.004
	[0.012]	[0.012]	[0.012]	[0.012]	[0.008]
sic4x	-0.023	-0.024	-0.022	-0.022	-0.026
	[0.011]**	[0.010]**	[0.011]**	[0.011]**	[0.007]***
sic5x	-0.033	-0.034	-0.034	-0.033	-0.035
	[0.011]***	[0.011]***	[0.011]***	[0.012]***	[0.007]***
sic7x	0.034	0.034	0.035	0.035	0.032
	[0.011]***	[0.011]***	[0.011]***	[0.011]***	[0.007]***
LeadIndic		0.000			
		[0.001]			
TB3mo			0.233		
			[0.109]**		
LIBOR3mo				0.130	0.273
				[0.082]	[0.086]***
Inflation					-0.005
					[0.001]***
Constant	0.200	0.198	0.196	0.200	0.167
	[0.012]***	[0.012]***	[0.012]***	[0.012]***	[0.009]***
Observations	196	196	196	196	196
$\hat{\eta}$	-0.55	-0.53	-0.67	-0.65	-0.22
s.e.	0.09	0.09	0.10	0.10	0.07

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Estimation by HAC IV–GMM. SD based on 25871 firm-year obs.

Table 7. Dispersion of Cash/Asset ratio for fin. constrained firms 1970–2000

	(1) RAT1_Sig	(2) RAT1_Sig	(3) RAT1_Sig	(4) RAT1_Sig	(5) RAT1_Sig
Lwcvgdp	-90.363	-79.050	-146.602	-148.866	-33.815
	[19.746]***	[18.640]***	[25.314]***	[26.887]***	[16.075]**
sic1x	-0.031	-0.030	-0.020	-0.021	-0.029
	[0.011]***	[0.011]***	[0.011]*	[0.011]*	[0.008]***
sic2x	-0.025	-0.026	-0.023	-0.023	-0.025
	[0.012]**	[0.012]**	[0.012]*	[0.012]*	[0.007]***
sic3x	-0.003	-0.000	-0.001	-0.002	-0.004
	[0.012]	[0.012]	[0.012]	[0.012]	[0.007]
sic4x	-0.025	-0.022	-0.017	-0.017	-0.023
	[0.010]**	[0.010]**	[0.010]*	[0.011]	[0.007]***
sic5x	-0.044	-0.043	-0.037	-0.038	-0.043
	[0.011]***	[0.011]***	[0.012]***	[0.012]***	[0.007]***
sic7x	0.025	0.026	0.028	0.027	0.023
	[0.011]**	[0.011]**	[0.011]**	[0.012]**	[0.007]***
LeadIndic		-0.001			
		[0.001]			
TB3mo			0.412		
			[0.108]***		
LIBOR3mo				0.299	0.445
				[0.083]***	[0.091]***
Inflation					-0.006
					[0.001]***
Constant	0.187	0.180	0.182	0.188	0.154
	[0.013]***	[0.012]***	[0.012]***	[0.013]***	[0.007]***
Observations	196	196	196	196	196
$\hat{\eta}$	-0.37	-0.32	-0.60	-0.61	-0.14
s.e.	0.08	0.08	0.11	0.11	0.07

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Estimation by HAC IV–GMM. SD based on 64546 firm-year obs.

Table 8. Dispersion of Cash/Asset ratio for fin. unconstrained firms 1970–2000

	(1) RAT1_Sig	(2) RAT1_Sig	(3) RAT1_Sig	(4) RAT1_Sig	(5) RAT1_Sig
Lwcvgdp	-40.975	-43.484	-39.132	-40.125	-17.146
	[12.846]***	[12.759]***	[17.657]**	[17.665]**	[12.362]
sic1x	-0.014	-0.015	-0.013	-0.013	-0.013
	[0.007]*	[0.007]**	[0.007]*	[0.007]*	[0.007]*
sic2x	-0.032	-0.032	-0.032	-0.032	-0.033
	[0.006]***	[0.006]***	[0.006]***	[0.006]***	[0.006]***
sic3x	-0.023	-0.023	-0.023	-0.022	-0.023
	[0.007]***	[0.007]***	[0.007]***	[0.007]***	[0.007]***
sic4x	-0.041	-0.042	-0.041	-0.041	-0.041
	[0.007]***	[0.007]***	[0.007]***	[0.007]***	[0.007]***
sic5x	-0.032	-0.032	-0.031	-0.031	-0.032
	[0.007]***	[0.007]***	[0.007]***	[0.007]***	[0.007]***
sic7x	0.027	0.026	0.027	0.027	0.027
	[0.007]***	[0.007]***	[0.007]***	[0.007]***	[0.007]***
LeadIndic		-0.000			
		[0.001]			
TB3mo			-0.002		
			[0.074]		
LIBOR3mo				-0.003	0.035
				[0.057]	[0.067]
Inflation					-0.001
					[0.001]*
Constant	0.151	0.153	0.150	0.151	0.143
	[0.008]***	[0.008]***	[0.008]***	[0.008]***	[0.007]***
Observations	196	196	196	196	196
$\hat{\eta}$	-0.18	-0.20	-0.18	-0.18	-0.08
s.e.	0.06	0.06	0.08	0.08	0.06

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Estimation by HAC IV–GMM. SD based on 29869 firm-year obs.

Table 9. Dispersion of Cash/Asset ratio for capital–intensive firms 1970–2000

	(1)	(2)	(3)	(4)	(5)
	RAT1_Sig	RAT1_Sig	RAT1_Sig	RAT1_Sig	RAT1_Sig
Lwcvgdp	-137.329	-132.331	-172.872	-174.406	-68.360
	[25.071]***	[24.304]***	[35.938]***	[37.309]***	[20.142]***
sic2x	-0.022	-0.023	-0.021	-0.020	-0.021
	[0.008]***	[0.008]***	[0.009]**	[0.009]**	[0.004]***
LeadIndic		-0.000			
		[0.001]			
TB3mo			0.199		
			[0.133]		
LIBOR3mo				0.136	0.340
				[0.097]	[0.120]***
Inflation					-0.006
					[0.001]***
Constant	0.192	0.190	0.194	0.197	0.158
	[0.013]***	[0.012]***	[0.014]***	[0.014]***	[0.010]***
Observations	56	56	56	56	56
$\hat{\eta}$	-0.63	-0.61	-0.82	-0.82	-0.32
s.e.	0.12	0.11	0.18	0.18	0.09

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Estimation by HAC IV–GMM. SD based on 38113 firm-year obs.

Table 10. Dispersion of Cash/Asset ratio for labor–intensive firms 1970–2000

	(1) RAT1_Sig	(2) RAT1_Sig	(3) RAT1_Sig	(4) RAT1_Sig	(5) RAT1_Sig
Lwcvgdp	-107.769	-97.864	-161.006	-161.035	-42.503
	[29.954]***	[28.132]***	[38.253]***	[39.288]***	[21.185]**
sic2x	-0.026	-0.028	-0.022	-0.022	-0.023
	[0.009]***	[0.009]***	[0.009]**	[0.010]**	[0.005]***
LeadIndic		-0.001			
		[0.001]			
TB3mo			0.330		
			[0.153]**		
LIBOR3mo				0.233	0.413
				[0.112]**	[0.127]***
Inflation					-0.006
					[0.001]***
Constant	0.182	0.177	0.182	0.187	0.146
	[0.014]***	[0.013]***	[0.015]***	[0.015]***	[0.012]***
Observations	56	56	56	56	56
$\hat{\eta}$	-0.48	-0.44	-0.74	-0.74	-0.19
s.e.	0.14	0.13	0.18	0.18	0.10

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Estimation by HAC IV–GMM. SD based on 32428 firm-year obs.