Financial Constraints Risk
Author(s): Toni M. Whited and Guojun Wu
Source: *The Review of Financial Studies*, Vol. 19, No. 2 (Summer, 2006), pp. 531-559
Published by: Oxford University Press. Sponsor: The Society for Financial Studies.
Stable URL: http://www.jstor.org/stable/3844005
Accessed: 11-05-2016 01:19 UTC

Financial Constraints Risk

Toni M. Whited
University of Wisconsin

Guojun Wu
University of Houston

We construct an index of firms' external finance constraints via generalized method of moments (GMM) estimation of an investment Euler equation. Unlike the commonly used KZ index, ours is consistent with firm characteristics associated with external finance constraints. Constrained firms' returns move together, suggesting the existence of a financial constraints factor. This factor earns a positive but insignificant average return. Much of the variation in this factor cannot be explained by the Fama–French and momentum factors. Cross-sectional regressions of returns on our index and other firm characteristics show that constrained firms earn higher returns and that the financial-constraints effect dominates the size effect.

We explore the impact of firms' external finance constraints on their stock returns. Motivation for this inquiry starts with a large body of micro-econometric studies that have provided some evidence of an impact of external finance constraints on investment. For example, Whited (1992), Bond and Meghir (1994), and Love (2003) show that augmentations of an investment Euler equation that account for financial constraints improve its fit. The question remains whether these effects are priced in asset markets. In other words, do financial constraints affect asset returns; and if so, is this risk diversifiable?

To tackle this question, we construct an index of financial constraints based on a standard intertemporal investment model augmented to account for financial frictions. The model predicts that external finance constraints affect the intertemporal substitution of investment today for investment tomorrow via the shadow value of scarce external funds. This shadow value in turn depends on observable variables. Generalized method of moments (GMM) estimation of the model provides fitted values of the shadow value, which we then use as our index. The most important advantage of this approach is its avoidance of serious sample selection, simultaneity, and measurement-error problems via structural

We thank two anonymous referees, Campbell Harvey (the editor), Tim Erickson, Kathleen Fuller, Tyler Shumway, Anjan Thakor, and seminar participants at the European Central Bank, the University of Michigan, and Penn State University for comments and discussion. We are responsible for all remaining errors. Address correspondence to Toni M. Whited, Department of Finance, University of Wisconsin, 975 University Avenue, Madison, WI 53706-1323, or email: twhited@bus.wisc.edu.

doi:10.1093/rfs/hhj012 Advance Access publication January 18, 2006

estimation with a large data set. As we demonstrate below, we fail to reject the overidentifying restrictions of this model.

We then use this index to study whether financial constraints represent a source of priced risk. We study this issue from both a time series and a cross-sectional perspective. We construct portfolios with different size and financial constraint rankings. Using monthly time series on these portfolios, we find that stock returns of constrained firms positively covary with the returns of other constrained firms. Hence, there is indeed common variation in stock returns associated with financial constraints. We use a method analogous to that in Fama and French (1993, 1995) to construct a "financial constraints factor." This factor earns a positive-risk premium of 2.18–2.76% on an annual basis over the sample period, but the premium is not statistically significant. We find that the cumulative return of the factor is counter-cyclical: the cumulative return on the factor either coincides or precedes recessions, and it declines sharply during expansions. A significant portion of the variation in the financial constraints factor cannot be explained by the Fama–French factors and the momentum factor.

Cross-sectional regressions of firm returns on the financial constraints index and other firm characteristics indicate that more constrained firms earn higher returns. The average coefficient on the financial constraints index is positive and statistically significant. Once we take account of financial constraints, smaller firms do not earn higher returns. Hence, the financial constraints risk premium is not an artifact of the well-known size effect, documented, for example, by Chan and Chen (1991) and Chan, Chen, and Hsieh (1985). Instead, it seems to explain part of the size effect.

The results in our article stand in contrast to the existing evidence, which provides at best weak support for the idea that financial constraints affect stock returns. Lamont, Polk, and Saá-Requejo (2001) construct an index of financial constraints based on regression coefficient estimates in Kaplan and Zingales (1997). They find that financially constrained firms' stock returns move together over time, suggesting that constrained firms are subject to common shocks. Yet, they find no risk premium associated with this systematic risk; and the factor constructed from their index has weak ability to price assets. Consistent with Lamont et al., Gomes, Yaron, and Zhang (2004) also uncover limited evidence that financing frictions are a source of priced risk. They use aggregate data to estimate a production-based asset pricing model augmented to account for costly external financing.

Our work builds upon these two studies. Like Lamont et al., we use an index of financial constraints to sort firms into constrained and unconstrained groups. However, we construct our own index rather than basing the index on the coefficient estimates in Kaplan and Zingales (1997).

Further, like Gomes, Yaron, and Zhang (2004), we use a structural model to construct this index. We opt for a structural model of financial constraints instead of traditional tests for financial constraints based on regressions of investment on Tobin's q and cash flow as in Fazzari, Hubbard, and Petersen (1988). The structural approach has the advantage of avoiding the difficult problem of measuring Tobin's q. As shown in Erickson and Whited (2000), Bond and Cummins (2001), and Cooper and Ejarque (2001), this measurement-error problem renders the reduced-form regression approach uninformative.

To understand the importance of our construction of a financial constraints index, it is useful to review Kaplan and Zingales (1997). They examine the annual reports of the 49 firms in Fazzari, Hubbard, and Petersen's (1988) "constrained" sample, using this information to rate the firms on a financial constraints scale from one to four. They then run an ordered logit of this scale on observable firm characteristics using data on these 49 firms from 1970 to 1984. Lamont et al. use these exact coefficients on data from a broad sample of firms to construct a "synthetic KZ index."

One difficulty with this approach is parameter stability both across firms and over time. Kaplan and Zingales demonstrate convincingly that the firms they classify as constrained do indeed have the characteristics one would associate with external finance constraints. For example, they have high debt to capital ratios, and they appear to invest at a low rate, despite good investment opportunities. However, using the index coefficients on a much larger sample of firms in a different time period leaves open the question of whether this index is truly capturing financial constraints. Furthermore, one of the variables in the KZ index is Tobin's q, which, as shown in Erickson and Whited (2000), contains a great deal of measurement error. Consistent with these difficulties, we find that the index constructed from our model does a better job than the KZ index of isolating firms with characteristics associated with financial constraints.

Our article is related to the literature on the macroeconomic effects of financial constraints. Theoretical works such as Bernanke and Gertler (1989), Calstrom and Fuerst (1997), and Kiyotaki and Moore (1997) argue that under asymmetric information, agency costs force firms to use collateral to borrow capital in the credit market. The value of collateral thus limits the extent to which a firm can finance its investment projects through external funds. Because adverse macroeconomic shocks typically reduce collateral values, financially constrained firms are forced to cut back investment more than unconstrained ones. The empirical work in Gertler and Gilchrist (1994) and Bernanke, Gertler, and Gilchrist (1996) supports this idea by finding evidence that small firms reduce their economic activity more sharply and sooner than large firms in response to adverse macroeconomic shocks. These findings that financial constraints influence macroeconomic behavior add credence to our results that financial constraints matter for asset returns.

Our work is also related to the small literature on the relationship between financial *distress* and stock returns.[1] The work in this area has concentrated on the hypothesis that financial distress can explain the significance of the book to market factor. Instead, we examine the effects of financial *constraints* on returns, finding that it explains some of the significance of the size factor. It is somewhat difficult to distinguish financial distress from financial constraints. We therefore find it useful to imagine the difference between a firm on the verge of bankruptcy and a young firm that would like to grow quickly but whose pace is restrained because of the lack of financing.

The rest of the article is organized as follows. In section 1, we briefly outline our structural model of investment and external finance constraints, and we present the results from estimating the Euler equation from this model. We then analyze the estimated financial constraints index and discuss its relation to various measures of firm characteristics. This section also compares the performance of our index with the KZ index. In section 2, we examine whether financial constraints represent a source of risk and if more constrained firms earn higher returns. We conduct both time series and cross-sectional tests to examine this important issue. Section 3 provides some concluding remarks.

1. Investment and Finance Constraints

1.1 The model

Our construction of a financial constraints index starts with a standard partial-equilibrium investment model, in which the firm takes factor prices, output prices, and interest rates as given. As noted in the introduction, this framework has been used successfully to identify firms facing external finance constraints. Our derivation follows Whited (1992, 1998).

The firm maximizes the expected present discounted value of future dividends, which are given by

$$V_{i0} = E_{i0} \sum_{t=0}^{\infty} M_{0,t} d_{it}. \tag{1}$$

Here, V_{i0} is the time zero value of firm i. E_{i0} is the expectations operator conditional on firm i's time zero information set; $M_{0,t}$ is the stochastic discount factor from time 0 to t; and d_{it} is the firm's dividend.

[1] See, for example, Fama and French (1995), Chen and Zhang (1998), Dichev (1998), and Griffin and Lemmon (2002).

The firm maximizes equation (1) subject to two identities. The first defines dividends:

$$d_{it} = \pi\left(K_{it,}v_{it}\right) - \psi\left(I_{it,}K_{it}\right) - I_{it} + B_{i,t+1} - (1 + r_t)B_{it}.$$

K_{it} is the beginning-of-period capital stock; I_{it} is investment during time t; $\psi(I_{it},\ K_{it})$ is the real cost of adjusting the capital stock, with $\psi_I > 0, \psi_K < 0,\ \psi_{II} > 0$; B_{it} is the stock of debt at the beginning of time t; r_t is the coupon rate on this debt; $\pi(K_{it},\ v_{it})$ is the firm's profit function, with $\pi_K > 0$; and v_{it} is a shock to the profit function that follows a Markov process and that is observed by the firm at time t. This formulation of technology does not incorporate any restrictions on homogeneity or competition. The relative price of capital goods is normalized to unity. Capital is the only quasi-fixed factor of production, and all variable factors have already been "maximized out" of the problem. For clarity of exposition, we omit taxes. Nonetheless, in the estimation that follows, the firm discount rate, the effective price of capital goods, and profits are all appropriately tax adjusted.

The second identity governs capital stock accumulation:

$$K_{i,t+1} = I_{it} + (1 - \delta_i)K_{it}, \tag{2}$$

where δ_i is the firm-specific constant rate of economic depreciation.

The firm also faces two constraints on outside finance:

$$d_{it} \geq d^*_{it} \tag{3}$$

$$B_{i,t+1} \leq B^*_{i,t+1}. \tag{4}$$

Here, d^*_{it} is the firm- and time-varying lower limit on dividends, and B^*_{it} is the firm- and time-varying upper limit on the stock of debt. Since this model does not allow for new share issues, Equation (3) limits the amount of outside equity financing, and a negative value for d^*_{it} implies that the firm is able to raise outside equity finance. Although negative dividends are not a feature of most equity markets, in the absence of taxes negative dividends can be considered equivalent to new share issues since on the margin both have the same effect on old shareholders. Both B^*_{it} and d^*_{it} are unobserved by the econometrician. These two constraints can be thought of as the end product of an information-theoretic model of external financing.

Let λ_{it} be the Lagrange multiplier associated with Equation (3). λ_{it} can be interpreted as the shadow cost associated with raising new equity, which implies that external (equity) financing is costly relative to internal finance. The Euler condition for K_{it} is

$$E_{it}\left(M_{t,t+1}\left(\frac{1+\lambda_{i,t+1}}{1+\lambda_{it}}\right)\left\{\pi_K\left(K_{i,t+1},v_{i,t+1}\right)-\psi_K\left(I_{i,t+1},K_{i,t+1}\right)\right.\right.$$
$$\left.\left.+(1-\delta_i)\left[\psi_I\left(I_{i,t+1},K_{i,t+1}\right)+1\right]\right\}\right)=\psi_I\left(I_{it,}K_{it}\right)+1. \tag{5}$$

This condition has a simple interpretation. The right side represents the marginal adjustment and purchasing costs of investing today. The left side represents the expected discounted cost of waiting to invest until tomorrow, which consists first of the marginal product of capital and the marginal reduction in adjustment costs from an increment to the capital stock. Second, even if the firm waits, it still must incur adjustment and purchasing costs. Optimal investment implies that on the margin, the firm must be indifferent between investing today and transferring those resources to tomorrow. If the outside equity constraint is binding, the effects of external finance constraints show up in the term $\Lambda_{i,t+1} \equiv (1 + \lambda_{i,t+1})/(1 + \lambda_{it})$, which is the relative shadow cost of external finance. In the absence of finance constraints, $\Lambda_{i,t+1} = 1$. On the other hand, if the equity constraint binds, then generally $\Lambda_{i,t+1} \neq 1$, unless $\lambda_{i,t+1} = \lambda_{it}$. As also noted in Gomes, Yaron, and Zhang (2004), this last observation implies that finance constraints can only affect investment if they are time varying. It is the shadow value of the constraint today, *relative* to tomorrow, that is important.

The Euler condition for B_{it} is

$$(1+\lambda_{it})=E_{it}\left[\left(1+\lambda_{i,t+1}\right)(1+r_t)M_{t,t+1}\right]+\gamma_{it}, \tag{6}$$

where γ_{it} is the Lagrange multiplier associated with Equation (4). From Equation (6), it is clear that a binding and time-varying debt constraint will affect the expected intertemporal transfer of resources. However, because debt is separable in the profit function, the existence of debt financing or the debt constraint does not affect the basic form of the Euler equation (5). Further, because both λ_{it} and γ_{it} are unobservable, and because both shadow values are likely to be affected by the same set of observable variables, separate identification of λ_{it} and γ_{it} is very difficult. For these two reasons, we choose below to focus on identifying λ_{it} via the Euler equation governing the capital stock.

1.2 Estimation

To estimate the model, we replace the expectations operator in Equation (5) with an expectational error, $e_{i,t+1}$, where $E_{it}(e_{i,t+1}) = 0$ and $E_{it}\left(e^2_{i,t+1}\right) = \sigma^2_{it}$. $E_{it}\left(e_{i,t+1}\right) = 0$ implies that $e_{i,t+1}$ is uncorrelated with any time t information, and $E_{it}\left(e^2_{i,t+1}\right) = \sigma^2_{it}$ implies that our error can be heteroscedastic. This assumption allows us to write Equation (5) as:

$$M_{t,t+1}\left(\frac{1+\lambda_{i,t+1}}{1+\lambda_{it}}\right)\left\{\pi_K\left(K_{i,t+1},v_{i,t+1}\right)-\psi_K\left(I_{i,t+1},K_{i,t+1}\right)\right. \\ \left.+(1-\delta_i)\left[\psi_I\left(I_{i,t+1},K_{i,t+1}\right)+1\right]\right\}=1+\psi_I(I_{it},K_{it})+e_{i,t+1}. \tag{7}$$

The rational expectations assumption also provides model identification since it implies that any variable known to the firm at time $t-1$ can be used as an instrument to estimate Equation (7). To parameterize the marginal product of capital, we assume firms are imperfectly competitive and set output price as a constant mark-up, μ, over marginal cost. In this case constant returns to scale implies

$$\pi_K(K_{it},v_{it})=\frac{Y_{it}-\mu C_{it}}{K_{it}}, \tag{8}$$

where Y_{it} is output and C_{it} is variable costs: the sum of "costs of goods sold" and "selling, general, and administrative expenses." As noted in Whited (1998), μ can also capture the effects of nonconstant returns to scale and therefore need not be strictly greater than one.

To parameterize the adjustment cost function, $\psi(I_{it}, K_{it})$, we follow Whited (1998) and use a flexible functional form that is linearly homogeneous but that allows for nonlinearities in the marginal adjustment cost function:

$$\psi(I_{it},K_{it})=\left[\alpha_0+\sum_{m=2}^{M}\frac{1}{m}\alpha_m\left(\frac{I_{it}}{K_{it}}\right)^m\right]K_{it}, \tag{9}$$

where α_m, $m = 2,\ldots, M$ are coefficients to be estimated, and M is a truncation parameter that sets the highest power of I_{it}/K_{it} in the expansion.

To determine M, we use the test developed by Newey and West (1987), which can be described as a GMM analog to a standard likelihood-ratio test. First, we choose a "high" starting value for M and estimate the model. Then, using the same optimal weighting matrix, we estimate a sequence of restricted models for progressively lower values of M, in which the corresponding coefficient, α_{M+1}, is set to zero. The appropriate maximum value for M will then be the highest one for which the exclusion restriction on the parameter α_{M+1} is not rejected. We initially set the truncation parameter at six and our final specification sets $M = 3$.

We arrive at the estimating equation by substituting Equation (8) into (7), differentiating Equation (9) with respect to I_{it} and K_{it}, and substituting the derivatives into Equation (7). The result is

$$
\begin{aligned}
&M_{t,t+1}\Lambda_{i,t+1}\left\{\frac{Y_{i,t+1}-\mu C_{i,t+1}}{K_{i,t+1}}-\left[\alpha_0-\sum_{m=2}^{M}\frac{m-1}{m}\alpha_m\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)^m\right]\right.\\
&\left.\quad+(1-\delta_i)\left[\sum_{m=2}^{M}\alpha_m\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)^{m-1}+1\right]\right\}\\
&\quad=\sum_{m=2}^{M}\alpha_m\left(\frac{I_{it}}{K_{it}}\right)^{m-1}+1+e_{i,t+1}.
\end{aligned}
\tag{10}
$$

Estimation of (10) requires two further assumptions. First, we adopt a reduced-form specification for the stochastic discount factor, using the three-factor model of Fama and French (1993):

$$
M_{t,t+1}=l_0+l_1MKT_{t+1}+l_2SMB_{t+1}+l_3HML_{t+1}. \tag{11}
$$

Here MKT_{t+1} is the return on the market; SMB_{t+1} is the return on an arbitrage portfolio that is long small firms and short large firms; and $HML_{t+1}$is the return on an arbitrage portfolio that is long firms with high book to market ratios and short firms with low book to market ratios.

Second, $\lambda_{i,t+1}$ is unobservable. To solve this problem, several authors have stepped out-side the strict confines of this model and parameterized $\lambda_{i,t+1}$ as a function of observable firm characteristics. See, for example, Whited (1992), Hubbard, Kashyap, and Whited (1995), and Love (2003). We also adopt this approach, starting with the following specification:

$$
\begin{aligned}
\lambda_{i,t+1}=b_0&+b_1TLTD_{i,t+1}+b_2DIVPOS_{i,t+1}+b_3SG_{i,t+1}\\
&+b_4LNTA_{i,t+1}+b_5ISG_{i,t+1}+b_6CASH_{i,t+1}\\
&+b_7CF_{i,t+1}+b_8NA_{i,t+1}+b_9IDAR_{i,t+1}.
\end{aligned}
\tag{12}
$$

Here, $TLTD_{i,t+1}$ is the ratio of the long-term debt to total assets; $DIVPOS_{i,t+1}$ is an indicator that takes the value of one if the firm pays cash dividends; $SG_{i,t+1}$ is firm sales growth; $LNTA_{i,t+1}$ is the natural log of total assets; $ISG_{i,t+1}$ is the firm's three-digit industry sales growth; $CASH_{i,t+1}$ is the ratio of liquid assets to total assets; $CF_{i,t+1}$ is the ratio of cash flow to total assets; $NA_{i,t+1}$ is the number of analysts following the firm as reported by I/B/E/S; and $IDAR_{i,t+1}$ is the three-digit industry debt to assets ratio. To estimate the parameter vectors b and l we substitute Equations (12) and (11) into Equation (7). The fitted value of $\lambda_{i,t+1}$ will be our index of financial constraints. The higher $\lambda_{i,t+1}$, the greater is the effect of finance constraints.

Our specification is much richer than those used by previous Euler equation studies. This departure is necessary because of our goal of constructing a financial constraints index that can explain asset returns. For example, if we only included the log of assets, our "financial constraints" index would pick up a size effect. Unlike Kaplan and Zingales (1997), we do not include Tobin's q in our index. This choice stems from the evidence in Erickson and Whited (2000) that Tobin's q contains a great deal of measurement error in its role as a proxy for investment opportunities. Instead, we include sales growth and industry sales growth to capture the intuition that only firms with good investment opportunities are likely to want to invest enough to be constrained. We expect to identify these firms as belonging to high-growth industries but as having low individual sales growth. We include analyst coverage as an indicator of asymmetric information. We include both the firm-level and industry-level debt to assets ratios to capture the idea that constrained firms are likely to have high debt but reside in low-debt capacity industries.[2] Our other four variables are indicators of financial health. We do not include a measure of interest coverage since a number of our firm-year observations have negative cash flow.

We estimate (7) in first differences to eliminate possible fixed firm effects—a procedure that requires us to use instruments dated at $t-2$. In other words, we use GMM to estimate conditional moment conditions of the form

$$E_{t-1}\left[z_{i,t-1} \otimes \left(e_{i,t+1} - e_{it}\right)\right].$$

The test in Holtz-Eakin (1988) rejects the null hypothesis that a nondifferenced specification is correct.

Our instruments include all of the Euler equation variables, as well as inventories, depreciation, current assets, current liabilities, the net value of the capital stock, and tax payments, all of which are normalized by total assets. We also include three extra variables found by Fama and French (2000) to be good predictors of profitability: the ratio of dividends to total assets, average profitability over the previous three quarters, and a dummy if profitability was positive in time $t-1$. In our application, "profitability" is represented by the ratio of cash flow to assets; and instead of deflating dividends by book equity, as do Fama and French, we deflate dividends by total assets to reduce heteroscedasticity problems. The Fama and French predictors also include a dummy for positive dividends, which is already in our instrument list, as well as current profitability minus the average profitability over the three previous periods. Because this last variable is a linear combination of current cash flow and lagged average cash

[2] Note that instead of "industry adjusting" sales growth and the debt-to-assets ratio, we simply include the industry-level variables separately. We opt for this method, because industry adjustments implicitly assume that the coefficient on the industry variable is of equal and opposite sign as the coefficient on the corresponding firm variable. We do not wish to impose this restriction on our model.

flow—two variables in our instrument list, we do not need to include it. Unlike previous Euler equation studies, we do not include time dummies, because we have sufficient time-series variation in our quarterly data to ensure that movements in $e_{i,t+1}$ induced by macroeconomic shocks will average out. We do, however, include seasonal dummies.

We impose two constraints on our estimation. First, we impose the weak unconditional moment restriction that the expected value of the stochastic discount factor is equal to $(1+r_f)^{-1}$, where r_f is the risk-free rate. This additional moment condition identifies λ_0. Second, because $\lambda_{i,t+1}$ is a shadow value, it must be nonnegative. Therefore, we minimize the GMM objective function subject to the inequality constraint that $E(\lambda_{i,t+1}) \geq 0$.

The intuition behind identifying the risk implications of financing constraints via this model warrants further discussion. First, because of the Markovian nature of the model, the Euler equation governs the firm's decision on how much to invest today *relative* to investment tomorrow. This feature is useful primarily because financing constraints expected to bind in the far future have already been incorporated in the optimal time t level of investment and have no direct impact on the time $t-1$ decision to invest now versus postpone. Therefore, it is possible to identify the effects of financing constraints via the cross-sectional and time-series variation in investment today versus investment tomorrow. Second, to determine whether this variation is induced by financial constraints or changes in productivity, we need to control for some measure of investment opportunities. Once again, the Markovian structure of the model provides substantial guidance along this line as it implies that we only need to control for capital productivity at time t, which we do via Equation (8). Finally, it is important that we have modeled traditional risk factors in the specification of the firm's discount rate since it will therefore be unlikely that our index is simply picking up these traditional factors.

1.3 Data and estimation results

Our firm-level data are from the quarterly, 2002 Standard and Poor's (S & P) COMPUSTAT industrial files. We select our sample by first deleting any firm-year observations with missing data or for which total assets, the gross capital stock, or sales are either zero or negative. To eliminate coding errors, we also delete any firm for which reported short-term debt is greater than reported total debt or for which reported changes in the capital stock cannot be accounted for by reported acquisition and sales of capital goods and by reported depreciation. We also delete any firm that experienced a merger accounting for more than 15% of the book value of its assets. We omit all firms whose primary SIC classification is between 4900 and 4999 or between 6000 and 6999 since our investment model is inappropriate for regulated or financial firms. We only include a firm if it has at least eight consecutive quarters of complete data and if it never has more than two quarters of negative sales growth. This last criterion is important since we want to look at firms that face external finance constraints rather than firms that are in financial distress. These screens leave us with an unbalanced panel between 131 and 1390 firms per quarter. The sample period runs from January, 1975 to April, 2001.

Details on the construction of the regression variables can be found in Whited (1992). The one departure from Whited (1992) is in our use of the replacement value of total assets (instead of the replacement value of the capital stock) to deflate the Euler equation variables. Our intent is to deflate *all* of our firm-level variables, including debt, by the same deflator, thereby reducing heteroscedasticity. Results from deflating our variables by the replacement value of the capital stock are broadly similar, though our models are less stable, possibly because of the existence of several firms with very small capital stocks.

Table 1 presents our Euler-equation estimation results. Column (1) contains estimates from the most general model, in which all nine of our financial-health variables are used to parameterize $\lambda_{i,t+1}$. Each subsequent column contains estimates from a model in which we have dropped the financial variable with the smallest t-statistic. We test for

Table 1
Euler equation estimates

	1	2	3	4	5
α_1	0.534 (0.190)	0.655 (0.174)	0.608 (0.179)	0.652 (0.167)	0.701 (0.152)
α_2	−0.354 (0.349)	−0.402 (0.399)	−0.490 (0.261)	−0.442 (0.228)	−0.437 (0.256)
μ	0.967 (0.012)	1.011 (0.019)	1.018 (0.024)	1.019 (0.023)	1.018 (0.023)
CF	−0.079 (0.034)	−0.063 (0.026)	−0.072 (0.025)	−0.091 (0.031)	−0.098 (0.031)
DIVPOS	−0.054 (0.022)	−0.062 (0.034)	−0.046 (0.021)	−0.062 (0.029)	−0.073 (0.030)
TLTD	0.026 (0.013)	0.011 (0.008)	0.025 (0.008)	0.021 (0.011)	0.013 (0.007)
LNTA	−0.077 (0.024)	−0.120 (0.030)	−0.040 (0.028)	−0.044 (0.023)	−0.054 (0.023)
ISG	0.121 (0.104)	0.117 (0.105)	0.066 (0.057)	0.102 (0.052)	0.085 (0.057)
SG	−0.031 (0.011)	−0.050 (0.025)	−0.024 (0.011)	−0.035 (0.023)	
NA	−0.004 (0.002)	−0.007 (0.004)	−0.019 (0.090)		
CASH	−0.001 (0.002)	−0.009 (0.011)			
IDAR	−0.011 (0.042)				
MKT	−0.539 (0.232)	−0.227 (0.685)	−0.780 (0.646)	−0.556 (0.318)	−0.276 (0.144)
SMB	1.285 (0.665)	1.033 (0.880)	1.020 (0.324)	1.083 (0.735)	0.936 (0.493)
HML	1.121 (0.492)	1.069 (1.500)	0.412 (0.652)	0.944 (0.770)	0.906 (0.556)
J-Test	0.216	0.242	0.229	0.193	0.024
L-Test		0.397	0.499	0.595	0.062

Calculations are based on a sample of nonfinancial firms from the quarterly 2002 COMPUSTAT industrial files. The sample period is January, 1975 to April, 2001. The model is given by equation (9). Nonlinear GMM estimation is done on the model in first differences with twice lagged instruments. α_1 and α_2 are adjustment cost parameters, and μ is a mark-up. *CF* is the ratio of cash flow to total assets; *DIVPOS* is an indicator that takes the value of one if the firm pays cash dividends; *TLTD* is the ratio of the long-term debt to total assets; *LNTA* is the natural log of total assets, *ISG* is the firm's 3-digit industry sales growth; *SG* is firm sales growth; *NA* is the number of analysts following the firm, as reported by I/B/E/S; *CASH* is the ratio of liquid assets to total assets; and *IDAR* is the firm's 3-digit industry debt-to-assets ratio. *MKT, SMB,* and *HML* are the Fama–French factors on market, size and book-to-market. Standard errors are reported in parentheses. The p-values of the J-test and L-test on model specification are reported in the last two rows.

the joint significance of the omitted financial variables in a manner exactly analogous to the way in which we choose the functional form for the adjustment cost function. As explained above, we examine the difference in the minimized GMM objective functions for the most general and for subsequently more parsimonious models. Each of these differences will have a chi-squared distribution with degrees of freedom equal to the number of variables excluded from the model. If a variable belongs in the Euler equation, its omission should produce a small p-value. We term this test of exclusion restrictions an "L-test."

Note that for the four most general models, the J-test of overidentifying restrictions does not produce a rejection. In other words, we cannot reject the hypothesis that these models, with their accompanying assumptions, are misspecified. This result is particularly important in light of the deterministic specification of Equation (12). If this equation does indeed have an error term associated with it, then the covariance between this additional error and the rest of the left side of Equation (7) will implicitly be contained in $e_{i,t+1}$. This covariance is clearly not sufficient, however, to force a rejection of the overidentifying restrictions. This result is even more convincing in light of the small, but significant, negative conditional correlation between the fitted value of $\Lambda_{i,t+1}$ from model Equation (5) and the term $\pi_K(K_{i,t+1}, v_{i,t+1}) - \psi_K(I_{i,t+1}, K_{i,t+1}) + (1-\delta_i)[\psi_I(I_{i,t+1}, K_{i,t+1}) + 1] \equiv LHS_{i,t+1}$. In other words, even though the observable component of $\Lambda_{i,t+1}$ is correlated with $LHS_{i,t+1}$, any potential unobserved component is not sufficiently strongly correlated to induce a rejection of the overidentifying restrictions.

This observed negative correlation between $\Lambda_{i,t+1}$ and $LHS_{i,t+1}$ has the following economic interpretation. In the absence of financing constraints, a positive expected productivity shock increases the left side of Equation (5). All else equal, the optimizing firm will then invest more today relative to tomorrow in anticipation of that shock, thereby equalizing the two sides of Equation (5). Once financing constraints enter the picture, the negative correlation between $\Lambda_{i,t+1}$ and $LHS_{i,t+1}$ implies a dampening of this intertemporal substitution effect.

The first model to produce a rejection of the exclusion restrictions is in column (5), where we have excluded the industry debt to assets ratio, the number of analysts, the ratio of cash to assets, and firm sales growth. Our final specification, therefore, is in column (4) and contains the ratio of cash flow to assets, the positive-dividend indicator, the debt-to-assets ratio, the log of assets, industry sales growth, and firm sales growth.[3] Note that all of these variables enter with the expected sign. For example,

[3] One concern with this approach to constructing a financial constraints index is parameter stability. To address this issue, we split the sample at 1988:1 and run separate Euler equations on the subsamples. The financial constraints indices that result from the split-sample estimation are highly correlated with our original financial constraints index: the correlations are 0.912 and 0.992, respectively.

the positive coefficient on the debt to assets ratio indicates that a more highly leveraged firm will have a higher shadow value of external funds; that is, it will be more financially constrained. Similarly, larger firms behave as if they have lower shadow values for external funds.

The other parameter estimates are also sensible. For example, the mark-up and adjustment-cost parameters are all positive and significantly different from zero, and the mark-up, as expected, is greater than one, though not significantly so. Also, although many of the factor loadings on the stochastic discount factor are not individually significant, they are jointly significant. Excluding these three variables forces a rejection of the corresponding exclusion restrictions.

1.4 Financial constraints index

The time t value of our index of financial constraints can therefore be read from the fourth column of Table 1:

$$-0.091CF_{it} - 0.062DIVPOS_{it} + 0.021TLTD_{it} - 0.044LNTA_{it} + 0.102ISG_{it} - 0.035SG_{it} \tag{13}$$

As used by Lamont et al., the KZ index is given by:

$$-1.001909CF_{it} + 3.139193TLTD_{it} - 39.36780TDIV_{it} - 1.314759CASH_{it} + 0.2826389Q_{it},$$

where $TDIV_{it}$ is the ratio of total dividends to assets and Q_{it} is Tobin's q.

Table 2 provides mean values of a variety of firm characteristics for groups of firms sorted into quartiles first by our index of financial constraints and second by the Kaplan–Zingales index. Results for the sort based on our index are in the first panel. The most notable feature here is the relationship between investment and Tobin's q. Although the level of q rises slightly with the level of financial constraints, the level of investment drops by 18%. Notice also the negative relationship between the level of financial constraints and the average number of analysts covering the firm. To the extent that lack of analyst coverage proxies for asymmetric information, this pattern also adds credence to our index. Whited (1992) uses the absence of a bond rating as a proxy for asymmetric information. Our results are also consistent with this measure: 23% of the least constrained firms have bond ratings, whereas only 0.3% of the most constrained firms have bond ratings. The ratio of cash to assets increases slightly in the level of financial constraints, and the ratio of debt to assets decreases slightly. Supporting this result is the idea that constrained firms practice precautionary savings; that is, they need to build up liquid assets to invest. Finally, the most constrained firms

Table 2
Summary statistics: full sample

	Least constrained			Most constrained
Firms sorted by structural index				
Investment/assets	0.095	0.095	0.088	0.078
Cash flow/assets	0.110	0.102	0.092	0.053
Total assets	1151.436	194.547	66.352	22.367
Debt assets	0.221	0.189	0.167	0.145
Positive dividends	0.549	0.292	0.119	0.031
Industry sales growth	−0.018	0.013	0.035	0.158
Sales growth	0.043	0.054	0.031	0.028
Cash/assets	0.081	0.105	0.122	0.128
Industry debt/assets	0.212	0.193	0.179	0.173
Number of analysts	1.414	0.871	0.459	0.123
Bond rating	0.231	0.074	0.017	0.003
Tobin's q	2.017	2.102	2.077	2.197
Structural index	0.588	0.666	0.724	0.803
Kaplan–Zingales index	1.094	1.004	0.935	0.944
Firms sorted by Kaplan–Zingales index				
Investment/assets	0.063	0.083	0.096	0.114
Cash flow/assets	0.144	0.095	0.074	0.045
Total assets	166.889	354.783	463.596	449.415
Debt assets	0.030	0.110	0.210	0.373
Positive dividends	0.279	0.259	0.249	0.205
Industry sales growth	0.039	0.050	0.052	0.047
Sales growth	0.029	0.040	0.048	0.059
Cash/assets	0.216	0.095	0.066	0.058
Industry debt/assets	0.147	0.175	0.202	0.234
Number of analysts	0.496	0.737	0.832	0.802
Bond rating	0.012	0.034	0.082	0.196
Tobin's q	1.926	2.033	2.041	2.392
Structural index	0.712	0.694	0.684	0.689
Kaplan–Zingales index	0.254	0.765	1.148	1.808

Calculations are based on a sample of nonfinancial firms from the quarterly 2002 COMPUSTAT industrial files. The sample period is January, 1975 to April, 2001. Investment/assets, sales/assets, and cash flow/assets are expressed at an annual rate. Industry sales growth is defined at the three-digit SIC level. Total assets are expressed in millions of 1997 dollars. The denominator of Tobin's q is the book value of total assets. The numerator is the book value of total assets minus the book value of equity minus balance-sheet deferred taxes plus the market value of equity.

belong to high sales growth industries but have low sales growth. In sum, the firms categorized as "constrained" by our index appear to have characteristics that one would associate with difficult access to external finance.

However, the same is not true for the firms sorted by the KZ index. The second part of the table shows that firms categorized as constrained by the KZ index have more analyst coverage and more bond ratings than the firms categorized as relatively unconstrained. Also, although the level of q increases with the level of constraints, the rate of investment increases much more quickly. Indeed, the implied elasticity of investment with respect to q is 3.35—a number far greater than the tiny estimates produced by most investment-q regressions. This pattern is clearly inconsistent with the existence of financial constraints. Similarly, the least constrained firms are the smallest and have the highest cash stock, whereas the most constrained firms have the highest sales growth and the second lowest industry sales growth. In sum, these anomalous results question the information content of the KZ index. Given the differences in the results from using our index versus using the KZ index, it is not surprising that the cross-sectionally de-meaned correlation between the two indices is near zero: –0.019.

These results are sufficiently paradoxical that they beg the question of how well the KZ index can classify Fazzari, Hubbard, and Petersen's original 49 firms. We have 45 of these firms in our data set, and we replicate the preceding results for these firms. We find in Table 3 that for the sample on which it was estimated, the KZ index categorizes as "constrained" firms with characteristics associated with external finance

Table 3
Summary statistics: KZ sample

	Least constrained			Most constrained
Firms sorted by structural index				
Investment/assets	0.098	0.096	0.076	0.092
Cash flow/assets	0.106	0.104	0.108	0.041
Total assets	3009.205	487.919	227.920	98.932
Debt assets	0.116	0.121	0.143	0.180
Positive dividends	0.342	0.335	0.082	0.008
Industry sales growth	−0.015	0.024	0.018	0.139
Sales growth	0.035	0.047	0.017	0.087
Cash/assets	0.131	0.097	0.082	0.067
Industry debt/assets	0.124	0.144	0.152	0.168
Number of analysts	2.723	1.959	1.706	0.997
Bond rating	0.444	0.070	0.004	0.012
Tobin's q	2.786	2.437	2.458	2.086
Structural index	0.552	0.619	0.665	0.723
Kaplan–Zingales index	0.938	0.896	1.011	1.120
Firms sorted by Kaplan–Zingales index				
Investment/assets	0.063	0.098	0.099	0.101
Cash flow/assets	0.136	0.100	0.084	0.041
Total assets	1650.666	787.019	683.659	694.077
Debt assets	0.036	0.081	0.169	0.270
Positive dividends	0.335	0.202	0.097	0.132
Industry sales growth	0.040	0.054	0.046	0.066
Sales growth	0.042	0.034	0.037	0.073
Cash/assets	0.119	0.114	0.075	0.068
Industry debt/assets	0.108	0.137	0.169	0.169
Number of analysts	1.668	2.052	1.788	1.864
Bond rating	0.125	0.109	0.121	0.171
Tobin's q	1.941	2.499	2.379	2.885
Structural index	0.620	0.637	0.645	0.660
Kaplan–Zingales index	0.424	0.794	1.110	1.606

Calculations are based on a sample of nonfinancial firms from the quarterly 2002 COMPUS-TAT industrial files. The sample period is January, 1975 to April, 2001. Investment/assets, sales/assets, and cash flow/assets are expressed at an annual rate. Industry sales growth is defined at the three-digit SIC level. Total assets are expressed in millions of 1997 dollars. The denominator of Tobin's q is the book value of total assets. The numerator is the book value of total assets minus the book value of equity minus balance-sheet deferred taxes plus the market value of equity.

constraints. The more constrained firms in this small sample have higher leverage, are smaller, and invest less relative to their investment opportunities than their less-constrained counterparts. Interestingly, our index *also* does a good job of sorting firms. Like the KZ-constrained firms, our constrained firms are smaller, have higher leverage, and invest less. However, whereas there appears to be little relationship between either analyst coverage or bond ratings and the KZ index, our index is once again associated with a much lower incidence of bond ratings and analyst coverage. The cross-sectionally de-meaned correlation between the two indices is again low at 0.108. In sum, these results underline the point made in the introduction that in a social science like economics, estimates from one nonexperimental sample need not be relevant to another nonexperimental sample.

2. The Financial Constraints Factor and Portfolio Returns

Having constructed an index of financial constraints and demonstrated that this index is likely to be more informative about the existence of financial constraints than the KZ index, we now examine whether and how financial constraints, as quantified by our index, affect asset returns. Recall that Lamont et al. demonstrate the existence of a financial constraints factor based on the KZ index; in particular, they find that returns on constrained firms appear to be subject to common shocks. They also find that the severity of financial constraints varies over time. However, given that our index and the KZ index clearly contain different information, it is interesting to determine whether this result holds up with the use of our structural index. We approach this task from a variety of angles.

2.1 Financial constraints portfolios

As a first step in this venture, we need to construct our own financial constraints portfolios. We start by using the structural index to form constrained and unconstrained portfolios. Next, we sort our firms independently based on size and our financial constraints index into the top 40, the middle 20, and the bottom 40%. Then, we classify all firms into one of nine groups: small size/low index (SL), small size/middle index (SM), small size/high index (SH), medium size/low index (ML), medium size/middle index (MM), medium size/high index (MH), large size/low index (BL), large size/middle index (BM), and large size/high index (BH). We form portfolios based on this sorting scheme, calculating value-weighted and equal-weighted average monthly portfolio returns with Center for Research in Security Prices (CRSP) monthly data.

This sort is analogous to that in Lamont et al. (2001) except along two dimensions. First, we use our financial constraints index instead of the KZ index. Second, they sort portfolios into terciles. We are unable to use this sorting scheme, because we occasionally find very few firms in the small size/unconstrained portfolio or the large size/constrained portfolio. Therefore, as an informal check on the robustness of our 40-20-40 scheme, we replicate the KZ financial constraints factor under both schemes, finding almost no difference between the resulting factor returns.

In addition to the nine size and financial constraints factor cross-sorted portfolios, we form three more portfolios that are linear combinations of the nine portfolios. The first, HIGHFC, is the equal-weighted average of the three most constrained portfolios in each of the size categories: $HIGHFC = (BH + MH + SH)/3$. The second portfolio, LOWFC, is the equal-weighted average of the three least constrained portfolios in each of the size category: $LOWFC = (BL + ML + SL)/3$. The third portfolio, FC, is the difference between these two portfolios: $FC = HIGHFC - LOWFC$. The FC portfolio is a zero-cost factor-mimicking portfolio for financial constraints. It is constructed in the same fashion as the Fama–French size and book-to-market benchmark factor portfolios.

Table 4 reports average returns and characteristics of these nine-size and financial-constraints cross-sorted portfolios. The sample used to construct this table is augmented from the sample used to estimate the Euler equations in two ways. First, we use extra observations not included in our Euler equation estimation. These observations were deleted because of our use of lagged instruments and I/B/E/S data. Including these extra observations increases our sample size by 51%, thereby allowing us to have a reasonably large number of observations in each of our nine groups.[4] Second, we add each firm's monthly returns from October, 1975 to December, 2001, expressed as percentages in excess of the one-month Treasury Bill yields. For each month, we value weight and equal weight returns and firm characteristics to obtain portfolio characteristics. We then time average portfolio returns and characteristics over the entire sample period to obtain mean returns and characteristics, which are reported in Table 4.

The average number of firms in each portfolio is reported in the first column. The nine portfolios contain a large number of firms, are fairly well diversified, and exhibit several interesting patterns. First, size is highly negatively correlated with being financially constrained: small firms are disproportionately constrained, and constrained firms are disproportionately small. This correlation is stronger when based on our financial-constraints index than when based on the KZ index. Second, financially constrained firms earn higher returns, except in the case of value-weighted small-cap firms. The difference between the value-weighted HIGHFC and LOWFC returns averages 0.18% over the sample period, although the t-statistics is 0.95 for the mean. Under equal weighting, the mean return of the FC portfolio is 0.23% with a t-statistics of 1.32. Therefore, based on the structural financial constraints index,

[4] When we re-calculate Table 2 using this expanded sample, we find very similar results.

Table 4
Portfolio characteristics and returns

			Value weighted				Equal weighted			
	Category label	Number of firms	Excess returns	D/A	B/M	Size	Excess returns	D/A	B/M	Size
Small-cap firms										
Low index	SL	37	0.89	0.54	1.92	0.03	0.87	0.56	2.18	0.03
Middle index	SM	85	0.66	0.38	1.30	0.03	0.82	0.43	1.52	0.03
High index	SH	349	0.83	0.23	0.89	0.03	1.15	0.28	1.12	0.02
Mid-cap firms										
Low index	ML	70	0.65	0.38	1.27	0.10	0.65	0.40	1.31	0.09
Middle index	MM	77	0.81	0.22	0.82	0.10	0.78	0.23	0.85	0.09
High index	MH	89	0.74	0.13	0.57	0.09	0.75	0.14	0.58	0.08
Large-cap firms										
Low index	BL	367	0.71	0.19	0.74	19.09	0.69	0.24	0.80	2.84
Middle index	BM	74	0.96	0.11	0.46	0.76	0.97	0.13	0.53	0.37
High index	BH	33	1.23	0.10	0.41	1.03	1.02	0.09	0.42	0.36
HIGHFC			0.93	0.15	0.63	0.38	0.97	0.17	0.71	0.15
LOWFC			0.75	0.37	1.31	6.41	0.74	0.40	1.43	0.98
FC			0.18	−0.22	−0.68	−6.03	0.23	−0.23	−0.72	−0.83
t-stat of FC			0.95				1.32			

B/M, book-to-market ratio; D/A, debt-to-assets ratio; FC, financial constraints factor; BH large size/high index; BL large size/low index; BM, large size/middle index; MH, medium size/high index; ML, medium size/low index; MM, medium size/middle index; SH, small size/high index, small size/low index; SM, small size/middle index.
This table reports summary statistics for nine value-weighted and nine equal-weighted portfolios formed by rankings of the market capitalization and the structural financial constraints index. The rankings are performed independently such that each portfolio contains firms that are both in a given size category and a given financial constraints category. Small-cap firms are firms that are in the bottom 40% of the sample in a given quarter sorted on market capitalization. Mid-cap firms are firms that are in the middle 20% of the sample. Large-cap firms are firms that are in the top 40% of the sample. Similarly, low, middle, and high index are firms that are in the bottom 40%, the middle 20%, and the top 40% of the sample sorted by the structural financial constraints index in a given quarter. HIGHFC = (BH + MH + SH)/3, LOWFC = (BL + ML + SL)/3, FC = HIGHFC − LOWFC. We report the sample mean of each portfolio's monthly returns in excess of one-month Treasury Bill yields in percentage. We also calculate average number of firms in each portfolio, D/A, B/M, and market capitalization in billions of dollars (size) by averaging over the entire sample period. The sample period is from October, 1975 to December, 2001.

financially constrained firms earn a positive, albeit statistically insignificant risk premium. The premium averages 2.18% for the value-weighted portfolio and 2.76% for the equal-weighted portfolio on an annual basis. Third, the debt-to-asset ratio (D/A) is higher for less constrained firms, reflecting their ability to use debt as a form of financing. Finally, the book-to-market ratio (B/M) is higher for less constrained firms. Hence, value stocks are on average less likely to be financially constrained as compared to growth stocks. These results contrast with the findings of Lamont et al., which is not surprising in light of the differences in the our index and the KZ index. Indeed, the correlation between our cross-sorted financial constraints factor and an analogously constructed KZ factor is low and insignificant at –0.283. After regressing out the effects of the Fama–French factors and the momentum factor, the correlation is even lower at –0.093.

2.2 Time series tests of common variation

We next follow Lamont et al. in conducting time-series tests of the existence of a financial constraints factor. As an informal start, we plot in Figure 1 the cumulative returns of the value- and equal-weighted financial-constraints portfolios; that is, the financial constraints factors.[5] To depict the cyclicality of the factor, we also indicate in this figure the beginning and end of NBER recessions with vertical dashed and solid lines, respectively. Two features stand out in the graph. First, the dynamic behavior of the value-weighted and equal-weighted factors is quite similar.

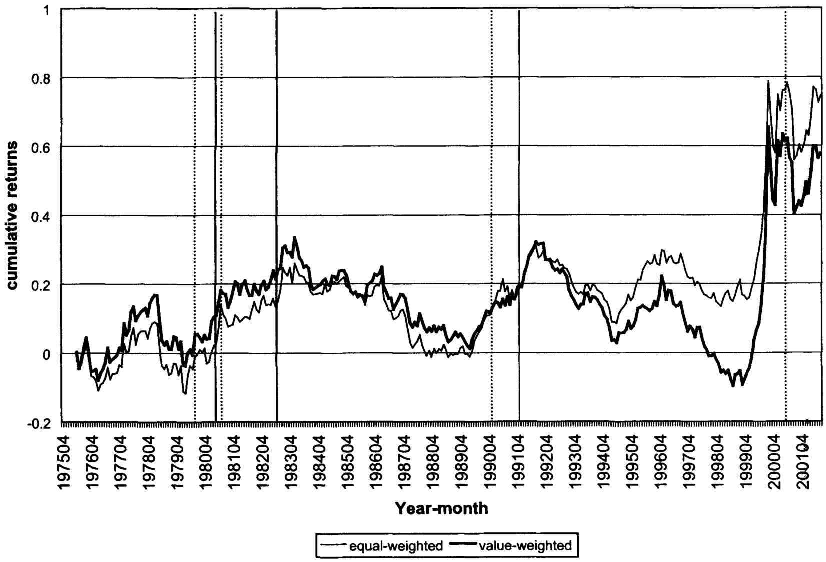

Figure 1
Monthly cross-sorted financial constraints factor
This figure plots the value-weighted and equal-weighted cross-sorted financial constraints factors. Based on independent sorts of the top 40, middle 20, and bottom 40% of size, and the financial constraints index, we classify all firms into one of nine groups: small size/low index (SL), small size/middle index (SM), small size/high index (SH), medium size/low index (ML), medium size/middle index (MM), medium size/high index (MH), large size/low index (BL), large size/middle index (BM), and large size/high index (BH). We form portfolios based on these sorts, using the quarterly financial constraints index estimated in our generalized method of moments (GMM) framework. Subsequent equal-weighted and value-weighted average monthly returns on these portfolios are calculated with Center for Research in Security Prices (CRSP) monthly data. Average constrained portfolio returns are computed as the mean of the SH, MH, and BH portfolio returns. Average unconstrained portfolio returns are computed as the mean of the SL, ML, and BL portfolio returns. The financial constraints factor is the average constrained portfolio returns minus the average unconstrained portfolio returns. We indicate the beginning and end of NBER recessions with vertical dashed and solid lines. The sample period is from October, 1975 to December, 2001.

[5] It is possible to re-estimate the Euler equation at this point, using the financial constraints factor in the pricing kernel. However, this exercise yields a marginally significant coefficient on the (value-weighted) financial constraints factor and an index that is nearly identical to our original index. The correlation between the two is 0.967.

The correlation coefficient between the two series is 0.939. The value-weighted factor seems to earn a slightly higher return for the first half of the sample but a slightly lower return for the second half of the sample. Second, the cumulative return is mostly positive for the sample period, yet in several periods, it declines steadily: for example, 1984–1989, 1992–1994, and 1997–1999. The cumulative returns spikes up for 2000 and 2001. The overall pattern helps explain the insignificant financial-constraints risk premium in Table 4. Although the returns on the factors are quite high in some periods, their long-run average is much lower.

A more detailed examination of the cumulative return of the financial constraints factor reveals a relationship between financial constraints risk and business cycles. The cumulative return increases from the beginning of sample in October of 1975, reaching a high level in 1983. Next, during the double dip recession in 1980–1982, the cumulative return increases steadily. The cumulative return then decreases until 1989. It then trends upward during the 1990–1991 recession. As in the expansion of the 1980s, it then declines again until 1999. Note finally the sharp upward spike that precedes the 2001–2002 recession period. Overall, we conclude that the cumulative return either coincides or precedes recessions and that it declines sharply during expansions. This counter–cyclical-realized *return* is consistent with a procyclical financial-constraints *risk premium*, in light of the evidence in, for example, Ferson and Harvey (1991), of a negative correlation between contemporaneous realized returns and expected future returns. Our evidence is also consistent with that in Gertler and Gilchrist (1994) and Bernanke, Gertler, and Gilchrist (1996), who find strong cyclical patterns in the expenditures of financially constrained firms.

Next, we test formally whether financially constrained firms have returns that move together, controlling for other sources of common variation, such as the market factor and the size factor. We regress returns of each of the nine-size and financial-constraints cross-sorted value-weighted portfolios listed in Table 4 on three reference portfolio returns. The first reference portfolio is a proxy for the market factor, the second reference portfolio is a proxy for the size factor, and the third reference portfolio is the value-weighted financial constraints factor.

Following Lamont et al., the market and size factor proxies are constructed using the portfolios in Table 4. The proxy for the market consists of the portfolios of less-constrained medium-sized and large-cap firms: $BIG = (BM + BL + MM + ML)/4$. The proxy for size consists of the less-constrained small firms: $SMALL = (SL + SM)/2$. To avoid spurious results in regressions for each of the nine portfolios, we exclude the left-hand-side portfolio from the construction of the right-hand-side reference portfolios.

We report in Table 5 the results of these nine regressions as well as the composition of the three reference portfolios for each of these regressions. First, not surprisingly, the loading on the BIG portfolio is larger for

Table 5
Covariance tests of portfolios

	Regression results					Variable definitions		
	Constant	BIG	SMALL	FC	R^2	BIG	SMALL	FC
Small-cap firms								
Low index (SL)	0.00 (0.66)	0.42 (5.25)	0.71 (10.11)	−0.10 (−1.60)	0.68	(BM + BL + MM + ML)/4	SM	(BH + MH − BL − ML)/2
Mid-index (SM)	−0.00 (−0.72)	0.56 (11.23)	0.34 (10.10)	0.13 (2.92)	0.76	(BM + BL + MM + ML)/4	SL	(BH + MH − BL − ML)/2
High index (SH)	0.00 (0.01)	0.43 (11.02)	0.50 (15.93)	0.29 (9.56)	0.88	(BM + BL + MM + ML)/4	(SM + SL)/2	(BH + MH − BL − ML)/2
Mid-cap firms								
Low index (ML)	−0.00 (−1.76)	0.64 (16.00)	0.43 (14.09)	0.01 (0.591)	0.88	(BM + BL + MM)/3	(SM + SL)/2	(BH + SH − BL − SL)/2
Mid-index (MM)	−0.00 (−0.23)	0.74 (21.76)	0.27 (10.06)	0.18 (6.83)	0.90	(BM + BL + ML)/3	(SM + SL)/2	(BH + SH − BL − SL)/2
High index (MH)	−0.00 (−1.55)	0.75 (18.84)	0.31 (9.84)	0.43 (14.30)	0.91	(BM + BL + MM + ML)/4	(SM + SL)/2	(BH + SH − BL − SL)/2
Large-cap firms								
Low index (BL)	0.00 (1.25)	0.83 (15.44)	−0.20 (−4.17)	−0.03 (−0.70)	0.66	(BM + MM + ML)/3	(SM + SL)/2	(MH + SH − ML − SL)/2
Mid-index (BM)	0.00 (1.49)	1.04 (22.32)	0.00 (0.11)	0.29 (7.02)	0.85	(BL + MM + ML)/3	(SM + SL)/2	(MH + SH − ML − SL)/2
High index (BH)	0.00 (1.40)	0.86 (9.99)	0.24 (3.34)	0.76 (9.31)	0.68	(BM + BL + MM + ML)/4	(SM + SL)/2	(MH + SH − ML − SL)/2

This table reports regression results of nine value-weighted portfolios described in Table 4. We regress the excess returns on each portfolio on three reference portfolios: a market proxy, a size factor proxy, and the financial constraints factor (FC). We construct our size and market proxies using the portfolios in Table 4 as follows. The proxy for overall market is the return on a portfolio of less-constrained medium-size and large firms, BIG = (ML + MM + BL + BM)/4, in excess of one-month Treasury Bill yield. The proxy for size is the return on a portfolio of less-constrained small firms, SMALL = (SL + SM)/2, in excess of one-month Treasury Bill yield. FC is defined in Table 4. In each regression, we omit the portfolio that is the dependent variable from the construction of the portfolios that constitute the regression's independent variables. In the case of FC, we also omit the matching portfolio on the short side. *T*-statistics are in parentheses. The sample period is from October, 1975 to December, 2001.

bigger firms, and the loading on the SMALL portfolio is larger for smaller firms. For each size category, more constrained firms always have larger loadings on the financial-constraints portfolio. For medium-constrained and high-constrained portfolios, the loadings on the financial-constraints factor are all positive and statistically significant. The results indicate that stock returns on constrained firms positively covary with the returns of other constrained firms. We conclude that this common variation indicates the presence of a financial constraints factor. These results are consistent with those in Lamont et al. However, because our index reflects different firm characteristics than the KZ index, we have clearly found evidence of a different source of common variation.

2.3 Preformation covariances

We find evidence above of the existence of a financial constraints factor, after we control for the market and the size effect. Daniel and Titman (1997) argue that forming portfolios based on a characteristic of interest (such as financial constraints) is likely to produce portfolios that share *other* common properties such as being in similar industries or regions. To show that there is indeed common variation in stock returns associated with financial constraints, we therefore conduct the Daniel–Titman test as refined by Lamont et al.

We split the sample of constrained firms into two groups: switchers and stayers. We start with the sample of all firms with six-quarter histories who are in the financial constraints portfolio in quarter t. Switchers are the firms whose constraint status differs between quarter $t - 5$ and quarter t. In other words, because we classify firms based on the end-of-period level of their financial constraints index, stayers are in the financially constrained group at the end of quarter $t - 6$ as well as at the end of quarter $t - 1$, and switchers are not. We construct two financial constraints portfolios. FC(stay) is a value-weighted portfolio that goes long on firms that are constrained in both quarter t and quarter $t - 5$ and goes short on firms that are unconstrained in both quarter t and quarter $t - 5$. FC(switch) is a value-weighted portfolio that consists of firms in the financial constraints portfolio in quarter t but not in FC(stay).

As explained by Lamont et al., constructing these two portfolios allows us to distinguish two hypotheses concerning common variation. First, under the hypothesis that the financial constraints factor is a spurious reflection of other factors, firms in the financially constrained portfolio in quarter t covary for reasons other than financial constraints. In this case, common variation should not be affected if firms switch status; that is, switchers should always covary with other switchers as well as with stayers. Second, under the hypothesis that the covariance is a function of constraint status, then switchers should covary less with each other and with stayers when their constraint status is different. Conversely, these covariances should be higher, the more the constraint status of the switchers is the same.

Table 6 summarizes the results for the two portfolios, FC(switch) and FC(stay). As in Lamont et al., we examine the returns on six different FC(switch) portfolios, each created with reference to a different quarter, from quarter $t-5$ to quarter t. The percent of FC(switch) firms in the same financial constraints third at the end of both quarter $t-j-1$ and quarter $t-1$ moves, by construction, from zero in quarter $t-5$ to 100 in quarter t.

The first test is to examine the variance of FC(switch). Moving from quarter $t-5$ to quarter t, Table 6 shows that variance rises by 65%, and the standard deviation rises by 29%. These increases are significant. In contrast, the standard deviation of FC(stay) declines slightly from quarter $t-5$ to t. Clearly the composition of FC(switch) becomes more homogenous from $t-5$ to t, which results in increased variance. In other words, covariance is higher when financial constraints status is more similar.

The second test focuses on the covariance between FC(switch) and FC(stay). If financial constraints drive the covariance of returns, the covariance between FC(switch) and FC(stay) should rise from quarter $t-5$ to quarter t. Table 6 summarizes that the covariance rises from 3.79 to 12.39. We also regress FC(switch) on FC(stay), finding that the coefficient on FC(stay) rises from 0.28 in quarter $t-5$ to 0.57 in quarter t. In words, increases in covariance accompany increases in the similarity of

Table 6
Preformation quarterly return variances and covariances

	FC(switch)			FC(stay)		FC(switch) and FC(stay) regression results		
	Percent switching	Variance	Standard deviation	Variance	Standard deviation	Covariance	Coefficient on FC(stay)	R^2
$t-5$	100	15.48	3.93	36.01	6.00	3.79	0.28 (5.68)	0.09
$t-4$	95	16.28	4.03	39.17	6.25	7.69	0.41 (7.62)	0.20
$t-3$	91	20.03	4.47	38.30	6.18	9.49	0.50 (9.24)	0.21
$t-2$	65	20.41	4.51	39.07	6.25	7.23	0.43 (7.68)	0.15
$t-1$	37	21.39	4.68	30.21	5.49	7.80	0.46 (8.07)	0.17
t	0	25.63	5.06	27.68	5.26	12.39	0.57 (9.61)	0.22

This table presents the time-series properties of the return on two portfolios, FC(switch) and FC(stay). It is constructed in a similar fashion to Table 4 of Lamont et al. (2001), except that we use the structural financial constraint index instead of the KZ index and we use quarterly accounting data instead of the annual data. The portfolios are constructed from the sample of all firms that are in the financial constraint portfolio in quarter t (so that they are in the top third or bottom third of all firms ranked by the structural financial constraint index at the end of quarter $t-1$) and which also have data available to construct the structural financial constraint index in quarter $t-6$. FC(stay) goes long on firms that are constrained in both quarter t and quarter $t-5$ and goes short on firms that are unconstrained in both quarter t and quarter $t-5$. FC(switch) consists of firms in the financial constraint portfolio in quarter t but which are not in FC(stay). "Percent switching" in quarter $t-j$ shows the percentage of firms in the FC(switch) portfolio that are not in the same bottom or top third of structural financial constraint index rankings as they are in quarter t. "covariance" is the time-series covariance of FC(switch) and FC(stay). Regression results show the ordinary least squares coefficient of FC(switch) on FC(stay), and t-statistics are reported in parentheses. The sample period is from February, 1975 to April, 2001.

constraint status. We conclude that there is indeed common variation in stock returns associated with financial constraints.

2.4 Relating the financial constraints factor to other known factors

We now examine whether the financial constraints factor reflects known empirical factors such as the market, size, book-to-market, and momentum. We regress the financial constraints factor on these factors. If these known factors correctly price the financial constraints factor, then the intercept from these regressions should be zero. Further, the R^2 in these regressions should be high. Otherwise, the financial constraints factor measures sources of variation independent of the known factors.

The first panel of Table 7 reports the full-sample results from regressions of the value-weighted and equal-weighted financial constraints factor on the three Fama–French factors and the momentum factor. The financial constraints factor is negatively correlated with the market and negatively correlated with the book-to-market factor. Not surprisingly, it is positively correlated with the size factor. Smaller firms are more likely to be financially constrained. The financial constraints factor is also positively correlated with the momentum factor. All coefficient estimates are statistically significant.

It is important to note that the t-statistics for the intercept lie between 1.92 and 4.33 for the four specifications; in other words, the four-factor model cannot correctly price our factor. Further, the R^2s fall between 37 and 50%, indicating that a significant portion of the variation in our factor cannot be explained by the current four factors. This result is important inasmuch as a finding of a high R^2 would suggest little independent role for our factor in explaining asset returns.

The second and third panels of Table 7 report analogous results for the first and second halves of the sample, respectively. These second two sets of results are broadly similar to the first, except along two dimensions. First, the R^2s are noticeably smaller in the first half of the sample, suggesting a larger independent role for our factor. Second, none of the intercepts from the first half of the sample are significantly different from zero.

2.5 Cross-sectional analysis of firm characteristics

We further examine whether financially constrained firms earn a positive-risk premium on a cross-sectional basis using individual stock returns. For our sample of firms with an estimated financial constraints index, we regress returns in excess of one-month Treasury Bill yield on characteristics such as size, the book-to-market ratio, momentum, and the financial-constraints index. Note that we regress firm returns directly on firm characteristics instead of the betas estimated from factor models. The benefit of using characteristics is that they are much more precisely measured than the betas from the factor models. The drawback of using characteristics directly is that it is more difficult to assign economic

Table 7
Relating the financial constraints factor to the four-factor model

Dependent variable	Constant	Market	SMB	HML	Momentum	R^2
Full Sample						
Value-weighted FC factor	0.0052 (3.37)	−0.1977 (−5.44)	0.3226 (6.34)	−0.5648 (−11.74)		42.91%
Value-weighted FC factor	0.0020 (1.98)	−0.1724 (−5.08)	0.3476 (7.25)	−0.4001 (−7.89)	0.2608 (6.77)	50.42%
Equal-weighted FC factor	0.0065 (4.33)	−0.2308 (−6.50)	0.1453 (2.93)	−0.5617 (−11.95)		37.02%
Equal-weighted FC factor	0.0027 (1.92)	−0.2019 (−6.23)	0.1740 (3.85)	−0.3732 (−7.72)	0.2988 (8.24)	48.34%
October, 1975–November, 1988						
Value-weighted FC factor	0.0007 (0.34)	−0.0512 (−1.08)	0.2965 (3.75)	−0.1889 (−2.35)		12.20%
Value-weighted FC factor	−0.0004 (−0.21)	−0.0747 (−1.59)	0.2605 (3.34)	−0.1507 (−1.90)	0.1809 (3.05)	17.22%
Equal-weighted FC factor	0.0015 (0.71)	−0.0777 (−1.62)	0.1567 (1.96)	−0.2151 (−2.65)		6.75%
Equal-weighted FC factor	−0.0002 (−0.09)	−0.1125 (−2.46)	0.1033 (1.36)	−0.1585 (−2.05)	0.2680 (4.64)	18.25%
December, 1988–December, 2001						
Value-weighted FC factor	0.0073 (3.40)	−0.3197 (−5.97)	0.2619 (4.07)	−0.7490 (−12.57)		62.19%
Value-weighted FC factor	0.0030 (1.36)	−0.2142 (−3.90)	0.3628 (5.67)	−0.4981 (−6.45)	0.2665 (4.70)	67.00%
Equal-weighted FC factor	0.0093 (4.63)	−0.3746 (−7.42)	0.0673 (1.11)	−0.7425 (−13.21)		59.16%
Equal-weighted FC factor	0.0052 (2.51)	−0.2715 (−5.27)	0.1659 (2.76)	−0.4972 (−6.86)	0.2604 (4.90)	64.73%

This table reports the estimates of models linking the value-weighted and equal-weighted financial constraint factor to the three Fama–French factors and the momentum factor. t-statistics are reported below the coefficients in parentheses. The sample period is from October, 1975 to December, 2001.

meaning to the estimated coefficients. However, the statistical significance of the coefficients is easy to determine, and it is the statistical significance that interests us. In other words, we want to determine whether more financially constrained firms earn higher returns, and we would like to know whether the difference is statistically significant.

We measure size by market capitalization in billions of dollars, and momentum by prior six-month mean returns, excluding the latest month to minimize any bid-ask bounce. Financial constraints is measured by the structural financial constraints index estimated earlier in the paper. Daniel and Titman (1997) noted that a simple linear or log-linear regression of returns on capitalization and book-to-market ratios may not be sufficient to characterize observed stock returns. We define an interaction term between size and book-to-market, size/BM, as the capitalization in billions of dollars divided by the book-to-market ratio. Smaller-sized or higher book-to-market firms are expected to earn higher returns. Hence, the likely sign on the interaction term is negative. We run these regressions month by month and report in Table 8 the sample mean and the time series t-statistics of the estimated coefficients.

Model 1 in Table 8 is a simple regression of excess returns on size. As expected, the sign is negative: smaller firms earn higher returns on average. However, this t-statistic is only –1.52. In Model 2, we regress returns

Table 8
Cross-sectional regression of returns on firm characteristics

Specification	Size	B/M	Size/BM	Momentum	FC index
Full sample					
Model 1	−0.0052 (−1.52)				
Model 2		0.0046 (5.10)			
Model 3	−0.0043 (−1.31)	0.0045 (5.08)			
Model 4	−0.0042 (−1.35)	0.0050 (6.04)		0.0278 (1.95)	
Model 5	−0.0056 (−1.54)	0.0050 (6.14)	0.0001 (0.55)	0.0273 (1.92)	
Model 6	0.0002 (0.58)	0.0051 (6.12)		0.0277 (1.99)	0.0349 (3.01)
Model 7	0.0002 (0.59)	0.0050 (6.10)	0.0001 (0.46)	0.0272 (1.97)	0.0363 (3.17)
October, 1975–November, 1988					
Model 6	0.0000 (0.07)	0.0067 (5.50)		0.0420 (2.35)	0.0204 (1.39)
Model 7	0.0000 (0.10)	0.0066 (5.53)	0.0000 (0.39)	0.0427 (2.42)	0.0191 (1.31)
December, 1988–December, 2001					
Model 6	0.0000 (2.30)	0.0036 (3.11)		0.0133 (0.62)	0.0498 (2.77)
Model 7	0.0000 (2.22)	0.0034 (3.06)	0.0000 (1.77)	0.0118 (0.54)	0.0537 (3.03)

B/M, book-to-market ratio; FC, financial constraints.
This table reports the results for the month-by-month cross-sectional regressions of firm excess returns on firm characteristics such as size, book-to-market ratio, momentum and financial constraints. Excess returns are computed in excess of one-month Treasury Bill yields. Size is measured by market capitalization in billions of dollars. Momentum is measured by prior six-month mean return excluding the latest month. Financial constraints are measured by the structural financial constraints index. We also define an interaction between size and book-to-market: size/BM equals market capitalization divided by the book-to-market ratio. We use the Fama–Macbeth technique to compute the means of the time series of regression coefficients. The time-series t-statistics are reported in parentheses. The sample period is from October, 1975 to December, 2001.

on the book-to-market ratio. The coefficient is positive and statistically significant. The results are similar when returns are regressed on both size and book-to-market. Adding momentum to the specification in Model 4 reveals that the momentum effect is positive with a *t*-statistic of 1.95. The coefficient on the interaction term between size and book-to-market is not statistically significantly different from zero.

In model specifications 6 and 7, we include the financial constraints index in the regressions. The coefficient is positive and statistically significant whether or not the interaction term is included. The coefficient on the book-to-market ratio does not change much, and it remains statistically significant. However, including the financial constraints index in the regressions changes the coefficient on size from –0.005 to 0.0002. The size effect basically disappears once financial constraints are taken into account. This finding is interesting since it suggests that the size effect may be in part explained by financial constraints risk.

As above, we once again split our sample into two time periods, rerunning models 6 and 7 for each subperiod. The results from the second half of the sample are almost identical to those from the full sample. However, for the first half of the sample, the statistical significance of the coefficient changes, although the average coefficient estimates continue to display the same pattern. The coefficient on the financial constraints index is no longer significant; and the coefficient on size, while remaining quite small, becomes significant. Because these changes in significance are clearly an artifact of differences in coefficient stability *within* each of the subperiods, and because the coefficient estimates are relatively unchanged, we do not attribute much economic significance to the changes in statistical significance.

3. Conclusion

In this study, we have constructed a new index of financial constraints using a structural investment model. Our GMM estimation yields a quarterly time series on this index for all firms in our sample. We have demonstrated that the firms categorized as "constrained" by this index exhibit characteristics typically associated with exposure to external finance constraints. This piece of evidence stands in sharp contrast to our finding that a widely used index of financial constraints, the KZ index, does not isolate firms with characteristics associated with finance constraints. Firms deemed constrained by our index are small, underinvest, have low analyst coverage, and do not have bond ratings. In contrast, firms deemed constrained by the KZ index are large, overinvest, have high analyst coverage, and have a markedly higher incidence of bond ratings than the population of firms as a whole.

We then construct portfolios with different size and financial constraint rankings. We conduct time-series tests and find that stock returns on constrained firms positively covary with the returns of other constrained firms. This evidence of common variation in stock returns associated with financial constraints points to a financial constraints factor in stock returns. We also find that a significant portion of the variation in the factor cannot be explained by the Fama–French factors and the momentum factor. Cross-sectional regressions of firm returns on the financial constraints index and other firm characteristics indicate that more constrained firms earn higher returns. More interestingly, once financial constraints are taken into account, the usual result that smaller firms earn higher returns disappears.

In sum, our results stand in contrast to the limited empirical work that has been executed to date on this topic. Instead of finding no effect of financial constraints on stock returns, we uncover evidence that firm-level external finance constraints do indeed represent a source of undiversifiable risk that is priced in financial markets. We attribute this difference to two factors. First, we have constructed a credible index of financial constraints. Second, we do not attempt to explain the time series of aggregate returns, instead concentrating on identifying classes of firms that have exposure to financial constraints risk. Having said this, however, we also note that our results are silent about the effects of financial constraints on private and venture capital-financed firms. To the extent that these firms are catalysts for technological development, further work to study the effects of external finance constraints in this area is also important.

References

Bond, S. D., and C. Meghir, 1994, "Dynamic Investment Models and the Firm's Financial Policy," *Review of Economic Studies*, 61, 197–222.

Bond, S. D., and J. G. Cummins, 2001, "Noisy Share Prices and the q Model of Investment," Working paper, Oxford University, Cambridge, MA.

Bernanke, B., and M. Gertler, 1989, "Agency Costs, Net Worth, and Business Fluctuations," *American Economic Review*, 79, 14–31.

Bernanke, B., M. Gertler, and S. Gilchrist, 1996, "The Financial Accelerator and Flight to Quality," *Review of Economics and Statistics*, 78, 1–15.

Calstrom, C. T., and T. S. Fuerst, 1997, "Agency Costs, Net Worth, and Business Fluctuations: A Computable General Equilibrium Analysis," *American Economic Review*, 87(5), 893–910.

Chan, K. C., and N. Chen, 1991, "Structural and Return Characteristics of Small and Large Firms," *Journal of Finance*, 46, 1467–1484.

Chan, K. C., N. Chen, and D. Hsieh, 1985, "An Exploratory Investigation of the Firm Size Effect," *Journal of Financial Economics*, 14, 451–471.

Chen, N., and F. Zhang, 1998, "Risk and Return of Value Stocks," *Journal of Business*, 71, 501–535.

Cooper, R., and J. Ejarque, 2001, "Exhuming Q: Market Power vs. Capital Market Imperfections," NBER Working Paper 8182, Oxford, UK.

Daniel, K., and S. Titman, 1997, "Evidence on the Characteristics of Cross Sectional Variation in Stock Returns," *Journal of Finance*, 52, 1–34.

Dichev, I., 1998, "Is the Risk of Bankruptcy a Systematic Risk?," *Journal of Finance*, 53, 1131–1147.

Erickson, T., and T. M. Whited, 2000, "Measurement Error and the Relationship Between Envestment and q," *Journal of Political Economy*, 108, 1027–1057.

Fama, E. F., and K. R. French, 1993, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics*, 33, 3–56.

Fama, E. F., and K. R. French, 1995, "Size and Book-to-Market Factors in Earnings and Returns," *Journal of Business*, 73, 161–175.

Fama, E. F., and K. R. French, 2000, "Forecasting Profitability and Earnings," *Journal of Business*, 73, 161–175.

Fazzari, S., R. G. Hubbard, and B. C. Petersen, 1988, "Financing Constraints and Corporate Investment," *Brookings Papers on Economic Activity*, 1, 141–195.

Ferson, W., and C. R. Harvey, 1991, "The Variation of Economic Risk Premiums," *Journal of Political Economy*, 99, 385–415.

Gertler, M., and S. Gilchrist, 1994, "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *Quarterly Journal of Economics*, 109, 309–340.

Gomes, J. F., A. Yaron, and L. Zhang, 2004, "Asset Pricing Implications of Firms' Financing Constraints," Working paper, University of Pennsylvania, Philadelphia, PA.

Griffin, J., and M. Lemmon, 2002, "Book-to-Market Equity, Distress Risk, and Stock Returns," *Journal of Finance*, 57, 2317–2336.

Holtz-Eakin, D., 1988, "Testing for Individual Effects in Autoregressive Models," *Journal of Econometrics*, 39, 297–307.

Hubbard, R. G., A. K. Kashyap, and T. M. Whited, 1995, "Internal Finance and Firm Level Investment," *Journal of Money, Credit, and Banking*, 27, 683–701.

Kaplan, S., and L. Zingales, 1997, "Do Financing Constraints Explain Why Investment is Correlated with Cash Flow?," *Quarterly Journal of Economics*, 112, 169–216.

Kiyotaki, N., and J. Moore, 1997, "Credit Cycles," *Journal of Political Economy*, 105, 211–248.

Lamont, O., C. Polk, and J. Saá-Requejo, 2001, "Financial Constraints and Stock Returns," *Review of Financial Studies*, 14, 529–544.

Love, I., 2003, "Financial Development and Financing Constraints, International Evidence from the Structural Investment Model," *Review of Financial Studies*, 16, 765–791.

Newey, W., and K. West, 1987, "Hypothesis Testing with Efficient Method of Moments Estimation," *International Economic Review*, 28, 777–787.

Whited, T. M., 1992, "Debt, Liquidity Constraints, and Corporate Investment, Evidence from Panel Data," *Journal of Finance*, 47, 1425–1460.

Whited, T. M., 1998, "Why do Investment Euler Equations Fail?," *Journal of Business and Economic Statistics*, 16, 469–478.