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External finance constraints and the intertemporal pattern of intermittent investment ☆

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Abstract

Do external finance constraints affect the timing of large investment projects? Simulations of a model with fixed capital-stock adjustment costs establish the hypothesis that external finance constraints lower a firm's investment hazard: the probability of undertaking a large project today as a function of the time since the last project. Hazard model estimation that controls for productivity and adjustment costs supports this hypothesis. Small firms that distribute cash to shareholders have higher hazards than small firms that do not; very small firms have lower hazards than small firms; small stand-alone firms have significantly lower hazards than small segments of conglomerates.

JEL classification: G31; E22

Keywords: Finance constraints; Lumpy investment; Hazard estimation

1. Introduction

The past two decades have seen a flood of empirical studies of the effects of external finance constraints on corporate investment. Such an outpouring of research stems from

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two important sources of interest. First, external finance constraints have implications for monetary policy transmission and tax policy. Second, financial economists are concerned with imperfections in financial markets, which have implications for capital structure, capital budgeting decisions, and the operation of internal capital markets.

The connection between finance and investment starts with any violation of the Modigliani-Miller theorem, usually modeled formally via imperfect information. These models show that information asymmetry leads to a divergence between the costs of internal and external funds or, at the extreme, to a rationing of external funds. However, these information theoretic models provide only qualitative guidance for empirical work, because few have both endogenous investment and finance decisions, and since few are, by nature, couched in terms of observable variables. Therefore, the empirical literature has turned to two loose arguments to motivate tests of the connection between finance and investment. One strand of the literature hypothesizes that finance constraints cause an excess sensitivity of investment to internal funds, and the second hypothesizes that constraints affect the firm's incremental intertemporal investment allocation. In contrast, this paper tackles the topic from an unexploited angle; briefly, one that examines the effects of finance constraints on the timing of large investment projects.

Specifically, I examine the effects of finance constraints on a capital stock adjustment hazard: the probability of a large change in the capital stock as a function of the time since the last large change. This sort of lumpy adjustment is often the outcome of models with nonconvex adjustment costs.[1] I use such a model to establish that the shape of the hazard depends both on the nature of physical adjustment costs and the presence of finance constraints. In the model lumpiness is optimal because the firm invests only when its capital stock is sufficiently far from the desired level, otherwise preferring to remain inactive to avoid any lump-sum costs. Therefore, after a recent adjustment, the desired capital stock is close to the actual, and the probability of another large adjustment is low. As time elapses, it becomes more likely that cumulated productivity shocks and depreciation will have changed the marginal profit of capital sufficiently to warrant further investment. In other words, the hazard slopes up. External financial constraints act as an additional cost of adjusting the capital stock, thereby furthering the delays between episodes of intense investment. The hazard of a constrained firm lies below that of an otherwise identical unconstrained firm. This implication is not equivalent to the idea that constrained firms underinvest. It is an implication for investment timing—not investment levels.

I estimate empirical hazards using a sample of firms and segments of firms from Compustat, finding evidence of the interdependence of finance and investment, in particular, investment in large projects. I find that groups of a priori constrained firms have lower hazards than their unconstrained counterparts, controlling for appropriate measures of investment opportunities, aggregation of individual decisions within firms, and unobservable capital-stock adjustment costs. Small firms that distribute cash to shareholders have higher hazards than small firms that do not; very small firms have lower hazards than small firms; and small stand-alone firms have lower hazards than small

[1]Models with fixed costs of adjustment have been used to show that lumpy adjustment and inactivity characterize a wide variety of economic decisions. For a model of inventories, see Caplin (1985); for a model of durables consumption, see Eberly (1994); for a model of capital structure, see Fischer et al. (1989); and for a model of portfolio choice, see Vayanos (1998).

segments of conglomerates. This paper leaves to further research the failure of previous empirical investment studies to isolate any differences between costly external finance and a hard finance constraint. Therefore, throughout the paper I use the terms "external finance constraints" and "costly external finance" interchangeably.

A discussion of the progenitors and relatives of the present paper aids in understanding this contribution. Most empirical research in this area has followed the approach in Fazzari et al. (1988), who argue and find that if groups of firms face finance constraints, their investment responds strongly to movements in cash flow, holding investment opportunities constant. They note that although measurement error can contaminate the usual tool to test this idea (regressions of investment on q and cash flow) little reason exists to assume that it does so to a greater extent for more constrained than for less constrained firms. Therefore, they argue that greater cash flow sensitivity for constrained firms is, nonetheless, evidence of finance constraints.

More recently, however, a number of papers have questioned this approach from both empirical and theoretical angles. On the empirical side Kaplan and Zingales (1997) and Cleary (1999) provide evidence that cash-flow sensitivity need not identify liquidity constrained firms; that is, sensitivity is not monotonic in the degree of constraints. Further, Erickson and Whited (2000), Bond and Cummins (2001), Cooper and Ejarque (2001), and Cummins et al. (2003) demonstrate that observed cash-flow sensitivity is likely an artifact of measurement error in the usual proxy for investment opportunities: Tobin's q. In particular, Erickson and Whited (2000, pp. 1049–1051) explain that measurement error can account for differential investment-cash flow sensitivities across groups of firms, if combined with at least one of the following, purely mechanical, effects: differences in the variance of cash flow, differences in the covariance between investment and q, and, as also noted by Poterba (1988), differences in the amount of measurement error in q.

On the theoretical side, Gomes (2001) and Alti (2003) simulate dynamic investment models, demonstrating that financing frictions do not necessarily generate significant cash flow coefficients. Conversely, Gomes shows that financing frictions are not sufficient to generate significant coefficients on cash flow. In sum, these recent papers question whether the large body of research on cash-flow sensitivity has revealed much about whether external finance constraints affect investment. Cash flow is correlated with investment, but it is not a given that this correlation is an indication of finance constraints. Thus, this newer work has reopened the door to understanding the mechanism whereby finance and investment interact.

Another line of related research estimates directly the Euler equation of an intertemporal investment model: an approach that avoids the difficult problem of measuring q. Here, Whited (1992) and Bond and Meghir (1994) show that augmentations of the Euler equation that account for financial constraints improve its fit, and that external finance constraints affect the rate of intertemporal substitution between investment today and investment tomorrow. However, recent work by Gomes et al. (2006) finds little evidence of financing constraints using a closely related approach. Further, the methodology suffers from two drawbacks. First, any parsimonious structural model, such as the usual investment Euler equation, is fragile. In particular, relaxation of any assumption, not just the assumption of perfect capital markets, used in its derivation can force an empirical rejection. This problem makes it difficult to disentangle the effects of finance constraints from the effects of other factors such as, for example, irreversibility or learning. Second, like the investment-q-cash flow literature, these papers examine only marginal decisions, because both approaches are based on models with convex capital-stock adjustment costs.

In contrast, common intuition suggests that finance constraints should not only affect incremental decisions, but also decisions about undertaking a large project or not; that is, they ought to have lumpy in addition to smooth effects. Loosely speaking, although finance constraints could affect a firm's decision to spread out the building of a new plant over an extra month (a marginal intertemporal decision), they are more likely to affect a firm's decision to delay the entire new-plant project (a lumpy intertemporal decision).

Two further considerations motivate the study of finance constraints in the context of lumpy investment. First, several studies have found a great deal of lumpy adjustment in plant-level data. For example, Doms and Dunne (1998) find that from 25% to 40% of an average plant's cumulative investment over 17 years is concentrated in a single year. In addition, Cooper et al. (1999) find evidence of upward sloping hazards in plant-level data. If, as this evidence suggests, investment decisions are lumpy, then external finance constraints are likely to have lumpy effects. Second, a focus on large investments in identifying finance constraints has a precedent in Cummins et al. (1994), who examine the impact of internal funds on investment during tax reforms. They study how the, typically large, investments that occur after a tax reform respond to arguably exogenous tax-induced, discrete shifts in investment opportunities and internal funds. They find a strong impact of tax reforms on investment, as well as a non-negligible effect of internal funds. Cummins et al. emphasize that studying large investments need not necessarily rely on strict belief in a fixed-costs model. This interpretation is important inasmuch as a pure fixed costs model, such as the one used to motivate my empirical work, cannot completely characterize firms in Compustat, most of which invest at least a small amount every year. A model with a combination of fixed and convex costs, as in Cooper and Haltiwanger (2006), generates the same general prediction that the constrained hazard lies below the unconstrained hazard.

The continuous or discrete nature of investment has not been an important issue in the theoretical literature on costly external finance, with some studies, such as Gale and Hellwig (1985), opting to model continuous investment, and others, such as Hart and Moore (1998), opting to model lumpy investment. However, the issue is of central importance to the empirical literature, because the nature of investment dictates the form of the null hypothesis of no financial frictions. Euler equation estimation requires the assumption of differentiable convex adjustment costs and its consequence of incremental investment. Moreover, linear regressions of investment on q require the further assumption that these differentiable, convex adjustment costs be quadratic. (See Abel and Eberly, 1994.) Because all tests for finance constraints revolve around rejecting the null of frictionless finance, a correct null model is clearly important. Given the empirical evidence of the existence of lumpy adjustment, the null models used in previous studies likely are inappropriate. A new approach that allows for lumpy investment is clearly needed.

Although I find evidence of finance constraints, I am not the first, which begs the question of whether hazard estimation is better at detecting finance constraints than previous approaches. To sort out this issue, I estimate investment-q-cash flow regressions as well as an investment Euler equation, following exactly the procedures in Erickson and Whited (2000) and Bond and Meghir (1994), respectively. I find that the q model provides no evidence of finance constraints. However, financial variables enter significantly in the investment Euler equation, suggesting a connection between real and financial decisions. I also find evidence of misspecification in the Euler equation, which suggests that the significance of the financial variables can be an artifact of omitted regressors or an incorrect functional form. Given the inability of the cash flow regressions to detect finance constraints, and given the specification problems with the Euler equation, my approach appears a viable alternative.

The paper is organized as follows. Section 2 outlines a simple model that incorporates both fixed capital-stock adjustment costs and external finance constraints, and Section 3 presents the model simulations. Section 4 describes the data. Section 5 discusses estimation strategies and contains the hazard-model results. Section 6 compares the approach in this paper with previous methods for detecting finance constraints, and Section 7 concludes. The details of the simulation are in the appendix.

2. A simple model of lumpy investment

To motivate the empirical work and to provide guidance for the choice of the control variables in my estimation, I consider a discrete-time, infinite-horizon, partial-equilibrium investment model. Because my empirical approach does not involve structural estimation of this model, its design is only rich enough to produce clean, testable implications. A risk-neutral producer uses capital, k, to produce output. The producer's per period revenue function is given by $\pi(k,z)$, where $\pi(k,z)$ is continuous, $\pi(0,z)=0$, $\pi_z(k,z)>0$, $\pi_k(k,z)>0$, $\pi_{kk}(k,z)<0$, and $\lim_{k\to\infty}\pi_k(k,z)=0$. The revenue function, $\pi(k,z)$, can be thought of as a reduced-form production function in which variable factors of production have already been maximized out of the problem. Concavity of $\pi(k,z)$ results from decreasing returns in production, a downward sloping demand curve, or both. The combination demand and productivity shock is denoted by z. It is observed by the producer before he makes his current period decisions, but not observed by the econometrician. The technology shock z takes values in $[\underline{z},\bar{z}]$ and follows a first-order Markov process with transition probability $q(z',z)$, where a prime indicates a variable in the subsequent period and $q(z',z)$ has the Feller property. Without loss of generality, k can be confined to lie in a compact set. As in Gomes (2001), define $\overline{k}$ as

$$\pi(\overline{k},\overline{z})-d\overline{k}\equiv 0. \tag{1}$$

Concavity of π and $\lim_{k\to\infty}\pi_k(k,z)=0$ ensure that $\overline{k}$ is a well-defined quantity. Since $k>\overline{k}$ is not economically profitable, k lies in the interval $[0,\overline{k}]$. Because $\pi(k,z)$ is continuous and the state space is compact, it is bounded.

The firm purchases and sells capital at a price of one and incurs a fixed cost, ck, whenever investment is not equal to zero. The fixed cost is proportional to the capital stock so that the firm can never grow out of the fixed cost. For example, a fixed adjustment cost of six million would be daunting for a small start-up restaurant but inconsequential for Microsoft. Other sources of lumpy adjustment, such as irreversibility, indivisible capital goods, and different purchase and sale prices for capital, can be though of as examples or extreme cases of nonconvex adjustment costs. The capital stock evolves according to

$$I\equiv k'-(1-d)k, \tag{2}$$

in which d is the constant rate of depreciation, $0<d<1$.

Internal funds include not only current cash flow but also savings. This extension is important, because it allows the separation of the effects of costly external finance from any pure liquidity effects. The firm saves an amount p via a riskless one-period discount bond that earns an interest rate r. To ensure compactness of the choice set, I assume an arbitrarily high upper bound on corporate saving, $\bar{p}$. This assumption is not restrictive, because the firm would never want to save more than $\overline{k}$. Therefore, the interval $[0, \bar{p}]$ contains p. Also, the firm cannot go into debt. Instead, all external finance takes the form of equity. Although inappropriate for the study of capital structure, this simplification does not affect the qualitative outcome of the simulations that follow.

Thus far the model is fairly standard and says nothing about financing costs. It would be ideal to model external finance costs endogenously. However, for the purpose of understanding the behavior of investment hazards, such an approach becomes analytically intractable. Therefore, I model external finance costs loosely after the idea of the pecking-order theory of capital structure (Myers, 1984). Specifically, I take the approach in Gomes (2001) by assuming that whenever desired investment exceeds revenue, the firm can proceed only if it obtains external funds at a premium. This assumption can be thought of as the outcome of an information theoretic model of external finance. To quantify the idea, I define the excess of desired investment over internal resources as $e(k, p, k', p', z) \equiv k' - (1-d)k - \pi(k, z) + p(1+r) - p' + ck$ and then specify a financing cost function $\phi(e(k, k', p, p', z))$, where $\phi(e) = 0$ if $e \leqslant 0$ and $\phi(e) > 0$ if $e > 0$. I assume the function $\phi(e)$ is continuous, except possibly at the point $e = 0$, and everywhere bounded. Clearly, if the optimal choice of I remains smaller than available internal funds, the firm uses these funds for investment.

The model can be thought of either as a partial equilibrium model of a firm or as a model of a general equilibrium economy with production and consumption, in which a representative consumer has utility linear in both consumption and leisure.[2] The producer chooses (k', p') each period to maximize the value of expected future cash flows, discounting them at the opportunity cost of funds, r. Let $V(k, p, z)$ denote the current value of the firm, defined as

$$V(k, p, z) = \max\{V^i(k, p, z), V^n(k, p, z)\}, \tag{3}$$

in which the superscripts i and n refer to investment and no investment, respectively. Define

$$v^n(k, p, p', z) \equiv \pi(k, z) + p(1+r) - p' \tag{4}$$

and

$$v^i(k, k', p, p', z) \equiv \pi(k, z) + p(1+r) - p' - (k' - (1-d)k) - ck - \phi(e(k, k', p, p', z)). \tag{5}$$

The corresponding Bellman equations are:

$$V^n(k, p, z) = v^n(k, p, p', z) + \frac{1}{1+r}\int V(k(1-d), p', z')\,\mathrm{d}q(z', z) \tag{6}$$

and

$$V^i(k, p, z) = \max_{k', p'}\left\{ v^i(k, k', p, p', z) + \frac{1}{1+r}\int V(k', p', z')\,\mathrm{d}q(z', z)\right\}. \tag{7}$$

[2]Risk aversion or decreasing marginal utility of leisure do not change the qualitative model predictions.

The definition of $\phi(\cdot)$ allows Eq. (7) to represent the decisions to invest both with and without external finance.

The model satisfies the conditions for Theorem 9.6 in Stokey and Lucas (1989), which guarantees a solution for Eqs. (6) and (7). Theorem 9.8 in Stokey and Lucas (1989) ensures a unique optimal policy function, $\{k', p'\} = g(k, p, z)$, if $v^n(k, p, p', z)$ and $v^i(k, p, k', p', z)$ are weakly concave in their first two arguments. This requirement puts easily verified restrictions on $\phi(\cdot)$, which are satisfied by all functional forms chosen below.

3. Simulations

I investigate the implications for the solution to this problem via simulation. To do so, I need to choose functional forms for the revenue, adjustment cost, and financing functions and the stochastic process for the productivity shocks. I also need to assign values to the fixed cost of adjustment, the discount factor, and the depreciation rate. Because I am not estimating this structural model, the intent of the design is simply to generate qualitative conclusions that are robust to perturbations in the design parameters. Details are in the Appendix. I solve the model via value function iteration, which yields the policy and value functions. I simulate the model for 100,000 time periods to generate the hazard functions. In these simulations I define an adjustment spike as a rate of net investment that exceeds $\bar{\imath} = 20\%$ and the hazard function as $\Pr(I/k > \bar{\imath} \mid k, p)$.[3]

Before presenting the simulation results I examine the properties of the simulated policy function. I start with the saving rule, which depends on whether the firm faces costly external finance. If the firm does not, then it never saves. Because internal and external finance are equally costly, it is optimal to distribute excess funds to shareholders. If the firm does face costly external finance, it saves as much as possible in each period that it is not investing, unless it hits $\bar{p}$. It then uses these funds for investment in the periods that it does invest, not saving further during investment episodes. In other words, the firm follows a bang-bang policy with regard to saving. Given this cash policy, the firm makes distributions only if it does not face costly external finance or has hit $\bar{p}$.

The firm's capital stock rule, whether constrained or unconstrained, is a two-sided (S, s) policy, with a single return point if the firm is unconstrained. The policy has two return points if the firm is constrained. That is, even though the firm can make small adjustments, it chooses not to. Further, a firm that faces costly external finance and that is allowed to save adjusts more frequently than an otherwise identical firm that is not allowed to save. Finally, the inaction bands are much wider for a constrained than for an unconstrained firm.

Fig. 1 presents the hazard functions from the simulations of the constrained and unconstrained firms. The horizontal axis measures the amount of time since the previous adjustment of the capital stock, and the vertical axis measures the adjustment hazard. The hazard of the unconstrained firm slopes upward steeply, which is a pattern consistent with the presence of fixed costs of adjustment.[4] The hazard of the constrained firm also slopes

[3]For reference, approximately 8% of my investment observations and approximately 20% of the plant-level observations in Doms and Dunne (1998) lie above this threshold. Although I use several thresholds in the hazard estimations, for expositional brevity I limit myself to one threshold in the simulations.

[4]It is also consistent with convex costs, because it is possible to generate upward-sloping hazards from my theoretical even if one substitutes convex costs for fixed costs. However, this sort of behavior occurs only if the profit shock is very highly serially correlated and has a very high variance. Because these two parameters must be

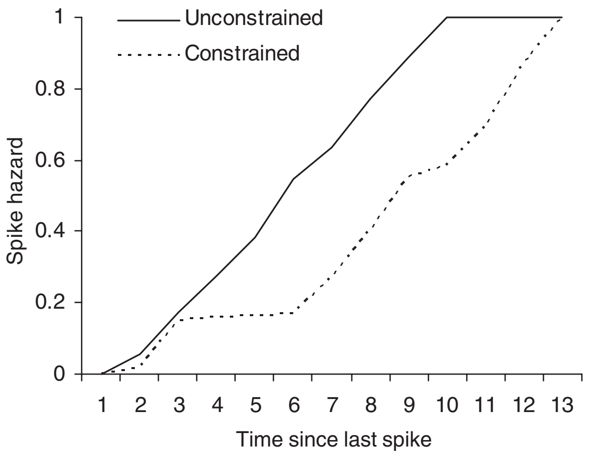

Fig. 1. Theoretical adjustment hazards: single-segment firms. The hazard functions are simulated from the investment model in Section 2. The horizontal axis measures the length of time since the last investment spike, and the vertical axis measures the probability of a spike, given that the firm has remained inactive up to that time. Unconstrained refers to a firm without costly external finance, and constrained refers to a firm with costly external finance, where the cost function contains a fixed component and a linear variable component.

upward, but it is lower. Because the firm essentially faces an extra fixed cost of adjusting its capital stock, it will do so less frequently. The external finance function affects not only the cost of adjustment but also the marginal productivity of capital. On the margin capital adds to production and also alleviates the external finance premium. This second component of the marginal productivity of capital raises the investment hazard, because a firm should adjust more often if it is more productive. However, because of decreasing returns to scale, the direct negative cost-of-adjustment effect is stronger.

It is interesting to compare the testable implication of this model (a difference in hazard height) with previous approaches to understanding investment under external finance constraints. First, the difference in hazard height is not a dynamic equivalent of underinvestment. These simulations produce little difference in the long-run average levels of investment in the constrained and unconstrained firms, because the long-run average level is primarily governed by average productivity and depreciation. As in the case of an investment Euler equation, the model produces results in terms of intertemporal investment substitution, not in terms of investment levels.[5] Second, in this model the sensitivity of investment to cash flow, holding constant either marginal or average q, is not an indicator of finance constraints. These sensitivities are almost identical for the constrained and unconstrained firms, because in the model cash flow is decoupled from intermittent investment and because it proxies primarily for productivity and secondarily for liquidity.

(*footnote continued*)
set at a level inconsistent with the time-series properties of profits for Compustat firms, the observed upward sloping hazards are likely consistent with fixed costs.

[5]Intertemporal substitution effects can have important macroeconomic implications, because they can prolong recessions and inhibit economic growth. See Gurley and Shaw (1955).

The difference in hazard height is robust to a wide variety of different model parameterizations and to a variety of different forms for the external finance cost function. The simulation in Fig. 1 is based on $\phi(e) = 0.0341 + 0.0241e$. Fig. 2 presents the results from using alternate cost functions. The hazards labeled "unconstrained" and "baseline" are replicates of the "unconstrained" and "constrained" hazards in Fig. 1. The hazard labeled "linear" is based on $\phi(e) = 0.0241e$, thus eliminating the discrete difference in the cost of funds when the firm moves from internal to external sources. The intent here is to see whether the fixed component drives the results. Next, the hazard labeled "quadratic" corresponds to a functional form that could result from adverse selection: $\phi(e) = 0.0001e^2$. Finally, the hazard labeled "decreasing" corresponds to $\phi(e) = 0.0341\exp(-e)$. Decreasing costs of external finance arise, for example, in Cleary et al. (2004). The main result apparent in Fig. 2 is that all of the constrained hazards lie below the unconstrained hazard, although the alternative cost structures yield hazards slightly higher than the original.

Although the differences in the hazards of constrained and unconstrained firms is the central empirically testable implication of my model, a number of other factors affect hazards, which are factors that need to be accounted for in any tests. One such important issue is aggregation of asynchronous actions within a firm, which is of particular concern since many of the firms in Compustat are composed of several different decision making units. If these units act in unison, then firm behavior resembles the behavior of an individual unit, and investment occurs episodically. However, this scenario is unlikely. To the extent that individual units act asynchronously, their aggregated investment appears to be smoothed out over time. The problem could confound any empirical findings. For example, if I compare the investment of a conglomerate with the investment of a

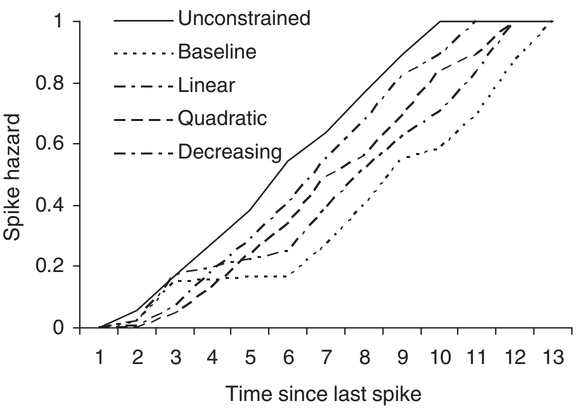

Fig. 2. Theoretical adjustment hazards: alternative financing costs. The hazard functions are simulated from the investment model in Section 2. The horizontal axis measures the length of time since the last investment spike, and the vertical axis measures the probability of a spike, given that the firm has remained inactive up to that time. The unconstrained and baseline hazards are the same as the unconstrained and constrained hazards in Fig. 1. The baseline constrained hazard is from an external finance cost function contains a fixed component and a linear variable component. The hazard labeled linear is from a cost function that eliminates the fixed portion of the cost from the baseline case. The hazard labeled quadratic is from a cost function with no fixed component and a quadratic variable component. The hazard labeled decreasing corresponds to a cost function with a fixed component and a negative exponential variable component.

single-segment firm, then the two can have differently shaped hazards even though neither faces external finance constraints.

The effects of aggregation are illustrated in Fig. 3, which contains graphs of the hazards from two types of conglomerate firms, in which each type can be constrained or unconstrained. I construct the conglomerates by assuming they are composed of either two or six independently and identically distributed units, each of which is identical to the unit represented in Fig. 1. For each type of conglomerate, I allow the individual units to be either all constrained or all unconstrained. Because the conglomerates are composed of independently and identically distributed units, they represent a worst-case scenario of the difficulties induced by aggregation, because a firm composed of units whose decisions are positively correlated behaves in a manner more like an individual unit.

As in Fig. 1, the hazard for the constrained small conglomerate in Fig. 3 lies below the hazard for the unconstrained small conglomerate, though both are lower than those in Fig. 1. The pattern exhibited by the pair of hazards for the large conglomerates is different. Both are at the same low level. Here, because of the asynchronous actions of the conglomerate units, and because a spike is defined with respect to total conglomerate assets, total conglomerate investment rarely crosses a spike defining threshold, even though the individual units of the conglomerate behave exactly as those depicted in Fig. 1. Also, adding costly external finance to the model affects the hazard little, because the effect of aggregation dwarfs the effect of the finance constraint. Although not modeled here, the inclusion of an internal capital market in the conglomerate would further diminish the difference in the behavior of the constrained and unconstrained conglomerates. Segments of a constrained firm that do not adjust can devote their profits to the segments that do find it optimal to adjust. To control for aggregation in the estimation that follows, I limit my sample to small segments of conglomerates and small single-segment firms, because small segments or single-segment firms are less likely to be composed of a large number of

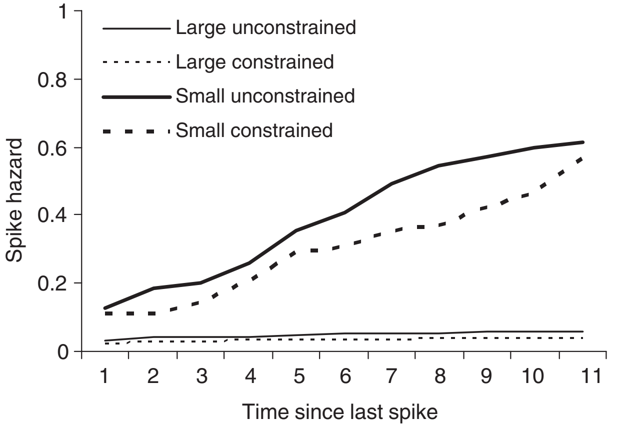

Fig. 3. Theoretical adjustment hazards: conglomerates. The hazard functions are simulated from the investment model in Section 2. The horizontal axis measures the length of time since the last investment spike, and the vertical axis measures the probability of a spike, given that the firm has remained inactive up to that time. Unconstrained refers to a firm without costly external finance, and constrained refers to a firm with costly external finance. A large conglomerate contains six units, and a small conglomerate contains two units.

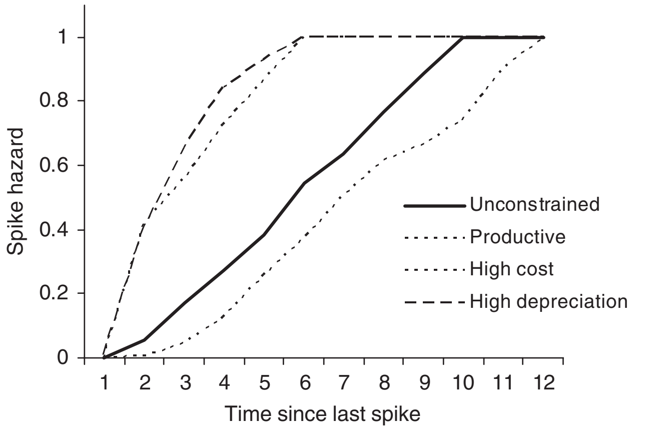

Fig. 4. Theoretical adjustment hazards: alternate technologies. The hazard functions are simulated from the investment model in Section 2. The horizontal axis measures the length of time since the last investment spike, and the vertical axis measures the probability of a spike, given that the firm has remained inactive up to that time. Unconstrained refers to a firm without costly external finance. All other hazards result from perturbations of the basic model. Productive refers to a firm with a shock to total factor productivity with a mean of 0.1 instead of 0. High cost refers to a firm with a doubled fixed cost of adjustment, and high depreciation refers to a firm with a doubled depreciation rate.

decision making units. Although not reported here, estimated hazards from groups of large and diversified are low and flat.

Three further factors that affect the heights of the hazards are productivity, adjustment costs, and depreciation. Starting with the model of an unconstrained firm, to model high productivity, I adjust the mean of the innovation of z to be 0.1 instead of 0; to model high adjustment costs, I double the value of c; and to model high depreciation, I double the value of d. The results from these experiments are in Fig. 4, where the hazard of the more productive firm is higher than that of the unconstrained firm, the hazard of the firm with high adjustment costs is lower, and the hazard of the firm with high depreciation is higher. The intuition behind these findings is that firms with high productivity, low adjustment costs, or high depreciation should optimally want to replace capital more often, all else equal. The estimation that follows therefore controls for these three factors.

Two factors that do not affect the hazard are the curvature of the production function and the variance of the innovation to z. In the case of curvature, two offsetting effects are at work. First, higher curvature implies that shocks move the marginal product of capital less. Because it is the cumulation of shocks that triggers adjustment, adjustment occurs less frequently. However, higher curvature also implies that adjustments are smaller, so that adjustment occurs more frequently. In the case of the innovation variance, two effects again cancel each other out. When z has a high variance, the marginal product of capital is more likely to hit an adjustment threshold. However, the firm responds by widening the inaction interval. For similar intuition, see Bertola and Caballero (1990).

4. Data and summary statistics

The data are from the firms in the combined annual, research, and full coverage 2002 Standard and Poor's Compustat industrial files that are also covered by the Compustat business information files, which start in 1982. In late 1997 Statement of Financial Accounting Standards 131 changed the way in which firms define their segments. The concepts of industrial and geographic segments have been replaced by operating segments as defined by the company's management. This change renders data from 1998 inconsistent with earlier data. Because I want long consistent time series on the segments, I use segment data only from 1982 until 1997.

I select the sample by first deleting any firm-year observations with missing data. Next, I delete any observations for which total assets (Compustat item 6), the gross capital stock (item 7), or sales (item 12) are either zero or negative. Further, I delete any observations if the sum of segment assets deviates by more than 25% from reported total firm assets. I next delete observations whose values of the rate of investment (the difference between items 30 and 107 divided by item 6), sales growth, cash flow (the sum of items 18 and 14, divided by item 6) lie in the upper and lower first percentiles of the distributions of these variables. I also delete any firm that experienced a merger accounting for more than 25% of the book value of its assets. Finally, I include a firm or segment only if it has at least nine consecutive years of complete data; and I omit all firm- and segment-level observations whose primary Standard Industrial Classification code is between 4900 and 4999 or between 6000 and 6999, because my model of investment is inappropriate for regulated or financial firms. If a manufacturing conglomerate has, for example, a financial subsidiary, the conglomerate is in the sample, but that subsidiary is not. I end up with between 883 and 1917 single-segment firms per year, between 545 and 879 multiple-segment firms per year, and between 1152 and 2395 segments of multiple-segment firms per year.

Table 1 provides summary statistics for five subsamples: large and small single-segment firms, multiple-segment firms, and large and small segments of multi-segment firms. I classify a firm or segment as small if its real assets are below the 33rd percentile of the real assets of the stand-alone firms in the first year that the firm or segment in question appears in the sample. Two aspects of this definition are important. First, defining smallness on a year-by-year basis allows for real growth in the cutoff point. Second, the definition implies that the composition of the samples does not change, which allows me to avoid serious sample selection issues that could arise by isolating only slow-growing firms. One drawback of this second feature is that firms or segments that grow quickly and perhaps become not-small remain in the small samples, exacerbating aggregation issues. However, the data analysis suggests that this issue is not important. Large firms are defined analogously, except that the cutoff point is above the 67th percentile.

Table 1 shows that the multi-segment firms are substantially larger than even the large single-segment firms. Further, the small segments and small stand-alone firms are much smaller. Their mean real assets are only \$13.6 million and \$10.2 million in 1997 dollars, respectively. Aggregation is therefore unlikely to be an important issue for either group. The two groups do differ in important ways. The small single-segment firms have much higher sales growth than the small segments, and the segments have slightly higher cash flow and investment.

Table 2 examines large investment projects. Because most firms in Compustat invest at least a small bit every period, the definition of a large project requires thought. Low observed rates of investment probably occur because of maintenance and because some types of investment could be subject to convex adjustment costs. However, when a firm undertakes a large project, one ought to observe a much higher than normal rate of

Table 1
Summary statistics

Calculations are based on a sample of nonfinancial firms and segments of firms from the combined annual and full coverage 2002 Standard and Poor's Compustat industrial files that are also covered by Compustat's business information file. The sample period is 1983–1997. Assets are expressed in millions of 1997 dollars.

Subsample	Variable	Mean	Median	Standard deviation
Small single-segment firms				
	Investment/assets	0.063	0.042	0.062
	Depreciation/assets	0.050	0.042	0.038
	Cash flow	0.132	0.144	0.145
	Sales growth	0.104	0.070	0.261
	Assets	18.360	13.665	17.141
Large single-segment firms				
	Investment/assets	0.078	0.061	0.061
	Depreciation/assets	0.051	0.044	0.032
	Cash flow	0.186	0.186	0.110
	Sales growth	0.101	0.069	0.214
	Assets	1271.160	190.399	5996.989
Multiple-segment firms				
	Investment/assets	0.071	0.060	0.050
	Depreciation/assets	0.048	0.044	0.024
	Cash flow	0.179	0.182	0.087
	Sales growth	0.061	0.048	0.181
	Assets	4226.560	517.002	14584.145
Small segments				
	Investment/assets	0.081	0.049	0.098
	Depreciation/assets	0.065	0.049	0.064
	Cash flow	0.166	0.163	0.186
	Sales growth	0.063	0.041	0.273
	Assets	15.142	10.278	15.592
Large segments				
	Investment/assets	0.080	0.063	0.073
	Depreciation/assets	0.057	0.050	0.047
	Cash flow	0.191	0.176	0.165
	Sales growth	0.059	0.040	0.216
	Assets	1769.324	369.672	6466.749

investment. To capture this idea I define an investment spike in terms of the deviation of the ratio of investment to total assets from the firm-level median of this ratio. A spike occurs if the ratio of investment to assets is 2, 2.5, or 3 times greater than the firm median. I use several spike thresholds to check the robustness of my results to the criteria for measuring spikes.[6]

Table 2 provides some prima facia evidence of fixed costs of adjustment, because in a world with convex adjustment, I ought to see few rates of investment greater than any of my spike thresholds. The table shows that this is not the case. The percentage of small single-segment firms or segments experiencing two-times-the-median spikes is slightly

[6]Earlier versions of this paper define a spike as an instance in which net investment crosses a fixed threshold or investment is sufficiently larger than an industry median. Results using these definitions are similar.

Table 2
Investment spikes and inaction spells

Calculations are based on a sample of nonfinancial firms and segments of firms from the combined annual and full coverage 2002 Standard and Poor's Compustat industrial files that are also covered by Compustat's business information file. The sample period is 1983–1997. Thresholds for defining investment spikes are expressed in terms of 2, 2.5, and 3 times the firm median investment rate.

Subsample	Statistic	2 times	2.5 times	3 times
Small single-segment firms				
	Fraction of spikes	0.183	0.142	0.090
	Number of spells	1222	822	600
	Average length	2.783	3.135	3.172
	Fraction censored	0.293	0.322	0.333
	Average length censored	4.197	4.585	4.910
	Fraction uncensored	0.707	0.678	0.667
	Average length uncensored	2.339	2.448	2.307
Large single-segment firms				
	Fraction of spikes	0.122	0.070	0.042
	Number of spells	1601	882	555
	Average length	3.075	3.412	3.761
	Fraction censored	0.293	0.327	0.363
	Average length censored	4.954	5.565	5.791
	Fraction uncensored	0.707	0.673	0.637
	Average length uncensored	2.295	2.366	2.602
Multiple-segment firms				
	Fraction of spikes	0.108	0.063	0.040
	Number of spells	1255	783	559
	Average length	3.013	3.127	3.265
	Fraction censored	0.272	0.293	0.306
	Average length censored	5.111	5.515	5.573
	Fraction uncensored	0.728	0.707	0.694
	Average length uncensored	2.229	2.136	2.245
Small segments				
	Fraction of spikes	0.210	0.146	0.106
	Number of spells	1042	728	537
	Average length	2.639	2.773	2.905
	Fraction censored	0.273	0.307	0.320
	Average length censored	3.409	3.537	3.889
	Fraction uncensored	0.727	0.693	0.680
	Average length uncensored	2.350	2.434	2.441
Large segments				
	Fraction of spikes	0.102	0.059	0.036
	Number of spells	1125	579	462
	Average length	3.186	3.265	3.397
	Fraction censored	0.294	0.322	0.344
	Average length censored	5.397	5.688	5.933
	Fraction uncensored	0.706	0.678	0.656
	Average length uncensored	2.265	2.117	2.070

larger than the 14% figure reported by Cooper and Haltiwanger (2006). The similarity suggests that the sort of lumpy adjustment observed in plants can also be present in small firms.

The rest of the table examines inaction spells; that is, the time between spikes. For each group of observations, I present the number and average length of spells corresponding to each of my spike-defining thresholds. The conglomerates and the large firms and segments have longer spells than either the single-segment firms or the segments, a result consistent with the aggregation of asynchronous actions. The similar investment rates across the small segments and small firms manifest themselves here in the similarity between their mean spell length. Given the difference in sales growth, one would expect the single-segment firms to be adjusting more often. Perhaps external finance constraints are hindering adjustment.

5. Estimation

This section outlines the econometric methodology and the model specification. It next specifies the hypotheses to be tested and presents the results and their interpretation. It concludes by examining the robustness of the results with respect to alternative specifications.

5.1. Methods

Two strategies have dominated the empirical literature on estimating and testing investment models with nonconvexities. First, as illustrated, for example, in Caballero et al. (1995) and Caballero and Engel (1999), one can construct a measure of the gap between the firm's actual and desired capital stock, in which the latter typically comes from a theoretical frictionless model. Testable hypotheses emerge from this characterization because the reaction of investment to the gap depends on the nature of adjustment costs. However, as pointed out in Cooper and Willis (2004), because specifying an optimal capital stock requires a specific structural model and because an optimal capital stock needs to be defined in terms of a model with frictions, the gap is easily mismeasured, which raises a problem can lead to misleading inferences. The problem is analogous to the difficulty of measuring q, and it is also a generic problem with estimation of a structural model, because the resulting inferences can be fragile with respect to the choice of model assumptions.

The second, less structural, method is hazard estimation. I opt for this second approach primarily to minimize measurement problems. A number of different techniques exist for estimating hazard functions. The simplest method consists of calculating for each length of an inaction spell and, for each year, the ratio of the number of firms that experience spikes to the number of all firms that have remained inactive for at least as long. These simple empirical hazards could then be compared with the simulated hazards. However, this approach can lead to biased hazard function estimates unless one controls for cross-sectional heterogeneity. To see this point in the context of investment spikes, suppose a cross section contains two types of firms that face fixed adjustment costs: low cost and high cost. Suppose also that there are twice as many low-cost firms as high-cost firms. If a long time series on each firm could be observed, all would have upward-sloping hazards. However, because the low-cost firms replace their capital more often than the high-cost firms, in a cross section more replacements of relatively new capital are seen than of older capital, and a simple empirical hazard slopes downward.

Difficulties such as this can be solved by using a duration model, because it can account for observable time-varying covariates, such as productivity, as well as unobservable heterogeneity across firms. Loosely speaking, the simple empirical hazard can be thought of as a sort of histogram, whereas the results from estimating a duration model can be thought of as a conditional histogram. The most likely candidate for the source of unobservable heterogeneity is the level of adjustment costs, because I can control for other important nonfinancial determinants of investment. Caballero and Engel (1999) emphasize that cross-sectional heterogeneity in adjustment costs is likely to exist, and they find that a structural investment model that allows for heterogeneity explains aggregate investment better than a model that does not. Using a model that incorporates cross-sectional heterogeneity lowers the probability that my results are an artifact of an incidental correlation between real adjustment costs and measures of access to external financial markets.

I use the estimation technique in Meyer (1990), which accounts for observable and unobservable heterogeneity and which allows the shape of the hazard to be estimated nonparametrically. Meyer (1990) starts with a mixed proportional hazards specification:

$$\lambda_i(t) = \omega_i \lambda_0(t) \exp(x_i(t)'\beta), \tag{8}$$

where t is the length of a spell, $\lambda_i(t)$ is the hazard function, $x_i(t)$ is a column vector of covariates, β is the corresponding vector of unknown coefficients, $\lambda_0(t)$ is called the baseline hazard, and ω_i is a random variable that represents unobserved heterogeneity. It is assumed to be independent of $x_i(t)$ and to have a zero-mean gamma distribution. The existence of the covariates allows the hazard to shift up and down depending on their values and on β.

The specification is parametric along two dimensions: the linear modeling of the covariates and the distributional assumption on ω_i.[7] The latter assumption is sufficient to derive a closed-form likelihood function. The nonparametric part is the baseline hazard, which is only restricted to be a step function of discrete spell lengths.

The Meyer technique also allows for right-censoring of spells. Define C_i as the censoring time for an individual inaction spell. For example, if a firm experiences a spike in 1994, if it never experiences another, and if the data on the firm end in 1997, the censoring time is three. I also censor any spell lengths longer than nine years, because nine years is the longest spell length present in all of my subsamples. Depending on the spike threshold and sample, this nine-year rule affects from 7.6% to 28.2% of the observations, in which, not surprisingly, the larger percentages occur in the samples of large firms, which have long spells.

Estimating the parameters of a hazard is analogous to estimating the parameters of a density via maximum likelihood. Meyer (1990) expresses the likelihood for this problem by dividing time into discrete units: $(t = 0, 1, 2, 3, \ldots)$. Let T_i be the actual spell length;

[7] Heterogeneity can be modeled as in Cooper et al. (1999) as a discrete number of firm types. Another possibility is nonparametric estimation of the distribution of ω_i, as in Horowitz (1999). However, using these techniques on my sample produces large standard errors, undoubtedly because the more nonparametric estimation methods have greater data requirements.

define $\delta_i = 1$ if $T_i \leqslant C_i$ and 0 otherwise; and define $h_i = \min(T_i, C_i)$. The log-likelihood is

$$L(\gamma, \beta) = \sum_{i=1}^{N} \ln \left\{ \left[1 + \sigma^2 \sum_{t=0}^{h_i - 1} \exp(x_i(t)'\beta + \gamma(t)) \right]^{-(1/\sigma^2)} - \delta_i \left[1 + \sigma^2 \sum_{t=0}^{h_i} \exp(x_i(t)'\beta + \gamma(t)) \right]^{-(1/\sigma^2)} \right\}, \tag{9}$$

where

$$\gamma(t) \equiv \ln \left(\int_t^{t+1} \lambda_0(s)\, \mathrm{d}s \right)$$

and σ is the variance of the gamma distribution. The estimation procedure chooses the shape of the hazard to maximize the likelihood of observing the inaction spells in the sample.

5.2. Control variables

My specification of the model allows $x_i(t)$ to contain two-digit industry dummies and year dummies. As proxies for investment opportunities, I include the ratio of cash flow to assets and real sales growth, both measured between the current and previous spike. It is also possible to control for liquidity by including the stock of cash. However, cash is not available in the segment data, and inserting this variable has almost no effect on the firm-level results.

The year dummies allow the baseline hazard to be conditioned on aggregate shocks to interest rates and the business cycle. The industry dummies capture several factors that could affect the hazard. First, differences in competitiveness across industries could have a strategic affect on a firm's decision to invest. Second, differences in the types of capital used across industries could affect depreciation rates, returns to scale, and adjustment costs. Finally, technology is likely to vary more across industries than across firms within an industry.

The model of Section 2 sheds light on the suitability of the proxies for investment opportunities. I consider two plausible proxies. The first is cash flow. In models such as these with fixed costs of adjustment that occur with each project (as opposed to per unit of time), Caballero and Leahy (1996) and Caballero (1999) show that the relation between investment and marginal q is not a function but a correspondence. Further, they show that the firm makes decisions using the expected discounted sum of the marginal products of capital between investment spikes. The latter quantity is measurable under constant returns to scale and perfect competition, because the ratio of cash flow to capital then equals the marginal product of capital. Therefore cash flow in all years between spikes is an appropriate proxy. The use of cash flow as a proxy for investment opportunities also occurs in the Euler equation literature. The similarity is not accidental, because, as with hazard estimation, Euler equation estimation needs to control for capital productivity only in the period between investment expenditures. As explained in Whited (1992), this task is substantially easier than controlling for marginal q, which is the expected present value of all future capital productivity, and which is the required measure of investment opportunities in reduced-form investment regressions.

There exist three reasons to believe that this proxy is flawed. First, firms perhaps are not perfectly competitive or do not have constant returns to scale. Second, using realized instead of expected cash flow introduces an expectational error that can be correlated with realized cash flow. However, Section 5.6 shows that these two problems are unlikely to affect my qualitative inference. Third, many authors argue that cash flow contains information about liquidity in addition to information about profitability. However, this ambiguity is beneficial for the problem at hand, because, if cash flow does proxy for internal liquidity, any estimated differences in hazard height are not the result of this liquidity effect but of the information on access to external capital markets in my sample splitting variables.

Second, I consider real firm sales growth as a direct proxy for the innovation to the z shock. It is straightforward to show in my model that if the firm has a homogeneous revenue function and if the firm invests just enough to replace depreciated capital, expected sales growth is equal to the mean of the innovation to the z shock, and observed sales growth equals the innovation, which is the fundamental driving force behind changes in the marginal product of capital. Therefore, the correlation between z and sales growth is one. Because optimal behavior implies that firms either remain completely inactive or invest in large spikes, average sales growth is an imperfect proxy for the mean of the innovation. As in the case of cash flow, I demonstrate that these misspecifications are not serious.

5.3. Null and alternative hypotheses

Following much of the literature on external finance constraints, my tests are based on comparing the behavior of subsamples of firms, categorized according to their access to external financial markets. The null hypothesis for the three tests that follow is that the baseline hazard is equal across groups of financially constrained and unconstrained groups. The rest of the hazard is allowed to vary across groups. This feature is important, because constraining the reaction of investment spikes to the variables included in $x_i(t)$ can bias the tests if this constraint is not satisfied. The alternative hypothesis is that the baseline hazard for a financially constrained group is lower than that for an unconstrained group.

5.4. Results

First, I run separate hazard models on my group of small single-segment firms and a group of same-size segments of conglomerates. This experiment is based on the idea that large conglomerates have better relations with external capital markets than small single-segment firms, thus allowing the conglomerate segments access to less costly finance. Estimates from these models are in Table 3, which shows that the firms have higher hazard rates than the segments. Here, the differences are significant at the 5% level in all but seven of the 27 instances. Further, I can reject at the 5% level a test of the joint null hypothesis that the two hazards are equal at all time horizons. The difference in the hazard rates for the three-times-the-median threshold is illustrated in Fig. 5. Here, significant differences in the heights of the hazards at each time horizon have been noted with dots. To the extent that belonging to a conglomerate is an indicator of easy access to finance, the results also

Table 3
Semiparametric hazard model estimates: small single-segment firms versus small segments

Calculations are based on a sample of nonfinancial firms from the combined annual and full coverage 2000 Standard and Poor's Compustat industrial files that are also covered by Compustat's business information file. The sample period is 1983–1997. Single-segment firms refer to estimates from a sample of small single-segment firms. Segments refer to estimates from a sample of small segments of conglomerates. A firm or segment is classified as small if its real assets are below the 33rd percentile of the real assets of the stand-alone firms in the first year that the firm or segment appears in the sample. Cash flow is the sum of net income and depreciation divided by total assets. Sales growth is the growth rate of sales, deflated by the producer price index. The rows labeled $\exp(\gamma_i)$ contain estimates of the baseline hazard, and the subscript refers to the number of years since the last spike. A spike is defined as an investment rate that exceeds a threshold, and the thresholds are expressed in terms of 2, 2.5, and 3 times the firm median investment rate. The row labeled σ^2 contain-estimates of the variance of cross-sectional heterogeneity of the hazards. Standard errors are in parentheses under the parameter estimates.

Coefficient	Single-segment firms			Segments		
	2 times	2.5 times	3 times	2 times	2.5 times	3 times
Cash flow	0.8774	1.0527	0.4797	0.4042	0.3775	0.5283
	(0.0292)	(0.0480)	(0.1029)	(0.0612)	(0.0897)	(0.1262)
Sales growth	1.8134	1.8509	1.5902	0.1940	0.8306	1.2169
	(1.0206)	(1.0252)	(1.0377)	(1.0427)	(1.0336)	(1.0493)
$\exp(\gamma_1)$	0.0530	0.0587	0.0718	0.1448	0.1986	0.1543
	(0.0045)	(0.0066)	(0.0083)	(0.0080)	(0.0153)	(0.0154)
$\exp(\gamma_2)$	0.1511	0.1336	0.0710	0.1371	0.1400	0.1170
	(0.0081)	(0.0088)	(0.0111)	(0.0120)	(0.0122)	(0.0308)
$\exp(\gamma_3)$	0.1063	0.1315	0.1783	0.1354	0.1975	0.1938
	(0.0107)	(0.0177)	(0.0071)	(0.0065)	(0.0153)	(0.0174)
$\exp(\gamma_4)$	0.2707	0.1117	0.0568	0.4346	0.3062	0.2495
	(0.0108)	(0.0097)	(0.0043)	(0.0120)	(0.0169)	(0.0190)
$\exp(\gamma_5)$	0.3711	0.3515	0.2714	0.5442	0.4382	0.3921
	(0.0157)	(0.0246)	(0.0318)	(0.0103)	(0.0190)	(0.0214)
$\exp(\gamma_6)$	0.5462	0.4865	0.3989	0.6811	0.6720	0.6119
	(0.0166)	(0.0227)	(0.0339)	(0.0223)	(0.0489)	(0.0336)
$\exp(\gamma_7)$	0.6094	0.5762	0.3636	0.8003	0.7466	0.7925
	(0.0205)	(0.0194)	(0.0125)	(0.0176)	(0.0368)	(0.0498)
$\exp(\gamma_8)$	0.8414	0.8274	0.6641	0.8430	0.8356	0.8699
	(0.0204)	(0.0260)	(0.0387)	(0.0251)	(0.0372)	(0.0354)
$\exp(\gamma_9)$	0.8116	0.8737	0.8898	0.8097	0.8695	0.8989
	(0.0169)	(0.0222)	(0.0324)	(0.0297)	(0.0307)	(0.0407)
σ^2	1.8788	1.9185	1.1435	0.6299	0.9908	0.9980
	(0.0509)	(0.0745)	(0.0761)	(0.0549)	(0.0725)	(0.0886)
Log-likelihood	−1479.7853	−898.5251	−470.1256	−1043.5121	−695.8656	−428.0099
Sample size	1222	822	600	1042	728	537

are consistent with the idea that external finance constraints affect investment. Finally, both hazards are upward sloping, a feature consistent with models of lumpy adjustment.

Although related to the idea in Williamson (1975) that conglomerates operate internal capital markets, the result says little about the efficiency of these markets, because efficiency tests need to compare the behavior of all the segments within a firm. At the very least, it appears that internal capital markets are not inefficient enough to render the behavior of small segments the same as the behavior of small single-segment firms.

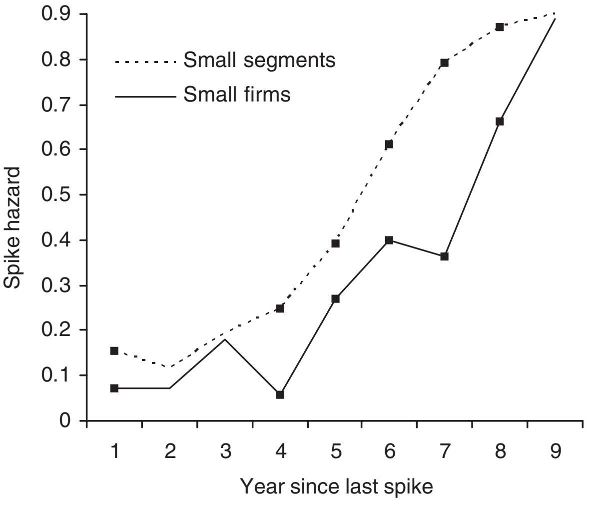

Fig. 5. Estimated hazards: small firms versus small segments. Estimates are from the three-times-the-median columns of Table 3. Small firms refer to estimates from a sample of small single-segment firms. Small segments refer to estimates from a sample of small segments of conglomerates. The horizontal axis measures the length of time since the last investment spike, and the vertical axis measures the probability of a spike, given that the firm has remained inactive up to that time. Dots indicate that the two hazard estimates are significantly different from one another at the 5% level. Calculations are based on a sample of single-segment nonfinancial firms from the combined annual and full coverage 2002 Standard and Poor's Compustat industrial files that are also covered by Compustat's business information file. The sample period is 1983–1997.

Second, I compare small single-segment firms that differ in their distribution policies. As noted in Fazzari et al. (1988), because cash distributions to shareholders are prima facia evidence of the availability of internally generated funds, one can assume that a firm that distributes cash is unlikely to be affected by costly external finance and that at least some firms that do not distribute are affected. I group small firms according to whether they have a consistent history of distributing cash or not, where distributions include both dividends and share repurchases. The constrained group consists of observations from firms with a consistent history of no cash distributions before the end of an inaction spell. The unconstrained group consists of all other observations. I deviate from Fazzari et al. by using lagged distribution behavior instead of current dividend policy as a classification variable. My scheme mitigates the well-known simultaneity problem that arises because distributions and investment are joint decisions. (See, for example, Alti, 2003.) In other words, this sample splitting variable is at the very least predetermined, if not exogenous. Table 4 shows that the estimated baseline hazards for both groups are upward sloping and that those for the positive distribution group are significantly higher than those for the zero distribution group in all but two instances. Once again, a test of the joint null of equal hazards produces a rejection. This difference is illustrated in Fig. 6.

Third, I split my sample of small firms by size, using the same splitting scheme that divides the entire sample into small and large firms. I use size in part because it is a commonly used measure of access to external finance, in part because it is arguably exogenous to the current investment decision, and in part because I want to determine

Table 4
Semiparametric hazard model estimates: small single-segment firms grouped by lagged distributions

Calculations are based on a sample of nonfinancial firms from the combined annual and full coverage 2000 Standard and Poor's Compustat industrial files that are also covered by Compustat's business information file. The sample period is 1983–1997. No distributions refer to estimates from a sample of small single-segment firms that have a consistent history of zero distributions since their previous spell of low investment. Distributions refer to estimates from the complement sample of small single-segment firms. A firm is classified as small if its real assets are below the 33rd percentile of the real assets of the stand-alone firms in the first year that the firm appears in the sample. Cash flow is the sum of net income and depreciation divided by total assets. Sales growth is the growth rate of sales, deflated by the producer price index. The rows labeled $\exp(\gamma_i)$ contain estimates of the baseline hazard, and the subscript refers to the number of years since the last spike. A spike is defined as an investment rate that exceeds a threshold, and the thresholds are expressed in terms of 2, 2.5, and 3 times the firm median investment rate. The row labeled σ^2 contains estimates of the variance of cross-sectional heterogeneity of the hazards. Standard errors are in parentheses under the parameter estimates.

Coefficient	No distributions			Distributions		
	2 times	2.5 times	3 times	2 times	2.5 times	3 times
Cash flow	0.5988	0.5373	0.5601	1.3417	1.2855	1.0620
	(0.1246)	(0.1659)	(0.2093)	(0.0347)	(0.1154)	(0.0813)
Sales growth	1.6561	1.9234	2.0775	1.7250	1.5435	1.7657
	(1.0376)	(1.0430)	(1.0590)	(1.0264)	(1.0378)	(1.0434)
$\exp(\gamma_1)$	0.0866	0.0814	0.0981	0.0483	0.0441	0.0380
	(0.0081)	(0.0108)	(0.0153)	(0.0061)	(0.0070)	(0.0086)
$\exp(\gamma_2)$	0.1090	0.0974	0.0987	0.1028	0.0480	0.0746
	(0.0118)	(0.0138)	(0.0068)	(0.0114)	(0.0105)	(0.0070)
$\exp(\gamma_3)$	0.0800	0.0881	0.1070	0.2866	0.2700	0.3855
	(0.0052)	(0.0090)	(0.0125)	(0.0261)	(0.0101)	(0.0544)
$\exp(\gamma_4)$	0.1386	0.0766	0.0416	0.5997	0.3896	0.4168
	(0.0073)	(0.0061)	(0.0034)	(0.0290)	(0.0103)	(0.0120)
$\exp(\gamma_5)$	0.3263	0.2850	0.1812	0.7595	0.6558	0.5836
	(0.0141)	(0.0162)	(0.0101)	(0.0329)	(0.0463)	(0.0970)
$\exp(\gamma_6)$	0.5545	0.5968	0.4221	0.8942	0.7020	0.7308
	(0.0235)	(0.0676)	(0.0330)	(0.0314)	(0.0318)	(0.0339)
$\exp(\gamma_7)$	0.5428	0.4063	0.4948	0.8735	0.8526	0.6642
	(0.0187)	(0.0183)	(0.0125)	(0.0401)	(0.0392)	(0.0275)
$\exp(\gamma_8)$	0.6234	0.6606	0.5116	0.9634	0.7415	0.7044
	(0.0392)	(0.0509)	(0.0288)	(0.0348)	(0.0251)	(0.0430)
$\exp(\gamma_9)$	0.7048	0.7701	0.7671	0.8907	0.8873	0.7639
	(0.0308)	(0.0391)	(0.0761)	(0.0320)	(0.0138)	(0.0382)
σ^2	1.0816	1.0254	1.0690	2.1129	1.4165	2.3478
	(0.0581)	(0.0748)	(0.0937)	(0.0832)	(0.1058)	(0.1501)
Log-likelihood	−580.2604	−361.0985	−219.8119	−783.2616	−396.6451	−277.0324
Sample size	638	432	315	584	390	285

whether aggregation effects are present in my sample of small firms. With regard to this last point, aggregation effects can occur in a small firm that is composed of even smaller subsegments. Although the upward sloping hazards for the small firms and segments suggest that this scenario is implausible, I explore the possibility by noting that if the subsegment problem is important (and finance constraints are not), then tiny firms should have higher hazards than the firms that are merely small. Table 5 reveals that this is not the

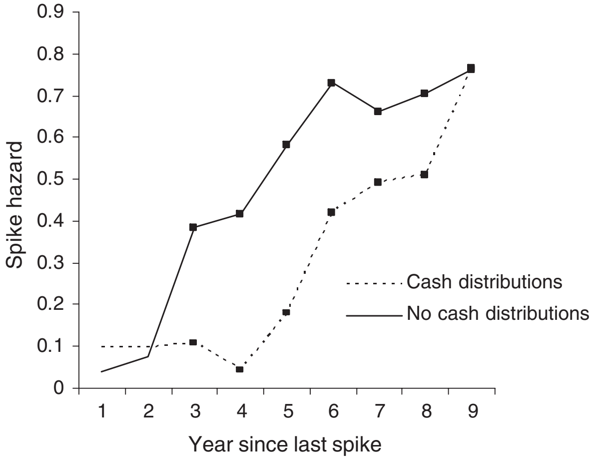

Fig. 6. Estimated hazards: cash distributions versus no cash distributions. Estimates are from the three-times-the-median columns of Table 4. No cash distributions refer to estimates from a sample of small single-segment firms that never distribute cash. Cash distributions refer to estimates from a sample of small single-segment firms that have distributed cash at least once. The horizontal axis measures the number of years since the last investment spike, and the vertical axis measures the probability of a spike, given that the firm has remained inactive up to that time. Dots indicate that the two hazard estimates are significantly different from one another at the 5% level. Calculations are based on a sample of single-segment nonfinancial firms from the combined annual and full coverage 2002 Standard and Poor's Compustat industrial files that are also covered by Compustat's business information file. The sample period is 1983–1997.

case: the micro firms have lower hazards than rest of the small firms. The differences are significant at the 5% level jointly and in all but four instances for the individual time horizons. Illustrated in Fig. 7 for the three-times-the-median threshold, this result suggests strongly that aggregation does not affect my sample of small firms and that the micro firms face more serious external finance constraints than the rest of the small firms.[8]

5.5. *Interpretation*

Several concerns arise in interpreting all of these results. First, are conglomerate segments and stand-alone firms too fundamentally different to be compared via a simple model? On the one hand, Maksimovic and Phillips (2002) provide evidence that small peripheral conglomerate segments tend to be less productive than main segments. More important, they find that investment is much more responsive to productivity for single-segment firms than it is for small conglomerate segments. On the other hand, my model does allow for differential sensitivity of spell length to my measures of investment opportunities. Further, the Maksimovic and Phillips results pertain to a comparison of small segments with all stand-alone firms, whereas my comparison is of small segments

[8]Two other popular splitting variables are the existence of a corporate bond rating and the index of financial constraints in Kaplan and Zingales (1997). I cannot use the first because few of the small firm have bond ratings. I choose not to use the second, because Whited and Wu (2005) demonstrate that it does not isolate constrained firms.

Table 5
Semiparametric hazard model estimates: micro versus small single-segment firms

Calculations are based on a sample of nonfinancial firms from the combined annual and full coverage 2000 Standard and Poor's Compustat industrial files that are also covered by Compustat's business information file. The sample period is 1983–1997. Microfirms refer to estimates from a sample of the smallest third of the small single-segment firms. Other small firms refer to estimates from the rest of the small single-segment firms. A firm is classified as small if its real assets are below the 33rd percentile of the real assets of the stand-alone firms in the first year that the firm appears in the sample. Cash flow is the sum of net income and depreciation divided by total assets. Sales growth is the growth rate of sales, deflated by the producer price index. The rows labeled $\exp(\gamma_i)$ contain estimates of the baseline hazard, and the subscript refers to the number of years since the last spike. A spike is defined as an investment rate that exceeds a threshold, and the thresholds are expressed in terms of 2, 2.5, and 3 times the firm median investment rate. The row labeled σ^2 contains estimates of the variance of cross-sectional heterogeneity of the hazards. Standard errors are in parentheses under the parameter estimates.

Coefficient	Micro firms			Other small firms		
	2 times	2.5 times	3 times	2 times	2.5 times	3 times
Cash flow	0.6325	0.5328	0.4962	1.3974	0.8669	1.8521
	(0.0873)	(0.1488)	(0.1220)	(0.0392)	(0.0745)	(0.0707)
Sales growth	0.9885	0.8895	0.8754	1.9039	2.0505	1.9854
	(1.0602)	(1.0729)	(1.0863)	(1.0286)	(1.0405)	(1.0525)
$\exp(\gamma_1)$	0.0568	0.0557	0.0491	0.0614	0.0875	0.1860
	(0.0051)	(0.0060)	(0.0075)	(0.0086)	(0.0161)	(0.0131)
$\exp(\gamma_2)$	0.0699	0.0474	0.0623	0.2264	0.1601	0.1759
	(0.0092)	(0.0077)	(0.0106)	(0.0122)	(0.0152)	(0.0150)
$\exp(\gamma_3)$	0.0557	0.1207	0.0836	0.4511	0.3182	0.2941
	(0.0037)	(0.0181)	(0.0066)	(0.0294)	(0.0268)	(0.0154)
$\exp(\gamma_4)$	0.1139	0.0700	0.0566	0.6118	0.3084	0.3098
	(0.0070)	(0.0048)	(0.0039)	(0.0222)	(0.0162)	(0.0208)
$\exp(\gamma_5)$	0.4029	0.2094	0.2101	0.6000	0.5192	0.4213
	(0.0340)	(0.0302)	(0.0233)	(0.0171)	(0.0440)	(0.0237)
$\exp(\gamma_6)$	0.4419	0.2815	0.2262	0.7970	0.6668	0.4982
	(0.0145)	(0.0286)	(0.0117)	(0.0314)	(0.0478)	(0.0291)
$\exp(\gamma_7)$	0.4607	0.2865	0.1767	0.8030	0.6773	0.5407
	(0.0140)	(0.0161)	(0.0103)	(0.0373)	(0.0366)	(0.0283)
$\exp(\gamma_8)$	0.7857	0.8407	0.5611	0.8752	0.8332	0.6679
	(0.0360)	(0.0499)	(0.0284)	(0.0263)	(0.0434)	(0.0378)
$\exp(\gamma_9)$	0.8380	0.8739	0.7597	0.9202	0.8176	0.7577
	(0.0275)	(0.0271)	(0.0580)	(0.0268)	(0.0412)	(0.0403)
σ^2	1.0750	0.9871	1.0955	2.0341	2.0356	2.4231
	(0.0694)	(0.0819)	(0.0860)	(0.0779)	(0.1182)	(0.1203)
Log-likelihood	−716.1582	−442.7317	−302.2381	−663.5456	−372.3581	−207.3240
Sample size	678	463	354	544	359	246

with small stand-alones. Finally, my results are not an artifact of the segments belonging to different industries than the firms. Industry dummies should capture any important technological differences between the two groups of observations, and my groups of small firms and small segments have an approximately 90% overlap in industry composition.

A second concern is based on the idea that firms respond to finance constraints by undertaking more frequent projects that are reduced in size but that still qualify as spikes.

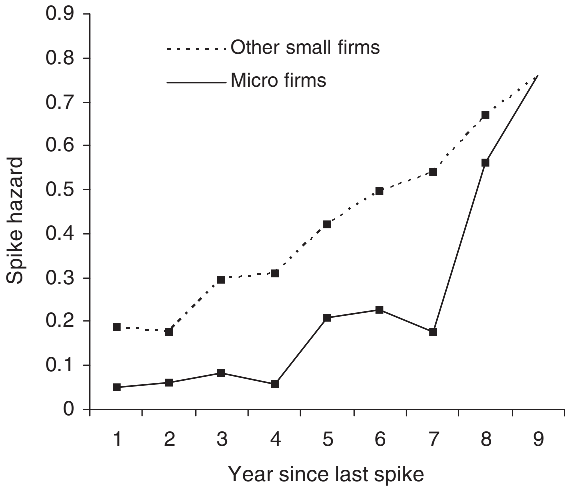

Fig. 7. Estimated hazards: micro firms versus small firms. Estimates are from the three-times-the-median columns of Table 5. Micro firms refer to estimates from a sample of small single-segment firms whose assets are below the 33rd percentile of small single-segment firms in the first year they appear in the sample. Other small firms refer to estimates from the rest of the sample of small single-segment firms. The horizontal axis measures the number of years since the last investment spike, and the vertical axis measures the probability of a spike, given that the firm has remained inactive up to that time. Dots indicate that the two hazard estimates are significantly different from one another at the 5% level. Calculations are based on a sample of single-segment nonfinancial firms from the combined annual and full coverage 2002 Standard and Poor's Compustat industrial files that are also covered by Compustat's Business Information File. The sample period is 1983–1997.

In that case constrained firms should have higher hazards, and the interpretations of all of the above results should be reversed. From a theoretical point of view, however, this intertemporal smoothing policy is optimal only if the firm faces convex adjustment costs, or if the cost of external finance is convex and greater than any nonconvex physical adjustment costs. Because convex costs almost always induce downward sloping hazards, and because all of the subsamples of firms and segments have upward sloping hazards, this explanation is unlikely.

A third concern is size of the investments both during and outside of spikes. For example, suppose that the groups labeled "constrained" either invest more in the off-spike periods or invest more during the spike periods than the groups labeled "unconstrained". Either scenario could lead to spikes that are spaced further apart, even in the absence of finance constraints. To examine this issue I compare the mean off-spike and on-spike investment rates of the three pairs of groups. Because I find no statistical differences, I am comfortable concluding that this explanation is not driving my results.

A fourth concern is the argument in Abel and Eberly (2002) that firm size is endogenously determined with a popular indicator of finance constraints: the sensitivity of investment to cash flow. However, this concern is not applicable to my tests. In my model firm size is primarily governed by the curvature of the production function, and curvature affects the height of the hazard little.

One final important issue arises concerning these sample splits. The sample-splitting variables can accidentally classify firms along the lines of technological differences.

Therefore, differences in investment would stem more from technology than finance constraints. However, I view this scenario as unlikely for several reasons. First, I include controls for productivity as well as industry dummies. Second, even if my proxies for productivity are imperfect, for all of my sample splits, the a priori constrained groups have higher sales growth and Tobin's q than the unconstrained groups. Therefore, even if I am accidentally sorting along the lines of unobserved productivity, this problem should cause me to see higher hazards in the constrained groups; that is, the issue should bias me in the direction of finding no evidence of finance constraints. Third, I use a variety of sample-splitting schemes to mitigate the difficulties with using imperfect sample splitters. The consistency of results across all of my sample splitting schemes adds credence to the idea that financial constraints are driving the observed differences in investment.

5.6. Robustness

The question remains whether this particular mixed proportional hazards model is appropriate for estimation of investment spike hazards. Two issues stand out: measurement error in my proxies for investment opportunities and a possible correlation between ω_i and $x_i(t)$.

I deal with measurement error in two ways. First, I rely on the idea that cash flow and sales growth should be high-quality proxies for investment opportunities, if in a simulation they are highly correlated with the marginal product of capital and the innovation mean, respectively. Cash flow is intended to represent the portion of investment opportunities that comes from the marginal product of capital, and sales growth is intended to represent the portion that comes from the mean of the innovation to the z shock. To examine these correlations, I use the model of Section 2 to simulate one thousand firms. For each firm the innovation mean is drawn from a truncated lognormal distribution. The squared cross-sectional correlation between the marginal product of capital and average cash flow is 0.810, and the corresponding figure for sales growth is 0.835. In other words, variation in cash flow and sales growth account for a substantial portion of the variation in the marginal product of capital and in the innovation mean. In contrast, the corresponding figure for Tobin's q found by Erickson and Whited (2000) is only approximately 40%.

Although this simulation mitigates concern about the degree of measurement error, it says nothing about the effects of measurement error on estimation. To address this issue, I use Monte Carlo experiments to evaluate the performance of the Meyer (1990) estimator when $x_i(t)$ is measured with error. I am, in particular, interested in the amount of measurement error necessary to generate a significant change in the hazard height. I therefore compare the results from a properly specified Monte Carlo with those from Monte Carlos contaminated by measurement error.

For my baseline uncontaminated Monte Carlo, I generate samples of size one thousand by simulation from Eq. (8), in which ω_i has a zero-mean, unit-variance gamma distribution. The vector $x_i(t)$ has two elements, which are designed to mimic sales growth and cash flow. Specifically, I let the first be distributed lognormally and the second be distributed normally, with first and second moments of these two simulated variables equal to the first two moments of sales growth and cash flow. The lognormal distribution for the cash-flow variable captures its highly skewed real-data distribution. I set β to $[1, 1]$, which is close to the average of my point estimates of the coefficients on sales growth and cash flow in Tables 3–5; and I model $\lambda_0(t) = 0.113t$, which corresponds roughly to a linearization of the three-times-the-median baseline hazard for the small single-segment firms. Finally, I generate a random censoring threshold with a normal distribution with a mean of six and a standard deviation of three. This threshold approximates the amount of censoring my data.

The measurement-error contaminated Monte Carlos differ from the baseline as follows. Suppose that $x_i(t)$ is a vector of two separate observable proxies for a *scalar* $\chi_i(t)$, and let $\varepsilon_i(t)$ be the vector of two measurement errors, with

$$x_i(t) = \chi_i(t) + \varepsilon_i(t), \tag{10}$$

in which $\varepsilon_i(t)$ is independent of $\chi_i(t)$. The population R^2 of these equations are the indices of measurement quality used above: the squared correlations between the proxies and the underlying true variables. I set these R^2s equal to $(0.8, 0.8)$, $(0.55, 0.55)$, and $(0.3, 0.3)$ in three separate simulations.

To generate data for the measurement-error simulations, I let $\chi_i(t)$ be a normal variable; I let the first element of $\varepsilon_i(t)$ be a normal variable raised to the fourth power; and I let the second element of $\varepsilon_i(t)$ be a normal variable. The means and covariance matrix of $\varepsilon_i(t)$ are specified so that the means and covariance matrix of $x_i(t)$ are equal to the means and covariance matrix of sales growth and cash flow. All other simulation features are the same as in the baseline case.

The results from these Monte Carlo experiments are in Table 6. The first column lists the parameter and the second the true parameter value. The third through sixth columns present the average over ten thousand Monte Carlo trials of the parameter estimates. Each column corresponds to the degree of measurement error present, the first column representing no measurement error, and the next three representing the three R^2 pairs. Not surprisingly, with a sample size of one thousand, the no-measurement-error baseline case produces almost unbiased parameters. The next columns shows that measurement error, as expected, produces bias in the estimates of β and $\exp(\gamma(t))$: β is biased downward and $\exp(\gamma(t))$ upward. It appears, however, that the main effect of measurement error is on β. As seen in the last column, the pair of R^2s must be as low as $(0.30, 0.30)$ before the baseline hazard is biased by as much as 0.1, a number smaller than many of the observed height differences in Tables 3–5. Because it is unlikely that my proxies are of such low quality, I conclude that measurement error in investment opportunities is not driving my results.

I now turn to the possibility of a correlation between ω_i and $x_i(t)$, which can arise if ω_i primarily represents differences in adjustment costs. Because adjustment costs influence optimal decisions, they are likely to be correlated with cash flow and sales growth. As a first pass at this problem, I examine the performance of the Meyer (1990) technique in my simulated economy. For this experiment, I take 40 draws of the innovation to the z shock from a truncated lognormal. For each of these individual draws, I then take 40 draws of the adjustment cost parameter, c, from a truncated lognormal, leaving me with 1600 combinations. For each combination I then use both my constrained and unconstrained models to simulate one hundred years of data, using only the last 20 as my sample. I end up with 3200 simulated firms over 20 years. The estimation results are shown in Fig. 8. Here, the solid lines represent theoretical hazards, and the dotted lines represent estimated hazards. The model does a good job of estimating the upward slope of the hazards as well as the height difference between the hazards of the constrained and unconstrained firms.

Table 6
Cash flow coefficients for large versus small firms

Calculations are based on a sample of nonfinancial firms and segments of conglomerates from the combined annual and full coverage 2002 Standard and Poor's Compustat industrial files that are also covered by Compustat's business information file. The sample period is 1983–1997. Estimates are from a regression of the ratio of investment to the capital stock on Tobin's q, the ratio of cash flow to the capital stock, a dummy variable if the firm falls into the constrained category, and the interaction of this dummy with cash flow. Constrained firms are those whose real assets are below the 33rd percentile of the real assets of the stand-alone firms in the first year that the firm appears in the sample. Estimation is done by ordinary lease squares (OLS) and the fourth-order generalized method of moments estimator (GMM4) from Erickson and Whited (2000). The coefficients on cash flow and the interaction term are presented. A positive coefficient on the interaction term indicates that the constrained group has a higher cash-flow coefficient. Standard errors are in parentheses under the parameter estimates.

Year	Large–small split			
	OLS		GMM4	
	Cash flow	Interaction	Cash flow	Interaction
1983	0.354	0.073	0.148	0.046
	(0.132)	(0.065)	(0.145)	(0.081)
1984	0.332	0.004	0.170	−0.006
	(0.102)	(0.059)	(0.138)	(0.061)
1985	0.282	−0.122	0.047	−0.048
	(0.097)	(0.030)	(0.183)	(0.041)
1986	0.338	0.019	0.139	0.003
	(0.067)	(0.033)	(0.119)	(0.035)
1987	0.177	−0.048	0.102	−0.058
	(0.051)	(0.029)	(0.122)	(0.084)
1988	0.353	−0.076	0.079	−0.063
	(0.068)	(0.030)	(0.140)	(0.054)
1989	0.181	−0.046	−0.185	−0.054
	(0.055)	(0.017)	(0.217)	(0.035)
1990	0.253	−0.046	0.121	−0.039
	(0.104)	(0.028)	(0.147)	(0.028)
1991	0.245	−0.061	0.093	−0.038
	(0.067)	(0.026)	(0.109)	(0.031)
1992	0.042	−0.033	−0.001	0.067
	(0.020)	(0.016)	(0.165)	(0.046)
1993	0.092	−0.067	−0.063	0.070
	(0.067)	(0.035)	(0.159)	(0.046)
1994	0.131	−0.095	−0.061	−0.074
	(0.059)	(0.043)	(0.085)	(0.056)
1995	0.090	0.074	0.034	0.084
	(0.059)	(0.132)	(0.149)	(0.131)
1996	0.097	−0.129	−0.016	−0.088
	(0.088)	(0.077)	(0.240)	(0.075)
1997	0.107	−0.106	−0.092	0.099
	(0.044)	(0.057)	(0.133)	(0.076)

Although no guarantee that the duration model performs well on real data, this result is a necessary condition for the duration model to be able to uncover differential hazard height.

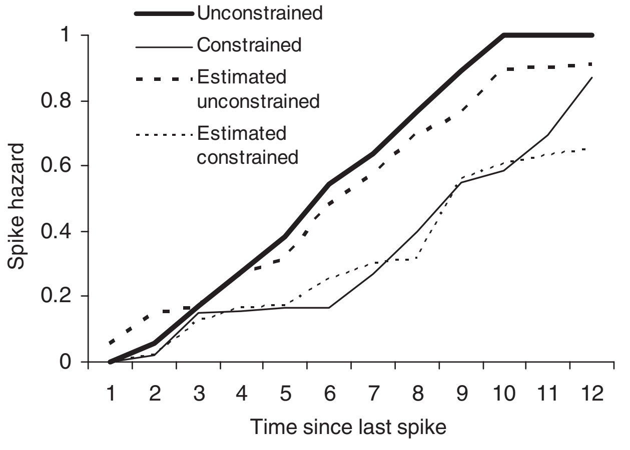

Fig. 8. Theoretical and estimated adjustment hazards. The constrained and unconstrained hazard functions are simulated from the investment model in Section 2. The estimated constrained and unconstrained hazard functions are estimated using the methods described in Section 4, with data simulated from the investment model in Section 2. The horizontal axis measures the length of time since the last investment spike, and the vertical axis measures the probability of a spike, given that the firm has remained inactive up to that time.

As a second pass at the problem, I use the estimator in Horowitz and Lee (2004), which relaxes the assumption that ω_i is independent of $x_i(t)$, using the panel nature of the data to treat ω_i as a fixed instead of a random effect. [9] This technique estimates the baseline hazard using a kernel, and it allows for dependent right censoring, which is a feature of my data. One drawback of the estimator is that $x_i(t)$ is not allowed to be time varying. A further drawback is that a firm must have two spells to be included in the sample.

This second drawback results in a sufficient drop in sample size that I can only obtain significant results for the two-times-the-median threshold for my entire sample of small firms and for my segments. I can use 938 of the firm-level observations and 752 of the segment-level observations. The results from this estimation are in Fig. 9, which I produce using the second-order kernel in Horowitz and Lee (2004) and the data-driven bandwidth selection that they provide. As in Fig. 6, the hazards are upward sloping, though not to the same degree. Further, the hazard for the segments always lies above the hazard for the firms, significantly above from years one through three. Because Figs. 6 and 9 provide the same qualitative inference, I conclude that possible dependence between ω_i and $x_i(t)$ is not driving my results.

6. Alternative approaches

Although the evidence presented here supports the idea that external finance constraints affect the timing of large investment projects, it does not shed light on the question of whether hazard model estimation provides a more discriminating approach for detecting finance constraints. This section considers the two models most widely used in this area: reduced-form regressions of investment on q and cash flow and Euler equation estimation.

[9] I thank Simon (Sokbae) Lee for the use of his computer programs.

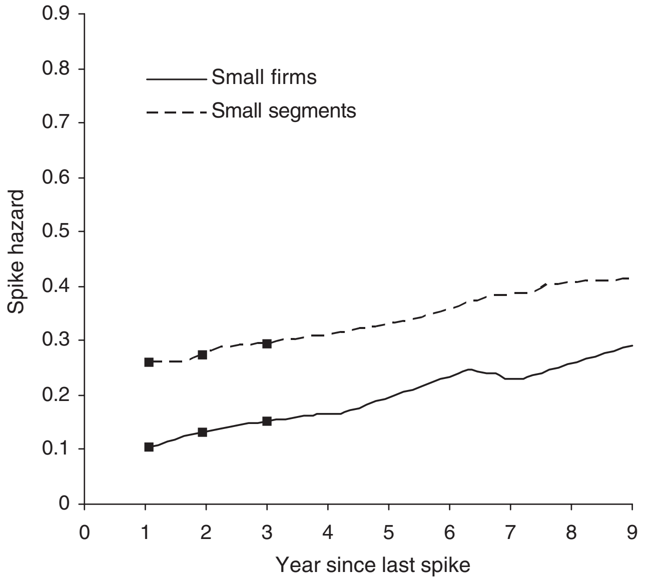

Fig. 9. Kernel estimates of hazards: small firms versus small segments. Estimates are from the second-order kernel estimator in Horowitz and Lee (2004). Small firms refer to estimates from a sample of small single-segment firms. Small segments refer to estimates from a sample of small segments of conglomerates. The horizontal axis measures the number of years since the last investment spike, and the vertical axis measures the probability of a spike, given that the firm has remained inactive up to that time. Dots indicate that the two hazard estimates are significantly different from one another at the 5% level. Calculations are based on a sample of single-segment nonfinancial firms from the combined annual and full coverage 2002 Standard and Poor's Compustat industrial files that are also covered by Compustat's business information file. The sample period is 1983–1997.

Reduced form regressions have serious drawbacks in that the sensitivity of investment to cash flow need not indicate the presence of finance constraints or in that it be an artifact of measurement error. To ascertain whether zero sensitivity holds up in my data, I run regressions of the ratio of investment to the replacement value of the capital stock on Tobin' q, the ratio of cash flow to the replacement value of the capital stock, a dummy variable that indicates membership in a constrained group, and the interaction of this dummy with the cash flow ratio. I then compare the results of using ordinary least squares on the regression with the results using the fourth order moment estimator in Erickson and Whited (2000).[10] All variables are defined and constructed as in Erickson and Whited (2000). The first constraint indicator is membership in the group of small (as opposed to large) firms, and the second two constraint indicators correspond to my second two sample-splitting schemes.

The results for the large and small split are in Table 6, which presents yearly estimates, as the technique in Erickson and Whited (2000, 2002) applies only to cross sections. For brevity, I report only the cash-flow coefficient and the coefficient on the interaction term.[11]

[10]The results from the third through sixth order moment estimators are similar. I therefore report the results only from the fourth order moment estimator, which in Erickson and Whited (2000) has the best finite sample properties.

[11]The identification tests in Erickson and Whited (2000) provide rejections of the null of no identification in all years but 1995, and the overidentifying restrictions of the model are rejected in only two instances.

As has been widely demonstrated, the ordinary least squares estimates of the cash flow coefficient are almost all positive and significant. The majority of the coefficients on the interaction term are significantly negative, an anomalous result that has also been found by Kaplan and Zingales (1997) and Kadapakkam et al. (1998). However, the measurement-error consistent estimates of the two coefficients are almost all insignificantly different from zero. Given this result, it is not surprising to find in Table 7 that these coefficients remain insignificant for the other two constraint indicators. The results add to the mounting evidence that cash flow sensitivities are not interesting measures of finance constraints (Table 9).

Next I turn to Euler equation estimation, where I follow the methods in Bond and Meghir (1994). Specifically, I use generalized method of moments with lagged instruments to estimate

$$\left(\frac{I}{K}\right)_{it} = b_1\left(\frac{I}{K}\right)_{i,t-1} + b_2\left(\frac{I}{K}\right)^2_{i,t-1} + b_3\left(\frac{C}{K}\right)_{i,t-1} + b_4\left(\frac{Y}{K}\right)_{i,t-1} + b_5\left(\frac{B}{K}\right)^2_{i,t-1} + f_t + a_i + v_{it}. \tag{11}$$

I/K is the ratio of investment to the capital stock, C is firm cash flow, Y is output, B is the stock of long-term debt, f_t is a fixed time effect, and a_i is a fixed firm effect. As in Bond and Meghir, the instruments are dated at $t-3$, and the instrument set includes all of the Euler equation variables, as well as the ratios of inventories, cash, dividends, and interest expense to the capital stock. All variables are constructed according to the Appendix to Bond and Meghir (1994). The estimation includes time dummies, and the fixed effects are treated with the forward differencing procedure in Arellano and Bover (1995).

The results are in Table 8, which shows separate estimations for each of my subsamples of firms. The coefficient estimates are qualitatively similar to those in Bond and Meghir (1994). Most important, I find that both cash flow and the debt to capital ratio have significant coefficients. This finding supports the hypothesis that financial and real decisions interact. However, I also find that the overidentifying restrictions of the model are rejected at the 10% level for all but one group and at the 5% level for all but two groups. This finding is not surprising. As shown in Abel and Eberly (1994), in the presence of fixed costs of adjustment or differing purchase and sales prices of capital goods, the first-order conditions for optimal investment preclude the derivation of an Euler equation of the form in Eq. (11). In sum, I find that traditional methods of detecting the presence of finance constraints, both of which are based on models of smooth adjustment, either lack power to detect financial frictions or suffer from potential misspecification problems.

7. Conclusion

This paper has tackled the question of the interaction between finance and investment from a new angle, one that examines the timing of large investment projects. A contribution of this different approach is its basis in a realistic view of firm investment decisions. Instead of relying on predictions from models with smooth costs of adjustment, the paper operates on the assumption that the most important costs of adjusting the capital stock are fixed. This choice stems from the intuitive observation that external finance constraints are more likely to affect large investment projects than incremental additions to the capital stock. A second advantage of this approach deals with measurement issues.

Table 7
Cash-flow coefficients for samples split by size and distributions

Calculations are based on a sample of nonfinancial firms and segments of conglomerates from the combined annual and full coverage 2002 Standard and Poor's Compustat industrial files that are also covered by Compustat's business information file. The sample period is 1983–1997. Estimates are from a regression of the ratio of investment to the capital stock on Tobin's q, the ratio of cash flow to the capital stock, a dummy variable if the firm falls into the constrained category, and the interaction of this dummy with cash flow. On the left side of the table constrained firms are those whose real assets are below the 33rd percentile of the small firms. On the right side constrained firms are those with a consistent history of zero dividends. Estimation is done by ordinary lease squares (OLS) and the fourth-order generalized method of moments estimator (GMM4) from Erickson and Whited (2000). The coefficients on cash flow and the interaction term are presented. A positive coefficient on the interaction term indicates that the constrained group has a higher cash-flow coefficient. Standard errors are in parentheses under the parameter estimates.

Year	Micro split				Zero distribution split			
	OLS		GMM4		OLS		GMM4	
	Cash flow	Interaction	Cash flow	Interaction	Cash flow	Interaction	Cash flow	Interaction
1983	0.233	0.133	0.142	−0.052	0.109	0.100	0.113	0.020
	(0.122)	(0.076)	(0.291)	(0.065)	(0.043)	(0.144)	(0.151)	(0.078)
1984	0.289	0.051	0.048	−0.031	0.042	−0.033	−0.041	0.096
	(0.104)	(0.021)	(0.060)	(0.035)	(0.043)	(0.065)	(0.069)	(0.059)
1985	0.229	0.070	0.057	−0.038	0.020	0.105	0.053	0.068
	(0.065)	(0.032)	(0.037)	(0.036)	(0.027)	(0.059)	(0.063)	(0.045)
1986	0.243	0.093	−0.001	−0.074	0.110	0.076	0.078	0.027
	(0.109)	(0.038)	(0.045)	(0.117)	(0.045)	(0.054)	(0.056)	(0.066)
1987	0.072	−0.010	−0.004	−0.002	0.065	−0.005	0.006	0.022
	(0.041)	(0.032)	(0.033)	(0.009)	(0.028)	(0.026)	(0.027)	(0.096)
1988	0.266	0.056	−0.023	0.004	0.113	0.035	0.020	0.084
	(0.052)	(0.026)	(0.063)	(0.023)	(0.064)	(0.033)	(0.057)	(0.099)
1989	0.187	−0.006	−0.005	−0.053	0.093	−0.045	−0.040	0.012
	(0.046)	(0.017)	(0.017)	(0.014)	(0.032)	(0.030)	(0.030)	(0.017)
1990	0.321	−0.017	0.001	0.215	0.243	0.022	0.022	0.053
	(0.145)	(0.026)	(0.043)	(0.129)	(0.064)	(0.003)	(0.036)	(0.135)
1991	0.121	−0.012	−0.008	−0.016	0.067	−0.012	−0.010	−0.009
	(0.027)	(0.013)	(0.016)	(0.009)	(0.022)	(0.024)	(0.025)	(0.006)
1992	0.015	0.056	0.097	0.075	0.032	0.072	0.045	0.001
	(0.040)	(0.020)	(0.051)	(0.056)	(0.023)	(0.035)	(0.088)	(0.017)
1993	0.055	−0.007	0.023	0.022	0.060	0.062	0.016	0.002
	(0.062)	(0.024)	(0.037)	(0.037)	(0.018)	(0.019)	(0.069)	(0.009)
1994	0.080	−0.041	−0.046	−0.007	0.094	−0.057	−0.071	0.018
	(0.058)	(0.044)	(0.047)	(0.027)	(0.046)	(0.035)	(0.056)	(0.020)
1995	0.162	0.114	0.101	−0.078	0.403	0.146	0.142	−0.056
	(0.172)	(0.049)	(0.150)	(0.116)	(0.278)	(0.085)	(0.108)	(0.139)
1996	0.127	−0.075	−0.074	0.054	0.094	−0.063	−0.080	0.061
	(0.069)	(0.076)	(0.071)	(0.169)	(0.040)	(0.065)	(0.075)	(0.052)
1997	0.078	−0.026	−0.048	0.045	0.083	0.086	0.048	−0.089
	(0.121)	(0.068)	(0.097)	(0.077)	(0.042)	(0.040)	(0.259)	(0.214)

I argue that, because my model offers guidance in finding simple, easily measured controls for productivity, the measurement issues are not as severe as those facing regressions of investment on q and cash flow. Finally, for researchers interested in the interaction between

Table 8
Euler equation estimates

Calculations are based on a sample of nonfinancial firms and segments of conglomerates from the combined annual and full coverage 2002 Standard and Poor's Compustat industrial files that are also covered by Compustat's business information file. The Euler equation is

$$\left(\frac{I}{K}\right)_{it} = \beta_1\left(\frac{I}{K}\right)_{i,t-1} + \beta_2\left(\frac{I}{K}\right)^2_{i,t-1} + \beta_3\left(\frac{C}{K}\right)_{i,t-1} + \beta_4\left(\frac{Y}{K}\right)_{i,t-1} + \beta_5\left(\frac{B}{K}\right)^2_{i,t-1} + f_t + a_i + v_{it}.$$

I/K is the ratio of investment to the capital stock, C is firm cash flow, Y is output, B is the stock of long-term debt, f_t is a fixed time effect, and a_i is a fixed firm effect. The model is estimated via generalize method of moments with instruments that are dated at $t-3$. The instrument set includes all of the Euler equation variables, as well as the ratios of inventories, cash, dividends, and interest expense to the capital stock. The sample period is 1983–1997. Small firms are those whose real assets are below the 33rd percentile of all firms. Large firms are those whose real assets are above the 67th percentile of all firms. Microfirms are those whose real assets are below the 33rd percentile of small firms. Other small firms are those whose real assets are above the 67th percentile of small firms. A positive coefficient on the interaction term indicates that the constrained group has a higher cash-flow coefficient. Standard errors are in parentheses under the parameter estimates.

Coefficient	Large	Small	Micro	Other small	Small, zero distributions	Small, positive distributions
$\left(\frac{I}{K}\right)_{i,t-1}$	0.1006	0.3811	0.4910	0.4921	0.3807	0.3921
	(0.0517)	(0.1625)	(0.0842)	(0.1920)	(0.1818)	(0.1361)
$\left(\frac{I}{K}\right)^2_{i,t-1}$	−0.2789	−0.1475	−0.2242	−0.3178	−0.2780	−0.4316
	(0.1039)	(0.1050)	(0.1950)	(0.1779)	(0.1540)	(0.1343)
$\left(\frac{C}{K}\right)_{i,t-1}$	0.1796	0.1436	0.1725	0.1121	0.1425	0.0939
	(0.0599)	(0.0432)	(0.0669)	(0.0461)	(0.0297)	(0.0724)
$\left(\frac{Y}{K}\right)_{i,t-1}$	0.0035	0.0045	0.0021	0.0039	0.0021	0.0031
	(0.0019)	(0.0018)	(0.0015)	(0.0015)	(0.0036)	(0.0042)
$\left(\frac{B}{K}\right)^2_{i,t-1}$	−0.1457	−0.1075	−0.1217	−0.2746	−0.1782	−0.1784
	(0.0401)	(0.0323)	(0.0449)	(0.1273)	(0.0366)	(0.0732)
J-statistic p-value	0.0241	0.0470	0.0508	0.0415	0.0277	0.1452

finance and investment, a new angle appears necessary, given the contradictory and inconclusive evidence from almost two decades of cash-flow sensitivity and Euler equation tests.

I use a simple theoretical model of lumpy adjustment to show that, ceteris paribus, costly external finance lowers the hazard function for investment spikes. In other words, given that a firm has not undertaken a large investment project for a certain length of time, it is less likely to undertake another if it faces costly external finance than if it does not. I also demonstrate that the aggregation of decisions in large firms can mask this result.

I take this idea to data by using a hazard model in which I control for firm size, industry, macroeconomic effects, and arguably good proxies for productivity. First, I find evidence of lumpy investment in firm-level data, which adds credence to the idea of testing for financial constraints in the context of fixed costs of physical adjustment. Second, I find evidence that access to cheap finance lowers investment hazards. Small single-segment

Table 9
Monte Carlo simulation of hazard estimation with covariate mismeasurement

Indicated averages are based on 10,000 Monte Carlo trials. The hazard model estimated via the technique in Meyer (1990) in each trial is

$$\lambda_i(t) = \omega_i \lambda_0(t) \exp(x_i(t)'\beta),$$

in which ω is a random variable with a zero-mean, unit-variance gamma distribution, $\lambda_0(t)$ is the baseline hazard, $x_i(t)$ is a vector of covariates, and β is the vector of coefficients on these covariates. The variable ω has a gamma distribution, $\lambda_0(t) = 0.113t$, and the vector $x_i(t)$ contains two correlated variables that mimic cash flow and sales. Perfect measurement refers to a Monte Carlo in which the elements of $x_i(t)$ contain no measurement error. The numbers that label the last three columns refer to Monte Carlos in which $x_i(t)$ does contain measurement error. These numbers are the squared correlations between the elements of true $x_i(t)$ and their proxies. Lower numbers indicate more measurement error.

Parameter	True value	Perfect measurement	(0.8, 0.8)	(0.55, 0.55)	(0.3, 0.3)
β_1	1.000	0.986	0.812	0.621	0.352
β_2	1.000	1.002	0.855	0.663	0.407
$\lambda_0(1)$	0.113	0.111	0.120	0.143	0.169
$\lambda_0(2)$	0.226	0.227	0.256	0.279	0.301
$\lambda_0(3)$	0.339	0.341	0.380	0.419	0.425
$\lambda_0(4)$	0.452	0.449	0.475	0.512	0.536
$\lambda_0(5)$	0.565	0.565	0.603	0.639	0.663
$\lambda_0(6)$	0.678	0.680	0.722	0.767	0.782
$\lambda_0(7)$	0.791	0.789	0.841	0.876	0.892

firms that distribute cash to shareholders have significantly higher hazards than small single-segment firms that do not. In addition, the smallest of the small single-segment firms have the lowest hazards; and small segments have significantly higher hazards than their stand-alone counterparts.

In sum, the paper provides a new type of evidence that access to external finance influences firms' real investment decisions. Because looking for evidence of finance constraints in the context of models with real nonconvexities appears to be fruitful, future research could explore other ways to exploit these models. One avenue consists of looking at plant-level data. Another, more methodological avenue is structural estimation, based on models such as those in Abel and Eberly (1998) and Caballero and Leahy (1996). One challenge to structural estimation is the lack of closed-form solutions for many models with nonconvexities, a challenge possibly solved with simulation estimators.

Appendix A. Simulation design

Production takes place according to

$$\pi(K, z) = zK^{\theta}. \tag{12}$$

Ideally, I would like to estimate θ with my data from Compustat. However, because these data do not contain sufficient information on payments to variable factors to estimate a production function, I calibrate θ using two ingredients. The first is the estimates of labor share in Rotemberg and Woodford (1999), which hover around 0.7 for the time period spanned by my data set. The second ingredient is an estimate of the markup of price over marginal cost. Here I follow Rotemberg and Woodford (1992) and set the parameter to

1.2. These figures, along with the assumption of a Cobb–Douglas production function and a constant-elasticity demand function, imply that $\theta = 0.75$.

Next, I consider the financing function, whose shape requires considerably more thought. External finance can be more costly than internal finance for several reasons. First, information asymmetries can induce external investors to require a lemons premium. Similarly, external investors can require premia because external equity exacerbates manager-shareholder conflicts, and because debt can cause underinvestment problems. Second, monitoring costs are important for bank loans, and transactions costs are important for seasoned debt and equity offerings, as well as bank loans. Because little research has been done to quantify the first type of costs, I follow Gomes (2001) and focus only on transactions costs. This strategy provides a conservative estimate of the costs of external finance. To quantify the costs I use the estimates in Altinkilic and Hansen (2000) for seasoned equity issues. (See their Table 2.) Their regression results imply an external finance function of the form

$$\phi(e) = 0.0341 + 0.0241e, \tag{13}$$

where e is a dummy variable for the gross amount of financing as a percentage of firm assets. To find a value for the fixed cost, c, I turn to the estimates in Cooper and Haltiwanger (2006) and set $c = 0.05$. Finally, I set the interest rate equal to 2%, which implies a discount factor $\beta = 0.980$; and I set the depreciation rate equal to the average in my data of depreciation divided by the net capital stock: 0.157. Fifty percent changes in the above parameters result in identical qualitative conclusions.

Next, I specify a stochastic process for the shock, z. Following Caballero and Leahy (1996), I assume that z follows an $AR(1)$ in logs,

$$\ln(z') = 0.53 \ln(z) + u', \tag{14}$$

where $u' \sim \mathrm{N}(0, 0.15^2)$. I obtain the autoregressive parameter and the error variance from my data by performing a panel autoregression of the variable $\ln(\text{Sales}/\text{Assets}^{\theta})$. (See Holtz-Eakin et al., 1988.)

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

$$[\overline{k}(1-d)^{50}, \ldots, \overline{k}(1-d), \overline{k}(1-d)^{1/2}, \overline{k}].$$

I let the productivity shock have 40 points of support, transforming Eq. (14) into a discrete-state Markov chain using the method in Tauchen (1986). Finally, I let p have ten equally spaced points of support in the interval $[0, \overline{p}]$.

I solve the model via iteration on the Bellman equation, which produces the value function $V(k, p, z)$ and the policy function $\{k', p'\} = h(k, p, z)$. The model simulation proceeds by taking a random draw from the conditional (on z) distribution z' shock, and then computing $V(k, p, z)$ and $h(k, p, z)$, the latter of which is defined as $\Pr(I/k > \bar{\imath} \mid k, p)$, with $\bar{\imath} = 20\%$.

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