Corporate Financing and Investment: On the Dynamics of the Credit Multiplier

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Abstract

We analyze the dynamic credit multiplier of asset tangibility on investment when firm financing and investment are simultaneously determined. We do this in a real options framework that allows for capital markets imperfections. For financially constrained firms, acquiring assets that can be used as collateral alleviates default risk and enlarges debt capacity. This accelerates investment and boosts equity values. Our model shows that constrained firms with more tangible assets invest more and borrow more in response to positive shocks to investment opportunities. This works via an endogenous financing–investment feedback effect that propagates itself over time ("credit multiplier"). Using a large sample of manufacturing firms over the 1971–2005 period, we find robust results that strongly support our model's predictions. Consistent with our identification strategy, the credit multiplier is absent from samples of unconstrained firms and constrained firms with low incremental debt capacity.

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1 Introduction

Does financial contracting affect real corporate outcomes? How do contracting frictions affect firm value? Are contracting imperfections a relevant issue for how firms finance their investment? Understanding the dynamics of interactions between real and financial decisions is arguably one of the most important issues in financial economics. Accordingly, there exists a large corporate finance literature that examines when firms should invest and how they should finance their investment. Unfortunately, the literature often overlooks the impact of contracting frictions on firms' ability to raise funds and invest. As a result, the investment process is seen as *exogenous* to financial status, financing choices, and financing terms.

Contracting imperfections manifest themselves in many different ways. They typically make it harder for firms to raise fairly-priced funds to finance their investment. As a result, the availability of financing, rather then the availability of investment opportunities, drives firms' investment spending. One of the most commonly observed financing imperfections is the limited enforceability of contracts. Firms often choose to default on outstanding financial obligations when their liquidation values are too low to keep investors committed to termination (e.g., Gilson et al. (1990) and Altman (1991)). Theoretical models have recognized this problem and characterized financing arrangements that commit investors to enforce costly termination (e.g., Harris and Raviv (1990), Bolton and Scharfstein (1990), and Hart and Moore (1994)). Although they vary in their design, a key feature that makes these contracts enforceable has a common real-world counterpart: the "tangibility" of a firm's assets. Assets that are more tangible are easier to verify and repossess, which increases the value investors recover in the event of default.[1] As such, the degree of tangibility of a firm's assets may not only be tied to the firm's underlying investment process, but also to its ability to raise external financing.

This paper characterizes the *endogenous* relation between firms' real and financial decisions in the presence of financing imperfections. Using a real options framework, we examine a dynamic model in which financing frictions distort the firm's investment process and valuation, subsequently affecting the firm's ability to raise external funding. To wit, because the tangibility of a firm's asset affects its ability to pledge collateral, asset tangibility not only enlarges the firm's debt capacity but also reduces its default risk. In addition, by expanding the firm's capital base, the dynamic investment process engenders a feedback effect in which new investment (in tangible assets) helps relax

[1] Hereinafter, the term "asset tangibility" is meant to summarize the *liquidation value* and *ease of redeployment* of a borrower's assets from the perspective of outside investors.

financing constraints further. Our model formalizes the endogenous mechanism via which asset tangibility amplifies the impact of shocks to the firm's opportunity set onto investment (spending and timing) and financing (debt taking and equity valuation) across time — the dynamic credit multiplier. Our model yields novel testable predictions regarding the influence of asset tangibility on interactions between firm financing and investment following innovations to the firm's investment opportunities. To our knowledge, this paper presents the first study to formally derive and empirically test the cross-sectional implications of asset tangibility for financing–investment interactions.[2]

Our theory's central insights guide us in performing novel empirical tests on the extensively studied relationship between corporate investment and Tobin's q (Q). Our model shows, for example, that an increase in the borrower's equity value following a positive industry shock improves both current output levels and future investment prospects by way of relaxing financing constraints. Corporate outcomes of this type characterize the dynamic credit multiplier of our framework: exogenous industry-wide shocks affect firms' investment as well as operating policies (and hence Q) in a way that the initial shock gets amplified through its impact on firms' access to credit. The model predicts that the credit multiplier will be stronger for financially constrained firms and that it will increase with the tangibility of the (constrained) firms' assets. Empirically, both Q and asset tangibility are expected to explain investment behavior, but the model's credit multiplier implies that the *interaction* of these two variables should have a strong positive effect on investment in the cross section of financially constrained firms. Put differently, our theory implies that positive innovations to investment prospects prompt stronger responses in observed investment spending when assets are more tangible and the firm solves a constrained optimization problem.[3,4]

As is standard in the corporate investment literature, our model's testable predictions are identified based on comparisons between firms that are likely to face pronounced financing constraints and firms that are likely unconstrained. Theoretically, we define as *financially constrained*, those firms that are unable to undertake valuable investment opportunities due to limited access to funds in the credit markets. Following the literature standard (e.g., Bernanke et al. (1996) and Kiyotaki

[2] In the macroeconomics literature, Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) provide alternative characterizations of the credit multiplier. The only two papers in the corporate finance literature that consider ideas related to ours are Almeida and Campello (2007) and Hennessy et al. (2007). As we discuss shortly, their analyses, goals, and results are very different from ours.

[3] In the unconstrained solution, observed investment spending may naturally respond to shocks to investment opportunities, but this is *not* magnified by asset tangibility.

[4] We give a thorough treatment to the potential problem that Q is a proxy for investment opportunities that is measured with errors. Importantly, note that the conventional concern with Q is that mismeasurement will lead to an "attenuation bias." This bias makes it *more difficult* to find any effect of Q on investment.

and Moore (1997)), we consider that creditors may offer arms'-length debt to fund new investment conditional on firms' net worth. Unlike previous papers, however, we also allow for various degrees of financing constraints, ranging from a possibly binding *quantity constraint* (i.e., access to only risk-free debt, limited by creditors' available collateral) to a less restrictive *pricing constraint* (i.e., access to risky debt that is priced as a function of the probability of default). Accordingly, another feature of our model is that it enriches the real options theory of investment by allowing for varying degrees of financing constraints. This allows us to consider new cross-sectional implications for the role of asset tangibility in underlying dynamic interactions between financing and investment.[5]

We perform tests of our theory using a large sample of manufacturing firms over the 1971–2005 period. In our baseline tests, we estimate regressions over subsamples that are identified according to the likelihood that firms have constrained access to external finance. Following the existing literature, we employ multiple approaches to split the data into constrained and unconstrained subsamples; these are based on observable firm characteristics such as payout policy, size, and debt ratings (bond and commercial paper ratings). Moreover, we consider both firm- and industry-level measures of asset tangibility. Our firm-level proxy gauges the expected liquidation value of a firm's main categories of operating assets: fixed capital, inventories, and accounts receivable (based on Berger et al.'s (1996) study on asset liquidation values). Our industry-level proxy captures the ease with which lenders may redeploy a borrower's assets. Specifically, Bureau of Census data on the demand for used capital are employed to measure the level of activity in the market for second-hand assets amongst high-value users of a firm's capital; that is, amongst other firms in the same industry (cf. Shleifer and Vishny (1992)).[6]

Consistent with our model's main predictions, we find that under each one of our constraint partition schemes, asset tangibility promotes investment through a credit multiplier for constrained firms, but not for unconstrained firms. More precisely, our first set of tests reveals the economically and statistically significant role played by asset tangibility in influencing investment of constrained firms. Because of the role of asset tangibility in simultaneously boosting credit and investment, our theory implies that the credit multiplier would be more finely identified by interacting asset tangibility with Q. Consistent with this prediction, our second set of tests shows that estimates for this interaction term reliably explain investment across financially constrained firms. As we

[5] Notably, although insufficient debt capacity has been customarily emphasized by the work on financing imperfections, equity flotation may also be more costly for firms that have limited ability to issue debt. As we later explain, this feature of financing constraints is also considered in our framework.

[6] To construct this measure, we hand-collect data on capital acquisitions from the Bureau of Census' *Annual Survey of Manufacturers*. Given the availability of data from the relevant surveys, the industry-level proxy we use in our tests are based on annual observations from 1980 to 1996.

later detail, this interaction effect is even more pronounced in a third set of results, in which we stratify constrained firms into subsamples with low and high incremental debt capacity.[7] In particular, in line with our model's implications, we find that constrained firms with largely untapped debt capacity display the strongest relation between investment and tangibility interacted with Q. Remarkably, *none* of the effects just described are found across financially unconstrained firms.

To verify that our baseline results survive under alternative test specifications and methods, we perform numerous robustness checks on the findings that asset tangibility positively influences financing–investment interactions for constrained firms, but not for unconstrained firms. We show, for example, that our results do not rely on *a priori* assignments of firms into financial constraint categories (recall, following the literature, our base tests assign firms to constraint categories based on *ex-ante* observables such as size). Accordingly, throughout the analysis we also employ a switching regression estimation framework in which the probability that firms face constrained access to credit is jointly estimated with the investment equations — i.e., constraint assignments are *endogenous* to investment. More generally, our results also obtain when we use maximum likelihood estimations (switching regressions), GMM regressions, error-consistent estimations in which Q is replaced with Cummins et al.'s (2006) *RealQ* (based on analysts' earnings forecasts), and OLS regressions that employ a projection of Q on industry prices in lieu of Q. In each of these alternative tests, the impact of asset tangibility on constrained firms' financing–investment interactions remains economically and statistically significant. Similarly, our inferences are invariant to the use of firm- or industry-level proxies for asset tangibility.

Finally, we also look at the effect of asset tangibility on the interplay between firms' leverage choices and investment opportunities. Surprisingly, there is very little empirical work on the link between asset tangibility and capital structure. Early empirical studies were limited to documenting a positive correlation between the ratio of fixed-to-total assets and financial leverage (e.g., Titman and Wessels (1988) and Rajan and Zingales (1995)). More recently, research on financial development shows that industries with "harder" assets obtain more creditor financing in countries with poor contractual enforceability (e.g., Braun (2003) and Claessens and Laeven (2003)). These pieces of evidence are broadly consistent with the idea that asset tangibility matters for raising external financing. However, they are silent on the role of asset tangibility in underlying a collateral channel between financial contracting and outcomes such investment and market valuation. Our empirical tests reveal that asset tangibility also magnifies the effect of shocks to investment opportunities on debt taking when firms are financially constrained, but not when they are unconstrained. In other words,

[7] These partitions are based on the component of long-term debt that is *not explained* by asset tangibility.

the same amplification effect that is found for tangibility on investment spending is also observed for debt policies in the cross section when firms face financing frictions. The evidence we report for leverage decisions goes in tandem with the predictions of our endogenous credit multiplier story.

The papers closest to ours are Almeida and Campello (2007) and Hennessy et al. (2007).[8] Almeida and Campello's empirical methodology sheds new light on the sensitivity of investment to cash flow. Those authors emphasize the importance of tangible capital in credit markets, showing that cash flow shocks have a larger impact on capital spending when the tangibility of capital is high. In contrast to their paper, we develop a full-fledged model for the role played by asset tangibility in financing–investment interactions; in particular, how exogenous industry shocks propagate in a real options framework of irreversible investment. Differently from Almeida and Campello, we do not seek to take a stand on the interpretation of the sensitivity of investment to cash flows. Finally, their paper does not examine financing decisions. Hennessy et al. (2007) develop a Q-theoretical investment model under financing constraints that features risk-free debt (only) and external equity. With their financing mix as a special case, our model encompasses arbitrary mixtures of risky debt and costly external equity to fund investment. Moreover, our tests complement their findings in that we focus on an alternative empirical specification and employ different methods for empirical identification. Finally, we note that Hennessy et al.'s study is silent on the credit multiplier, which is the focus of our analysis.

The remainder of the paper is organized as follows. Section 2 embeds asset tangibility and financial constraints into a real options framework for analyzing financing–investment interactions. Motivated by the model's main prediction, Section 3 implements our empirical methodology to examine the role of asset tangibility in a large sample of manufacturing firms in the United States over 35-year window. Section 4 concludes. All technical developments gathered in the Appendix.

2 The Model

We build a partial equilibrium framework to study the impact of asset tangibility on financing and investment decisions of financially constrained firms; that is, firms that currently cannot undertake profitable investment opportunities.[9] Capital market frictions make the Modigliani and Miller theorem inapplicable and hence create interesting interactions between financing and investment. In particular, those frictions can lead to endogenous relations between financing and investment decisions.

[8]In contrast to our focus on the investment, Morellec (2001) shows that more liquid assets exacerbate bondholder-shareholder conflicts over disinvestment, providing a role for bond covenants that restrict disposition of assets.

[9]See Bernanke et al. (2000) for a dynamic general equilibrium model that relates to our framework.

2.1 Setting

2.1.1 Production

In an industry with stochastic demand, we consider a firm that sells nonstorable output, which it produces with fixed inputs (physical capital) and variable inputs (labor). The firm is risk-neutral and discounts profits at a constant interest rate $r > 0$. Time is continuous and uncertainty is modeled by a complete probability space $(\Omega, \mathcal{F}, \mathcal{P})$. At time t, K_t, and N_t denote respectively the stock of fixed and variable inputs. While labor, N_t, is freely and instantaneously adjustable, physical capital, K_t, is irreversible and cannot be adjusted freely. The industry is competitive and output price evolves stochastically according to a diffusion process:

$$dP_t = \mu\left(P_t, t\right) dt + \sigma\left(P_t, t\right) dW_t, \tag{1}$$

where $\mu(\cdot)$ is the drift rate of output price changes, $\sigma(\cdot)$ is the standard deviation of output price changes, dW_t denotes the increment of a Wiener process, and the initial level of the output price equals P_0.[10] The diffusion process for the industry's state variable in Eq. (1) is sufficiently general to allow for competitive dynamics that may affect the path of P_t. For instance, an Ornstein-Uhlenbeck process would proxy for cyclical patterns in the industry resulting from entry and exit, while a geometric process would capture trend effects in rising or declining industries. Exogenous shocks to technology, consumer preferences, input prices, etc. may change competitive dynamics in the industry, and hence firms' investment opportunity set. Our later empirical tests emphasize the consequences of such changes to investment demand.

The firm's operating profits, that is, revenue minus cost of variable inputs, are given at time t by:

$$\pi(K_t, P_t) = P_t K_t^x N_t^y - w N_t, \tag{2}$$

where the cost per unit of input in N_t is denoted by w.[11] We assume that the Cobb-Douglas revenue function in Eq. (2) displays decreasing returns to scale with respect to the variable input (i.e., $y < 1$) but increasing returns to scale when both inputs are variable (i.e., $x + y > 1$).

2.1.2 Financing

Following Bernanke et al. (1996), the firm has preexisting debt with perpetual coupon payments b_0. We assume that this is an outcome of past financing decisions; for instance, debt was issued in

[10] We assume that drift and volatility satisfy the necessary conditions for the existence of a unique solution to the stochastic differential equation (see, e.g., Karatzas and Shreve (1988) for regularity conditions).

[11] For a detailed motivation of this standard production technology see, among others, Abel and Eberly (2002).

the past to finance the existing stock of physical assets K_0 at an installation cost $\lambda_0 > 0$. The firm can expand its capital stock by adjusting its capital from K_0 by the amount $K_1 > 0$ to $K_0 + K_1$. At the time of investment, the firm incurs an irreversible adjustment cost $\lambda_1 \equiv 1$ per unit of new capital. At time t, investment $I_t = \lambda_1 K_1$ may be financed by (1) equity, (2) debt, or (3) a mix of debt and equity, with $\theta \in (0, 1)$ denoting the fraction of I_t that is equity-financed.[12]

We model the pledgeability of the firm's assets by assuming that transfer of those assets to creditors in default entails firm- and industry-specific transaction costs that are proportional to the firm's physical assets (e.g., Almeida and Campello (2007)). More precisely, if the firm's assets are seized by its lenders at time t, contracting frictions, that plague the relations between borrowers and creditors, only allow for recovery of a fraction, τ, of the firm's physical capital, K_t. The firm and industry characteristic τ is a natural function of the tangibility of the firm's physical assets as well as industry characteristics, such as capital utilization rates and used capital redeployability.

Following Bernanke et al. (1996), we assume that creditors may offer additional arms'-length debt with perpetual coupon payments b_1. Our analysis, however, goes further in considering "degrees" of financing constraints. In particular, creditors may impose a net worth covenant at time t ensuring $B(K_t, P_t, b_1) \leq \rho R(K_t, P_t)$ where $\rho \geq 1$. Unless $\rho = 1$ (i.e., a *quantity constraint* to make debt risk-free), creditors permit issuance of risky debt (i.e., a *pricing constraint* to value debt as a function of the probability of default). Accordingly, the covenant parameter ρ influences the degree to which the firm is financially constrained in that a higher value of ρ corresponds to more availability of risky debt.

The amount of risky debt is limited by the firm's debt capacity at time t, which is defined by:

$$\overline{b}(K_t, P_t) \in \arg\max_{b_t} B(K_t, P_t, b_t), \tag{3}$$

where $B(\cdot)$ denotes debt value and $b_t \in \{b_0, b_0 + b_1\}$. The maximum amount of additional debt (i.e., the firm's incremental debt capacity) thus equals:

$$\overline{B}(K_t, P_t) = \min\left\{\rho\left[R(K_t, P_t) - b_0/r\right], B\left(K_t, P_t, \overline{b}(K_t, P_t) - b_0\right)\right\}, \tag{4}$$

where $R(\cdot)$ denotes the value of recoveries. Eq. (4) suggests that stricter net worth covenants via lower values of ρ and more preexisting debt hinder debt-financed investment in a lower region of output prices in that the available proceeds from new debt with a stream of coupon payments $b_1 \leq \overline{b}(K_t, P_t) - b_0$ may be insufficient to fund the adjustment cost. That is, the firm is financially constrained if $I_t > \overline{B}(K_t, P_t)$.

[12] The total dollar value of I_t may be due to convex and non-convex adjustment costs as in Cooper and Haltiwanger (2006). However, such a distinction would not affect the empirical implications of our model.

Finally, our model also allows for equity financing. In particular, to fill its financing gap, the firm may float new equity or use a mix of debt and equity. For the equity-financed portion of investment costs, θI_t, we assume that it may incur flotation costs.[13] That is, each equity-financed dollar of investment costs $\$(1+\iota)$, where $\iota > 0$ is interpreted as issuance costs.

To distinctly model a *constrained firm*, we suppose that an *unconstrained firm* does not face constraints on debt issuance (i.e., $\rho \to \infty$), nor does it incur relevant equity flotation costs (i.e., $\iota \approx 0$).[14]

2.2 Optimal Policies

2.2.1 Operating Policies (Static Effects)

Before analyzing the impact of tangibility on the link between debt capacity and corporate investment, we need to determine operating policies for variable and fixed production inputs. Optimizing the firm's operating profits in Eq. (2) with respect to the variable production inputs, N_t, implies that variable input at time t is chosen according to:

$$N_t^*(K_t, P_t) = \left(\frac{yP_t}{wK_t^{-x}}\right)^{1/(1-y)}. \tag{5}$$

As a result of optimizing behavior, the firm's operating profits are given by:

$$\pi(K_t, P_t) = \Pi(w, x, y)\, K_t^{\alpha} P_t^{\beta}, \tag{6}$$

where $\Pi(w,x,y) = (y^{\alpha y} - y^{\alpha})\, w^{-\alpha y} > 0$, $\alpha = x/(1-y) > 1$, and $\beta = 1/(1-y) > 1$.

For any output price level and installed capital level, the firm thus determines an optimal level of variable inputs according to Eq. (5). Observe that the opportunity to adjust variable inputs instantaneously introduces additional curvature into the firm's operating profits in Eq. (6). In this way, shocks to the industry's output price have an immediate impact on optimally chosen variable inputs, output levels, and hence operating profits. To the extent that output price changes, dP_t, have contemporaneous *production effects* in this framework, the optimal policy in Eq. (5) amplifies changes in the firm's profitability through the price elasticity parameter $\beta > 1$. When variable inputs are chosen according to Eq. (5), the specification of the revenue function in Eq. (2) implies increasing returns to scale for investment into fixed inputs, which is captured by the capital elasticity parameter $\alpha > 1$. Finally, notice that the constant $\Pi(w,x,y)$ is a multiplicative productivity factor, which depends on the price elasticity β, the unit cost for variable inputs w, and the elasticity of variable inputs y.

[13] Smith (1977) and Altinkilic and Hansen (2000) provide estimates of equity issuance costs.
[14] Equivalently, issuance costs are normalized to zero for unconstrained firms in that this is a relative statement.

2.2.2 Investment and Funding Policies (Dynamic Credit Multiplier)

After selecting variable inputs optimally, we now turn to optimizing the firm's operating profits in Eq. (6) with respect to the fixed inputs, which leads to our model's main prediction. Treating the firm's financial status as a given at time $t = 0$, default and investment become endogenously related across time: (1) the firm installs more capital when the output price rises the first time to the critical investment threshold $p^i \geq P_0$ selected by shareholders, and (2) the firm defaults on its debt when the output price declines the first time to the critical default threshold $p^d \leq P_0$ selected by creditors. For $t > 0$, the firm thus resides in a region of optimal inaction as long as the industry's output price P_t fluctuates within $\left(p^d, p^i\right)$.[15] As we show in this section, changes in the industry's output prices, dP_t, not only have static production effects but also dynamic implications, which further amplify changes in equity valuation (and hence changes in Q) for constrained firms. The combination of these financing–investment interactions characterizes the dynamic credit multiplier.

To understand the credit multiplier, we need to derive the values of corporate securities (i.e., debt and equity), taking into account current and future capital levels. Let $\mathcal{T}^i$ denote the first time that the output prices rises to the critical investment threshold p^i, while $\mathcal{T}^d$ and $\widetilde{\mathcal{T}}^d$ denote the default passage times before and after investment. The value of creditors' claims on the firm is then given by:

$$\begin{aligned} B\left(K_0, P_0, b_0\right) = \mathbb{E}^{P_0} \Bigg[\int_0^{\mathcal{T}^d \wedge \mathcal{T}^i} & \underbrace{e^{-rt} b_0}_{\text{Debt service}} \, dt + \underbrace{1_{\mathcal{T}^d < \mathcal{T}^i} e^{-r\mathcal{T}^d} R\left(K_{\mathcal{T}^d}, P_{\mathcal{T}^d}\right)}_{\text{Pre-investment recoveries}} + \\ & 1_{\mathcal{T}^d > \mathcal{T}^i} \times \left(\int_{\mathcal{T}^i}^{\widetilde{\mathcal{T}}^d} \underbrace{e^{-rt}\left(b_0 + b_1\right)}_{\text{Debt service}} dt - \underbrace{e^{-r\mathcal{T}^i}(1-\theta) I_{\mathcal{T}^i}}_{\text{Investment cost}} + \underbrace{e^{-r\widetilde{\mathcal{T}}^d} R\left(K_{\widetilde{\mathcal{T}}^d}, P_{\widetilde{\mathcal{T}}^d}\right)}_{\text{Post-investment recoveries}} \right) \Bigg], \end{aligned} \tag{7}$$

where $\mathbb{E}^{P_t}[\cdot]$ denotes the conditional expectation operator when the current output price is P_0 and $K_t \in \{K_0, K_0 + K_1\}$. The value of shareholders' claims on the firm is then given by:

$$\begin{aligned} S(K_0, P_0, b_0) = \mathbb{E}^{P_0} \Bigg[\int_0^{\mathcal{T}^d \wedge \mathcal{T}^i} & \underbrace{e^{-rt}\left[\pi(K_0, P_t) - b_0\right]}_{\text{Pre-investment dividends}} dt + \\ & 1_{\mathcal{T}^d > \mathcal{T}^i} \times \int_{\mathcal{T}^i}^{\widetilde{\mathcal{T}}^d} \underbrace{e^{-rt}\left[\pi\left(K_0 + K_1, P_t\right) - \left(b_0 + b_1\right)\right]}_{\text{Post-investment dividends}} dt - \underbrace{e^{-r\mathcal{T}^i}\theta(1+\iota) I_{\mathcal{T}^i}}_{\text{Investment cost}} \Bigg], \end{aligned} \tag{8}$$

where 1_ω is the indicator function of ω, $R\left(K_t, P_t\right) = \tau V\left(K_t, P_t\right)$, and

$$V\left(K_t, P_0\right) = \mathbb{E}^{P_0}\left[\int_0^\infty e^{-r(s-t)} \pi\left(K_t, P_s\right) ds\right]. \tag{9}$$

[15] See Cooper and Haltiwanger (2006) for evidence that structural models with inaction regions can replicate observed investment patterns.

The expressions in Eqs. (7)–(9) illustrate sources and uses of firm value among creditors and shareholders. The unlevered firm value, V, provides the basis for recoveries, R, that lenders can capture in the event of default. Firms with more tangible assets (i.e., higher τ) have a smaller wedge between recoveries and unlevered firm value. Noteworthy, the values of debt and equity have the familiar form. The value of debt in Eq. (7), denoted B, is equal to the discounted value of coupon payments plus total recoveries in the event of default (before and after investment). In addition, debt value reflects the expected injection of funds $(1-\theta)I_{\mathcal{T}^i}$ at the investment time $t = \mathcal{T}^i$, which is the critical point in time when coupon flows to creditors and recoveries switch to a higher level. The value of equity in Eq. (8), denoted S, is equal to the discounted value of operating profits net of debt coupon payments (before and after investment) with truncation of payments in the event of default, minus the discounted value of the equity-financed portion of investment costs $\theta(1+\iota)I_{\mathcal{T}^i}$.

After determining creditors' and shareholders' claim values in a general setting, we can now characterize financing and investment policies in the presence of financial market imperfections. This leads to our central proposition. (All derivations are given in the Appendix A.)

Proposition 1 *Let $\mu(P_t, t) = \mu P_t$ and $\sigma(P_t, t) = \sigma P_t$ in Eq. (1) and suppose that β, μ, σ, and r satisfy the parameter condition $\beta\mu + \beta(\beta-1)\sigma^2/2 < r$. The value of the firm's physical assets at time t equals the present value of the expected stream of operating profits:*

$$V(K_t, P_t) = \frac{K_t^{\alpha}\ P_t^{\beta}\ \Pi(w, x, y)}{r - \beta\mu - \beta(\beta-1)\sigma^2/2}. \tag{10}$$

The value-maximizing policy is to invest when the output price P_t reaches the upper threshold p^i the first time from below. If a mixture of debt and equity is used to finance investment (i.e., $0 < \theta < 1$), then p^i is the smallest value that simultaneously solves

$$(1-\theta)I_t \leq \min\left\{\rho\left[R\left(K_0 + K_1, p^i\right) - b_0/r\right], B\left(K_0 + K_1, p^i, \bar{b}\left(K_0 + K_1, p^i\right) - b_0\right)\right\}, \tag{11}$$

where the debt coupon that solves (3) is given by

$$\bar{b}(K_0 + K_1, P_t) = \frac{P_t^{\beta}}{\tilde{\gamma}}\left[\left(\frac{\beta-\nu}{\beta}\right)\left(1 - \frac{r\,\tilde{\gamma}\,\tau\ (K_0 + K_1)^{\alpha}\ \Pi(w, x, y)}{r - \beta\mu - \beta(\beta-1)\sigma^2/2}\right)\right]^{\beta/\nu}, \tag{12}$$

where $\nu < 0$ is the negative root of the quadratic equation $z\mu + z(z-1)\sigma^2/2 - r = 0$, and

$$\partial S(K_0, P_t, b_t)/\partial P_t|_{P_t = p^i} = \partial S(K_0 + K_1, P_t, b_t)/\partial P_t|_{P_t = p^i}\,. \tag{13}$$

Finally, creditors seize the firm's assets when the output price P_t reaches the lower threshold before (or after) investment the first time from above

$$p^d = (\gamma b_t)^{1/\beta} \ \ (\text{or } \tilde{p}^d = (\tilde{\gamma} b_t)^{1/\beta}\ ), \tag{14}$$

where the constants $\gamma, \tilde{\gamma} \in \Re_+$ are governed by the degree of financial constrainedness $\rho \geq 1$.

Proposition 1 shows that the tangibility of a firm's assets matters because of two distinct yet related effects: (1) a *debt capacity effect* and (2) a *default risk effect.* Both effects engender an endogenous financing–investment feedback mechanism that propagates across time and, as a consequence thereof, influences the firm's investment process. For financially constrained firms, investment is more sensitive to collateral values. Over time, their collateral values are determined by the degree of their financing constraints, which in turn is affected by these firms' investment. Hence fluctuations in industry prices lead to larger fluctuations of constrained firms' credit. In particular, more pledgeable assets not only enhance debt capacity, but also alleviate default risk, which in turn accelerates investment. These dynamic interactions between debt capacity, default risk, and investment amplify the impact of exogenous shocks on equity value (and hence Q).

Let us highlight the key features of Proposition 1. First, notice that the condition in Eq. (11) applies to a firm with untapped debt capacity in the polar case of $\theta = 0$ (i.e., debt-financed investment). It indicates that financing and investment decisions are closely intertwined and hinge upon various factors, such as debt covenants and debt capacity. For example, a low value of ρ in Eq. (11) captures a higher degree of constrainedness in that the firm can issue very little risky debt or, in the limit, only risk-free debt. Note, however, that $R(\cdot)$ increases with τ and hence even a severely constrained firm's debt capacity grows with asset tangibility. As displayed in Eq. (12), the firm's capacity for issuing risky debt is a function of various firm and industry characteristics, such as growth rate and volatility of output prices, price elasticity, the stock of physical capital, and asset tangibility. In particular, observe that $\partial\bar{b}(K_t, P_t)/\partial\tau > 0$, hence a higher level of tangibility provides the firm with larger incremental debt capacity (*debt capacity effect*).

Second, default is determined by the creditors' collateral requirements, which in turn are driven primarily by debt level and degree of constrainedness (i.e., b_t and ρ). The parameters γ and $\tilde{\gamma}$ in Eq. (14) map creditors' collateral requirements from stipulated recoveries (e.g., $R\left(K_t, p^d\right) - b_0/r$ in case of risk-free debt) into critical output prices for seizing the firm's assets. On the one hand, stricter financial constraints (i.e., lower values of ρ and hence higher values of γ and $\tilde{\gamma}$) imply that the firm defaults at higher output price levels (before and after investment). On the other hand, the firm's assets are more valuable at any given output price level if they are more tangible. In particular, observe that $\partial p^d/\partial\tau < 0$, hence a higher level of tangibility generates a reduction in the default threshold (*default risk effect*).

Finally, observe that, in the general mixed-finance case for an arbitrary $\theta \in (0, 1)$, investment is determined jointly by Eqs. (11) and (13). The condition in Eq. (13) applies to equity-financed investment (i.e., $\theta = 1$), which arises, for example, when the firm has a low incremental debt capacity or simply no access to debt finance. In this general case, the *debt capacity effect* and the *default risk effect* jointly amplify the influence of output price changes on investment spending. For instance, an increase in output price due to a positive industry shock raises current operating profits, but also improves future investment prospects, which is stronger for firms with more valuable collateral (i.e., $\partial p^i/\partial\tau < 0$). This last result is the heart of the dynamic credit multiplier in our model: industry-wide shocks affect production and investment policies in a way that the initial shock on equity value (and hence Q) will be amplified. Similarly, asset tangibility amplifies the impact of exogenous shocks to the firm's investment opportunity set onto financing (debt taking and equity valuation) and investment (spending and timing). As we illustrate in the following simulations, our theory predicts that the credit multiplier is stronger for constrained firms and that it increases with tangibility of the (constrained) firm's capital.

2.3 Simulations

In this section, we simulate our model to demonstrate the central elements and insights of the solution in Proposition 1, namely when and how financial market frictions distort the firm's investment process and its valuation, subsequently affecting the firm's ability to raise external financing. That is, our simulations reinforce the intuition behind our real options framework in a succinct way. To illustrate the endogenous financing–investment feedback mechanism that propagates across time, we select the following baseline parameter values: $\mu = 0.01$, $\sigma = 0.2$, $\rho = 1.5$, $\iota = 1.1$, $b_0 = 20$, $r = 0.08$, $w = 0.1$, $x = 0.75$, $y = 0.5$, $K_0 = 1$, $K_1 = 1$, $\lambda_1 = 375$, and $P_0 = 1$. In this baseline environment, the investment opportunity has a net preset value of zero at the initial output price.

Figures 1A and 1B chart "spare" debt capacity, $\bar{b}$, and default threshold, p^d, as a function of asset tangibility for various degrees of financing constraints. In particular, the dashed (dotted) lines consider lower (higher) contracting frictions, while the solid lines reflect the baseline scenario of $\rho = 1.5$. The first figure reveals that, consistent with economic intuition, more constrained firms have a lower incremental debt capacity; that is, a more constrained firm can only access a given amount of additional debt at a higher output price than an otherwise identical but less constrained firm. This captures the aforementioned *debt capacity effect*. Figure 1B shows that more constrained firms have a higher default threshold (i.e., creditors seize their assets earlier). Crucially, the figure also shows that, as asset tangibility increases, the default threshold declines. This represents the *default risk effect*. Put differently, asset tangibility affects the firm's ability to pledge collateral and hence higher tangibility not only eases access to debt capital but also reduces the risk of default.

Notably, the effects above may influence the investment threshold, p^i, and hence the firm's equity valuation, $S(K_0, P_0, b_0)$, in subtle ways, feeding back into debt capacity and default risk. We therefore consider the two polar cases of debt-financed investment (i.e., $\theta = 0$) in Figures 1C-1D and equity-financed investment (i.e., $\theta = 1$) in Figures 1E-1F.[16] In the former case, the dashed (dotted) lines consider lower (higher) contracting frictions, while the solid lines reflect the baseline scenario of $\rho = 1.5$. In the latter case, the dashed (dotted) lines consider lower (higher) contracting frictions, while the solid lines reflect the baseline scenario of $\iota = 1.1$.

Figure 1D shows that, consistent with intuition, the *debt capacity effect* helps the financially constrained firm to fund new investment sooner. Crucially, the time to invest declines further with increases in the tangibility of the constrained firm's assets. As shown in Figure 1C, the constrained firm's equity value increases as a result of its more valuable investment opportunity set when it already has more tangible assets. Perhaps surprisingly, the equity-financed investment threshold in Figure 1F is largely invariant to asset tangibility. Nevertheless, asset tangibility still plays a role for the firm's investment process in this limiting case (i.e., $\theta = 1$) due to survival of the *default risk effect*, which provides larger equity values for firms with more tangible assets (see Figure 1E). Interestingly, if we gradually introduce external debt-financing (i.e., $\theta < 1$), the *debt capacity effect* will reinforce the *default risk effect*, which reduces the investment threshold and hence increases equity value further. The marginal impact of asset tangibility on investment in this model is therefore non-standard. While equity's investment incentives are largely unaffected by asset tangibility, the credit multiplier leads to a strongly positive relation between asset tangibility and investment for financially constrained firms and for firms with more tangible assets.

In our model, corporate decisions are driven by industry dynamics; in particular, industry prices. Constrained firms with more tangible assets invest more and borrow more in response to positive shocks to investment opportunities or output prices, with endogenous financing–investment interactions that propagate across time. Said differently, the option to expand the firm's physical capital is a valuable one and hence the investment process engenders a feedback effect in which new investment (in tangible assets) helps relax financing constraints. These simulations are particularly useful in illustrating two central features of our model: (1) the credit multiplier is more pronounced for constrained firms and (2) the credit multiplier is more pronounced for firms with more tangible capital. It remains as an empirical question if and when the credit multiplier influence firms' investment process.

INSERT FIGURE 1 ABOUT HERE

[16] Notice that intermediate scenarios are simply convex combinations of these polar cases.

2.4 Testable Implications

The model's central insights guide us in performing novel empirical tests on the extensively studied relationship between corporate investment and Q. Our dynamic credit multiplier suggests that exogenous (e.g., industry-wide) shocks can affect investment and operating policies in a way in which the initial shocks are amplified. Notably, the model predicts that this multiplier effect will be stronger for financially constrained firms and that it will increase with the tangibility of those firms' assets. Naturally, Q and tangibility are expected to explain investment behavior, but if the model's credit multiplier is present in the data, then the *interaction* of these two variables should even more so explain investment in the cross section of financially constrained firms. Put differently, our multiplier model implies that positive innovations to investment prospects prompt stronger responses in investment spending (and debt taking) when assets are more tangible and the firm solves a constrained optimization problem.

To test the theory's main prediction, we need to specify an empirical model relating a firm's investment spending, I_t, to Q and τ. In doing so, we closely follow the intuition behind Proposition 1 in that we emphasize the marginal contribution of asset tangibility to the credit multiplier:

$$i_t = \alpha_0 + \alpha_1 Q_{t-1} + \alpha_2 \tau_{t-1} + \alpha_3 \left(Q_{t-1} \times \tau_{t-1}\right) + \varepsilon_t, \tag{15}$$

where $i_t = I_t / K_{t-1}$ denotes capital-normalized investment.

As shown in Proposition 1, tangible assets enlarge debt capacity and reduce default risk, which is capitalized into equity value prior to investment. Hence the firm's ability to issue additional debt for financing investment creates a positive externality on investment. If financially constrained firms have more tangible assets, then they have a higher Q because they can offer better collateral to creditors and also enjoy more incremental debt capacity. That is, the credit multiplier of asset tangibility predicts that the interaction term $Q \times \tau$ has a *positive* coefficient in an investment equation like (15). On the other hand, if the debt capacity and default risk effects are weak and/or investment is largely financed by equity, then the credit multiplier is muted. Hence the model predicts in this alternative case that the interaction term $Q \times \tau$ has no significance in the above regression model.

Empirically, the tension between the presence versus absence of a credit multiplier phenomenon depends on numerous industry and firm characteristics, such as the industry's investment opportunities, the redeployability of physical assets within the industry, the firm's degree of financial (constraint) status, the firm's (incremental) debt capacity, the sources of external financing, etc. The tests that follow will feature empirical counterparts to each of one these elements.

3 Data and Test Design

As we have discussed, to test our model's main predictions we need to specify an empirical model relating investment to tangibility and Q. We shall address this issue after describing our firm sample.

3.1 Data Description

Our sample selection approach is roughly similar to that of Gilchrist and Himmelberg (1995), Almeida et al. (2004), and Almeida and Campello (2007). We consider the universe of manufacturing firms (SICs 2000–3999) over the 1971–2005 period with data available from COMPUSTAT's P/S/T and Research tapes on total assets, market capitalization, capital expenditures, cash flow, and plant property and equipment (capital stock). We eliminate firm-years for which the value of capital stock is less than \$1 million, those displaying real asset or sales growth exceeding 100%, and those with negative Q or with Q in excess of 10 (we define Q shortly). The first selection rule eliminates very small firms from the sample, for which linear investment models are likely inadequate (see Gilchrist and Himmelberg (1995)). The second rule eliminates those firm-years registering large jumps in business fundamentals (size and sales); these are typically indicative of mergers, reorganizations, and other major corporate events. The third data cut-off is introduced as a first, crude attempt to address problems in the measurement of investment opportunities in the raw data and in order to improve the fitness of our investment demand model. Among others, Abel and Eberly (2001) and Cummins et al. (2006) use similar cut-offs and discuss the poor empirical fit of linear investment equations at high levels of Q. We deflate all series to 1971 dollars using the CPI.

Our basic sample consists of an unbalanced panel with 65,508 firm-year observations with 6,316 unique firms. Table 1 describes the computation and reports summary statistics for the variables used in our main tests. Since both our sampling and variable construction approaches follow that of the literature, it is not surprising that the numbers we report in Table 1 resemble those found in related studies (e.g., Almeida and Campello (2007)). In the interest of brevity, we omit discussion of the sample descriptive statistics.

<u>INSERT TABLE 1 ABOUT HERE</u>

3.2 Empirical Specification

As noted earlier, our framework's primary prediction concerns investment. However, a second testable implication about debt taking follows from our analysis. Accordingly, we develop two similar empirical models that are based on our real options framework's implications.

First, we experiment with a parsimonious model of investment demand, augmenting the standard Q-theory investment equation with a proxy for asset tangibility and an interaction term that allows the role of Q to vary with asset tangibility. Define investment $Investment$ as the ratio of capital expenditures (COMPUSTAT item #128) to beginning-of-period capital stock (lagged item #8). Q is our basic proxy for investment opportunities, calculated as the market value of assets divided by the book value of assets, or (item #6 + (item #24 × item #25) − item #60 − item #74) / (item #6). Our first empirical model can be written as follows:

$$\begin{aligned} Investment_{i,t} &= \alpha_1 Q_{i,t-1} + \alpha_2 Tangibility_{i,t-1} + \alpha_3 \left(Q \times Tangibility\right)_{i,t-1} \\ &\quad + \sum_i Firm_i + \sum_t Year_t + \varepsilon_{i,t}, \end{aligned} \tag{16}$$

where $Firm$ and $Year$ capture firm- and year-specific effects, respectively. All of our estimations correct the regression error structure for within-firm correlation (clustering) and heteroskedasticity using White-Huber's consistent estimator.

Second, we study a model of debt taking. Define $DebtIssuance$ as the change in the ratio of short- and long-term debt (item #9 + item #34) to lagged book value of assets (item #6). We then regress this measure of debt taking on Q, a proxy for asset tangibility, and an interaction term that allows the role of Q to vary with asset tangibility, so that our second empirical model can be expressed as follows:

$$\begin{aligned} DebtIssuance_{i,t} &= \alpha_1 Q_{i,t-1} + \alpha_2 Tangibility_{i,t-1} + \alpha_3 \left(Q \times Tangibility\right)_{i,t-1} \\ &\quad + \sum_i Firm_i + \sum_t Year_t + \varepsilon_{i,t}. \end{aligned} \tag{17}$$

Following the standard literature, we allow the coefficient vector $\boldsymbol{\alpha}$ to vary with the degree to which the firm faces financial constraints by way of estimating our empirical models separately across samples of constrained and unconstrained firms. In contrast to much of the literature, we also estimate $\boldsymbol{\alpha}$ via maximum likelihood methods in which constrained and unconstrained firm assignments are determined jointly with the investment (or debt taking) process.

According to our theory, the extent to which Q matters for constrained investment (alternatively, debt taking) should be an increasing function of asset tangibility. While Eq. (16) (Eq. (17)) is a direct linear measure of the influence of asset tangibility on investment (debt) sensitivities, note that its interactive form makes the interpretation of the estimated coefficients less obvious. In particular, if one wants to assess the partial effect of Q on investment (debt), one has to read off the result from $\alpha_1 + \alpha_3 \times Tangibility$. Hence, in contrast to other papers in the literature, the estimate returned for α_1 alone says little about the impact of Q on investment demand (debt taking). That coefficient represents the impact of average Q when tangibility equals zero, a point that lies outside of the empirical distribution of our measures of asset tangibility. The summary statistics reported in Table 1 will aid in the interpretation of our empirical estimates below.

3.3 Proxies for Asset Tangibility

We measure asset tangibility (*Tangibility*) in two alternative ways. First, we construct a firm-level measure of expected asset liquidation values that borrows from Berger et al. (1996). In determining whether investors rationally value their firms' abandonment option, Berger et al. gather data on the proceeds from discontinued operations reported by a sample of manufacturing firms over the 1984–1993 period. The authors find that a dollar of book value yields, on average, 72 cents in exit value for total receivables, 55 cents for inventory, and 54 cents for fixed assets. Following their study, we estimate liquidation values for the firm-years in our sample via the computation:

$$Tangibility = 0.715 \times Receivables + 0.547 \times Inventory + 0.535 \times Capital,$$

where *Receivables* is COMPUSTAT item #2, *Inventory* is item #3, and *Capital* is item #8. As in Berger et al., we add the value of cash holdings (item #1) to this measure and scale the result by total book assets. Although we believe that the nature of the firm production process will largely determine the firm's asset allocation across fixed capital, inventories, etc., there could be some degree of endogeneity in this measure of tangibility. In particular, one could argue that whether a firm is constrained might affect its investments in more tangible assets and thus its debt capacity. The argument for an endogeneity bias in our tests along these lines, nonetheless, becomes weak as we use an alternative measure of tangibility that is exogenous to the firm's policies.[17]

The second measure of tangibility that we use is a time-variant, industry-level proxy that gauges the ease with which lenders can liquidate a firm's productive capital. Following Kessides (1990) and Worthington (1995), we measure redeployability using the ratio of used to total (i.e., used plus new) fixed depreciable capital expenditures in an industry. The idea that the degree of activity in asset resale markets (i.e., demand for second-hand capital) affects financial contractibility along the lines we explore here was first proposed by Shleifer and Vishny (1992). To construct the intended measure, starting from 1981, we hand-collect data for used and new capital acquisitions at the four-digit SIC level from the Bureau of Census' *Annual Survey of the Manufacturers*. Data on plant

[17] To tackle this point even further, our switching regression estimations (later discussed) explicitly include asset tangibility as a determinant of the firm's financial constraint status.

and equipment acquisitions are compiled by the Bureau every year, but the last survey identifying both used and new capital acquisitions was published in 1996. We match the COMPUSTAT data set with the Census series, but note that estimations based on this measure of asset tangibility use smaller sample sizes since not all of COMPUSTAT's SIC codes are present in the Census data.

3.4 Financially Constrained and Financially Unconstrained Groupings

Our tests require splitting firms according to measures of financing constraints. There are many plausible approaches to sorting firms into financially "constrained" and "unconstrained" categories. Since we do not have strong priors about which approach is best, we adopt multiple alternative schemes to categorize the firms in our sample.

Our basic approach follows the standard literature, using *ex-ante* financial constraint sortings that are based on firm observables, such as payout policy, size, and debt ratings. In particular we adopt the sorting schemes discussed in Almeida et al. (2004) and Acharya et al. (2007):

- Scheme #1: In every year over the 1971–2005 period, we rank firms based on their payout ratio and assign to the financially constrained (unconstrained) category those firms in the bottom (top) three deciles of the payout distribution. We compute the payout ratio as the ratio of total distributions (dividends plus stock repurchases) to assets.[18] The intuition that financially constrained firms have lower payout follows from Fazzari et al. (1988), who argue that reluctance to distribute funds is caused by a wedge between the costs of internal and external financing.

- Scheme #2: We rank firms based on their total assets throughout the 1971–2005 period and assign to the financially constrained (unconstrained) category those firms in the bottom (top) three deciles of the asset size distribution. The rankings are again performed on an annual basis. This approach resembles Gilchrist and Himmelberg (1995) and Erickson and Whited (2000), who distinguish groups of financially constrained and unconstrained firms on the basis of size. The argument for size as a good measure of financial constraints is that small firms are typically young and less well known and thus more likely to face capital market frictions.

- Scheme #3: We retrieve data on firms' bond ratings and categorize those firms that never had their public debt rated during our sample period as financially constrained. Given that unconstrained firms may choose not to use debt financing and hence not obtain a debt rating, we

[18] Accordingly, firms that do not pay dividends but do substantial stock repurchases are not classified as constrained. Note that the deciles are set according to the distribution of the payout ratios reported by the firms (rather than according to the distribution of the reporting firms). This yields an unequal number of observations being assigned to each of the constraint groups as many firms have a zero payout policy.

only assign to the constrained subsample those firm-years that both lack a rating and report positive debt (see Faulkender and Petersen (2006)).[19] Financially unconstrained firms are those whose bonds have been rated during the sample period. Related approaches for characterizing financial constraints are used by Gilchrist and Himmelberg (1995) and Cummins et al. (2006). The advantage of this measure of constraints over the former two is that it gauges the *market*'s assessment of a firm's credit quality. The same rationale applies to the next measure.

- Scheme #4: We retrieve data on firms' commercial paper ratings and categorize as financially constrained those firms that never display any ratings during our sample period. Observations from those firms are only assigned to the constrained subsample in years in which positive debt is reported. Firms that issued rated commercial paper at some point during the sample period are considered unconstrained. This approach follows from the work of Calomiris et al. (1995) on the characteristics of commercial paper issuers.

Table 2 reports the number of firm-years under each of the financial constraint categories used in our analysis. According to the payout scheme, for example, there are 27,658 financially constrained firm-years and 19,549 financially unconstrained firm-years. The table also shows the extent to which the four classification schemes are related. For example, out of the 27,658 firm-years classified as constrained according to the payout scheme, 12,857 are also constrained according to the size scheme, while a much smaller fraction, 3,689 firm-years, are classified as unconstrained. The remaining firm-years represent payout-constrained firms that are neither constrained nor unconstrained according to size. In general, there is a positive association among the four measures of financial constraints. For example, most small (large) firms lack (have) bond ratings. Also, most small (large) firms make low (high) payouts. However, the table also makes it clear that these cross-group correlations are far from perfect. This works against our tests finding consistent results across all classification schemes.

INSERT TABLE 2 ABOUT HERE

One potential drawback of the *ex-ante* sorting approach described above is that it does not allow the investment process to work as a determinant of the financial constraint status — the constraint categorization is exogenously given. In turn, we also use an alternative categorization approach that endogenizes the constraint status together with other variables in a structural model. The approach, borrowed from Hovakimian and Titman (2006), uses a switching regression framework with

[19] Firms with no bond ratings and no debt are not considered constrained, but our results are unaffected by how we treat these firms. We use the same approach for firms with no commercial paper ratings and no debt in Scheme #4 below.

unknown sample separation to estimate investment regressions. One advantage of this estimator is that we can simultaneously use all of the above sorting information (i.e., dividend policy, size, bond ratings, and commercial paper ratings) together with asset tangibility to categorize firms. Almeida and Campello (2007) provide a detailed description of the switching regression estimator (see also Hu and Schiantarelli (1998)). Hence we provide here only a brief summary of this methodology.

Assume that there are two different investment regimes, which we denote by "regime 1" and "regime 2." While the number of investment regimes is given, the points of structural change are not observable and are estimated together with the investment equations. The model is composed of the following system of equations (estimated simultaneously):

$$I_{1it} = \mathbf{X}_{it}\alpha_1 + \varepsilon_{1it} \tag{18}$$

$$I_{2it} = \mathbf{X}_{it}\alpha_2 + \varepsilon_{2it} \tag{19}$$

$$y_{it}^* = \mathbf{Z}_{it}\phi + u_{it}. \tag{20}$$

Eqs. (18) and (19) are the structural equations of the system; they are essentially two different versions of our baseline investment model in Eq. (16). Let $\mathbf{X}_{it}$ be the vector of explanatory variables, and $\boldsymbol{\alpha}$ be the vector of coefficients that relates the variables in $\mathbf{X}$ to investment I_{1it} and I_{2it}. Differential investment behavior across firms in regime 1 and regime 2 is captured by differences between α_1 and α_2. Eq. (20) is the selection equation that establishes the firm's likelihood of being in regime 1 or regime 2. The vector $\mathbf{Z}_{it}$ contains the determinants of a firm's propensity of being in either regime. Observed investment is given by:

$$\begin{aligned} I_{it} &= I_{1it} \text{ if } y_{it}^* < 0 \\ I_{it} &= I_{2it} \text{ if } y_{it}^* \geq 0, \end{aligned} \tag{21}$$

where y_{it}^* is a latent variable that gauges the likelihood that the firm is in the first or in the second regime.

The parameters α_1, α_2, and ϕ are estimated via maximum likelihood. To estimate those parameters we assume that the error terms ε_1, ε_2, and u are jointly normally distributed. Critically, the estimator's covariance matrix allows for nonzero correlation between shocks to investment and shocks to firms' characteristics — this makes the model we use an *endogenous switching regression*.[20] The extent to which investment spending differs across the two regimes and the likelihood that firms are assigned to either regime are simultaneously determined.

[20] To be precise, the covariance matrix has the form $\Omega = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{1u} \\ \sigma_{21} & \sigma_{22} & \sigma_{2u} \\ \sigma_{u1} & \sigma_{u2} & 1 \end{bmatrix}$, where var$(u)$ is normalized to 1.

Finally, to identify the system we need to determine which regime is the constrained one and which regime is the unconstrained one. The algorithm in Eqs. (18)–(21) creates two groups of firms that differ according to their investment behavior, but it does not tell the econometrician which firms are constrained. To achieve identification, we need to use priors about which firm characteristics are associated with financial constraints. We do so, by utilizing the same four characteristics used in the *ex-ante* sortings (payout, size, bond ratings, and commercial paper ratings). We also include *Tangibility*, since as we hypothesize, asset tangibility can help relax financing constraints.

4 Empirical Results

Following the model's predictions, we first examine corporate spending and then turn to cross-sectional patterns in debt financing.

4.1 Tests on Investment Spending

For the cross-sectional analysis of corporate investment, we estimate a base regression and an interactive regression. In addition, we perform numerous robustness tests to rule out alternative explanations of our main findings.

4.1.1 The Base Regression Model

We build intuition for our paper's main tests, which are those concerning the credit multiplier, by way of estimating a simpler version of Eq. (16). In this version, corporate investment is modeled as a linear function of only Q and *Tangibility*. We would expect both of these variables to retain some explanatory power over the cross-sectional variation of investment. In particular, absent empirical biases, investment spending should respond to proxies for investment opportunities across all sets of firms (both financially constrained and unconstrained firms). As for asset tangibility, we would expect it to be a strong driver of investment across financially constrained firms, carrying less importance (if any) in the cross section of financially unconstrained firms.

Table 3 reports estimation results for the base regression model using financial constraint partitions that are based on our four *ex-ante* characterizations. Panel A collects the results returned when we use our firm-level measure of asset tangibility (based on Berger et al. (1996)). Panel B has the same layout, but uses the industry-level measure of asset tangibility (based on the Bureau of Census data). For each of the eight constrained/unconstrained comparison pairs in the table (both panels), we observe that *Investment* responds very significantly to Q across all estimations and partitions. Interestingly, Q is particularly strong across financially constrained firms. This is noteworthy since much of the debate about empirical biases in investment regressions in the last decade (e.g., Erickson and Whited (2000)) revolved around an attenuation bias that appeared to affect constrained firms' Q in a pronounced fashion. Like other recent studies (e.g., Baker et al. (2003) and Campello and Graham (2007)), however, we find no evidence that attenuation bias in Q disproportionately affects financially constrained firms.

Insert Table 3 About Here

Also noteworthy is the response of *Investment* to *Tangibility*. Consistent with the basic logic of our theory, asset tangibility is systematically, positively associated with investment spending when firms are financially constrained. Our estimates suggest that this relation is economically strong. For example, the estimate associated with the first partition we report in Table 3 (see row 1 in Panel A) implies that a one standard deviation increase in *Tangibility* leads to an increase in *Investment* of 6.7% ($= 0.5605 \times 0.1196$), an increase that is equivalent to 25.6% ($= 0.0670/0.2617$) of the average investment rate of our sample. The same is not true for financially unconstrained firms. For those firms, the coefficients returned for *Tangibility* are either significantly lower than those returned for constrained firms (Panel A) or even negative (Panel B).

Table 4 reports estimations that are similar in nature to those in Table 3; however, they employ a switching regression approach with endogenous (as opposed to exogenous) sample separation. We observe the same patterns discussed just above. Notably, this happens regardless of the proxy used for asset tangibility (see Panels A and B).

Insert Table 4 About Here

4.1.2 The Multiplier Effect (Interactive Model)

Our theory's central prediction is related to the amplifying effect of asset tangibility on the response of investment spending to investment opportunities in the presence of financial constraints — the dynamic credit multiplier. As previously discussed, a direct way to gauge the multiplier effect in the data is to interact Q with *Tangibility*. We now perform tests of the main prediction of our model, estimating Eq. (16) across various subsamples.

Our main empirical findings are reported in Table 5, which has the same layout as Table 3. The results presented are remarkably strong: in every single comparison, the interaction term of Q and *Tangibility* is highly significant and positive for constrained firms, while either negative or indistinguishable from zero for unconstrained firms. Indeed, one can generally reject with high confidence the hypothesis that the coefficients of interest are similar across the two constraint types.

Noteworthy, the table reveals not only the existence of an important interactive (multiplier) effect of *Tangibility* across financially constrained firms, but also that much of the unconditional impact of Q on *Investment* for those firms (as reported in Table 3) is indeed transmitted via *Tangibility*. Simply put, the direct effect of Q on *Investment* across constrained firms, though still positive, dwarfs in comparison with the effect that comes via its interaction with *Tangibility*.

The findings in Panels A and B of Table 5 are overwhelmingly consistent with the credit multiplier. Essentially, they show that, in the presence of financing frictions, investment spending responds more strongly to the arrival of new investment opportunities when a firm's assets provide more valuable collateral. To illustrate the economic importance of the estimates in the table, consider again the one reported in the first row of Panel A in the table. While Q alone (i.e., uninteracted) has a negligible effect on investment, a one standard deviation change in Q (= 0.5196), measured at the average level of *Tangibility* (= 0.5583), leads to a 6.0% (= 0.0148+0.0456) increase in *Investment* (approximately 23.1% of the average sample rate of investment).

An extension of our model along the lines of Hennessy (2004) suggests that asset tangibility may magnify debt overhang and hence, rather than increase, decrease investment. In essence, he derives an empirical proxy for debt overhang, which is increasing in tangibility. For 278 firms during the 1992–1995 period, Hennessy finds that his proxy relates negatively and reliably to investment, with the economic magnitude being larger for firms with a lower bond rating. Similarly, Panel A of Table 5 reveals for several constraint partition schemes that investment of unconstrained firms exhibits a reliably negative relation to Q interacted with *Tangibility*. Arguably, one could thus speculate that our interaction term also proxies for debt overhang of unconstrained firms, which tend to have higher levels of preexisting debt than constrained firms that are the focus of our study.[21] Indeed, one of Hennessy's sample selection criteria is that firms have a bond rating, which is broadly consistent with our results in this table. Yet, we do not pursue the debt overhang interpretation of unconstrained firms' investment further because the negative coefficients do not survive our robustness tests and, more importantly, our study centers on the credit multiplier of constrained firms.

<u>INSERT TABLE 5 ABOUT HERE</u>

Similar to what we did for the last set of tests using the base regression model, we also perform tests for the interactive model in which firm assignments to constrained/unconstrained partitions are selected endogenously with the investment process. The results for these switching regressions

[21] Faulkender and Petersen (2004) report that firms with a public debt rating (either a long-term bond rating or commercial paper rating) have significantly higher leverage ratios than firms without a debt rating, and the difference cannot be explained by firm characteristics previously found to determine leverage choice.

are reported in Table 6. The estimates in that table are fully consistent with those presented in Table 5. They, too, suggest the functioning of a multiplier effect in which *Tangibility* amplifies the impact of Q on *Investment* when firms are constrained, but not when they are unconstrained.

4.1.3 Robustness of the Multiplier Effect

This subsection collects a battery of tests designed to verify the robustness of our central findings. Notice that the tables above already show evidence of robustness for our results in that these tests are performed under various alternative proxies for the main empirical wrinkles of the model (financing constraints and asset tangibility) as well as under various alternative empirical methods (least square regressions and maximum likelihood estimations). In what follows, we experiment with additional estimation procedures, consider the issue of mismeasurement in Q, and examine our model's notion that changes in investment opportunities that originate from industry price shocks are magnified by asset tangibility. To save space, we only report estimation results associated with the firm-level proxy for asset tangibility.[22]

GMM Estimations OLS estimations of investment models are known to suffer from a number of potential empirical biases. While handling those biases is still a question of debate, one could wonder about the robustness of our main results relative to estimation approaches that ameliorate issues such as endogeneity and heteroskedasticity.

In Table 7, we re-estimate the interactive models of Table 5 (our main results) via GMM. We use up to 3 lags of the variables included in Eq. (16) in our set of instruments. While those included variables are in *level* form, our instruments are in *differenced* form. The GMM estimations return coefficients that are both economically and statistically more significant than those from the OLS model, yet the inferences that we obtain are similar. Again, *Tangibility* significantly strengthens the effect of Q on *Investment* for financially constrained firms, but not for unconstrained firms.

<u>INSERT TABLE 7 ABOUT HERE</u>

In the last two columns of Table 7, we report the diagnostic test statistics associated with our instrumental set. Those instruments seem to be well-suited for the equations we fit to the data. For instance, note that the *lowest* p-value associated with Hansen's (1982) test of overidentifying restrictions is as high as 20%. Moreover, the partial F-statistics from the (first-stage) regression of the endogenous regressors on the set of excluded instruments is highly significant in each of the models estimated. Simply put, these diagnostic statistics suggest that our instruments are valid and relevant.

[22]Results from tests using the industry-level measure of tangibility are available from the authors.

Mismeasurement in the Proxy for Investment Opportunities Prior work on investment estimations has cited concerns with the possibility that the standard proxy for investment opportunities, Q, may suffer from pronounced measurement (e.g., Cummins et al. (2006) and Erickson and Whited (2000)). The problem with mismeasurement is that it introduces a downward bias in the variable affected by it.[23] In our application, the possibility that Q is severely mismeasured would lead the OLS estimator to over-reject the hypothesis that Q is different from zero. As we have shown in our base tests, however, Q is statistically significant in *all* of the regressions in which it is not further interacted with *Tangibility*. When we interact Q with *Tangiblity*, Q still remains the main driver of investment, only now via the interaction term.

It is hard to argue that an attenuation bias in Q could underlie our findings. Nevertheless, we note that the literature suggests potential remedies for mismeasurement in Q. Bond and Cummins (2000, 2001) and Cummins et al. (2006), for example, contend that Q is likely to capture the firm's investment opportunities with error because equity market values (in the numerator of Q) often deviate from firm fundamentals, thereby misrepresenting the firm's marginal product of investment. Those papers propose, instead, a proxy for Q (called *RealQ*) that is derived from earnings projections made by financial analysts. The empirical implementation of *RealQ* mimics exactly that of standard Q, except that one proxies for the unobserved future marginal products of capital with an approximation for the future average products based on long-term earnings forecasts from IBES.[24] Studies using *RealQ* show that it systematically outperforms standard Q in empirical investment regressions. A limitation of this approach, however, is that only a small subset of firms in COMPUSTAT have long-term earnings forecasts reported in IBES. Additionally, note that IBES only consistently reports earnings forecasts starting in 1989. These data considerations significantly reduce the sample used in our *RealQ* tests.

In Table 8, we re-estimate the interactive models of Table 5 replacing Q with *RealQ*. We again find strong support for our theory's main prediction: *Tangibility* reliably amplifies the impact of Q (i.e., *RealQ*) on *Investment* for financially constrained firms, but not for unconstrained firms.

<u>INSERT TABLE 8 ABOUT HERE</u>

Proxying for Investment Opportunities with Shocks to Industry Prices The literal interpretation of our model suggests that exogenous shocks to industry prices have an impact on

[23] By performing a series of Monte Carlo experiments, we document in Appendix B that coefficient estimates of an interaction term that contains one (or two) mismearured variables are biased toward zero in simulated data sets.

[24] Relevant details and program codes needed to compute *RealQ* can be found in the following website: http://www.aeaweb.org/articles/issue_detail.php?journal=AER&volume=96&issue=3&issue_date=June%202006.

investment demand that is magnified by the tangibility of the firm's asset. It is thus feasible to tie the empirics closer to the model by checking whether changes in industry prices that are reflected in the firm's Q — and not just Q in general — lead to the same investment dynamics that we have reported in our empirical tests thus far. To do so, we isolate the component of firm-level Q that is associated with industry prices in a straightforward manner. In particular, we regress Q on changes in product price indices (PPI) for manufacturing industries and focus on the relevance of that projected value, denoted *ProjQ*, for investment spending under financial constraints. The PPI series are collected at the four-digit SIC level from the Bureau of Labor Statistics. These series are reported on a monthly basis and we compute the annual average index for each industry before differencing those series. A limitation of this test is that while for most industries in our sample PPIs were computed by the Bureau starting in the early 1970's, for others that calculation only starts in the mid-1980's. Moreover, the Bureau discontinued the computation of PPIs for SIC-defined industries in 2003.

In Table 9, we re-estimate the interactive models of Table 5 replacing Q with the projection of Q on changes in product market prices (*ProjQ*). The increase in the significance of our proposed proxy for investment opportunities, *ProjQ*, relative to that of the standard approach, Q, is noteworthy. More importantly, this table again confirms the multiplier effect of *Tangibility* in magnifying the influence of Q (i.e., *ProjQ*) on *Investment* for financially constrained firms.

Insert Table 9 About Here

4.2 Tests on Debt Capacity and Debt Taking

Our theory on the multiplier effect of asset tangibility on investment is predicated on the notion that tangibility expands external financing capacity; in particular, that it helps support debt financing. While the results thus far are consistent with this hypothesis, we have not fully characterized the link between debt taking and investment that underlies the credit multiplier. We do so in this subsection. Specifically, expanding our testing approach, we perform a number of experiments considering firms' incremental ("spare") debt capacity and debt taking decisions.

4.2.1 Debt Capacity

Our results suggest that asset tangibility helps constrained firms obtain more credit following positive innovations to investment opportunities. As a result, they invest more in response to those innovations. Until now, the tests concerning this idea were performed without accounting for the firm's finances. In other words, we did not consider whether or not the firm's *ex-ante* indebtness would allow it to take advantage of the expanded debt capacity provided by new investment in tangible assets. For instance, if a firm is already highly indebted prior to the positive shock to investment, then it should be less able to invest as a function of asset tangibility; that is, according to the model the credit multiplier would be weaker or even fail. In contrast, the credit multiplier is likely to be more pronounced when innovations affect firms with more spare debt capacity.

Of course, it is difficult to gauge a firm's *ex-ante* debt capacity. However, our theory provides for a viable, albeit incomplete, characterization of incremental debt capacity. Recall, we argue that the ability to obtain credit is a positive function of asset tangibility.[25] As such, the correlation between a firm's leverage and the degree of its asset tangibility may provide information about the firm's spare debt capacity. If a firm carries more (less) leverage on its balance sheet than other firms with assets of similar asset tangibility, then that firm may have less (more) incremental debt capacity.

This logic helps us to construct an empirical proxy for spare debt capacity. That proxy is the component of a firm's long-term debt that is *not* explained by the firm's asset tangibility. This component may be gauged from the residuals of a regression of *Leverage* (or, item #9/item #6) on *Tangibility.* While the magnitude of those residuals may be of little economic interpretation, they are useful in assessing spare debt capacity in that they may be used to rank firms into different categories. We proceed in this way, ranking firm-years into a "high" ("low") debt capacity category if the leverage regression residuals associated with those firm-years fall into the bottom (top) three deciles of the distribution of the residuals. To ensure that the results we obtain from this experiment are economically sensible, we also rank firms into low and high debt capacity according to their lagged, raw leverage ratios.[26] Both of these rankings are performed on an annual basis.

Table 10 shows what happens when we condition our interactive models on firms' debt capacity. Panel A presents results for the debt capacity sorting scheme that is based on leverage residuals. Panel B is similarly structured, but high and low debt capacity are based on rankings of raw leverage ratios. Only financially constrained firms are used to perform the tests in Table 10, since we find only their investment is affected by the credit multiplier. The results presented in Panels A and B of Table 10 are remarkably strong and internally consistent. They show that, amongst constrained firms, the credit multiplier reported in previous tables (e.g., Table 5) is strong across those firms with high debt capacity, and nonexistent across those firms with low debt capacity. Notably, this is what one

[25] For example, Campello (2006) use measures of asset tangibility that are similar to ours as instruments for leverage.

[26] Of course, one must recognize that a firm may display a "relatively high" leverage ratio and still have the ability to take on more additional debt. Because of this ambiguity, one may be careful in interpreting our second debt capacity ranking scheme. Yet, at a minimum, the raw leverage ranking is likely to contain some useful information for observations on the extremes of the leverage distribution in our sample.

should expect, given the dynamics of the credit multiplier our theory and tests have characterized.

<u>Insert Table 10 About Here</u>

4.2.2 Debt Taking

We now turn to another element that, according to our theory, should underlie the credit multiplier that we have documented. Specifically, we demonstrate that asset tangibility magnifies the impact of investment opportunities on observed investment spending through a financing channel (i.e., collateral and debt capacity). In our model, this happens because of a feedback effect between investment and financing in the presence of financial constraints. Simply put, financing and investment are endogenous when the firm solves a constrained optimization problem, and the two processes therefore move together. We now examine the idea that this relation exists in the data by looking at firms' debt taking behavior. We do so in a regression framework in which debt taking is the left-hand side variable, while on the right-hand side we use the same set of drivers we used for tests involving investment. This empirical specification is represented by Eq. (17) above.

Table 11 reveals several interesting aspects of our debt taking tests. First, as documented in many existing studies, leverage increases are negatively associated with Q and positively associated with *Tangibility*. Second, the estimates for tangibility interacted with Q seem to substantiate the dynamics of our credit multiplier: when firms are constrained, they take on more debt in response to investment opportunities when their assets are more tangible. This interactive model for debt taking thus provides further evidence on our model's prediction that *Tangibility* and Q jointly influence investment via a financing channel (i.e., debt taking) for financially constrained firms, but not for unconstrained firms. Finally, the results in Table 11 suggest that firms with very high asset tangibility (above the 75^{th} percentile of the distribution of *Tangibility*) observe no relation between Q and $DebtIssuance$ — i.e., the Q-interaction dominates Q-intercept term. Remarkably, as shown in the table, this is similar to the relation between Q and $DebtIssuance$ across financially unconstrained firms. At lower levels of *Tangibility*, in contrast, increases in Q are met with sharp declines in debt.

These last findings are arguably at the very heart of the impact of financing constraints on corporate policies. Contracting frictions, such as agency problems, may lead to a negative association between investment opportunities and external financing. Our estimates suggest that while these problems are ameliorated by variables such as asset tangibility, they are not resolved. This is essentially consistent with the arguments made by Bernanke et al. (1996, 2000) in their pioneering work on the credit multiplier. Looking at the aggregate economy, they hypothesize that the impact of financing imperfections stemming from agency problems and asymmetric information issues are minimized when firms have enough collateral. In that case, firms borrow from the capital markets whenever they are hit by positive innovations in investment opportunities. As collateral values drop, however, contracting frictions become more relevant. Firms with good prospects may then shy away from borrowing funds in the credit markets.

<u>INSERT TABLE 11 ABOUT HERE</u>

5 Concluding Remarks

We analyze a dynamic credit multiplier of asset tangibility on investment spending when financing and investment are simultaneously determined. Allowing for capital markets imperfections in a real options framework, we study firms that sell output in an industry with stochastic demand and want to expand their tangible capital. For financially constrained firms, acquiring assets that can be used as collateral alleviates default risk and enlarges debt capacity. This accelerates investment and boosts equity value. Our theory predicts that constrained firms with more tangible assets invest more and borrow more in response to positive shocks to investment opportunities, with endogenous financing–investment feedback effects that propagate across time.

Our model's central insights guide us in exploring a novel identification scheme — based on the roles of asset tangibility and capital market frictions — to shed new light on the relation between investment spending and Tobin's q. More specifically, both Q and *Tangibility* are expected to explain investment behavior, but the model's credit multiplier predicts that the *interaction* of these two variables should have an even stronger positive impact on investment in the cross section of financially constrained firms. For a large sample of manufacturing firms over the 1971–2005 period, we find robust results that strongly support our model's main prediction. Consistent with our identification strategy, we document that the credit multiplier is absent from samples of financially unconstrained firms and financially constrained firms with low incremental debt capacity.

Appendix A

In this appendix, we derive the results for the general model with $\theta \in (0,1)$, since the results for the polar cases of fully debt-financed and equity-financed investment are subsumed as special cases of the general model's solution. Given (1), the value $F(P_t, t)$ of an arbitrary claim paying $\phi\, P_t^{\beta} \,+\, \kappa$ satisfies the equilibrium condition:

$$r\,F(P_t,t) \;=\; \phi\,P_t^{\beta} \,+\, \kappa \,+\, \frac{1}{dt}\,\mathbb{E}^{P_t}\big[F(P_{t+dt},t)\big]\;. \tag{A.1}$$

The expression on the l.h.s. of (A.1) is the equilibrium return an investor requires. The first two terms on the r.h.s. of (A.1) are the flow benefits in period t, while the third term is the expected capital gain from period t to $t+dt$. Applying Itô's Lemma to (A.1) yields a partial differential equation:

$$r\,F(P_t,t) \;=\; \phi\,P_t^{\beta} \,+\, \kappa \,+\, \frac{\partial F(P_t,t)}{\partial t} \,+\, \frac{1}{2}\,\sigma^2(P_t,t)\,P_t^2\,\frac{F(P_t,t)}{\partial P_t^2} \,+\, \mu(P_t,t)\,P_t\,\frac{\partial F(P_t,t)}{\partial P_t}\;, \tag{A.2}$$

which under the assumption of $\mu\,(P_t,t) = \mu P_t$ and $\sigma\,(P_t,t) = \sigma P_t$ has the general solution:

$$F(P_t) \;=\; A_1\,{P_t}^{\nu} \,+\, A_2\,P_t^{\vartheta} \,+\, \frac{\phi\,P_t^{\beta}}{r - \beta\mu - \beta\,(\beta-1)\,\sigma^2/2} \,+\, \frac{\kappa}{r}\;, \tag{A.3}$$

where $\nu < 0$ and $\vartheta > 1$ denote the characteristic roots of the quadratic equation: $r \,=\, 0.5\,\sigma^2\,(x - 1)\,x \,+\, \mu\,x$. Suitable boundary conditions pin down the unknown constants A_1 and A_2.

When we evaluate (9), both constants in (A.3) are equal to zero, which yields together with $\phi = 1$ and $\kappa = 0$ unlevered firm value V in (10). The solution to (7) for debt value before investment is:

$$\begin{aligned} B\,(K_0,P_t,b_0) \;=\;& \frac{b_0}{r}\left[1 - \mathcal{L}\,(P_t) - \mathcal{H}\,(P_t)\left(\frac{p^i}{\tilde{p}^d}\right)^{\nu}\right] + R\left(K_0,p^d\right)\mathcal{L}\,(P_t) \\ &+\left\{\frac{b_1}{r}\left[1-\left(\frac{p^i}{\tilde{p}^d}\right)^{\nu}\right] + R\left(K_0+K_1,\tilde{p}^d\right)\left(\frac{p^i}{\tilde{p}^d}\right)^{\nu} - (1-\theta)\,\lambda_1 K_1\right\}\mathcal{H}\,(P_t)\,, \end{aligned} \tag{A.4}$$

which follows from $\phi = 0$ and $\kappa = b_0$ in (A.3) as well as the value-matching conditions

$$B\left(K_0,p^d,b_0\right) = R\left(K_0,p^d\right), \tag{A.5}$$

and

$$B\left(K_0,p^i,b_0\right) = B\left(K_0+K_1,p^i,b_t\right) - (1-\theta)\,\lambda_1 K_1, \tag{A.6}$$

where debt value after investment follows from similar arguments:

$$B\,(K_0+K_1,P_t,b_t) = \frac{b_t}{r}\left[1-\left(\frac{P_t}{\tilde{p}^d}\right)^{\nu}\right] + R\left(K_0+K_1,\tilde{p}^d\right)\left(\frac{P_t}{\tilde{p}^d}\right)^{\nu}, \tag{A.7}$$

and where $b_t = b_0$ if no additional debt is issued and $b_t = b_0 + b_1$ if additional debt with perpetual payments b_1 is issued. In the expression for $B\,(K_0,P_t,b_0)$, the stochastic discount factors $\mathcal{L}\,(P_t)$ and

$\mathcal{H}(P_t)$ for reaching the lower threshold (p^d) or the higher threshold (p^i) from the current output price $P_t \in (p^d, p^i)$ are defined by

$$\mathcal{L}(P_t) = \frac{(p^i)^{\vartheta} P_t^{\nu} - (p^i)^{\nu} P_t^{\vartheta}}{(p^i)^{\vartheta} (p^d)^{\nu} - (p^i)^{\nu} (p^d)^{\vartheta}} \tag{A.8}$$

and

$$\mathcal{H}(P_t) = \frac{P_t^{\vartheta} (p^d)^{\nu} - P_t^{\nu} (p^d)^{\vartheta}}{(p^i)^{\vartheta} (p^d)^{\nu} - (p^i)^{\nu} (p^d)^{\vartheta}}. \tag{A.9}$$

The solution to (8) for equity value before investment is:

$$\begin{aligned} S(K_0, P_t, b_0) \quad = \quad & \left[V(K_0, P_0) - \frac{b_0}{r}\right] - \left[V\left(K_0, p^d\right) - \frac{b_0}{r}\right] \mathcal{L}(P_t) + \Bigg\{V\left(K_0 + K_1, p^i\right) - \frac{b_1}{r} \\ & -V\left(K_0, p^i\right) - \left[V\left(K_0 + K_1, \tilde{p}^d\right) - \frac{b_t}{r}\right] \left(\frac{p^i}{\tilde{p}^d}\right)^{\nu} - \theta(1-\iota)\lambda_1 K_1 \Bigg\} \mathcal{H}(P_t), \end{aligned}$$

which follows from $\phi = 1$ and $\kappa = -b_0$ in (A.3) as well as the value-matching conditions:

$$S\left(K_0, p^d, b_0\right) = 0, \tag{A.10}$$

and

$$S\left(K_0, p^i, b_0\right) = S\left(K_0 + K_1, p^i, b_0 + b_1\right) - \theta(1-\iota)\lambda_1 K_1, \tag{A.11}$$

where equity value after investment follows from similar arguments:

$$S(K_0 + K_1, P_t, b_t) = \left[V(K_0 + K_1, P_t) - \frac{b_t}{r}\right] - \left[V\left(K_0 + K_1, \tilde{p}^d\right) - \frac{b_t}{r}\right] \left(\frac{P_t}{\tilde{p}^d}\right)^{\nu}. \tag{A.12}$$

To derive the firm's debt capacity $\overline{b}(K_t, P_t)$ in (12), we first notice that at the first instant after investment has been undertaken debt value turns into (A.7). For a sufficiently large value of ρ, the quantity constraint in (4) does not bind and hence the bank debt capacity that solves (3) is then determined by maximizing the expression in (A.7) with respect to b_t and simplifying.

Finally, based on standard smooth-pasting arguments [see e.g., Dumas (1991)], the optimality condition in (13) is equivalent to the first-order condition

$$\frac{\partial S(K_0, P_t, b_t)}{\partial p^i} = \frac{\partial S(K_0 + K_1, P_t, b_t)}{\partial p^i}, \tag{A.13}$$

where equity value after investment on the r.h.s. of (A.13) is given in (A.12).

Appendix B

In this appendix, we examine the effect of mismeasurement in explanatory variables on coefficient estimates for Q interacted with $Tangibility$. In particular, we study the role of measurement error in one or two independent variables employing Monte Carlo experiments. In a first set of experiments, we simulate our interactive model in which only one right-hand side variable is measured with error:

$$Investment_{i,t} = \alpha_0 + \alpha_1 Q_{i,t-1} + \alpha_2 Tangibility_{i,t-1} + \alpha_3 \left(Q \times Tangibility\right)_{i,t-1} + e_{i,t}, \quad \text{(B.1)}$$

where the innovations e_i are $i.i.d.$, and the observable variable Q is potentially mismeasured, i.e.,

$$Q_{i,t} = Q^*_{i,t} + \varepsilon_{i,t}, \quad \text{(B.2)}$$

where Q^* is the unobservable variable, and the measurement error $\varepsilon_{i,t}$ is $i.i.d.$ and independent of $e_{i,t}$. This specification is equivalent to assuming $cov(Q^*_{i,t}, \varepsilon_{i,t}) = 0$ and $cov\left(Q_{i,t}, \varepsilon_{i,t}\right) = var\left(\varepsilon_{i,t}\right)$, which corresponds to the classical errors-in-variables assumption.

More specifically, to study the potential bias in estimates of α_3 due to measurement error in Q, we consider three different distributions for innovations $\left(e_i, \varepsilon_i\right)'$: (1) standard normal distribution, (2) log-normal distribution, and (3) chi-square distribution with 3 degrees of freedom. Without loss of generality, we normalize the simulated parameter values of α_i to unity for all $i \in \{0, 1, 2, 3\}$. To allow for various correlation structures, we generate random samples of Q and $Tangibility$ from the above distributions and then multiply the resulting vectors by the matrix $var(Q, Tangibility)$. We use four alternative correlation matrices, where the diagonal elements are equal to 1 and off-diagonal elements equal to 0, 0.25, 0.5, and 0.75. We perform simulations for various sample sizes. Since the estimation results are qualitatively similar across different sample sizes, we tabulate the ones for $n = 500$. Finally, for each simulation the number of repetitions is 10,000.

Table B.1.
Mismeasurement in Q

		Correlation Structure			
Distribution		0	0.25	0.5	0.75
Normal	α_1	0.4996	0.4518	0.3093	0.1097
	α_2	1.0024	1.2580	1.5519	1.8540
	α_3	0.4994	0.5640	0.6699	0.7501
Log-normal	α_1	0.5043	–0.4706	–1.2694	–2.2365
	α_2	0.9950	0.6526	1.6451	3.2811
	α_3	0.5007	0.9230	0.9598	0.9431
Chi-square	α_1	0.4995	–0.3904	–1.8363	–3.5637
	α_2	0.9952	1.5044	2.8623	5.3707
	α_3	0.5003	0.7052	0.8072	0.8192

Table B.1 collects the least-squares estimates based on our simulated data. The table shows that the coefficients involving Q are generally biased toward zero: (1) as expected, the estimates of α_1 reveal that the bias is indeed downward; (2) notably, estimates of α_3 are also biased downward; (3) the interaction term's "attenuation bias" is weakest in the log-normal case for a positive correlation (i.e., estimates are not statistically different from one); and (4) the bias in estimates of α_2 could be downward or upward depending on the correlation structure.

In a second set of experiments, we examine the case in which two explanatory variables are mismeasured. That is, both independent variables Q and $Tangibility$ suffer from measurement error. For this more general case, we incorporate another mismeasurement equation into the simulation framework; that is, the simulated data is now generated by equations (B.1), (B.2), and

$$Tangibility_{i,t} = Tangibility^*_{i,t} + \epsilon_{i,t}, \tag{B.3}$$

where $Tangibility^*$ is the additional unobservable variable, and the additional measurement error ϵ_i is *i.i.d.* and independent of e_i and ε_i.

Table B.2.
Mismeasurement in Q and $Tangibility$

		Correlation Structure			
Distribution		0	0.25	0.5	0.75
	α_1	0.5009	0.6100	0.6921	0.7539
Normal	α_2	0.4997	0.6096	0.6918	0.7525
	α_3	0.2499	0.3058	0.4217	0.5318
	α_1	0.5075	–0.9881	–1.7457	–1.9533
Log-normal	α_2	0.4978	–1.0091	–1.7624	–1.9655
	α_3	0.2498	0.8279	1.0075	1.0499
	α_1	0.5010	–0.2923	–1.5517	–2.2807
Chi-square	α_2	0.4968	–0.2915	–1.5593	–2.2929
	α_3	0.2500	0.5076	0.7473	0.8691

Table B.2 summarizes our findings for the second set of Monte Carlo experiments. The estimation results for the case when Q and $Tangibility$ are imprecisely measured are similar to the ones for the case when only Q is measured with error. The main difference between the two sets of results is that estimates of α_2 are now downwardly biased too. Thus, both simulation exercises provide overwhelming evidence that coefficients are biased downward when there are measurement errors in one or two explanatory variables. Noteworthy, this is extends the conventional notion that mismeasurement of Q leads to an "attenuation bias" to an interactive model. Moreover, these results indicate that mismeasurement of Q and $Tangibility$ leads also to an "attenuation bias." Altogether, these potential biases make it therefore more difficult to detect an economically meaningful influence of Q interacted with $Tangibility$ on $Investment$ in the data.

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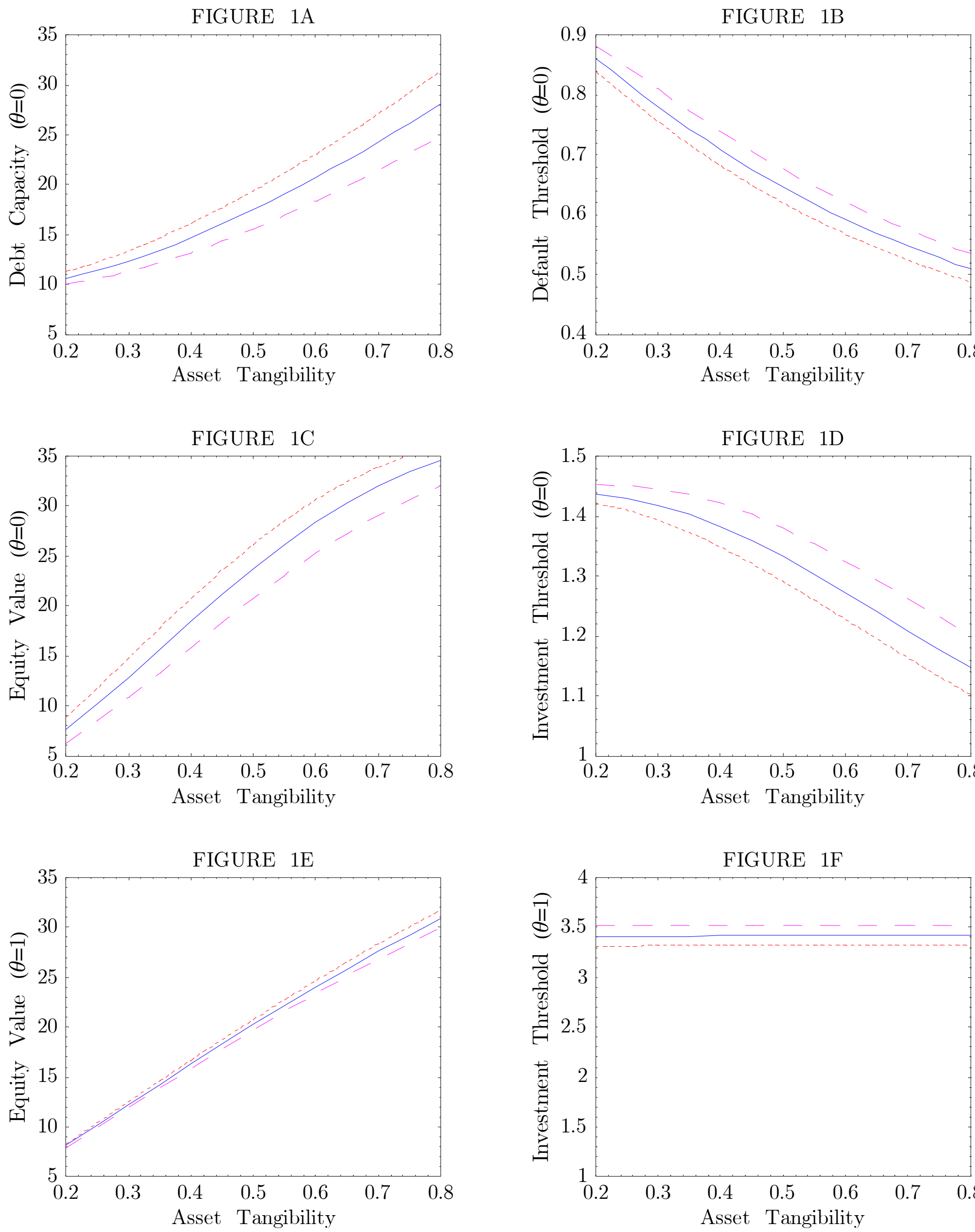

Figure 1. Asset Tangibility, Financing Constraints, and Investment.

For $\theta = 0$ (i.e. debt-financed investment), Figures 1A-1D plot debt capacity, $\bar{b}$, default threshold, p^d, equity valuation, $S(K_0, P_0, b_0)$, and investment threshold, p^i, as a function of asset tangibility, τ, when financing constraints are $\rho = 1.5$ (solid line), $\rho = 1.4$ (dashed line), and $\rho = 1.6$ (dotted line). For $\theta = 1$ (i.e. equity-financed investment), Figures 1E-1F chart equity valuation, $S(K_0, P_0, b_0)$, and investment threshold, p^i, as a function of asset tangibility, τ, when financing constraints are $\iota = 1.1$ (solid line), $\iota = 1.2$ (dashed line), and $\iota = 1.01$ (dotted line). The input parameter values are $\mu = 0.01$, $\sigma = 0.2$, $\rho = 1.5$, $\iota = 1.1$ $b_0 = 20$, $r = 0.08$, $w = 0.1$, $x = 0.75$, $y = 0.5$, $K_0 = 1$, $K_1 = 1$, $P_0 = 1$, and $\lambda_1 = 375$; that is, the investment opportunity has a net present value of zero at the initial output price.

Table 1. Sample Descriptive Statistics

This table displays summary statistics for the main variables used in the empirical estimations. All firm data are collected from COMPUSTAT's annual industrial tapes over the 1971–2005 period. The sample firms are from manufacturing industries (SICs 2000–3999). *Assets* is the firm's total assets (COMSPUSTAT's item #6), expressed in millions of CPI-adjusted 1971 dollars. *Investment* is the ratio of fixed capital expenditures (item #128) over lagged fixed capital stock (item #8). Q is computed as the market value of assets divided by the book value of assets, or (item #6 + (item #24 × item #25) – item #60 – item #74) / (item #6). There are two baseline measures of asset tangibility (*Tangibility*) that we construct at an annual frequency. The first is based on a firm-level proxy for expected value of assets in liquidation (the computation follows Berger et al. (1996)). The second is an industry-level measure of asset redeployment; available from 1981 through 1996 (data taken from the Bureau of Census' *Annual Survey of Manufacturers*). *Leverage* is computed as item #9 divided by item #6. *DebtIssuance* is the change in long- (Δitem #9) and short-term debt (Δitem #34) over lagged total assets.

Variables	Statistics					
	Mean	Median	Std. Dev.	25^{th} Pct.	75^{th} Pct.	Obs.
Assets	155.6	14.1	690.2	4.3	60.8	65,107
Investment	0.2617	0.1884	0.2584	0.1159	0.3088	58,633
Q	0.8733	0.7695	0.5196	0.6355	0.9494	65,107
Tangibility (two definitions)						
Firm-Level Asset Liquidation	0.5583	0.5648	0.1196	0.5035	0.6118	64,788
Industry-Level Asset Redeployment	0.0742	0.0573	0.0522	0.0410	0.0899	14,402
Leverage	0.1713	01404	0.1655	0.0377	0.2573	64,788
DebtIssuance	0.0015	–0.0079	0.1449	–0.0485	0.0242	57,087

Table 2. Cross-Classification of Financial Constraint Types

This table displays firm-year cross-classifications for the various criteria used to categorize firms as either financially constrained or unconstrained (see text for definitions). To ease visualization, we assign the letter (C) for constrained firms and (U) for unconstrained firms in each row/column. All firm data are collected from COMPUSTAT's annual industrial tapes over the 1971–2005 period. The sample firms are from manufacturing industries (SICs 2000–3999).

Financial Constraints Criteria		Div. Payout		Firm Size		Bond Ratings		CP Ratings	
		(C)	(U)	(C)	(U)	(C)	(U)	(C)	(U)
1. Payout Policy									
Constrained Firms	(C)	27,658							
Unconstrained Firms	(U)	0	19,549						
2. Firm Size									
Constrained Firms	(C)	12,857	2,750	19,550					
Unconstrained Firms	(U)	3,689	9,849	0	19,549				
3. Bond Ratings									
Constrained Firms	(C)	23,723	14,786	19,108	11,391	52,915			
Unconstrained Firms	(U)	3,935	4,763	442	8,158	0	12,192		
4. Comm. Paper Ratings									
Constrained Firms	(C)	26,964	16,896	19,533	15,106	52,822	7,571	60,393	
Unconstrained Firms	(U)	694	2,653	17	4,443	93	4,621	0	4,714

Table 3. Investment Spending, Q, and Asset Tangibility: Base Regressions Using Ex-Ante Constraint Partitions

This table displays OLS-FE (firm- and year-fixed effects) estimation results of the baseline investment model (Eq. (16) in the text). The estimations use pre-determined firm selection into "financially constrained" and "financially unconstrained" categories. Constraint category assignments use ex-ante criteria based on firm dividend payout, asset size, bond ratings, and commercial paper ratings (see text for details). *Investment* is the ratio of fixed capital expenditures (item #128) over lagged fixed capital stock (item #8). Q is computed as the market value of assets divided by the book value of assets, or (item #6 + (item #24 × item #25) – item #60 – item #74) / (item #6). In Panel A, *Tangibility* is an annual, firm-level proxy for expected value of assets in liquidation (the computation follows Berger et al. (1996)). In Panel B, *Tangibility* is an annual, industry-level measure of asset redeployment; available from 1981 through 1996 (data taken from the Bureau of Census' *Annual Survey of Manufacturers*). All firm data are collected from COMPUSTAT's annual industrial tapes over the 1971–2005 period. The sample firms are from manufacturing industries (SICs 2000–3999). The estimations correct the error structure for heteroskedasticity and clustering using the White-Huber estimator. Robust standard errors reported in parentheses.

Panel A: Tangibility proxied by annual, firm-level liquidation values (based on Berger et al. (1996))

Dependent Variable *Investment*	Independent Variables Q	*Tangibility*	R^2	Obs.
Financial Constraints Criteria				
1. Payout Policy				
Constrained Firms	0.1284***	0.5605***	0.07	22,512
	(0.0088)	(0.0328)		
Unconstrained Firms	0.0605***	0.0891*	0.02	17,915
	(0.0065)	(0.0458)		
2. Firm Size				
Constrained Firms	0.1090***	0.6491***	0.06	15,259
	(0.0104)	(0.0455)		
Unconstrained Firms	0.0663***	0.1557***	0.05	17,949
	(0.0073)	(0.0235)		
3. Bond Ratings				
Constrained Firms	0.0940***	0.4251***	0.05	45,226
	(0.0056)	(0.0252)		
Unconstrained Firms	0.0804***	0.0787**	0.03	11,051
	(0.0104)	(0.0321)		
4. Comm. Paper Ratings				
Constrained Firms	0.0939***	0.3978**	0.05	51,893
	(0.0055)	(0.0229)		
Unconstrained Firms	0.0780***	0.0857	0.06	4,384
	(0.0097)	(0.0574)		

Note: ***, **, and * indicate statistical significance at the 1-, 5-, and 10-percent (two-tail) test levels, respectively.

Table 3. – Continued

Panel B: Tangibility proxied by annual, industry-level asset redeployability (based on redeployment of used capital)

Dependent Variable	Independent Variables		R^2	Obs.
Investment	*Q*	*Tangibility*		
Financial Constraints Criteria				
1. Payout Policy				
Constrained Firms	0.1958***	0.1459*	0.05	5,795
	(0.0191)	(0.0847)		
Unconstrained Firms	0.0978***	–0.0743*	0.03	3,509
	(0.0145)	(0.0431)		
2. Firm Size				
Constrained Firms	0.1840***	0.2148*	0.04	3,715
	(0.0268)	(0.1127)		
Unconstrained Firms	0.1173***	–0.0677	0.05	3,470
	(0.0152)	(0.0463)		
3. Bond Ratings				
Constrained Firms	0.1670***	0.1604***	0.05	10,744
	(0.0142)	(0.0531)		
Unconstrained Firms	0.1793***	–0.0438	0.05	1,779
	(0.0299)	(0.0696)		
4. Comm. Paper Ratings				
Constrained Firms	0.1685***	0.1505***	0.05	11,874
	(0.0140)	(0.0489)		
Unconstrained Firms	0.1487***	–0.1116	0.08	649
	(0.0434)	(0.0797)		

Note: ***, **, and * indicate statistical significance at the 1-, 5-, and 10-percent (two-tail) test levels, respectively.

Table 4. Investment Spending, Q, and Asset Tangibility: Base Regressions Using Endogenous Constraint Partitions

This table displays results from the baseline investment model estimated via switching regressions. The equations are estimated with firm- and time-fixed effects. The switching regression estimations allow for endogenous selection into "financially constrained" and "financially unconstrained" categories via maximum likelihood methods. The"regime selection" regression (unreported) uses payout ratio, asset size, a dummy for bond ratings, a dummy for commercial paper ratings, and *Tangibility* as selection variables to classify firms into constraint categories. *Investment* is the ratio of fixed capital expenditures (item #128) over lagged fixed capital stock (item #8). Q is computed as the market value of assets divided by the book value of assets, or (item #6 + (item #24 × item #25) – item #60 – item #74) / (item #6). In Panel A, *Tangibility* is an annual, firm-level proxy for expected value of assets in liquidation (the computation follows Berger et al. (1996)). In Panel B, *Tangibility* is an annual, industry-level measure of asset redeployment; available from 1981 through 1996 (data taken from the Bureau of Census' *Annual Survey of Manufacturers*). All firm data are collected from COMPUSTAT's annual industrial tapes over the 1971–2005 period. The sample firms are from manufacturing industries (SICs 2000–3999). The estimations correct the error structure for heteroskedasticity and clustering using the White-Huber estimator. Robust standard errors reported in parentheses.

Panel A: Tangibility proxied by annual, firm-level liquidation values (based on Berger et al. (1996))

Dependent Variable	Independent Variables		R^2	Obs.
Investment	Q	*Tangibility*		
Constrained Firms	0.0708***	0.2906***	0.05	56,252
	(0.0039)	(0.0153)		
Unconstrained Firms	0.0842***	0.1315	0.02	56,252
	(0.0150)	(0.1376)		

Panel B: Tangibility proxied by annual, industry-level asset redeployability (based on redeployment of used capital)

Dependent Variable	Independent Variables		R^2	Obs.
Investment	Q	*Tangibility*		
Constrained Firms	0.2779***	0.1511***	0.11	9,522
	(0.0588)	(0.0573)		
Unconstrained Firm	0.1281***	0.0263	0.05	9,522
	(0.0129)	(0.0334)		

Note: ***, **, and * indicate statistical significance at the 1-, 5-, and 10-percent (two-tail) test levels, respectively.

Table 5. Investment Spending, Q, and Asset Tangibility: The Credit Multiplier Effect Using Ex-Ante Constraint Partitions

This table displays OLS-FE (firm- and year-fixed effects) estimation results of the credit multiplier investment model (Eq. (16) in the text). The estimations use pre-determined firm selection into "financially constrained" and "financially unconstrained" categories. Constraint category assignments use ex-ante criteria based on firm dividend payout, asset size, bond ratings, and commercial paper ratings (see text for details). *Investment* is the ratio of fixed capital expenditures (item #128) over lagged fixed capital stock (item #8). Q is computed as the market value of assets divided by the book value of assets, or (item #6 + (item #24 × item #25) – item #60 – item #74) / (item #6). In Panel A, *Tangibility* is an annual, firm-level proxy for expected value of assets in liquidation (the computation follows Berger et al. (1996)). In Panel B, *Tangibility* is an annual, industry-level measure of asset redeployment; available from 1981 through 1996 (data taken from the Bureau of Census' *Annual Survey of Manufacturers*). All firm data are collected from COMPUSTAT's annual industrial tapes over the 1971–2005 period. The sample firms are from manufacturing industries (SICs 2000–3999). The estimations correct the error structure for heteroskedasticity and clustering using the White-Huber estimator. Robust standard errors reported in parentheses.

Panel A: Tangibility proxied by annual, firm-level liquidation values (based on Berger et al. (1996))

Dependent Variable	Independent Variables			R^2	Obs.
Investment	Q	*Tangibility*	$Q \times Tangibility$		
Financial Constraints Criteria					
1. Payout Policy					
Constrained Firms	0.0285	0.4214***	0.1571***	0.07	22,512
	(0.0310)	(0.0525)	(0.0505)		
Unconstrained Firms	0.1139***	0.1656***	–0.0884*	0.02	17,915
	(0.0312)	(0.0510)	(0.0524)		
2. Firm Size					
Constrained Firms	0.0165	0.5264***	0.1421**	0.07	15,259
	(0.0423)	(0.0693)	(0.0692)		
Unconstrained Firms	0.1311***	0.2572***	–0.1099**	0.05	17,949
	(0.0290)	(0.0521)	(0.0526)		
3. Bond Ratings					
Constrained Firms	0.0196	0.3239***	0.1177***	0.05	45,226
	(0.0244)	(0.0400)	(0.0408)		
Unconstrained Firms	0.1357***	0.2664***	–0.0962	0.03	11,051
	(0.0486)	(0.0844)	(0.0869)		
4. Comm. Paper Ratings					
Constrained Firms	0.0247	0.3026***	0.1101***	0.05	51,893
	(0.0236)	(0.0382)	(0.0393)		
Unconstrained Firms	0.1691***	0.2377***	–0.1596**	0.06	4,384
	(0.0470)	(0.0743)	(0.0786)		

Note: ***, **, and * indicate statistical significance at the 1-, 5-, and 10-percent (two-tail) test levels, respectively.

Table 5. – Continued

Panel B: Tangibility proxied by annual, industry-level asset redeployability (based on redeployment of used capital)

Dependent Variable	Independent Variables			R^2	Obs.
Investment	Q	*Tangibility*	$Q \times$ *Tangibility*		
Financial Constraints Criteria					
1. Payout Policy					
Constrained Firms	0.0832***	–0.0819	0.5800***	0.05	5,795
	(0.0210)	(0.2610)	(0.2186)		
Unconstrained Firms	0.0941***	–0.1651	0.1269	0.03	3,509
	(0.0161)	(0.1506)	(0.2034)		
2. Firm Size					
Constrained Firms	0.0488***	–0.4246	0.8431***	0.05	3,715
	(0.0206)	(0.3025)	(0.2386)		
Unconstrained Firms	0.1091***	–0.3011	0.2966	0.05	3,470
	(0.0164)	(0.1997)	(0.2584)		
3. Bond Ratings					
Constrained Firms	0.0480***	–0.3033*	0.4689**	0.05	10,744
	(0.0148)	(0.1686)	(0.2223)		
Unconstrained Firms	0.1764***	–0.0953	0.0624	0.05	1,779
	(0.0323)	(0.1959)	(0.2534)		
4. Comm. Paper Ratings					
Constrained Firms	0.0511***	–0.2807*	0.4218**	0.05	11,874
	(0.0146)	(0.0125)	(0.2068)		
Unconstrained Firms	0.1457***	–0.1823	0.0927	0.08	649
	(0.0441)	(0.4421)	(0.6253)		

Note: ***, **, and * indicate statistical significance at the 1-, 5-, and 10-percent (two-tail) test levels, respectively.

Table 6. Investment Spending, Q, and Asset Tangibility: The Credit Multiplier Effect Using Endogenous Constraint Partitions

This table displays results from the credit multiplier investment model estimated via switching regressions. The equations are estimated with firm- and time-fixed effects. The switching regression estimations allow for endogenous selection into "financially constrained" and "financially unconstrained" categories via maximum likelihood methods. The"regime selection" regression (unreported) uses payout ratio, asset size, a dummy for bond ratings, a dummy for commercial paper ratings, and *Tangibility* as selection variables to classify firms into constraint categories. *Investment* is the ratio of fixed capital expenditures (item #128) over lagged fixed capital stock (item #8). Q is computed as the market value of assets divided by the book value of assets, or (item #6 + (item #24 × item #25) – item #60 – item #74) / (item #6). In Panel A, *Tangibility* is an annual, firm-level proxy for expected value of assets in liquidation (the computation follows Berger et al. (1996)). In Panel B, *Tangibility* is an annual, industry-level measure of asset redeployment; available from 1981 through 1996 (data taken from the Bureau of Census' *Annual Survey of Manufacturers*). All firm data are collected from COMPUSTAT's annual industrial tapes over the 1971–2005 period. The sample firms are from manufacturing industries (SICs 2000–3999). The estimations correct the error structure for heteroskedasticity and clustering using the White-Huber estimator. Robust standard errors reported in parentheses.

Panel A: Tangibility proxied by annual, firm-level liquidation values (based on Berger et al. (1996))

Dependent Variable	Independent Variables			R^2	Obs.
Investment	Q	*Tangibility*	$Q \times$ *Tangibility*		
Constrained Firms	0.1723*	0.1965	0.3996***	0.04	56,252
	(0.0911)	(0.1865)	(0.1339)		
Unconstrained Firms	0.0308*	0.2305***	0.0601	0.05	56,252
	(0.0171)	(0.0267)	(0.0393)		

Panel B: Tangibility proxied by annual, industry-level asset redeployability (based on redeployment of used capital)

Dependent Variable	Independent Variables			R^2	Obs.
Investment	Q	*Tangibility*	$Q \times$ *Tangibility*		
Constrained Firms	0.1098***	–0.1310	0.4048***	0.05	9,522
	(0.0134)	(0.1160)	(0.1484)		
Unconstrained Firm	0.2935***	–0.2796	–0.2334	0.11	9,522
	(0.0814)	(0.2891)	(0.7777)		

Note: ***, **, and * indicate statistical significance at the 1-, 5-, and 10-percent (two-tail) test levels, respectively.

Table 7. Investment Spending, Q, and Asset Tangibility: The Credit Multiplier Effect Using GMM Estimations

This table displays GMM-FE (firm- and year-fixed effects) estimation results of the credit multiplier investment model (Eq. (16) in the text). The estimations use pre-determined firm selection into "financially constrained" and "financially unconstrained" categories. Constraint category assignments use ex-ante criteria based on firm dividend payout, asset size, bond ratings, and commercial paper ratings (see text for details). *Investment* is the ratio of fixed capital expenditures (item #128) over lagged fixed capital stock (item #8). Q is computed as the market value of assets divided by the book value of assets, or (item #6 + (item #24 × item #25) – item #60 – item #74) / (item #6). *Tangibility* is an annual, firm-level proxy for expected value of assets in liquidation (the computation follows Berger et al. (1996)). The instruments include lags 1 through 3 of the model's differenced right-hand side variables. All firm data are collected from COMPUSTAT's annual industrial tapes over the 1971–2005 period. The sample firms are from manufacturing industries (SICs 2000–3999). The estimations correct the error structure for heteroskedasticity and clustering using the White-Huber estimator. Robust standard errors reported in parentheses. Diagnostic statistics for instrument overidentification restrictions (p-values for Hansen's J-statistics) and instrument relevance (first-stage p-values for F-statistics) are also reported.

Dependent Variable *Investment*	Independent Variables Q	*Tangibility*	$Q \times$ *Tangibility*	P-Value of Hansen's J-statistic	P-Value of First-Stage F-Test
Financial Constraints Criteria					
1. Payout Policy					
Constrained Firms	–0.4064**	–0.3889	0.9699***	0.58	0.00
	(0.2055)	(0.2816)	(0.3407)		
Unconstrained Firms	0.2091	0.0663	–0.0418	0.83	0.00
	(0.3174)	(0.4557)	(0.5428)		
2. Firm Size					
Constrained Firms	–0.3934**	–0.1949	0.7940***	0.20	0.00
	(0.1847)	(0.2365)	(0.3085)		
Unconstrained Firms	0.2875	0.2067	–0.1501	0.92	0.00
	(0.3858)	(0.6083)	(0.6678)		
3. Bond Ratings					
Constrained Firms	–0.3009**	–0.4071**	0.7964***	0.88	0.00
	(0.1402)	(0.1927)	(0.2379)		
Unconstrained Firms	0.1181	–0.0978	0.2431	0.22	0.00
	(0.3196)	(0.5197)	(0.5881)		
4. Comm. Paper Ratings					
Constrained Firms	–0.3330**	–0.4649**	0.8509***	0.96	0.00
	(0.1439)	(0.1990)	(0.2437)		
Unconstrained Firms	0.3489	0.1171	–0.1239	0.33	0.00
	(0.2962)	(0.4907)	(0.5224)		

Note: ***, **, and * indicate statistical significance at the 1-, 5-, and 10-percent (two-tail) test levels, respectively.

Table 8. Investment Spending, Q, and Asset Tangibility: The Credit Multiplier Effect Replacing Q with Cummins et al.'s (2006) $RealQ$

This table displays OLS-FE (firm- and year-fixed effects) estimation results of the credit multiplier investment model (Eq. (16) in the text), where conventional Q is replaced by Cummins et al.'s (2006) measurement-robust *RealQ* (based on long-term earning forecasts from IBES). IBES forecast are collected starting in 1989. The estimations use pre-determined firm selection into "financially constrained" and "financially unconstrained" categories. Constraint category assignments use ex-ante criteria based on firm dividend payout, asset size, bond ratings, and commercial paper ratings (see text for details). *Investment* is the ratio of fixed capital expenditures (item #128) over lagged fixed capital stock (item #8). *Tangibility* is an annual, firm-level proxy for expected value of assets in liquidation (the computation follows Berger et al. (1996)). All firm data are collected from COMPUSTAT's annual industrial tapes. The sample firms are from manufacturing industries (SICs 2000–3999). The estimations correct the error structure for heteroskedasticity and clustering using the White-Huber estimator. Robust standard errors reported in parentheses.

Dependent Variable *Investment*	Independent Variables *RealQ*	*Tangibility*	*RealQ* $\times$*Tangibility*	R^2	Obs.
Financial Constraints Criteria					
1. Payout Policy					
Constrained Firms	–0.0798	0.4653***	0.1757***	0.04	2,271
	(0.0587)	(0.0953)	(0.0547)		
Unconstrained Firms	0.1153**	0.1199**	–0.0479	0.03	3,162
	(0.0573)	(0.0589)	(0.0965)		
2. Firm Size					
Constrained Firms	0.0314	0.6304***	0.1343***	0.03	578
	(0.0783)	(0.1840)	(0.0437)		
Unconstrained Firms	0.0017	0.1585***	–0.1294	0.03	3,611
	(0.0622)	(0.0613)	(0.1000)		
3. Bond Ratings					
Constrained Firms	0.0255	0.2837***	0.1343**	0.03	5,307
	(0.0525)	(0.0667)	(0.0618)		
Unconstrained Firms	0.0068	0.2519***	–0.0568	0.02	1,673
	(0.0663)	(0.0741)	(0.1168)		
4. Comm. Paper Ratings					
Constrained Firms	–0.0169	0.2856***	0.1191***	0.03	6,161
	(0.0489)	(0.0608)	(0.0366)		
Unconstrained Firms	0.0104	0.1848***	0.0503	0.03	819
	(0.0486)	(0.0702)	(0.1006)		

Note: ***, **, and * indicate statistical significance at the 1-, 5-, and 10-percent (two-tail) test levels, respectively.

Table 9. Investment Spending, Q, and Asset Tangibility: The Credit Multiplier Effect Replacing Q with the Projection of Q on Industry Prices

This table displays OLS-FE (firm- and year-fixed effects) estimation results of the credit multiplier investment model (Eq. (16) in the text), where conventional Q is replaced by the projection of Q on industry-level PPI (from the Bureau of Labor Statisticcs). This construct is denoted $ProjQ$. The estimations use pre-determined firm selection into "financially constrained" and "financially unconstrained" categories. Constraint category assignments use ex-ante criteria based on firm dividend payout, size, bond ratings, and commercial paper ratings (see text for details). *Investment* is the ratio of fixed capital expenditures (item #128) over lagged fixed capital stock (item #8). *Tangibility* is an annual, firm-level proxy for expected value of assets in liquidation (the computation follows Berger et al. (1996)). All firm data are collected from COMPUSTAT's annual industrial tapes. The sample firms are from manufacturing industries (SICs 2000–3999). While for most industries the PPI series compilations start in the 1970's, for many it starts in the mid-1980's. All of the PPI series end in 2003. The estimations correct the error structure for heteroskedasticity and clustering using the White-Huber estimator. Robust standard errors reported in parentheses.

Dependent Variable	Independent Variables			R^2	Obs.
Investment	*ProjQ*	*Tangibility*	*ProjQ* ×*Tangibility*		
Financial Constraints Criteria					
1. Payout Policy					
Constrained Firms	0.9459***	0.0505	0.6176***	0.04	19,305
	(0.1409)	(0.1403)	(0.1756)		
Unconstrained Firms	0.3444***	0.0073	0.1187	0.00	14,869
	(0.1083)	(0.0817)	(0.1032)		
2. Firm Size					
Constrained Firms	0.6305***	0.2238	0.4859*	0.04	12,395
	(0.1980)	(0.2139)	(0.2612)		
Unconstrained Firms	0.5318***	0.0676	0.1167	0.02	14,979
	(0.0955)	(0.0695)	(0.0877)		
3. Bond Ratings					
Constrained Firms	0.4962***	0.1112	0.4109***	0.03	37,160
	(0.0910)	(0.0888)	(0.1101)		
Unconstrained Firms	0.4951***	0.0503	0.1307	0.01	9,348
	(0.1449)	(0.1141)	(0.1401)		
4. Comm. Paper Ratings					
Constrained Firms	0.4960***	0.1100	0.3717***	0.03	42,854
	(0.0848)	(0.0793)	(0.0987)		
Unconstrained Firms	0.4792***	0.0277	0.0606	0.02	3,654
	(0.1829)	(0.1223)	(0.1539)		

Note: ***, **, and * indicate statistical significance at the 1-, 5-, and 10-percent (two-tail) test levels, respectively.

Table 10. Investment Spending, Q, and Asset Tangibility: Debt Capacity and the Credit Multiplier Effect

This table displays OLS-FE (firm- and year-fixed effects) estimation results of the credit multiplier investment model (Eq. (16) in the text), where constrained firms are split into "high" and "low" debt capacity groups. In Panel A, firms are assigned into high and low debt capacity categories according to annual rankings of the residual of the regression of firm leverage on asset tangibility. Low (high) residuals are associated with high (low) incremental debt capacity. In Panel B, annual rankings based on raw leverage are used. Accordingly, firms ranked at the bottom (top) of the leverage distribution are considered to have high (low). *Investment* is the ratio of fixed capital expenditures (item #128) over lagged fixed capital stock (item #8). Q is computed as the market value of assets divided by the book value of assets, or (item #6 + (item #24 × item #25) – item #60 – item #74) / (item #6). *Tangibility* is an annual, firm-level proxy for expected value of assets in liquidation (the computation follows Berger et al. (1996)). *Leverage* is computed as item #9 divided by item #6. All firm data are collected from COMPUSTAT's annual industrial tapes over the 1971–2005 period. The sample firms are from manufacturing industries (SICs 2000–3999). The estimations correct the error structure for heteroskedasticity and clustering using the White-Huber estimator. Robust standard errors reported in parentheses.

Panel A: Debt capacity rankings based on the residuals of a regression of leverage on asset tangibility

Dependent Variable	Independent Variables			R^2	Obs.
Investment	Q	*Tangibility*	$Q \times$ *Tangibility*		
Financial Constraints Criteria					
1. Low Payout Firms					
High Debt Capacity	–0.0280	0.4258***	0.2443***	0.10	6,597
	(0.0418)	(0.0778)	(0.0719)		
Low Debt Capacity	0.0674	0.3860***	0.0341	0.03	8,002
	(0.0543)	(0.0941)	(0.0914)		
2. Small Firms					
High Debt Capacity	0.0103	0.5727***	0.1439***	0.08	5,945
	(0.0584)	(0.0988)	(0.0377)		
Low Debt Capacity	0.0354	0.5676***	0.0739	0.04	3,455
	(0.0635)	(0.1381)	(0.1167)		
3. Firms without Bond Ratings					
High Debt Capacity	0.0178	0.3544***	0.0903*	0.06	16,936
	(0.0311)	(0.0519)	(0.0517)		
Low Debt Capacity	0.0863	0.4581***	0.0320	0.04	9,806
	(0.0610)	(0.1031)	(0.1040)		
4. Firms without CP Ratings					
High Debt Capacity	0.0178	0.3544***	0.0903*	0.06	16,936
	(0.0311)	(0.0519)	(0.0517)		
Low Debt Capacity	0.0919*	0.3522***	0.0107	0.03	14,784
	(0.0492)	(0.0819)	(0.0848)		

Note: ***, **, and * indicate statistical significance at the 1-, 5-, and 10-percent (two-tail) test levels, respectively.

Table 10. − Continued

Panel B: Debt capacity rankings based on the distribution of leverage

Dependent Variable	Independent Variables			R^2	Obs.
Investment	Q	*Tangibility*	$Q \times Tangibility$		
Financial Constraints Criteria					
1. Low Payout Firms					
High Debt Capacity	1.4092***	–0.4615**	1.4497***	0.07	5,380
	(0.2857)	(0.2215)	(0.2811)		
Low Debt Capacity	0.6424***	0.1367	0.2384	0.02	7,569
	(0.1829)	(0.1768)	(0.2145)		
2. Small Firms					
High Debt Capacity	0.5042	0.0051	0.7951**	0.04	4,800
	(0.3178)	(0.3053)	(0.3762)		
Low Debt Capacity	0.7933**	0.3840	0.1874	0.03	3,376
	(0.3151)	(0.3367)	(0.4030)		
3. Firms without Bond Ratings					
High Debt Capacity	0.6233***	–0.0507	0.7382***	0.04	11,202
	(0.1767)	(0.1751)	(0.2174)		
Low Debt Capacity	0.7606***	0.4667**	–0.0400	0.02	8,211
	(0.2017)	(0.2285)	(0.2753)		
4. Firms without CP Ratings					
High Debt Capacity	0.6527***	–0.0681	0.7555***	0.06	16,936
	(0.1724)	(0.1619)	(0.2022)		
Low Debt Capacity	0.6620***	0.2577	0.0488	0.02	12,115
	(0.1564)	(0.1571)	(0.1901)		

Note: ***, **, and * indicate statistical significance at the 1-, 5-, and 10-percent (two-tail) test levels, respectively.

Table 11. Debt Taking, Q, and Asset Tangibility: The Credit Multiplier Effect on Debt Policy

This table displays OLS-FE (firm- and year-fixed effects) estimation results of the credit multiplier debt model (Eq. (17) in the text). The dependent variable is *DebtIssuance*, defined as the change in long- (Δitem #9) and short-term debt (Δitem #34) over lagged total assets. The estimations use pre-determined firm selection into "financially constrained" and "financially unconstrained" categories. Constraint category assignments use ex-ante criteria based on firm dividend payout, asset size, bond ratings, and commercial paper ratings (see text for details). *Investment* is the ratio of fixed capital expenditures (item #128) over lagged fixed capital stock (item #8). Q is computed as the market value of assets divided by the book value of assets, or (item #6 + (item #24 $\times$ item #25) – item #60 – item #74) / (item #6). *Tangibility* is an annual, firm-level proxy for expected value of assets in liquidation (the computation follows Berger et al. (1996)). All firm data are collected from COMPUSTAT's annual industrial tapes over the 1971–2005 period. The sample firms are from manufacturing industries (SICs 2000–3999). The estimations correct the error structure for heteroskedasticity and clustering using the White-Huber estimator. Robust standard errors reported in parentheses.

Dependent Variable	Independent Variables			R^2	Obs.
DebtIssuance	Q	*Tangibility*	$Q \times$ *Tangibility*		
Financial Constraints Criteria					
1. Payout Policy					
Constrained Firms	–0.0523**	0.1342***	0.0701**	0.01	22,714
	(0.0229)	(0.0349)	(0.0326)		
Unconstrained Firms	–0.0017	0.0587**	–0.0022	0.00	18,108
	(0.0236)	(0.0286)	(0.0369)		
2. Firm Size					
Constrained Firms	–0.0595**	0.1217***	0.0778**	0.01	15,432
	(0.0285)	(0.0335)	(0.0394)		
Unconstrained Firms	–0.0057	0.1227***	0.0041	0.00	18,130
	(0.0234)	(0.0397)	(0.0377)		
3. Bond Ratings					
Constrained Firms	–0.0399*	0.1060***	0.0501**	0.01	45,644
	(0.0224)	(0.0269)	(0.0224)		
Unconstrained Firms	0.1049	–0.0219	0.2082	0.01	11,181
	(0.0925)	(0.1501)	(0.1664)		
4. Comm. Paper Ratings					
Constrained Firms	–0.04337**	0.1049***	0.0598***	0.01	52,381
	(0.0219)	(0.0273)	(0.0222)		
Unconstrained Firms	0.0878	0.2740*	–0.1646	0.01	4,444
	(0.1070)	(0.1604)	(0.1829)		

Note: ***, **, and * indicate statistical significance at the 1-, 5-, and 10-percent (two-tail) test levels, respectively.