The Corporate Propensity to Save

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June 23, 2007

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Abstract

Why and how do corporations accumulate liquid assets? We show theoretically that intertemporal trade-offs between interest income taxation and the cost of external finance determine optimal savings. We find the striking result that saving and cash flow are negatively correlated because firms optimally lower cash reserves to invest after receiving a positive cash-flow shock, and vice versa. Consistent with theory, we estimate negative propensities to save out of cash flow. We also find that income uncertainty affects saving more than external finance constraints. Therefore, despite previous evidence to the contrary, saving propensities cannot be used to measure external finance constraints.
Why do corporations save; that is, why do they funnel their cash flow into liquid asset holdings rather than into physical capital or into distributions to shareholders? Although seemingly simple, this question is challenging because such financial decisions cannot be understood in isolation of the real decisions a corporation makes. Not only is the question challenging, but it is economically interesting in light of the tendency in recent years of both U.S. and European firms to accumulate a great deal of liquid assets. The question is also interesting on a different level because several recent studies—for example, Almeida, et al. (2004) and Khurana, et al. (2006)—have used firm saving behavior to gauge the cost of external finance for various groups of firms.

The goal of this paper is therefore twofold. Although we do not tackle directly the issue of the high level of corporate cash holdings, we shed light on this phenomenon by delving into the economics of the process whereby firms accumulate this cash. We also wish to determine whether corporate saving behavior is a useful indicator of whether firms face external finance constraints. We proceed on both a theoretical and empirical level, and we focus on two specific determinants of saving: income uncertainty and the cost of external finance.

On the theoretical side our model provides several insights. In our infinite-horizon framework firms invest, save, produce, raise external finance, and make distributions in the face of uncertainty, physical adjustment costs, taxation, and costs of issuing equity. Because interest on any cash balances is taxed, the firm faces a dynamic trade-off between this tax penalty and the reduction in expected future financing costs conferred by holding cash. The firm’s optimal saving policy therefore depends not only on the cost of external finance, but also on its expected future financing needs, which, in turn, depend on its technology and especially on the uncertainty it faces.

In this setting we find that firms hold higher precautionary cash balances when external finance is costly or income uncertainty is high. Firms also hold more cash when their optimal investment policy is lumpy because large investments typically entail costly outside financing. The connection in the model between cash holding and large investments is consistent with the high levels of corporate cash holding observed in recent years, because firms have been growing less via internal greenfield investment and more via large acquisitions.

Our most interesting predictions concern not the level of cash but the change in cash—saving. In
particular, we find that firms tend to dissave out of good cash-flow shocks, and vice versa. Although the result of a negative sensitivity of saving to cash flow is, at first, surprising, the intuition is straightforward. For example, if the firm faces positively serially correlated productivity shocks, a good shock means that the firm’s cash flow rises, that its capital goods become more productive, and that this productivity will revert back down to its mean slowly. The firm therefore shifts some of its financial asset holdings into physical capital; that is, it invests and dissave.

Naturally, this negative sensitivity of saving to cash flow increases with the degree of serial correlation of productivity shocks. It also falls as the shocks become more variable because the firm does not react strongly to the small amount of information in high-variance shocks. Finally, the sensitivity rises with the cost of external finance because the firm’s optimal level of cash increases with the cost of external finance. In comparison with a low-cost firm, a high-cost firm therefore has more slack with which to respond to profit shocks, and it saves or dissave more aggressively in large part to counteract these shocks.

This last result is particularly interesting because it points out that although the levels and changes in cash for a firm are clearly related, a high cash level does not necessarily imply a high, positive sensitivity of the change in cash (saving) to cash flow; nor does a low cash level imply a low sensitivity. This distinction between levels and sensitivities would be impossible to uncover, for example, in a static, two-period model because in such a setting the change in cash is indistinguishable from the level. A dynamic model such as ours is therefore essential to understanding the trade-offs that affect corporate saving.

Our empirical work is closely tied to our model. To generate exact testable predictions, we solve the model numerically, use the solution to generate a panel of simulated data, and run a linear regression, from Almeida, et al. (2004), of the change in cash levels (saving) on Tobin’s q and cash flow. The coefficient on cash flow measures the saving sensitivity, which we also dub the propensity to save. Generating a testable prediction in this manner has precedents in Whited (2006) and Caggese (2006) and has the advantage that it defines away the usual endogeneity problems that plague regressions in empirical corporate finance. If an empirical prediction takes the form of a linear regression, then this regression by definition must have an orthogonal error term. Such is not
the case for empirical predictions that take the form of the sign of a partial derivative because they provide incomplete guidance on the entire regression specification.

We then run the same regression on real data, primarily from the United States, but also from Canada, France, Germany, Japan, and the United Kingdom. We find negative coefficients on cash flow in all six countries, and many are significant. Interestingly, these coefficients are only negative when we correct econometrically for the substantial measurement error in Tobin’s $q$ documented in Erickson and Whited (2000). As predicted by our model, we find a negative relation between saving propensities and the variability of income, as well as a positive relation between saving propensities and the serial correlation of income. However, we reject the prediction from our model that firms typically categorized as financially constrained have more negative saving propensities than their unconstrained counterparts. This result occurs because constrained firms also have highly variable income shocks, which lower their saving propensities. In sum, from our model and empirical evidence we conclude that income shocks are at least as important as the cost of external finance in determining corporate saving. Accordingly, although the sensitivity of saving to cash flow contains information about external finance constraints, too many factors influence this one correlation for it to be used as a summary measure of the cost of external finance.

Our paper fits into both the theoretical and empirical literatures on corporate saving. The theoretical model in this paper is most closely related to that in Whited (2006), in which a firm invests and saves in the face of costly external equity finance and fixed costs of capital adjustment. We extend the model by including a corporate income tax and convex adjustment costs, and we examine empirically the model’s implications for saving rather than for investment, as in Whited (2006). Our model is also closely related to the one in Eisfeldt and Rampini (2006), which characterizes the business-cycle properties of aggregate liquidity. They calibrate a general-equilibrium model with a rich specification of uncertainty. Although many of the same economic mechanisms at work in their model also operate in ours, the focus of the two papers is quite different in that we are interested in directly testing the implications of the model at the firm level, instead of calibration at the aggregate level. Another closely related theoretical paper is Gamba and Triantis (2006). Their model is quite general, allowing for cash holding as well as separate debt and equity finance,
although, unlike us, they omit physical adjustment costs. Their main contribution is an explanation of how debt flotation costs can lead to simultaneous cash and debt holdings.

Our paper is most closely related to Almeida et al. (2004). However, we reach very different theoretical and empirical conclusions. First, their model predicts a positive propensity to save and ours a negative. Their result occurs because an increase in cash flow in their model is not accompanied by an increase in the productivity of capital. The firm therefore has no incentive to transform liquid assets into physical assets, as in our model, and the increase in cash flow produces a pure positive income effect on saving. Second, they find a positive sensitivity in the data and we find a negative sensitivity. The difference lies in our correction for measurement error in Tobin’s $q$. This result is puzzling in light of the argument in Almeida, et al. (2004) that using the sensitivity of cash saving to cash flow as a measure of financing constraints is immune to the measurement error issue. They explain that under the null hypothesis of no financing frictions, saving should not depend on either cash flow or Tobin’s $q$. Therefore, the significance of cash flow can only be due to financial frictions. Although this argument is correct, it is incomplete. Measurement error in Tobin’s $q$ does nonetheless affect the sign and magnitude of the cash-flow coefficient, regardless of the variable on the left-hand-side of the regression. As explained in detail below, and also as noted in Greene (1997, p.440), measurement error in one regressor affects all of the coefficients in a regression if the regressors are correlated with one another, and the information about future investment opportunities contained in cash flow leads naturally to a positive correlation between Tobin’s $q$ and cash flow.


Our work is also somewhat related to recent empirical work on the determinants of the level of (as opposed to the change in) corporate cash holdings, such as Kim, Mauer, and Sherman (1998),

The paper is organized as follows. Section 1 presents the model. Section 2 describes the model simulation and its results. Section 3 describes the data, Section 4 presents the estimation procedure and results, and Section 5 concludes. Appendix A contains details concerning data construction, and Appendix B contains Monte Carlo simulations to assess the estimators’ finite-sample performance.

I. A Model of Cash Holding

To motivate our empirical work, we consider a discrete-time, infinite-horizon, partial-equilibrium model of investment and saving. First we describe the technology, financing, and taxation, and financial frictions. Then we move on to a description of the optimal financing policies.

A. Technology and Financing

A risk-neutral, price-taking firm uses capital, $k$, and variable factors of production, $l$, to produce output, and it faces a combination demand and productivity shock, $z$. Because the variable factors are costlessly adjustable, the firm’s per period profit function is given by $\pi(k, z)$, in which the variable factors have already been maximized out of the problem. The profit function $\pi(k, z)$ is continuous, with $\pi(0, z) = 0$, $\pi_z(k, z) > 0$, $\pi_k(k, z) > 0$, $\pi_{kk}(k, z) < 0$, and $\lim_{k \to \infty} \pi_k(k, z) = 0$. Concavity of $\pi(k, z)$ results from decreasing returns in production, a downward sloping demand curve, or both. The shock $z$ is observed by the producer before he makes his current period decisions. It takes values in $[z, \bar{z}]$ and follows a first-order Markov process with transition probability $g(z', z)$, in which a prime indicates a variable in the next period; $g(z', z)$ has the Feller property.

Without loss of generality, $k$ lies in a compact set. As in Gomes (2001), define $\bar{k}$ as

$$
(1 - \tau_c) \pi(\bar{k}, \bar{z}) - d\bar{k} \equiv 0,
$$

in which $d$ is the capital depreciation rate, $0 < d < 1$. Concavity of $\pi(k, z)$ and $\lim_{k \to \infty} \pi_k(k, z) = 0$ ensure that $\bar{k}$ is well-defined. Because $k > \bar{k}$ is not economically profitable, $k$ lies in the interval $[0, \bar{k}]$. Compactness of the state space and continuity of $\pi(k, z)$ ensure that $\pi(k, z)$ is bounded.
Investment, $I$, is defined as

$$I \equiv k' - (1 - d)k.$$  \hspace{1cm} (2)

The firm purchases and sells capital at a price of 1 and incurs adjustment costs that are given by

$$A(k, k') = ck \Phi_i + \frac{a}{2} \left( \frac{k' - (1 - d)}{k} \right)^2 k.$$  \hspace{1cm} (3)

The functional form of (3) is standard in the empirical investment literature, and it encompasses both fixed and smooth adjustment costs. See, for example, Cooper and Haltiwanger (2006). The first term captures the fixed component, $ck \Phi_i$, in which $c$ is a constant, and $\Phi_i$ equals 1 if investment is nonzero, and 0 otherwise. The fixed cost is proportional to the capital stock so that the firm has no incentive to grow out of the fixed cost.\(^1\) The smooth component is captured by the second term, in which $a$ is a constant. Although curvature of the profit function acts to smooth investment over time in the same way that the quadratic component of (3) does, we include the quadratic component to isolate the effects of smooth adjustment costs. In contrast, curvature of the profit function not only affects investment smoothing but also the relation between firm value and profit.

We now discuss financing. The firm can hold cash balances, $p$, via a riskless one-period discount bond that earns an interest rate $r$. We assume that both corporate operating and interest income is taxed at a rate $\tau_c$. For simplicity, we do not model personal interest and dividend taxes. What is important for our model is the existence of a tax penalty for saving, which is consistent with recent U.S. tax code. See Hennessy and Whited (2005). To ensure compactness of the choice set, we assume an arbitrarily high upper bound on corporate saving, $\bar{p}$. This upper bound is imposed without loss of generality, because our taxation assumptions ensure bounded saving.

All external finance takes the form of equity. Although it would be inappropriate for the study of capital structure, this simplification allows us to highlight the interaction between technology, finance constraints, and cash holdings. Further, the simple structure does not affect the qualitative outcome of the simulations that follow. To preserve tractability, we do not model costs of external equity as the outcome of an asymmetric information problem. Instead, we capture adverse selection costs and underwriting fees in a reduced-form fashion. Accordingly, we define the excess of cash

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\(^1\)Replacing $ck$ with a fixed number, $F$, changes the analysis little because the capital stock is bounded.
inflows over cash outflows as

\[ e(k, k', p, p', z) \equiv (1 - \tau_c) \pi(k, z) + p - \frac{p'}{(1 + r(1 - \tau_c))} - (k' - (1 - d)k) - A(k, k') \, . \]  

If \( e(k, k', p, p', z) > 0 \), the firm is making distributions to shareholders, and if \( e(k, k', p, p', z) < 0 \), the firm is issuing equity. The external equity-cost function is linear-quadratic and weakly convex:

\[
\Phi_e(e(k, k', p, p', z)) \equiv \Phi_e\left(-\lambda_0 + \lambda_1 e(k, p, k', p', z) - \frac{1}{2} \lambda_2 e(k, p, k', p', z)^2\right)
\]

\[ \lambda_i \geq 0 \quad i = 0, 1, 2, \]

in which \( \Phi_e \) equals 1 if \( e(k, p, k', p', z) < 0 \), and 0 otherwise. Convexity of \( \Phi_e(e(k, p, k', p', z)) \) is consistent with the evidence on underwriting fees in Altinkilic and Hansen (2000).

The firm chooses \((k', p')\) each period to maximize the value of expected future cash flows, discounting at the opportunity cost of funds, \( r \). The Bellman equation for the problem is

\[
V(k, p, z) = \max_{k', p'} \left\{ e(k, k', p, p', z) + \phi(e(k, k', p, p', z)) + \frac{1}{1 + r} \int V(k', p', z') \, dg(z', z) \right\} \, .
\]  

(5)

The model satisfies the conditions for Theorem 9.6 in Stokey and Lucas (1989), which guarantees a solution for (5). Theorem 9.8 in Stokey and Lucas (1989) ensures a unique optimal policy function, \( \{k', p'\} = h(k, p, z) \), if \( e(k, k', p, p', z) + \phi(e(k, k', p, p', z)) \) is weakly concave in its first and third arguments. This requirement puts easily verified restrictions on \( \phi(\cdot) \), which are satisfied by the functional form chosen below.

**B. Optimal Financial Policies**

This subsection develops the intuition behind the model by examining its optimality conditions.

To simplify the exposition of optimal policies, we assume in this subsection that \( V \) is concave and once differentiable. These assumptions are not necessary for the existence of a solution to (5) or of an optimal policy function. We present optimal financial policies, heuristically, in two steps. First, we determine optimal financing under the assumption that the manager ignores the fixed costs of external equity; that is, he or she treats \( \lambda_0 = 0 \). Second, we determine whether the intra-marginal benefits of equity issuance justify the fixed cost.

The optimal interior financial policy, obtained by solving the optimization problem (5), satisfies

\[
1 + (\lambda_1 - \lambda_2 e) \Phi_e = \frac{1 + r (1 - \tau_c)}{1 + r} \int V_2(k', p', z') \, dg(z', z) \, .
\]  

(6)
The right side represents the shadow value of cash balances, and the left side represents the marginal cost of external equity finance. To develop the intuition behind the optimal policy, we use the envelope condition to rewrite (6) as:

$$1 + (\lambda_1 - \lambda_2 e) \Phi_e = \frac{1 + r (1 - \tau_c)}{1 + r} \int (1 + (\lambda_1 - \lambda_2 e') \Phi_e') \, dg(z', z).$$

Rewriting (6) as (7) makes it clear that without costly external finance, equation (7) holds as an inequality. In this case the tax penalty for saving implies that the firm never saves; i.e., \( p = p' = 0 \).

In contrast, in the face of costly external finance, if a firm saves a dollar today, it reduces the probability of having to issue new equity tomorrow. It continues to save just until the gain from reducing future equity costs outweighs the tax penalty on saving.

In some instances the fixed costs of external equity will be larger than the intra-marginal gains from equity issuance. In these cases the firm is in a region of financial inertia in which it neither issues equity nor distributes funds to shareholders. Internal funds are the marginal source of funds and the firm saves any excess cash flows not used for positive NPV projects.

II. Simulations

We solve the model numerically and investigate its implications for reduced-form regressions via simulation. We first describe the parameterization of our baseline simulation and explain the properties of optimal firm behavior. We then explain the experiments we perform on the model and the results of these experiments. We conclude by considering the empirical predictions given by the model and by examining the robustness of the model to our various simplifying assumptions.

A. Model Calibration

The profit function is given by \( \pi(k, z) = zk^\theta \), in which we calibrate \( \theta \) from the estimates of labor shares and mark-ups in Rotemberg and Woodford (1992, 1999). Their estimates, along with the assumptions of a Cobb-Douglas production function and a constant-elasticity demand function, imply that \( \theta \approx 0.75 \). To specify a stochastic process for the shock \( z \), we follow Gomes (2001) and assume that \( z \) follows an \( AR(1) \) in logs,

$$\ln(z') = \rho \ln(z) + v',$$
in which \( v' \sim N \left( 0, \sigma_v^2 \right) \). Our baseline parameter choices for \( \rho \) and \( \sigma_v \) are the averages of the estimates of these two parameters in Hennessy and Whited (2006): \( \rho = 0.66 \) and \( \sigma_v = 0.121 \).

We again follow Hennessy and Whited (2006) to parameterize the financing function, setting \( \lambda_0 = 0.389 \), \( \lambda_1 = 0.053 \), and \( \lambda_2 = 0.0002 \). These settings are from their estimates of the costs of external equity finance for large firms and are therefore conservative, lying only slightly above the figures for underwriting costs in Altinkilic and Hansen (2000). We set the interest rate, \( r \), equal to 4\%, which lies between the values chosen by Hennessy and Whited (2006) and Gomes (2001).

To find values for the adjustment cost parameters, \( c \) and \( a \), we turn to Cooper and Haltiwanger (2006), who find that both convex and fixed costs of adjustment affect investment. From their estimates we set \( c = 0.039 \) and \( a = 0.049 \). We set the depreciation rate equal to 0.15, a figure approximately equal to the average in our data of the ratio of depreciation to the net capital stock.

Finally, to find a numerical solution we need to specify a finite state space for the three state variables. We let the capital stock lie on the points

\[
\left[ \bar{k} (1 - d)^{40}, \ldots, \bar{k} (1 - d)^{1/2}, \bar{k} (1 - d)^{1/4}, \bar{k} \right].
\]

We let the productivity shock have 25 points of support, transforming (8) into a discrete-state Markov chain using the method in Tauchen (1986). We let \( p \) have 30 equally spaced points in the interval \([0, \bar{p}]\), in which \( \bar{p} \) is set to \( \bar{k}/2 \). The optimal choice of \( p \) never hits this upper bound.

We solve the model via iteration on the Bellman equation, which produces the value function \( V(k, p, z) \) and the policy function \( \{k', p'\} = h(k, p, z) \). In the subsequent model simulation, the space for \( z \) is expanded to include 80 points, with interpolation used to find corresponding values of \( V, k, \) and \( p \). The model simulation proceeds by taking a random draw from distribution of \( z' \) (conditional on \( z \)), and then computing \( V(k, p, z) \) and \( h(k, p, z) \). We use these computations to generate an artificial panel of firms by simulating the model for 10,000 identical firms over 200 time periods, keeping only the last 20 observations for each firm.

**B. Optimal Policy Functions**

Before presenting our simulation results, we delve into the economics behind the model by examining the properties of the simulated policy function, \( \{k', p'\} = h(k, p, z) \). To show the implications
of this rule for optimal saving and investment, we plot optimal cash flow, investment (net of adjustment costs), saving, and distributions/equity issuance (net of issuance costs) as a function of $z$ for three different $(k, p)$ pairs: low $k$/medium $p$, medium $k$/medium $p$, and high $k$/medium $p$. By high, medium, and low we mean the maximum, median, and minimum values that $k$ and $p$ take in the baseline simulation. Cash flow is defined precisely as $(1 - \tau_c)\pi(k, z)/k^*$, investment as $((k' - (1 - d)k) - A(k, k'))/k^*$, saving as $(p' / (1 + r (1 - \tau_c)) - p)/k^*$, and net distributions/equity issuance as $(e(k, k', p, p', z) + \phi(e(k, k', p, p', z)))/k^*$, in which $k^*$ is the steady-state level of the capital stock. We deflate our variables of interest by $k^*$ for the three differently sized firms to facilitate comparisons between them.

Figure 1 contains these plots, with the three panels depicting a small, a medium, and a large firm, respectively. In all three panels cash flow naturally rises with the $z$ shock. These cash flows are, however, distributed differently depending on the size of the firm.

For the small firm investment rises smoothly with cash flows. Despite the presence of adjustment costs, the capital stock is so low and the marginal product of capital so high that a higher value of $z$ almost always means more investment. The behavior of saving, in contrast, is non-monotonic. Although the small firm always saves, saving initially rises with $z$ and then falls. This hump-shaped pattern reflects income and substitution effects. As $z$ rises, the firm expects that with positively correlated shocks, capital will be productive in the future and revert back to its mean slowly. The income effect implies that the firm saves more in order to lower the likelihood that it will have to turn to equity issuance to fund possible future investment. The substitution effect implies that the firm saves less because it wants to shift some of its liquid assets into physical assets that become increasingly productive with $z$. Clearly, the income effect dominates for low levels of $z$, and the substitution effect dominates for high levels of $z$. In the model distributions/equity issuance is a residual. For a small firm the marginal product of capital is sufficiently high that it is optimal for the firm to issue equity and pay issuance costs regardless of the level of the productivity shock.

The medium firm behaves quite differently. First, the optimal investment rule displays substantial inertia. For low levels of $z$ the firm sells capital, but for intermediate and high levels of $z$ the firm invests. Investment initially rises with $z$, but then flattens out, rising once again when $z$ is
high. Adjustment costs clearly produce this inertia. Saving also behaves differently in the medium-sized firm. Saving is always negative and always decreases with $z$ and with cash flow because the substitution effect always dominates the income effect. This negative correlation between cash flow and saving is crucial for understanding the saving sensitivity results that follow. Finally, for low levels of $z$, the firm finds it optimal to distribute excess funds to shareholders because the benefits of investing do not outweigh the costs of issuance. However, if $z$ rises to a sufficiently high level, the benefits from investing start to outweigh issuance costs, and the firm issues equity.

The large firm, not surprisingly, sells capital for low to intermediate levels of $z$ because the marginal product of capital is low. Although investment eventually becomes positive as $z$ rises, the presence of adjustment costs combined with the low marginal product cause the rate of investment to level out for very high levels of $z$. Saving initially declines with $z$ because of the substitution effect, which operates even though the firm is disinvesting. As $z$ rises, the firm moves to increasingly higher optimal levels of the capital stock and lower levels of cash. However, dissaving flattens out for high levels of $z$ because the model does not allow for negative cash (i.e. debt).

C. Experiments

With the model intuition in hand we now turn to our simulation results. We investigate two ways in which the model’s parameters affect the firm’s cash and saving policies. We first consider how the parameters affect the level of cash as a fraction of assets, which is defined in our model as the average of $p/k$ over all of the observations in the simulated panel. We then examine how the parameters affect a measure of saving behavior that first appears in Almeida, et al. (2004). Dubbed “the cash-flow sensitivity of cash,” this measure is defined in our model as the regression coefficient, $\alpha_1$, in the following regression:

$$\frac{p' - p}{k} = \alpha_0 + \beta \frac{V(k,p,z)}{k} + \alpha_1 \frac{\pi(k,z)}{k} + \alpha_2 \ln(k) + u,$$

in which $\alpha_0$, $\alpha_1$, $\alpha_2$, and $\beta$ are regression coefficients and $u$ is a regression disturbance, which in our simulations is, by definition, orthogonal to the regressors.\footnote{If we do not deflate the variables in (9) by $k$ or if we deflate the variables in (9) by total assets, $(k + p)$, rather than by $k$, the results change little.} This regression comes directly from Almeida, et al. (2004), and we estimate it with all of the observations in the simulated panel.
In thinking about the results that follow, it is crucial to separate cash levels from the cash-flow sensitivity of cash, the latter of which we also refer to as the saving sensitivity or as the propensity to save. It is also important to separate the average change in cash (saving) from the saving sensitivity, which is just the partial correlation between cash flow and saving. A positive or negative sensitivity does not imply that the firm always saves or always dissaves. Indeed, in most of our simulations, average saving as a fraction of $k$ is small and positive.

We examine the sensitivity of these two gauges of cash policy to eight key model parameters: the variance and serial correlation of income; the three equity-cost parameters, $\lambda_0$, $\lambda_1$, and $\lambda_2$; the curvature of the profit function, $\theta$; and the fixed and quadratic adjustment cost parameters, $c$ and $a$. In each of the experiments that follow, we set all but one of the parameters equal to their baseline levels as defined above, allowing the free parameter to range within a given interval. We allow $\theta$ to range between 0.6 and 0.9, $\rho$ to range from -0.8 to 0.8, $\sigma_v$ to range from 0.075 to 0.15, $\lambda_0$ to range from 0 to 0.8, $\lambda_1$ to range from 0 to 0.1, $\lambda_2$ to range from 0 to 0.0004, $c$ to range from 0 to 0.8, and $a$ to range from 0 to 0.1.

Figure 2 illustrates the dependence on the model parameters of our first measure—the ratio of the level of cash holdings to the capital stock. We first examine the parameters that govern the stochastic shock process. The first panel shows that the relation between the serial correlation of income, $\rho$, and cash holdings is slightly u-shaped. For both highly positively and highly negatively correlated shocks, the firm holds high cash balances, choosing lower balances if the shocks are less highly correlated. Two separate effects explain this result. First, as the serial correlation of the income process increases, the firm tends to invest in larger amounts because a positive productivity shock signals not only that capital is productive today, but also that it will continue to be productive in the future. The firm therefore wants higher cash balances so that it will be less likely to need external finance when it makes these large investments. Second, the higher the serial correlation of an AR(1) process, the higher its variance. If the firm faces an uncertain environment, it expects to tap external finance more often, and it holds higher cash balances. Both effects operate in the same direction for high levels of $\rho$, but they appear to offset each other for levels near zero. For levels of
\(\rho\) far below zero, the second effect dominates.\(^3\) The intuition about the variance of the process is also evident in the second panel, which depicts a positive relation between cash holdings and \(\sigma_u\), the variance of the innovations to \(z\).

We next examine the effects of the cost of external finance. The third through fifth panels illustrate the relations between each of the external finance parameters and cash holdings. Not surprisingly, the third and fourth panels show that cash increases with the fixed and linear components of the external finance function, \(\lambda_0\) and \(\lambda_1\), because the value of financial flexibility increases as external finance becomes more costly. However, the relation shown in the fifth panel between the quadratic component, \(\lambda_2\), and cash holdings is only slightly upward sloping. With \(\lambda_0\) and \(\lambda_1\) set to their baseline levels, the effect of \(\lambda_2\) is second-order.\(^4\) These results mirror those in the two-period model of Almeida, et al. (2004), which produces a partial derivative of cash with respect to internal funds that is positive for a financially constrained firm, and zero otherwise.

Finally, we examine the effects of technology in the sixth through eighth panels. The sixth panel shows that the effect of \(\theta\) on cash is hump-shaped, initially rising and then falling slightly. Two different economic forces create this pattern. First, as \(\theta\) rises, the production function becomes flatter, and the average size of desired investments rises. The firm holds more cash because large investments imply a greater likelihood of needing external finance. Second, as \(\theta\) rises, the firm is less likely to have to tap external finance because a higher \(\theta\) implies that a given capital stock can create more internal revenue, and the firm therefore needs to hold less cash. The first effect is stronger for lower levels of \(\theta\), and the second effect is stronger for higher levels of \(\theta\). The seventh panel shows that cash holding increases with the fixed cost of adjustment. This effect occurs because higher fixed adjustment costs lead to larger investments that occur less frequently. The firm then uses episodes of inaction to accumulate cash, which acts to lower the probability of the firm having to tap external finance when it does invest. Finally, the eighth panel shows the effect of an increase in the convex component of adjustment costs. Not surprisingly, convex adjustment costs have the

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\(^3\)Simulations in which \(\rho\) increases but the variance of the process is held constant produces a similar result, except that the rise in cash holdings for very low \(\rho\) flattens out.

\(^4\)This last result may possibly be an artifact of the presence of quadratic physical adjustment in the model because the latter would swamp the former. However, these two sets of costs appear to be operating on different margins because turning off the quadratic physical adjustment costs has almost no effect on the pattern observed for \(\lambda_2\).
opposite effect on cash holding. As $a$ increases, the firm makes smaller investment more often, is therefore less likely to have to tap external finance, and holds less cash.

These results on the level of cash balances reassuringly confirm those in Gamba and Triantis (2006), in particular their results on the effects of uncertainty and the cost of external finance. Our results on cash levels are also useful in providing intuition for the main focus of this paper, which is not cash levels, per se, but the propensity to save.

Figure 3 is analogous to Figure 2, except that it depicts the dependence on the model parameters of our second measure of cash policy—the coefficient $\alpha_1$ in (9); that is, sensitivity of saving to cash flow. A quick glance at the figure reveals that for almost all model parameterizations the sensitivity of saving of cash flow is negative. Because this result is the opposite of that produced by the model in Almeida et al. (2004), it is worthwhile to examine why. The answer lies in the difference between income and substitution effects. In our model when a firm receives a positive income shock, its cash flow rises, and if the effect of the shock is not too transitory, the current and future productivity of capital rise. The firm wants to save more in case it needs to finance future investment. However, this income effect is counteracted by a substitution effect, which implies that the firm wants to transform its financial assets into physical capital, that is, dissave. In a regression of saving on $q$ and cash flow, both $q$ and cash flow contain information about capital productivity. However, $q$ is the more forward looking of the two variables, so it picks up the income effect, which pertains to the financing of future investment. Cash flow then picks up the substitution effect, and we observe a negative coefficient on cash flow. In contrast, in the Almeida, et al. (2004) model the sensitivity of saving to cash flow is defined as the response of cash holding to an exogenous increase in the firm's endowment, which does not affect capital productivity. Therefore, their model produces a positive sensitivity because they only capture the income effect.

We now turn to a more detailed discussion of Figure 3. The first panel shows our most interesting simulation result, which is the effect of $\rho$ on $\alpha_1$. For a highly negatively correlated shock process, this sensitivity is large and positive; for a highly positively correlated shock process, it is large and negative; and for a predominantly serially uncorrelated income process, it is small and negative. This pattern arises out of the firm’s expectation about future needs to tap external finance and
about the current and future productivity of capital. If profits are negatively serially correlated, then a positive shock implies an expected productivity decline, which in turn implies a low need for external finance. This income effect promotes dissaving. A stronger substitution effect, however, promotes saving because the expected productivity decline implies that it is optimal for the firm to funnel cash flow into liquid assets and distributions rather than into investment. On the other hand, if the firm faces highly positively correlated income shocks, then when it experiences a positive shock, it expects capital to become more productive and remain productive. An income effect promotes saving because it expects to have to fund future investment. Once again, however, a stronger substitution effect promotes dissaving because the firm finds it optimal to transform liquid assets into productive assets.

The second panel illustrates the effect of the shock variance. Saving sensitivity is always negative, but becomes less so as $\sigma_v$ increases. As the firm’s environment becomes more uncertain, its level of cash holdings increases, but it also becomes more reluctant to change its cash holdings aggressively in response to shocks, which convey little information in an uncertain environment.

We now turn to the effects of the cost of external finance. The patterns evident in the third through fifth panels mirror those in the corresponding panels in Figure 2. In all cases, as the cost of external finance increases, the level of cash holdings increases, and the sensitivity of saving to cash flow becomes more negative. The firm accumulates financial slack when the cost of external finance rises. It can therefore respond to shocks more aggressively by changing the level of cash. For example, if a firm with a great deal of financial slack is hit by a positive profit shock, it will dissave a great deal in order to invest. An otherwise identical firm with little financial slack will not be able to dissave as much.

Finally, we examine technology. Saving sensitivity becomes more negative as $\theta$ increases; that is, as the production function becomes flatter. With a flat production function shocks induce large desired changes in the capital stock, and the firm dissaves to fund these investments. Saving sensitivity also becomes more negative as both types of adjustment costs increase. As higher adjustment costs cause investment policy to become less flexible, the firm compensates by making
its saving policy more flexible. This effect also operates in Gamba and Triantis (2006).\(^5\)

The preceding arguments are valid at points in time in which the firm is actively adjusting its capital stock. During periods of inaction, the sensitivity of saving to cash flow is positive because the firm funnels at least part of its cash flow into cash holdings in order to avoid tapping external finance in the future. Under almost all parameterizations of this model the firm adjusts more often than it remains inactive. The observations in which the saving sensitivity is negative therefore outweigh those in which it is positive, and average sensitivity is negative. If the firm faces very large fixed adjustment costs, however, it is inactive more often than it invests, the observations with positive sensitivity outweigh those with negative sensitivity, and average sensitivity is positive. We view this latter scenario as mostly likely for very small firms because they are the only ones whose investment tends to occur in large spikes.

The frequent adjustment in our model sets it apart from models of dynamic capital structure with adjustment costs. For example, in Fischer, Heinkel, and Zechner (1989), the firm adjusts its asset and liability composition infrequently. As pointed out in Strebulaev (2006), empirical predictions from this sort of model cannot be based solely on firm behavior at points in time at which the firm is active. The frequent adjustment in our model allows us to sidestep this critique. Frequent adjustment also explains why corporate propensities to save can be negative even though personal propensities to save are typically positive. Although consumers dissave when they purchase durables, these events are infrequent, and because consumers save out of income at other times, average saving propensities are therefore positive.

Because we are interested in the effect of measurement error in observed Tobin’s \(q\) in our data, we conduct a further simulation in which we introduce an additive \(i.i.d.\) measurement error to \(V(k, p, z)/k\). Measurement error biases the coefficient on \(V(k, p, z)/k\) downward, but it biases the coefficient on \(\pi(k, z)/k\) upward because of the strong positive correlation between \(\pi(k, z)/k\) and \(V(k, p, z)/k\). We find that the baseline simulation requires a great deal of measurement error to reverse the initially negative sign of the coefficient on cash flow. The error variance needs to be

\(^5\)Two parameters we have left out of the analysis are the depreciation rate, \(d\), and the interest rate, \(r\). Decreasing the depreciation rate or increasing the discount rate lowers the average size of investments, the need for external finance, and cash levels. The saving propensity remains negative but decreases in absolute value.
at least 8 times as large as the variance of $V(k,p,z)/k$. This result is not out of line with the empirical results that follow inasmuch as we find that the measurement quality of observed Tobin’s $q$ is extremely low, or equivalently, that the measurement error variance is high.

In sum, these experiments highlight three important pieces of economic intuition. First, corporate saving depends not only on the firm’s financial environment, but also on its technological environment. Second, variation in capital productivity is critical for our results, because a model cannot capture the firm’s desire to substitute capital for cash is the marginal product of capital is constant. Third, although the levels and changes in cash are clearly related, a high cash level does not necessarily imply a high positive sensitivity of saving to cash flow; nor does a low cash level imply a low sensitivity. We emphasize again that this distinction is impossible to uncover in a static model because the change in cash cannot be distinguished from the level of cash.

D. Empirical Predictions

The simulations in Figure 3 delineate the four central empirical predictions we wish to test. First, the sign of $\alpha_1$ in (9) should be negative. Because this prediction takes the form of the sign of a slope coefficient in a linear projection, and because the error term in a linear projection is by definition orthogonal to the right-hand-side variables, testing the prediction with an exactly equivalent real-data linear projection (regression) avoids the usual simultaneity problems that plague regressions in corporate finance. Testing this prediction in this manner also forms a strong link between the theory and its test, because the form of the real-data test is identical to the form of the simulated-data theoretical prediction. Second, $\alpha_1$ should increase in absolute value with the cost of external finance; third, $\alpha_1$ should decrease in absolute value with $\sigma_\varepsilon$; and fourth, $\alpha_1$ should increase in absolute value with $\rho$. We do not directly test any predictions concerning the relation between $\alpha_1$ and either profit function curvature or adjustment costs because proxies for these two model features are unavailable at the firm level. The simulations that examine curvature and adjustment costs do, however, provide intuition that assists with the interpretation of some of our results.
E. Model Robustness

The model is intentionally sparse to highlight the intuition behind the interaction between saving and investment, as well as the trade-off between the tax penalty on saving and the cost of external finance. To assuage concerns that our results are an artifact of the model’s simplicity, in this section we add a variety of more realistic features to the model to examine the robustness of our result of a negative propensity to save. First, in the baseline model the firm does not have access to a credit line. When we add riskless short-term debt that is secured by the capital stock, as in Hennessy and Whited (2005), the saving propensity of -0.78 in the baseline simulation drops in absolute value to -0.41. Our results are attenuated but not erased because the upper limit to the credit line causes cash to retain its value as a tool to avoid costly external finance. Second, the baseline firm does not smooth distributions to shareholders. To address this possibility, we penalize the firm by the amount of the linear equity issuance cost for every dollar that its distributions fall below the average level of distributions in the baseline simulation. This model feature produces increased cash hoarding because the firm wants to avoid missing a distribution. This higher cash cushion leads to a more negative propensity to save of -0.86. Third, the baseline firm has no fixed costs of production, which could, for example, represent the tendency of young firms to burn profits. We add a cost of production equal to 0.4\(k\), in which 0.4 is the approximate ratio of selling, general, and administrative expenses to assets in our U.S. sample. This addition to the model produces less cash holding relative to our baseline model because the firm has smaller profits to funnel into liquid assets. Accordingly, the saving propensity drops in absolute value to -0.26. Fifth, we consider the possibility that the firm may issue risky debt, which we model exactly as in Hennessy and Whited (2006). This approach necessitates the exclusion of any physical adjustment costs. In this case the firm hoards more cash than in the baseline simulation in order to avoid default, and the saving propensity rises in absolute value to -0.88. Finally, because our model contains only one source of uncertainty, productivity shocks and cash flow are almost perfectly correlated. Therefore, the dissaving that occurs with a positive productivity shock is necessarily accompanied by a rise in cash flow. To ascertain whether our finding of a negative saving propensity is hardwired by this feature of our in model, we allow the net revenue function to take the form \(zk^\theta - \eta\), in which \(\eta\)
is a normally distributed, zero-mean, \textit{i.i.d.} random variable with a variance equal to that of the \( z \) shock. This new cost shock takes four points of support, and its transition matrix is given by the method in Tauchen (1986). Not surprisingly, decoupling cash flows from the productivity shock produces a much smaller (in absolute value) propensity to save. It is, however, still negative at a value of -0.15. We choose to exclude these features from our baseline model because they do not change the qualitative outcomes of the simulation and because the empirical emphasis of the paper lends itself to a simple structure that stresses intuition.

The second set of robustness checks relates to the connection between estimating (9) with simulated data and with real data. The cross sections generated by the model contain 10,000 identical firms over 20 time periods. This simulated cross-section asymptotically generates the same results as a single time series with 200,000 observations. In contrast, our real data contains cross sections that contain heterogeneous firms. It is therefore interesting to see whether a simulated panel of heterogeneous firms can generate the same negative sensitivities as a simulated panel of identical firms. Otherwise, the connection between the theory and its tests becomes tenuous.

Adding heterogeneity to the simulated sample ought to produce a positive sensitivity only when most of the simulated firms come from an environment that generates a positive sensitivity. The predominantly negative sensitivities seen in Figure 3 indicate that a positive sensitivity is only likely to arise in a panel that is heterogeneous along the lines the serial correlation parameter, \( \rho \). Indeed, we find negative sensitivities when we add heterogeneity by varying the shock standard deviation \( (\sigma) \), issuance costs \( (\lambda_0, \lambda_1, \lambda_2) \), returns to scale \( (\theta) \), and fixed and smooth adjustment costs \( c, a \). In contrast, when we divide the cross section into 10 groups with values of \( \rho \) equally spaced between -0.8 and 0.8, we find a small positive sensitivity of 0.008. This result begs the question of the cross-sectional distribution of the serial correlation of income in our real data. To answer the question, we use our U.S. data to estimate a first-order autoregression of operating income either firm-by-firm or industry-by-industry, in which an industry is defined at the three-digit level. For the firm-by-firm autoregressions we find that only 7.1\% of our firms have negatively serially correlated income. For the industry-by-industry autoregressions we never find negatively serially correlated income. To add heterogeneity in serial correlation that approximates the situation in our data set, we rerun
our simulation with the cross section divided into 10 groups with values of \( \rho \) that approximate the firm-level cross-sectional distribution of income serial correlation in our real data. In this case we do find a negative sensitivity.

It is also interesting to see whether we can generate a positive sensitivity by adding heterogeneity to the sample by varying parameters not examined in Figure 3. We look at the discount factor \((\beta)\), the rate of capital depreciation \((d)\), and the drift of the shock process, the latter of which we model by adding an intercept to (8). In none of these cases are we able to generate a positive sensitivity. As a final note, we can generate a positive sensitivity by turning off the smooth adjustment costs and multiplying the fixed adjustment costs by a factor of 10. In this simulation the firm invests very sporadically in very large spikes, accumulating cash during the periods of inactivity. Because real-world firms invest almost every year, we view this simulation as a curiosity that is not relevant to our data analysis.

III. Data and Summary Statistics

We draw data from two sources. We obtain data on U.S. nonfinancial firms from the combined annual, research, and full coverage 2005 Standard and Poor’s Compustat industrial files. These data constitute an unbalanced panel that covers the period 1972 to 2004. We also draw data for international nonfinancial firms from Standard and Poor’s Compustat Global Issue and Industrial/Commercial for five more countries: Canada, France, Germany, Japan, and the United Kingdom. These data also constitute an unbalanced panel, but it covers a shorter period, 1997-2004, because Global Vantage does not have the depth of coverage that Compustat does. Summary statistics are in Table 1. We see large differences in most instances between our means and medians. This skewness is essential for identifying our econometric model. The mean and median measures of Tobin’s \( q \) (market to book) are greatest in the United States and lowest in Japan and France. Not surprisingly, the investment rates in Japan and France are low. Only France shows negative mean investment, but its median investment level is positive, though small compared with investment in the other countries. All means and medians of Tobin’s \( q \) are greater than 1. Although this pattern is commonly viewed as an indication of positive investment opportunities, adjustment and instal-
lation costs in the investment process and market power can leave \( q \) above 1 even for firms without positive investment opportunities. The average change in the cash stock is negative in the United Kingdom, Japan, France and Germany, whereas it is positive in the United States and Canada. The number of average number of observations per year is available is in the last column. The United States and Japan on average both have over 2,500 observations per year, whereas Canada, France, and Germany each have less than 400. Because our estimation method requires a great deal of data, the variation in sample size across countries manifests itself in the precision of the estimates we obtain from each country.

IV. Estimation

This section first outlines the econometric methodology. It next presents the results and their interpretation.

A. Methods

Our testing strategy is based on the estimators in Erickson and Whited (2000, 2002). These estimators employ the structure of the classical errors-in-variables model. Applied to a single cross section, this model can be written as

\[
y_i = w_i \alpha + \chi_i \beta + u_i, \tag{10}
\]

\[
x_i = \gamma + \chi_i + \varepsilon_i. \tag{11}
\]

In our application \( y_i \) is the ratio of the change in cash to assets, \( \chi_i \) is the true \( q \) of firm \( i \), \( x_i \) is an estimate of its true \( q \), and \( w_i \) is a row vector of perfectly measured regressors, whose first entry is 1, whose second entry is the ratio of cash flow to assets, and whose third entry is the natural log of total assets. The regression error, \( u_i \), and the measurement error, \( \varepsilon_i \), are assumed to be independent of each other and of \((w_i, \chi_i)\), and the observations, \((\varepsilon_i, u_i, w_i, \chi_i)\), \( i = 1, \ldots, n \), are \( i.i.d. \). The intercept, \( \gamma \), in (11) allows for systematic bias in the measurement of \( \chi_i \). We do not require any assumptions about the temporal dependence or independence of \((\chi_i, w_i, u_i, \varepsilon_i)\).

To derive a set of tractable moment conditions to be estimated by GMM, the vector of perfectly measured variables, \( w_i \), must be partialled out of equations (10) and (11). Let \((\hat{y}_i, \hat{x}_i, \hat{\chi}_i)\) be the...
residuals from the linear projection of \((y_i, x_i, \chi_i)\) on \(w_i\). Then (10) and (11) can be written as
\[\hat{y}_i = \beta \hat{x}_i + u_i\] (12)
\[\hat{x}_i = \hat{\chi}_i + \varepsilon_i.\] (13)

If we square (12), multiply the result by (13), and take unconditional expectations of both sides, we obtain
\[E (\hat{y}_i^2 \hat{x}_i) = \beta^2 E (\hat{\chi}_i^2).\] (14)

Analogously, if we square (13), multiply the result by (12), and take unconditional expectations of both sides, we obtain
\[E (\hat{y}_i \hat{x}_i^2) = \beta E (\hat{\chi}_i^3).\] (15)

As shown in Geary (1942), if \(\beta \neq 0\) and \(E (\hat{\chi}_i^3) \neq 0\), dividing (14) by (15) produces a consistent estimator for \(\beta\) that equals \(E (\hat{y}_i^2 \hat{x}_i) / E (\hat{y}_i \hat{x}_i^2)\). The assumptions, \(\beta \neq 0\) and \(E (\hat{\chi}_i^3) \neq 0\), are necessary for identification because one cannot divide by zero. These assumptions can be tested via the null hypothesis that \(E (\hat{y}_i^2 \hat{x}_i) = 0\) and \(E (\hat{y}_i \hat{x}_i^2) = 0\). We refer this test hereafter as an identification test. It is a useful regression diagnostic inasmuch as it provides information as to whether the coefficient estimates are reliable. For example, if \(\hat{\chi}_i\) is nearly normally distributed, the identification test will not produce a rejection and the coefficient standard errors will be large.

This estimator is a third-order moment estimator. The innovation in Erickson and Whited (2000, 2002) consists of combining the information in moment equations of orders two through seven via GMM to obtain a more efficient estimator for \(\beta\). It is possible to estimate many interesting quantities besides \(\beta\). For example, the coefficient of determination \(R^2\) for (11) is given by:
\[R^2 = \frac{\mu_y}{\mu_x} \frac{\text{var}(w_i) \mu_x + E (\hat{\chi}_i^2)}{\text{var}(w_i) \mu_x + E (\hat{\chi}_i^2) + E (\varepsilon_i^2)}.\] (16)

It is a useful index of measurement quality for our observable proxy for unobservable investment opportunities. A value close to one indicates a nearly perfect proxy, and a value close to zero indicates a nearly worthless proxy.\(^6\)

More important, we can estimate the coefficient vector \(\alpha\), which can be recovered by the identity
\[\alpha = \mu_y - \beta \mu_x.\] (17)

\(^6\)An exactly analogous formula provides the measurement-error consistent estimate of the \(R^2\) of (10).
in which \((\mu_y, \mu_x)\) are the vectors of coefficients in the population projection of \((y_i, x_i)\) on \(w_i\).

This identity is useful for understanding why measurement error in Tobin’s \(q\) biases the cash-flow coefficient even when saving is on the left side of the regression. To simplify the explanation, we isolate \(\alpha_1\), the cash-flow coefficient, and rewrite the second element of the vector equation (17) as

\[
\alpha_1 \equiv \mu_{1y} - \beta \mu_{1x}. \tag{18}
\]

The first term in (18), \(\mu_{1y}\), is the coefficient on cash flow one would obtain if one were to regress saving on only cash flow and firm size. The second term represents the extent to which \(\mu_{1y}\) changes when one controls for true unobservable Tobin’s \(q\). This term clarifies the way in which measurement error in Tobin’s \(q\) can bias the cash flow coefficient. It is well-known that measurement error biases \(\beta\) downward, and the amount of bias is approximately proportional to \(\tau^2\). If \(\mu_{1x} = 0\), then this downward bias has no effect on the coefficient on cash flow. However, if \(\mu_{1x} \neq 0\), then a downward biased \(\beta\) can affect the cash-flow coefficient, \(\alpha_1\). Recall that \(\mu_{1x}\) is the slope coefficient on cash flow one obtains from regressing observable Tobin’s \(q\) on cash flow and size. Because Tobin’s \(q\) and cash flow are positively correlated with one another, and because the variance of Tobin’s \(q\) is much greater than the variance of cash flow, \(\mu_{1x}\) can be large. In our application it ranges from 1 to 5. Therefore, a small downward bias in \(\beta\) can cause a large upward bias in the OLS estimate of the cash flow coefficient. Finally, it is crucial to note that the correlation between the left-hand-side variable and the right-hand-side variables has no effect on the bias in the coefficient, \(\alpha_1\). Instead, what matters is the covariance matrix of the regressors. Therefore, measurement error in Tobin’s \(q\) can bias other regression coefficients regardless of the left-hand-side variable.

The Appendix presents Monte Carlo simulations to assess the finite sample performance of these estimators on data closely resembling our own. Of particular interest in these Monte Carlos are the tests of the null hypothesis that the coefficient on cash flow equals its true value. The actual sizes of many of these tests are tiny relative to their nominal sizes. This result indicates that the finite-sample distribution of the GMM estimates of the t-statistics has thin tails. Also, this result is the opposite of that found in Erickson and Whited (2000) for investment regressions.

Because these estimators can only be applied to samples that are arguably i.i.d., we estimate (10) and (11) for each cross section of our unbalanced panel and then pool the yearly estimates.
from our unbalanced panel via the procedure in Fama and MacBeth (1973). We do not include firm fixed effects in our regressions for two reasons. First, the resulting model almost never passes the identification test because removing fixed effect removes a great deal of data variation and therefore a great deal of the skewness and kurtosis that identify the slope coefficients. Second, when we compare the results from running fixed-effects OLS with those from using the OLS and Fama-MacBeth approach, we find almost identical coefficient estimates. Further, when we do a standard Hausman test to determine whether a potential fixed effect is correlated with the regressors, we cannot reject the null of no correlation. This result suggests that the within-firm variation in saving and \( q \) mirrors the cross sectional variation. Although it is somewhat unconventional not to control for fixed effects when one has panel data available, if removing fixed effects produces no discernible differences in the results, then it is better not to do so because the procedure uses up valuable degrees of freedom and removes interesting data variation.\(^7\)

Recently, Petersen (2007) has re-emphasized that Fama-MacBeth standard errors are often inappropriate in panel data and that they can produce inflated t-statistics. Further, because we put no restrictions on the time series properties of \((\chi_i, u_i, \varepsilon_i)\), we open the door for the finite-sample critical values the Fama-MacBeth t-statistics to be much higher than the nominal critical values. We deal with this issue by using the bootstrap in Hall and Horowitz (1996) to calculate the finite-sample distribution of the t-statistics produced with the Fama-MacBeth standard errors. The unit of observation for resampling is the firm. Interestingly, we find that many of these bootstrapped critical values are only slightly higher than the asymptotic critical values, although in several instances we do find bootstrapped critical values for a nominal 5% two-sided t-test as high as five, especially in the case of the GMM estimates of the coefficient on \( \chi_i \).

B. Results

The Fama-MacBeth results from estimating (10) via OLS and from estimating (10) and (11) via GMM for each of our six countries are in Table 2. The left panel shows the OLS results, and the right panel shows the GMM results. We report the OLS estimate of the regression \( R^2 \) in column 3, and the

\(^7\)Because firms in the same industry may be cross-sectionally dependent, we also include two-digit industry fixed effects. The results are similar, although we find more unidentified models and consequently higher standard errors.
measurement-error consistent GMM estimate of the regression $R^2$ in column 6. Column 7 contains the estimate of our index of measurement quality: $\tau^2$. Coefficient of determination of (11) (denoted $\tau^2$), which is a useful index of measurement quality for our observable proxy for unobservable investment opportunities. Asymptotic standard errors are in parentheses below each parameter estimate. Asterisks mark parameter estimates whose t-statistics exceed the 5% bootstrapped critical values, and daggers mark those estimates whose t-statistics exceed the asymptotic 5% critical values.

For each country we test our first prediction that the coefficient on cash flow is negative in a regression of saving on $q$, cash flow, and size. Our OLS results corroborate earlier findings that the coefficients on both Tobin’s $q$ and cash flow are positive for all countries, as in, e.g., Almeida, et al. (2004) and Khurana, et al. (2006). However, when we apply the Erickson and Whited estimators to correct for measurement error in $q$, the results change. We find negative coefficients on cash flow in all six countries, and half of the cash-flow coefficients are statistically significant according to our bootstrapped critical values. These results correspond to our model simulation results for firms that have positively serially correlated income processes. The effect of treating measurement error can also be seen in the GMM coefficients on $q$, which are from seven to fifteen times as high as their OLS counterparts in the different countries. This result can be explained by the attenuation bias in the classical errors-in-variables model, which in this case is very large because of the low measurement quality of observed Tobin’s $q$, which can be seen in the low estimates for $\tau^2$. Finally, correcting for measurement error increases the regression $R^2$ substantially because measurement error obscures the contribution of true Tobin’s $q$ to the variation in saving.

The flip in the sign of the cash-flow coefficient can be understood as follows. On average in our regressions $\mu_{1y}$ is about 0.15, and $\mu_{1x}$ is about 2. The biased OLS estimates of $\beta$, which hovers around 0.02, therefore produce a positive cash-flow coefficient when plugged into the above identity, $\alpha_1 = \mu_{1y} - \beta \mu_{1x}$, with these values for $\mu_{1y}$ and $\mu_{1x}$. In contrast, the consistent GMM estimate of $\beta$, which hovers around 0.2, produces a negative cash-flow coefficient when plugged into this identity. The result is extreme because the measurement quality of the market-to-book ratio is so bad that its coefficient, $\beta$, is biased downward severely.

What are the economics behind this econometric result? Our simulations provide some insight.
Recall that in the regressions on simulated data, Tobin’s q picks up the positive income effect on saving. If one uses a noisy proxy for true Tobin’s q and therefore only controls only for part of its variation, cash flow ends up picking up this income effect. Although the model provides some intuition for the result, it does not provide a complete explanation, because it is difficult to believe that the income effect on saving is extremely strong. However, Tobin’s q picks up not only the income effect but also any other reasons for holding cash that are capitalized by the stock market. Clearly, not controlling for these motivations for cash holding causes cash flow to pick them up and contributes to making its OLS coefficient positive.

We now turn to the reliability of these regression results. Table 3 presents four summary statistics from the yearly regressions that underlie the Fama-MacBeth estimates in Table 2: the fraction of years with negative cash-flow coefficients, the fraction of years with cash-flow coefficients that are significantly negative at the 5% level, the fraction of years in which the overidentifying restrictions of the model are rejected at the 5% level, and the fraction of years in which the null of no model identification is rejected at the 5% level. In nearly all years for all countries we find negative cash flow coefficients, and in over 60% of the years we find significantly negative coefficients. Sample size almost assuredly affects our ability to find statistical significance when using the GMM estimator inasmuch as a great deal of data is required to estimate high order moments with precision. As is common when using international data, in some countries—particularly Canada, France, and Germany—we have smaller samples than we would like. Another difficulty that leaves us with insignificant coefficients is our frequent failure to reject the null of an unidentified model in three of the six countries: Canada, the United Kingdom, and Germany.8 This problem tends to manifest itself in high standard errors. Given these difficulties, our finding of a high incidence of significant coefficients is all the more striking.

Finally, Table 3 shows that we fail to reject the overidentifying restrictions from our yearly GMM estimates in all countries for most years. This result mitigates concerns about possible model misspecification. For example, although \( u_i \) is by construction uncorrelated with \( (\chi_i, w_i) \), it may not be independent of \( (\chi_i, w_i) \). Similarly, \( \varepsilon_i \) may not be independent of \( (\chi_i, w_i) \), or the true

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8 Several researchers have dubbed this test a “pre-sampling” test and have used it to select samples on which the estimator is identified. We do not follow this practice. Instead, we select our sample based on data availability.
form of the regression (10) may be nonlinear. Nonetheless, even though the classical errors-in-
variables model is not a perfect representation of the relationship between saving, cash flow, and
Tobin’s $q$, our tests indicate that we have a useful approximation. Our failure to reject is even more
interesting given the Monte Carlo result in the Appendix that this test has a slight tendency to
over-reject in finite samples. More important, the Appendix shows that this test has good power
to detect modest amounts of model misspecification.

Next we test our second prediction that the cash-flow coefficient is more negative for firms
with more costly external finance. To this end we split our sample of U.S. firms according to two
measures of financial constraints: firm size and the existence of a bond rating.\footnote{We omit other,
commonly used measures of finance constraints such as dividend payout and the KZ index (from
Kaplan and Zingales, 1997) because they are endogenously determined with investment. We omit the existence of a
commercial paper rating because too few firms have these.} We only have
enough observations to perform sample splits in the U.S. and Japanese data, and, for brevity, we
only present the results from the U.S. data. Although our results using Japanese data are similar,
Japanese firms are not sufficiently heterogeneous along our lines of interest for us to find any
significant differences between the different groups.

We define a firm as large if the book value of its assets lies above the 67\textsuperscript{th} percentile and small
if its assets lie below the 33\textsuperscript{rd} percentile. In the literature on external finance constraints, size
is often used as an indicator of the cost of raising external funds. Using size as an indicator of
the cost of external finance confers an important advantage over other indicators such as dividend
payout. It can be considered exogenous, because firm size is not a choice variable for the manager
in the short run and because our estimates exploit cross sectional data variation instead of time
series variation. The intuition behind using the existence of a bond rating is that a firm with a
bond rating has undergone a great deal of public scrutiny and will be less likely to encounter the
asymmetric information problems that lead to financial constraints. We regard bond ratings as
exogenous, because agencies that provide bond ratings tend to base their judgments more on a
consistent history of good financial and operating performance than on current operating decisions.

The first half of Table 4 present the results from these two sample splits. Our OLS results
confirm those in Almeida, et al. (2004) that small firms and firms without bond ratings have a
stronger response of saving to cash flow than their unconstrained counterparts. Our GMM estimates, however, paint a different picture. All of the estimates are negative, and the unconstrained groups of firms have cash-flow coefficients that are significantly more negative than those of the constrained firms. This result does not support the model’s prediction that firms with more costly external finance have more negative cash-flow coefficients. Because of the evidence in Hennessy and Whited (2006) that small firms face more costly external finance than large firms, we conjecture that the effect of the cost of external finance on saving operates in our sample but that the effect of uncertainty is stronger. When we examine differences between the large and small firms, one characteristic that stands out is the marked difference in the degree of uncertainty that they face. We estimate a first-order panel autoregression of the ratio of operating income to assets for both groups of firms, using the technique in Holtz-Eakin, Newey, and Rosen (1988). The standard deviations of the error term for the small firms and the firms without bond ratings are 0.144 and 0.118, respectively, whereas for the large firms and the firms with bond ratings they are only half as large at 0.077 and 0.067. As demonstrated in the model simulations, firms that face a great deal of uncertainty do not make large changes in their cash holdings in response to income shocks.

It is possible that the low sensitivity in the small firms may be due to the tendency of the investment of very small firms to occur infrequently, but in large spikes. During periods of inactivity the firm saves out of cash flow to avoid costly external finance when it does invest. However, we view this possibility as unlikely. In only 5.7% of the firm-year observations in this sample do we observe investment rates greater than twice the firm median. For further discussion of investment spikes in firm-level U.S. data, see Whited (2006).

It is natural look directly at the conjecture that uncertainty matters more than finance constraints by testing our third and fourth predictions; that is, to investigate the relation between saving propensities and the serial correlation and variance of operating income. To this end we estimate an $AR(1)$ for operating income (scaled by total assets) firm by firm, only using firms with at least six consecutive observations. We then sort our sample from the United States on the basis of the estimates of serial correlation and residual standard deviation, throw out the middle third, and compare saving propensities across the top and bottom thirds. We discard the middle
third because firm-by-firm estimates contain a great deal of noise, and we want to minimize the possibility that we incorrectly classify individual firms.¹⁰

The next four lines of Table 4 contain the results for firms grouped by the standard deviation of the residual of the $AR(1)$ process for operating income. As predicted by the model, the low standard deviation group has a large, significantly negative cash-flow coefficient, whereas the high standard deviation group has a cash-flow coefficient that, while statistically different from zero, is also statistically significant from the coefficient from the high standard deviation group. Not surprisingly, given the results on large and small U.S. firms, the low standard deviation group contains firms considerably larger than those in the high standard deviation group. The mean level of assets for the former is 5.264 million 1997 dollars, and the mean level of assets for the latter is 1.380 million 1997 dollars. This result is of further interest because it demonstrates that the degree of uncertainty is not proxying for financial constraints. Otherwise we should have seen a more negative cash-flow coefficient on the high-uncertainty firms, but we do not.

The results from the regressions that examine low and high serial correlation are in the final four lines of Table 4. The GMM estimates of the cash flow coefficient are significantly higher for the high serial correlation firms than for the low serial correlation firms. The former subsample the median serial correlation is near 0.8 and in the latter it is near zero. For the low serial correlation group the cash flow is only significant if one considers the asymptotic 5% critical value instead of the bootstrapped 5% critical value. These results support the simulation that shows a low saving sensitivity if the serial correlation of the income process is low, but a large negative saving sensitivity if the serial correlation is high.

Just as we do for our full-sample results, we also present in Table 5 summary statistics describing the yearly regressions underlying the Fama-MacBeth estimates. We once again find a very low incidence of overidentifying restriction rejections and a fairly high incidence of identification test rejections. Both of these pieces of evidence support the reliability of our split-sample results.

Given our evidence that high uncertainty firms do have lower cash-flow sensitivities, we test directly whether uncertainty matters as much as finance constraints by running a regression of

¹⁰We have also estimated these autoregressions on an industry level with almost identical results.
saving on Tobin’s $q$, the log of assets, cash flow, a constraint dummy, a low uncertainty dummy, the interaction of each of these dummies with cash flow, the interaction of the two dummies with each other, and the triple interaction of both of these dummies with cash flow. We use both of our measures of financial constraints. The results are in Table 6, in which for brevity we only report the cash-flow coefficient and the coefficients on the interactions cash flow with the dummy variables. For both size and the existence of a bond rating, we find a negative coefficient on cash flow, and a positive coefficient on the interaction of cash flow and the constraint dummy. These coefficient estimates confirm the differential sensitivity results in Table 4. Two pieces of evidence are of particular interest in Table 6 and both concern the coefficient reported in the last column of the table, which is the sum of the coefficients on the three interaction terms. It measures the net effect of being constrained and having low uncertainty. When we use size to proxy for finance constraints, this coefficient positive, but insignificantly different from zero if we use our bootstrapped critical values. When we use the bond-rating dummy, this coefficient is negative and significant. In the first case stripping away the high-uncertainty firms from the constrained group leaves no differential sensitivity between this smaller constrained group and the rest of the sample. In the second case stripping away the high-uncertainty firms allows the predicted negative relation between saving propensities and uncertainty to be apparent. Nonetheless, the main message of this table is that both uncertainty and finance constraints affect the cash flow coefficient and that whatever its sign, this coefficient cannot be used as a summary measure of finance constraints.

To conclude, we compare our results with those in Erickson and Whited (2000), who find that the measurement-error consistent estimates of the coefficients on cash flow in a regression of investment on $q$ and cash flow are near zero. This result is puzzling in light of our results on saving because the investment and saving regressions have the same right-hand-side variables and because measurement error bias propagates through the covariance matrix of the right-hand-side variables. The difference lies in a different proxy for investment opportunities in Erickson and Whited (2000). The estimates of $\tau^2$ for this proxy are about 0.4—twice as large as the estimates for our proxy. Therefore, even though both studies find positive OLS estimates of cash flow coefficients, the coefficients in the saving regression are more severely biased upward than the coefficients in the
investment regression. This differential bias implies that the true coefficient in the saving regression is negative and the true coefficient in the investment regression is zero. Not surprisingly, in results not reported for brevity, we are unable to find positive OLS cash-flow coefficients in our saving regressions when using the proxy from Erickson and Whited (2000); and, as is the case here, we find negative GMM estimates of the cash-flow coefficients.

V. Conclusion

The issue of corporate saving has recently received much attention, in large part because of the tendency in recent years of both U.S. and European firms to accumulate a great deal of liquid assets. Prior empirical research, including papers by Opler, Pinkowitz, Stulz, and Williamson (1999), Almeida, et al. (2004), Faulkender and Wang (2006), and Khurana, et al. (2006), has addressed two related issues: why firms hold cash and why firms save, that is, change their cash holdings. We have, for the most part, addressed the second issue. In so doing, we take care to model a firm’s saving, financing, and real investment decisions simultaneously in a stochastic, dynamic framework, to form a strong link between our theory and our empirical tests, and to account for measurement error in our empirical work.

This approach leads us to conclusions quite different from previous theoretical and empirical results. Our theoretical model predicts that in the face of costly external finance, uncertainty in income, and taxation, the firm counteracts movements in cash flow with opposite movements in saving. This negative propensity to save occurs because a positive productivity shock causes both cash flow and the marginal product of capital increase. The firm then wants to decrease its cash stock to buy capital goods that have become relatively more productive, that is, dissave and invest. In contrast, the sensitivity of saving to cash flow in earlier static models, such as the one in Almeida, et al. (2004), is typically positive because good cash flow news is modeled as an increase in the firm’s endowment. The marginal product of capital is unaffected, and the firm has no incentive to transform liquid assets into productive assets. Instead, the firm wants to hold high levels of cash to avoid costly external finance. This income effect operates in our model as well, but our model allows for the existence of a substitution effect, which is stronger. This distinction between
income and substitution effects requires an endogenous investment decision and variation in capital productivity, which earlier work did not consider explicitly. This work could not, therefore, reach our results.

We find strong empirical support for our negative-sensitivity result in data from six countries. When we initially examine this sensitivity using OLS regressions, we find the standard result in the literature that the sensitivity of saving to cash flow is positive. However, when we correct econometrically for measurement error in Tobin’s \( q \), we find the opposite result. We also find that the sensitivity of saving to cash flow increases in absolute value with the serial correlation of income and decreases with the variance of income shocks. Interestingly, the effect of uncertainty on the propensity to save is empirically at least as strong as the effect of financial constraints. A natural consequence of this result is that propensities to save cannot be used as summary measures of the cost of external finance.

Taken together, our simulations and empirical evidence demonstrate that income shocks are at least as important as financial constraints in determining corporate saving. Our results also reemphasize that researchers should determine if any model estimation involving Tobin’s \( q \) has similarly significant bias from mismeasurement. The variable \( q \) is important in many contexts, and its mismeasurement has the potential to bias results in any context where \( q \) is correlated with other variables in the model. Because \( q \) is a broad measure of firm health, it is likely that this correlation issue will be important in many situations, as it is here.
Appendix A. Data Definitions

We select the sample by first deleting any firm-year observations with missing data. Next, we delete any observations for which total assets, the gross capital stock, or sales are either zero or negative. Then for each firm we select the longest consecutive times series of data and exclude firms with only one observation. Finally, we omit all firms whose primary SIC classification is between 4900 and 4999, between 6000 and 6999, or greater than 9000, because our model is inappropriate for regulated, financial, or quasi-public firms.

We define data variables from Global Industrial/Commercial as follows: Book assets is Item 89; investment is Item 193; operating income is Item 14; cash now is the sum of Items 11 and 32; and cash is Item 60. The numerator of the market-to-book ratio is the sum of the market value of equity (Item 3 times Item 13 in Global Issue) and total book assets minus the book value of equity (Item 105+Item 135), and the denominator is book assets. For our U.S. data from Compustat we define book assets as item 6, operating income as item 13, cash flow is the sum of items 14 and 18, cash as item 1, the number of common shares as item 25, and the share price as item 199. In our regressions we scale both saving and cash flow by total assets. We delete the top and bottom 1% of our regression variables.

Appendix B. Monte Carlo Experiments

In order to allay skepticism of empirical results that have been produced by unusual estimators on fairly small samples, in Table 7 we report the results of a Monte Carlo simulation using artificial data similar to our real data, both in terms of sample size and observable moments. These simulations are of particular interest because these estimators have most commonly been used on investment regressions instead of saving regressions, and because saving and investment have different statistical properties. Most importantly, the distribution of investment is highly skewed, whereas the distribution of saving is much more symmetric.

We do three experiments. For each we generate 10,000 simulated cross sections from (12) and (13). The first has a sample size of 3,000, the second a sample size of 1,200, and the third a sample size of 200. These numbers correspond to the size of the largest and smallest cross sections in our
data set, as well as to an intermediate size. For each simulation we set the parameters $\beta$, $\alpha$, $r^2$, and $\tau^2$ approximately equal to the averages of the corresponding GMM estimates from Tables 2 through 7. Each observation is of the form $(y_i, x_i, w_i)$, generated according to (10)-(11) so that $(y_i, x_i, w_i)$ has, on average over the simulation samples, first and second moments equal to, and higher-order moments comparable to, the corresponding average sample moments from our real data.

For the third-, fourth-, fifth-, and sixth-order GMM estimators, Table 14 reports the mean value of the estimator of our parameter of interest, $\alpha_1$. It also reports its mean absolute deviation (MAD), the probability that an estimate is within 20% of its true value, and the actual size of a nominal 5% two-sided test of the null hypothesis that $\alpha_1$ equals its true value. For the small and intermediate sample sizes Table 14 shows that the fourth-order GMM estimator (GMM4) gives the best estimates in terms of expected value, MAD, and probability concentration. For the large sample size the GMM6 estimator performs best. Because the performance of the GMM4 and GMM6 estimators is similar for the large sample size, we therefore use the GMM4 estimator for our empirical work. Also of interest in this table are the tiny actual sizes of the test of the null hypothesis that $\alpha_1$ equals its true value for the intermediate and large sample sizes.

Table 8 explores the power of the J-test to detect misspecification. We examine three likely types of departures from the linear errors-in-variables model. Each is obtained by introducing one type of misspecification into the correctly specified baseline simulation described above. First, we make $y_i$ depend nonlinearly on $\chi_i$; second, we mismeasure the capital stock by multiplying $(y_i, x_i, w_i)$ from the baseline sample by an $i.i.d.$ lognormal variable; or we introduce a correlation between $u_i$ and $\chi_i$. We limit the degree of each misspecification so that the absolute biases in the GMM estimates of $\alpha_1$ do not exceed 0.3, which is approximately the absolute value of the cash flow coefficient estimated in our real data. We find that the fourth, fifth, and sixth order GMM J-tests exhibits usefully large power for the largest sample size, ranging from 0.403 to 0.995. The test is more powerful for larger sample sizes, and all of the power figures are larger than the fractions of rejections we obtain in our empirical work. Finally, we did not combine misspecifications, which we suspect would further increase test power.
References


Geary, R. C., 1942, Inherent relations between random variables, Proceedings of the Royal Irish Academy A 47, 63–76.


Table 1: Summary Statistics

<table>
<thead>
<tr>
<th>Country</th>
<th>Investment Mean</th>
<th>Investment Median</th>
<th>Market to Book Ratio Mean</th>
<th>Market to Book Ratio Median</th>
<th>Cash Flow Mean</th>
<th>Cash Flow Median</th>
<th>Cash Stock Mean</th>
<th>Cash Stock Median</th>
<th>Change in Cash Stock Mean</th>
<th>Change in Cash Stock Median</th>
<th>Average Obs. per Year</th>
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<tr>
<td>United States</td>
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<td>0.0652</td>
<td>1.3664</td>
<td>1.1684</td>
<td>0.0769</td>
<td>0.0767</td>
<td>0.0987</td>
<td>0.0558</td>
<td>0.0028</td>
<td>0.0006</td>
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</table>

Calculations are based on a sample of U.S. nonfinancial firms from Compustat from 1972 to 2004 and a sample of international firms from Global Vantage from 1997 to 2004. Investment, cash flow, the cash stock, and the change in the cash stock are all deflated by total assets.
### Table 2: Pooled Saving Regressions: All Countries

<table>
<thead>
<tr>
<th>Year</th>
<th>OLS</th>
<th>GMM4</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
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<tr>
<td></td>
<td>$q$</td>
<td>$CF$</td>
<td>$R^2$</td>
<td>$q$</td>
<td>$CF$</td>
<td>$R^2$</td>
<td>$\tau^2$</td>
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<td></td>
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<tr>
<td>United States</td>
<td>0.023*†</td>
<td>0.108*†</td>
<td>0.093*†</td>
<td>0.282*†</td>
<td>-0.436*†</td>
<td>0.379*†</td>
<td>0.262*†</td>
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<tr>
<td></td>
<td>(0.002)</td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.018)</td>
<td>(0.046)</td>
<td>(0.025)</td>
<td>(0.017)</td>
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<td></td>
</tr>
<tr>
<td>Canada</td>
<td>0.046*†</td>
<td>0.123*†</td>
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<td>0.246*†</td>
<td>-0.076</td>
<td>0.550*†</td>
<td>0.310*†</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.048)</td>
<td>(0.022)</td>
<td>(0.046)</td>
<td>(0.099)</td>
<td>(0.055)</td>
<td>(0.038)</td>
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<tr>
<td>United Kingdom</td>
<td>0.011†</td>
<td>0.142*†</td>
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<td>0.215</td>
<td>-0.516</td>
<td>0.333*†</td>
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<td></td>
<td>(0.005)</td>
<td>(0.033)</td>
<td>(0.007)</td>
<td>(0.133)</td>
<td>(0.362)</td>
<td>(0.049)</td>
<td>(0.035)</td>
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<td>Japan</td>
<td>0.020*†</td>
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<td>-0.298*†</td>
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<td>France</td>
<td>0.018†</td>
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<td>-0.071</td>
<td>0.225*†</td>
<td>0.280*†</td>
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<td></td>
<td>(0.008)</td>
<td>(0.095)</td>
<td>(0.019)</td>
<td>(0.058)</td>
<td>(0.187)</td>
<td>(0.032)</td>
<td>(0.031)</td>
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<td>Germany</td>
<td>0.023†</td>
<td>0.189*†</td>
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<td>(0.009)</td>
<td>(0.050)</td>
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<td>(0.078)</td>
<td>(0.056)</td>
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Calculations are based on a sample of U.S. nonfinancial firms from Compustat from 1972 to 2004 and a sample of international firms from Global Vantage from 1997 to 2004. GMM estimates are from the fourth-order estimator in Erickson and Whited (2000). The dependent variable is the change in the stock of cash divided by total assets. $CF$ stands for cash flow divided by total assets; $q$ stands for the market-to-book ratio; and $\tau^2$ is the coefficient of determination of the measurement equation. Fama-MacBeth standard errors are below the average estimates in parentheses. An asterisk indicates that the t-statistic exceeds the 5% bootstrapped critical value. A dagger indicates that the t-statistic exceeds the 5% asymptotic critical value.

### Table 3: Yearly Saving Regressions Summary: All Countries

<table>
<thead>
<tr>
<th>Fraction of Negative Cash Flow Coefficients</th>
<th>Fraction of Significant Negative Cash Flow Coefficients</th>
<th>Fraction of Overidentifying Restriction Rejections</th>
<th>Fraction of Identification Test Rejections</th>
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<tbody>
<tr>
<td>United States 0.970</td>
<td>0.788</td>
<td>0.212</td>
<td>0.758</td>
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<td>Canada 0.750</td>
<td>0.500</td>
<td>0.000</td>
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</tr>
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<td>United Kingdom 0.750</td>
<td>0.625</td>
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<td>Japan 1.000</td>
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<tr>
<td>France 0.750</td>
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<tr>
<td>Germany 1.000</td>
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<td>0.250</td>
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</table>

Calculations are based on a sample of U.S. firms from Compustat from 1972 to 2004 and a sample of international firms from Global Vantage from 1997 to 2004. The first column contains the fraction of the yearly estimates that are negative. The second column contains the fraction of the yearly estimates that are significantly negative at the 5% level, using asymptotic critical values. The third column contains the fraction of the yearly tests of overidentifying restrictions that produce rejections at the 5% level. The fourth column contains the fraction of the yearly identification tests that produce rejections at the 5% level.
Table 4: Split Sample Regressions: United States

<table>
<thead>
<tr>
<th>Year</th>
<th>OLS</th>
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<th>OLS</th>
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<tr>
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<td>0.036*†</td>
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<td>(0.003)</td>
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<td>(0.009)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.022)</td>
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<td>(0.030)</td>
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<td>Large</td>
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<td>(0.054)</td>
<td>(0.007)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>No Bond Rating</td>
<td>0.025*†</td>
<td>0.024</td>
<td>0.114*†</td>
<td>0.024</td>
<td>0.102*†</td>
<td>0.024</td>
<td>0.251*†</td>
<td>0.024</td>
<td>0.385*†</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.021)</td>
<td>(0.008)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>Bond Rating</td>
<td>0.013†</td>
<td>0.013</td>
<td>0.072*†</td>
<td>0.013</td>
<td>0.053*†</td>
<td>0.013</td>
<td>0.209*†</td>
<td>0.013</td>
<td>0.218*†</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.051)</td>
<td>(0.008)</td>
<td>(0.042)</td>
</tr>
<tr>
<td>High Standard Deviation</td>
<td>0.031*†</td>
<td>0.030</td>
<td>0.120*†</td>
<td>0.030</td>
<td>0.130*†</td>
<td>0.030</td>
<td>0.251*†</td>
<td>0.030</td>
<td>0.429*†</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.023)</td>
<td>(0.009)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>Low Standard Deviation</td>
<td>0.014*†</td>
<td>0.014</td>
<td>0.078*†</td>
<td>0.014</td>
<td>0.058*†</td>
<td>0.014</td>
<td>0.251*†</td>
<td>0.014</td>
<td>0.267*†</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.047)</td>
<td>(0.007)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>High Serial Correlation</td>
<td>0.020*†</td>
<td>0.020</td>
<td>0.088*†</td>
<td>0.020</td>
<td>0.090*†</td>
<td>0.020</td>
<td>0.292*†</td>
<td>0.020</td>
<td>0.374*†</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.057)</td>
<td>(0.007)</td>
<td>(0.047)</td>
</tr>
<tr>
<td>Low Serial Correlation</td>
<td>0.027*†</td>
<td>0.027</td>
<td>0.119*†</td>
<td>0.027</td>
<td>0.102*†</td>
<td>0.027</td>
<td>0.235*†</td>
<td>0.027</td>
<td>0.377*†</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.028)</td>
<td>(0.008)</td>
<td>(0.038)</td>
</tr>
</tbody>
</table>

Calculations are based on a sample of U.S. nonfinancial firms from Compustat from 1972 to 2004. GMM estimates are from the fourth-order estimator in Erickson and Whited (2000). The dependent variable is the change in the stock of cash divided by total assets. CF stands for cash flow divided by total assets; q stands for the market-to-book ratio; and $R^2$ is the coefficient of determination of the measurement equation. Serial correlation is the first-order autoregressive coefficient on the ratio of operating income to assets, and standard deviation is the standard deviation of the residual from this regression. Fama-MacBeth standard errors are below the average estimates in parentheses. An asterisk indicates that the t-statistic exceeds the 5% bootstrapped critical value. A dagger indicates that the t-statistic exceeds the 5% asymptotic critical value.
Table 5: Yearly Saving Regressions Summary: Split Samples

<table>
<thead>
<tr>
<th></th>
<th>Fraction of Negative Cash Flow Coefficients</th>
<th>Fraction of Significant Negative Cash Flow Coefficients</th>
<th>Fraction of Overidentifying Restriction Rejections</th>
<th>Fraction of Identification Test Rejections</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>0.727</td>
<td>0.212</td>
<td>0.061</td>
<td>0.727</td>
</tr>
<tr>
<td>Large</td>
<td>0.848</td>
<td>0.576</td>
<td>0.091</td>
<td>0.727</td>
</tr>
<tr>
<td>No Bond Rating</td>
<td>0.879</td>
<td>0.727</td>
<td>0.121</td>
<td>0.727</td>
</tr>
<tr>
<td>Bond Rating</td>
<td>0.727</td>
<td>0.455</td>
<td>0.030</td>
<td>0.515</td>
</tr>
<tr>
<td>High Standard Deviation</td>
<td>0.818</td>
<td>0.485</td>
<td>0.121</td>
<td>0.545</td>
</tr>
<tr>
<td>Low Standard Deviation</td>
<td>0.818</td>
<td>0.600</td>
<td>0.182</td>
<td>0.667</td>
</tr>
<tr>
<td>High Serial Correlation</td>
<td>0.848</td>
<td>0.606</td>
<td>0.242</td>
<td>0.606</td>
</tr>
<tr>
<td>Low Serial Correlation</td>
<td>0.818</td>
<td>0.303</td>
<td>0.121</td>
<td>0.606</td>
</tr>
</tbody>
</table>

Calculations are based on a sample of U.S. nonfinancial firms from Compustat from 1972 to 2004. The first column contains the fraction of the yearly estimates that are negative. The second column contains the fraction of the yearly estimates that are significantly negative at the 5% level, using asymptotic critical values. The third column contains the fraction of the yearly tests of overidentifying restrictions that produce rejections at the 5% level. The fourth column contains the fraction of the yearly identification tests that produce rejections at the 5% level.

Table 6: Uncertainty versus Finance Constraints

<table>
<thead>
<tr>
<th>Year</th>
<th>( CF )</th>
<th>( CF \times D_C )</th>
<th>( CF \times D_L )</th>
<th>( CF \times D_C \times D_L )</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>-0.399*†</td>
<td>0.258*†</td>
<td>-0.592*†</td>
<td>0.468*†</td>
<td>0.134†</td>
</tr>
<tr>
<td></td>
<td>(0.063)</td>
<td>(0.045)</td>
<td>(0.081)</td>
<td>(0.082)</td>
<td></td>
</tr>
<tr>
<td>Bond Rating</td>
<td>-0.423*†</td>
<td>0.186*†</td>
<td>-0.798*†</td>
<td>0.401*†</td>
<td>-0.212*†</td>
</tr>
<tr>
<td></td>
<td>(0.085)</td>
<td>(0.058)</td>
<td>(0.092)</td>
<td>(0.068)</td>
<td></td>
</tr>
</tbody>
</table>

Calculations are based on a sample of U.S. nonfinancial firms from Compustat from 1972 to 2004. GMM estimates are from the fourth-order estimator in Erickson and Whited (2000). The dependent variable is the change in the stock of cash divided by total assets. \( CF \) stands for cash flow divided by total assets; \( D_C \) is a dummy variable that takes a value of 1 if a firm is classified as constrained, and 0 otherwise. \( D_L \) is a dummy variable that takes a value of 1 if a firm is classified as having low uncertainty, and 0 otherwise. “Sum” refers to the sum of the coefficients in columns 3–5. Size and bond rating are the two constraint indicators. Fama-MacBeth standard errors are below the average estimates in parentheses. An asterisk indicates that the t-statistic exceeds the 5% bootstrapped critical value. A dagger indicates that the t-statistic exceeds the 5% asymptotic critical value.
Table 7: Monte Carlo Performance of GMM and OLS Estimators

<table>
<thead>
<tr>
<th>Sample Size = 200</th>
<th>OLS</th>
<th>GMM3</th>
<th>GMM4</th>
<th>GMM5</th>
<th>GMM6</th>
</tr>
</thead>
<tbody>
<tr>
<td>( E(\hat{\alpha}_1) )</td>
<td>0.180</td>
<td>-0.234</td>
<td>-0.223</td>
<td>-0.168</td>
<td>-0.201</td>
</tr>
<tr>
<td>( \text{MAD}(\hat{\alpha}_1) )</td>
<td>0.481</td>
<td>0.409</td>
<td>0.299</td>
<td>0.326</td>
<td>0.342</td>
</tr>
<tr>
<td>( P(\hat{\alpha}_1 - \alpha_1 \leq 0.2 \mid \alpha_1 )</td>
<td>0.001</td>
<td>0.085</td>
<td>0.130</td>
<td>0.150</td>
<td>0.130</td>
</tr>
<tr>
<td>T-test Size</td>
<td>0.032</td>
<td>0.062</td>
<td>0.074</td>
<td>0.090</td>
<td></td>
</tr>
<tr>
<td>J-test Size</td>
<td>0.235</td>
<td>0.329</td>
<td>0.529</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Sample Size = 1200 |
|--------------------|------|------|------|------|------|
| \( E(\hat{\alpha}_1) \) | 0.183 | -0.349 | -0.329 | -0.275 | -0.288 |
| \( \text{MAD}(\hat{\alpha}_1) \) | 0.483 | 0.277 | 0.134 | 0.094 | 0.087 |
| \( P(\hat{\alpha}_1 - \alpha_1 \leq 0.2 \mid \alpha_1 \) | 0.000 | 0.151 | 0.357 | 0.486 | 0.565 |
| T-test Size       | 0.001 | 0.008 | 0.007 | 0.011 |       |
| J-test Size       | 0.136 | 0.323 | 0.394 |       |       |

| Sample Size = 3000 |
|--------------------|------|------|------|------|------|
| \( E(\hat{\alpha}_1) \) | 0.184 | -0.348 | -0.331 | -0.292 | -0.300 |
| \( \text{MAD}(\hat{\alpha}_1) \) | 0.484 | 0.201 | 0.078 | 0.049 | 0.043 |
| \( P(\hat{\alpha}_1 - \alpha_1 \leq 0.2 \mid \alpha_1 \) | 0.000 | 0.221 | 0.507 | 0.704 | 0.796 |
| T-test Size       | 0.000 | 0.002 | 0.001 | 0.001 |       |
| J-test Size       | 0.096 | 0.317 | 0.418 |       |       |

Indicated expectations and probabilities are estimates based on 10,000 Monte Carlo samples. The samples are generated by

\[
\begin{align*}
y_i &= q_i \beta + w_i \alpha + u_i \\
x_i &= \gamma + \chi_i + \varepsilon_i,
\end{align*}
\]

in which \( \chi_i \) and \( \varepsilon_i \) are distributed as a chi-squared variables. \( u_i \) is distributed as a negative chi-squared variable. GMM\( n \) denotes the GMM estimator based on moments up to order \( M = n \). OLS denotes estimates obtained by regressing \( y_i \) on \( x_i \) and \( w_i \). MAD denotes mean absolute deviation. “T-Test Size” refers to the actual size of a nominal 5% test of the null hypothesis that \( \alpha_1 \) equals its true value. “J-Test Size” refers to the actual size of a nominal 5% test of the overidentifying restrictions.

**True Value:** \( \alpha_1 = -0.3 \).
<table>
<thead>
<tr>
<th></th>
<th>GMM4</th>
<th>GMM5</th>
<th>GMM6</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sample Size = 200</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonlinear Regression</td>
<td>0.275</td>
<td>0.289</td>
<td>0.661</td>
</tr>
<tr>
<td>Mismeasured Denominator</td>
<td>0.246</td>
<td>0.362</td>
<td>0.636</td>
</tr>
<tr>
<td>Correlated Error Regressor</td>
<td>0.410</td>
<td>0.425</td>
<td>0.671</td>
</tr>
<tr>
<td><strong>Sample Size = 1200</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonlinear Regression</td>
<td>0.424</td>
<td>0.558</td>
<td>0.848</td>
</tr>
<tr>
<td>Mismeasured Denominator</td>
<td>0.325</td>
<td>0.403</td>
<td>0.600</td>
</tr>
<tr>
<td>Correlated Error Regressor</td>
<td>0.542</td>
<td>0.743</td>
<td>0.918</td>
</tr>
<tr>
<td><strong>Sample Size = 3000</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonlinear Regression</td>
<td>0.504</td>
<td>0.725</td>
<td>0.960</td>
</tr>
<tr>
<td>Mismeasured Denominator</td>
<td>0.403</td>
<td>0.466</td>
<td>0.651</td>
</tr>
<tr>
<td>Correlated Error Regressor</td>
<td>0.676</td>
<td>0.936</td>
<td>0.995</td>
</tr>
</tbody>
</table>

The table reports the fraction of J-test rejections at a 5% nominal critical value. The samples are generated by

\[ y_i = q_i \beta + w_i \alpha + u_i \]
\[ x_i = \gamma + \chi_i + \varepsilon_i, \]

in which \( \chi_i \) and \( \varepsilon_i \) are distributed as a chi-squared variables. \( u_i \) is distributed as a negative chi-squared variable. GMMn denotes the GMM estimator based on moments up to order \( M = n \).
This figure depicts the optimal response of investment, saving, cash flow, and distributions/equity issuance in response to the productivity shock, $z$, in the revenue function $zk^θ$. The first panel depicts the response of the smallest firm in the simulated sample, the second panel depicts the response of the median firm in the simulated sample, and the third depicts the response of the largest firm in the simulated sample.
This figure depicts the relation between various model parameters and the ratio of the stock of cash to assets. The serial correlation of income shocks is $\rho$; the standard deviation of the innovations to these shocks is $\sigma_v$; $\lambda_0$, $\lambda_1$, and $\lambda_2$ are fixed, linear, and quadratic costs of external finance; $\theta$ is the curvature of the production function; and $c$ and $a$ are fixed and quadratic costs of adjusting the capital stock.
Figure 2: The Cash-Flow Sensitivity of Cash

This figure depicts the relation between various model parameters and the sensitivity of the change in the cash stock to cash flow, holding constant Tobin’s q. The serial correlation of income shocks is $\rho$; the standard deviation of the innovations to these shocks is $\sigma_v$; $\lambda_0$, $\lambda_1$, and $\lambda_2$ are fixed, linear, and quadratic costs of external finance; $\theta$ is the curvature of the production function; and $c$ and $a$ are fixed and quadratic costs of adjusting the capital stock.