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. Finally, accumulation of liquid assets raises hazards, and accumulation of debt lowers hazards.

I. Introduction

The past fifteen years have seen a flood of empirical studies of the effects of external finance constraints on corporate investment. 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, such models provide little guidance for the direction of empirical work, since few have both endogenous investment and finance decisions, and since few are couched in terms of observable variables. Therefore, empirical studies have turned to two loose arguments to motivate tests of the connection between finance and investment. First, finance constraints cause an excess sensitivity of investment to internal funds; and second, they affect the firm's incremental intertemporal investment allocation. This paper tackles this topic from a new, unexploited angle; briefly, one that examines the effects of finance constraints on the timing of large investment projects.

To understand the contribution of this idea, it is useful to discuss the two basic issues confronting this line of research. Any empirical examination of the interaction of finance and investment must specify a "correct" investment model and find an "accurate" way of measuring access to external capital markets. Problems arise when both requisites fail. For example, if the investment model is misspecified, then to the extent that the measure of financing constraints is correlated with the explanatory variables left out of the investment model, any estimates of the effects of the finance-constraint proxy on investment will be biased. On the other hand, if the investment model is well specified, then, as discussed at more length in Erickson and Whited (2000), using a noise-ridden proxy for finance constraints will only dampen the estimated effect of this proxy-variable on investment. I will argue and provide evidence below that my investment model, while not "perfect," is much better than those used by the bulk of this research and that any noise in my proxies for finance constraints is unlikely to affect my qualitative inference.

A discussion of the progenitors and relatives of the present paper also aids in understanding its contribution. Most of the empirical research in this area has followed the methods first outlined in Fazzari, Hubbard, and Petersen (1988), who argued and found that if a firm cannot obtain outside finance, its investment will respond strongly to movements in cash flow, holding investment opportunities constant. More recently, however, Kaplan and Zingales (1997) and Cleary (1999) have provided evidence that cash-flow sensitivity need not identify *a priori* liquidity constrained firms. Further, the simulations in Gomes (2001) and the empirical work in Erickson and Whited (2000), Bond and Cummins (2001), and Cooper and Ejarque (2001) have demonstrated that the results from these earlier papers are due to measurement error in the usual proxy for investment opportunities: Tobin's q. In sum, these recent papers question whether the large body of research on cash-flow sensitivity has taught us much about the way in which external finance constraints affect investment. Cash flow is correlated with investment, but because the underlying investment model is plagued by problems of measurement error, this correlation may not be an indication of finance constraints. Thus, this newer work has re-opened the door to understanding the mechanism whereby finance and investment interact.

A different line of research estimates directly the Euler equation of an intertemporal investment model using generalized method of moments. For example, Whited (1992) and Bond and Meghir (1994) show that augmentations of the Euler equation that account for financial constraints improve its fit. This approach has the advantage of avoiding the difficult problem of measuring q. Euler equation studies have provided convincing evidence that external finance constraints affect the rate of intertemporal substitution between investment today and investment tomorrow. However, these papers examine only marginal decisions, since they are based on models with convex capital-stock adjustment costs.

In contrast, common intuition suggests that finance constraints are at least as likely to alter a firm's decision 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). Further motivation for studying finance constraints in the context of lumpy investment comes from studies that have found a great deal of lumpy adjustment in plant-level data (Doms and Dunne, 1998; Cooper, Haltiwanger, and Power, 1999). 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. If, as this evidence suggests, investment decisions are lumpy, then external finance constraints are quite likely to have lumpy effects.

To test this idea, I examine the effects of finance constraints on a capital stock adjustment hazard: the relationship between the probability of a large change in the capital stock at a certain point in time and the length of 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 only invests 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. Evidence of upward sloping hazards has been found in plant-level data by Cooper, Haltiwanger, and Power (1999). 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 will lie below that of an otherwise identical unconstrained firm.

I then test the idea on a sample of firms and segments of firms from COMPUSTAT. These data have the obvious disadvantage that a firm, especially a large firm, is an aggregation of several different decision making units. If these individual units act in unison, then their behavior should resemble the behavior of an individual unit, and investment should occur

[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, Heinckel, and Zechner (1989); and for a model of portfolio choice, see Vayanos (1998).

episodically. However, this scenario is unlikely; and to the extent that these individual units act asynchronously, their aggregated investment will appear to be smoothed out over time. This problem could confound any empirical findings. For example, if I compare the investment of a firm composed of many units with the investment of a firm composed of one unit, then the two may have very differently shaped hazards even though neither face external finance constraints. To mitigate this problem, I limit my sample to small segments of conglomerates and small single-segment firms, since small segments or single-segment firms are less likely to be composed of a large number of decision making units.

Estimates obtained from these samples show evidence of upward sloping hazards, suggesting that it is appropriate to use a framework of nonconvex adjustment to study external finance constraints. The central contribution of the paper, however, is new evidence of the interdependence of finance and investment. I find that groups of *a priori* constrained firm have lower hazards than their unconstrained counterparts. 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 segments of conglomerates. I also find that accumulation of liquid assets raises hazards and that accumulation of debt lowers hazards.[2]

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, and section 6 concludes. The details of the simulation are in the appendix.

II. A Simple Model of Lumpy Investment

To motivate the empirical work below, and especially to provide structure for the choice of the control variables in my estimation, I consider a discrete-time partial-equilibrium model of a

[2]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. The word constraint should be interpreted as a surpassable obstacle, rather than an unsurpassable obstacle.

producer that uses current-period capital, K, to produce output. The producer's per period revenue function is given by $\Pi(K,z)$, where $\Pi(0,z) = 0$, $\Pi_z(K,z) > 0$, $\Pi_K(K,z) > 0$, $\Pi_{KK}(K,z) < 0$, and $\lim_{K\to\infty} \Pi_K(K,z) = 0$. z is a combination demand/productivity shock, observed by the producer before he makes his current period decisions, but not observed by the econometrician. It has support on the interval $(0,\infty)$ and has a stationary Markov transition function $q(z',z)$, where a prime denotes a variable in the subsequent period. $\Pi(K,z)$ can be thought of as a reduced-form production function where variable factors of production have already been maximized out of the problem. The concavity of $\Pi(K,z)$ results from decreasing returns in production and/or a downward sloping demand curve.

The firm purchases and sells capital at a price of 1 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. Other sources of lumpy adjustment, such as irreversibility, indivisible capital goods, and different puchase and sale prices for capital, can be though of as examples or extreme cases of nonconvex adjustment costs. .

The capital stock evolves according to a standard capital stock accounting identity:

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

where d is the constant rate of depreciation, $0 < d < 1$. The producer is risk neutral and maximizes the value of future cash flows, discounting them at a constant factor, β, $0 < \beta < 1$. This model can be thought of either as a partial equilibrium model of a firm or, equivalently, as a model of a general equilibrium economy with production and consumption, where a representative consumer has utility linear in both consumption and leisure.[3]

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). Following Gomes (2001), I assume that whenever the optimal choice of I remains smaller than revenue, the firm uses internal funds for investment.

[3]Adding risk aversion or decreasing marginal utility of leisure to the model changes its quantitative but not qualitative predictions.

However, whenever desired investment exceeds revenue, the firm can only proceed if it obtains external funds at a premium. This assumption can be thought of as the outcome of a an information theoretic model of external finance. To quantify the idea I define the excess of desired investment over revenue as $e(K,z) \equiv I - \Pi(K,z)$ and then specify a financing cost function $\phi(e(K,z))$, where $\phi(e(K,z)) = 0$ if the firm faces no external finance constraints or if $e(K,z) \leq 0$. If $e(K,z) > 0$, $\phi(e(K,z)) > 0$ and $\phi_e(e(K,z)) > 0$. Note the discrete difference between the cost of funds when the firm moves from internal to external sources. Although the financing function is uninformative about the source of external funds, it is nonetheless appropriate for a model that focuses on investment behavior.[4]

Let $V(K,z)$ denote current value of the firm and define it as:

$$V(K,z) = \max\left\{V^i(K,z), V^n(K,z)\right\}, \tag{2}$$

where the superscripts "i" and "n" refer to investment and no investment, respectively. The corresponding Bellman equations are

$$V^n(K,z) = \Pi(K,z) + \beta \int V(K(1-d), z')\, dq(z',z) \tag{3}$$

$$V^i(K,z) = \max_I \left\{\Pi(K,z) - I - cK - \phi(I - \Pi(K,z)) + \beta \int V(K', z')\, dq(z',z)\right\}. \tag{4}$$

Note that definition of $\phi(\cdot)$ allows (4) to represent the decisions to invest both with and without external finance. A unique solution to this maximization problem requires that $\Pi_K(K,z)[1 + \phi_e(e(K,z))e_K(K,z)]$ be decreasing in the capital stock. The existence of a unique solution to (2) is then guaranteed by Theorem 9.6 in Lucas and Stokey (1989). I characterize the solution to this problem by the value function $V(K,z)$ and the policy function $I = g(K,z)$.

III. Simulations

I investigate the implications for the solution to this problem via simulation. In order to do so, I need to choose functional forms for the revenue, adjustment cost, and financing

[4] Instead of using a financing function to model costly external finance, one can specify that $I \leq A$, where A is the stock of financial assets, which are governed by the intertemporal budget constraint $A' = A/\beta + \Pi(K,z) - I$. This model produces identical qualitative conclusions.

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 literally estimating this structural model, the intent of the design is simply to generate qualitative conclusions that are robust to perturbations in the design parameters and to the time series properties of the shock. Details are in the appendix.

I solve the model via value function iteration, which yields the policy and value functions. Whether constrained or unconstrained, the firm follows a two-sided (S, s) policy, with a single return point if the firm is unconstrained or if the firm is constrained but chooses not to use external finance. The policy has two return points if the firm is constrained and does use external finance. It is worth noting that even though the firm can make small adjustments, it chooses not to. Further, the inaction bands are much wider for a constrained firm than for an unconstrained firm. I simulate the model for 10,000 time periods to generate the hazard functions. In these simulations I define an adjustment or "spike" as a rate of net investment that exceeds 20%.[5]

Figure 1 presents the hazard functions from the simulations of the constrained and unconstrained firms. In this figure the horizontal axis measures the amount of time since the previous adjustment of the capital stock, and the vertical axis measures the adjustment hazard. Notice the difference between the hazards of the unconstrained and constrained firms. The hazard of the unconstrained firm slopes upward steeply, which, as noted in the introduction, is a pattern consistent with the presence of fixed costs of adjustment. The hazard of the constrained firm also slopes 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 the marginal productivity of capital. On the margin capital not only adds to production, but it alleviates the external finance premium. This addition to the marginal productivity of capital will raise the investment hazard, since 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

[5]Although I use a variety of thresholds in the following hazard estimations, for expositional brevity I limit myself to one threshold in my simulations.

is stronger. This result is robust to a wide variety of different model parameterizations.

Although the differences in the hazards of constrained and unconstrained firms is an empirically testable implication of my model, a number of other factors affect hazards: factors that need to be accounted for in any tests. One such important issue is aggregation of asynchronous actions within a firm. The effects of aggregation are illustrated in Figure 2, which contains graphs of the hazards from two types of "conglomerate" firms, where each type can be constrained or unconstrained. I construct the conglomerates by assuming they are composed of either two or six *i.i.d.* units, each of which is identical to the unit represented in Figure 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 *i.i.d.* units, they represent a worst-case scenario of the difficulties induced by aggregation, since a firm composed of units whose decisions are positively correlated will behave in a manner more like an individual unit. As in Figure 1, the hazard for the constrained "small" conglomerate in Figure 2 lies below the hazard for the unconstrained small conglomerate, though both are lower than those in Figure 1. The pattern exhibited by the pair of hazards for the "large" conglomerates is quite different: both are at the same low level. Here, because of the asynchronous actions of the conglomerate units, and because the rate of investment contains total conglomerate assets in the denominator, the rate of investment for the conglomerate as a whole rarely crosses a spike defining threshold, even though the individual units of the conglomerate behave exactly as those depicted in Figure 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 in any given period could devote their profits to the segments that do find it optimal to adjust. This simulation result underlines the importance of considering aggregation when trying to uncover the effects of external finance constraints with COMPUSTAT data, which covers many large diversified firms.

Three further factors that could 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 rather than 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 Figure 3, 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. This theoretical finding indicates the importance of controlling for all of these factors when comparing the hazards of different groups of firms. One further factor that could affect the hazard is the variance of the innovation to z. However, changes in this variable affect the hazard little under a wide variety of model parameterizations. Intuitively, when z has a high variance, the marginal product of capital is more likely to hit one of the thresholds. On the other hand, the firm will respond by widening the inaction interval. These two effects appear to cancel each other out. For similar intuition, see Bertola and Caballero (1990).[6]

Finally, it is worth noting that the hazard of a firm facing convex adjustment costs slopes downward. Intertemporal smoothing induced by this convexity implies that a large investment is likely be followed closely by another, but is less likely to be followed by another in the distant future. Therefore, examining the slope of the hazard provides information on whether an environment of nonconvex adjustment is indeed appropriate for understanding external finance constraints. Intense episodes of investment *can* occur with convex adjustment costs, if productivity shocks are high-variance and persistent. However, convexity nonetheless causes intertemporal investment smoothing so that investment will not be "lumpy."

IV. Data and Summary Statistics

My data are from the combined annual, research, and full coverage 2001 Standard and Poor's COMPUSTAT industrial files that are also covered by the COMPUSTAT business informa-

[6]All of these results can also be obtained from a model in which a firm with assets in place encounters growth options that arrive randomly. In this sort of model a "productive" firm is one in which these options arrive at a high rate.

tion files, which cover the years 1982 through 2000. In late 1997 SFAS 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 only use data 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, the gross capital stock, or sales 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. Finally, I include a firm or segment only if it has at least five consecutive years of complete data; and I omit all firm- and segment-level observations whose primary SIC classification is between 4900 and 4999 or between 6000 and 6999, since my model of investment is inappropriate for regulated or financial firms. Note that if a manufacturing conglomerate has, for example, a financial subsidiary, the conglomerate will be in the sample, but that subsidiary will not. I end up with between 1018 and 2082 single-segment firms per year, between 563 and 952 multiple-segment firms per year, and between 1358 and 2640 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 these multi-segment firms. I classify a firm or segment as "small" if its real assets are below the thirty-third 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. Three 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 composition of the samples does not change. Third, this type of definition allows me to avoid serious sample selection issues that could arise by isolating only slow-growing firms. On one hand, firms or segments that grow quickly and perhaps become "not-small" remain in the sample, exacerbating the aggregation issues discussed above. On the other, the data analysis below suggests that this issue is minor in the samples of small firms and segments.

Table 1 shows that the multi-segment firms are substantially larger than even the large the single-segment firms. Note also that the small segments and small stand-alone firms are indeed quite small: their mean real assets are only 12.1 and 14.7 million 1997 dollars, respectively. Aggregation is therefore unlikely to be an important issue for either group. These two groups do have some important differences: 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 the extent to which firms engage in large investment projects. Since 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 may well 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 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 two-digit industry mean of this ratio. Using an industry-specific measure of a spike allows cross-sectional variation in the "normal" rate of investment across industries. I define a spike as an observation in which the ratio of investment to assets is greater than 1, 1.5, or 2 standard deviations from the mean. I use several spike thresholds in order to check the robustness of my results to the criteria for measuring spikes.[7] This table provides some *prima facia* evidence of fixed costs of adjustment, since in a world with convex adjustment, I ought to see very 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 one standard-deviation spikes is not much smaller than the 14 percent figure reported by Cooper and Haltiwanger (2002). This similarity suggests that the sort of lumpy adjustment observed in plants may also be present in firms.

The rest of the table examines inaction spells. 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 wiht the aggregation of asyn-

[7]An earlier version of this paper defines a spike as an instance when net investment crosses a fixed threshold. Results using this sort of definition are broadly similar.

chronous actions. The similar investment rates across the small segments and small firms manifest themselves here in the similarity between their mean spell lenght. Given the difference in sales growth, one would expect the single-segment firms to be adjusting more often; so perhaps external finance constraints are hindering adjustment. Providing more specific evidence of this conjecture is the subject of the rest of the paper.

V. Estimation

A. Methods

Two strategies have dominated the empirical literature on estimating and testing investment models with nonconvexities. First, as illustrated, for example, in Caballero, Engel, and Haltiwanger (1995) and Caballero and Engel (1999), one can construct a measure of the "gap" between the firm's actual and desired capital stock, where 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 (2001), 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, it is easy to mismeasure the gap: a problem that can lead to misleading inferences. This problem is analogous to the difficulty of measuring q, and it is also a generic problem with estimation of a structural model, since the resulting inferences can be fragile with respect to the choice of model assumptions.

The second method, less structural, method is hazard estimation. I have opted 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 to 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 we observe a cross section containing 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 we could observe a long time series on each firm, 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 we see more replacements of relatively new capital than of older capital, and a simple empirical hazard will slope downward.

Difficulties such as this can be solved by using a duration model, since it is possible to account for observable time-varying covariates, such as productivity, as well as unobservable heterogeneity across firms. Loosely speaking, an 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, since I can control for other important non-financial determinants of investment. Caballero and Engle (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. The following brief description of this technique follows Meyer (1990), who starts with a proportional hazards specification:

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

where $\lambda_i(t)$ is the hazard function, $x_i(t)$ is a column vector of covariates, β is the corresponding vector of unknown coefficients, and $\lambda_0(t)$ is called the baseline hazard. The parametric part of this specification is the linear modelling of the covariates. The nonparametric part is the baseline hazard, which is not restricted to take any particular shape. Note that the existence of the covariates allows the hazard to shift up and down depending on their values and on β. Equivalently, the existence of the covariates essentially changes the units in which time is measured.

Estimating the parameters of a hazard function is exactly analogous to estimating the parameters of a density. However, since time is measured at discrete intervals, to write down a likelihood function, it is convenient to express the hazard at time t as the product of the hazards for the time intervals leading up to time t. As a first step in this process, note that the probability that an inaction spell will last until time $t+1$, given that it has lasted to time t can be written as a function of $\lambda_i(t)$ as follows:

$$\begin{aligned} \Pr(T_i \geq t+1 \mid T_i \geq t) &= \exp\left[-\int_t^{t+1} \lambda_i(s)\, ds\right] \\ &= \exp\left[-\exp\left(x_i(t)'\beta\right)\int_t^{t+1} \lambda_0(s)\, ds\right]. \end{aligned} \tag{5}$$

Define

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

Then (5) can be written as

$$\Pr(T_i \geq t+1 \mid T_i \geq t) = \exp\left[-\exp\left(x_i(t)'\beta + \gamma(t)\right)\right].$$

I can use this specification to write down the likelihood function. First, 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 seven years, where I have chosen this number because it is the largest for which I can estimate all of the elements of $\gamma(t)$ for all of my samples. Depending on the spike threshold and sample, this seven-year rule affects from 7.6 to 28.2 percent of the observations, where, not surprisingly, the larger percentages occur in the samples of large firms, who have long spells. The likelihood function that accounts for this sort of right censoring for a sample of N individual spells can be written as

$$\mathcal{L}(\gamma,\beta) = \prod_{i=1}^{N}\left\{\left[1-\exp\left(-\exp\left(x_i(h_i)'\beta+\gamma(h_i)\right)\right)\right]^{\delta_i} \times \prod_{t=1}^{h_i-1}\exp\left(-\exp\left(x_i(t)'\beta+\gamma(t)\right)\right)\right\},$$

where $\gamma \equiv [\gamma(0), \gamma(1), \ldots \gamma(T-1)]'$, $\delta_i = 1$ if $T_i \leq C_i$ and 0 otherwise, and $h_i = \min(T_i, C_i)$. The first term in square brackets is 1 if the inaction spell is censored, and the second term is just the probability of a spell lasting at least until h_i. The corresponding log-likelihood can be written as

$$L(\gamma,\beta)=\sum_{i=1}^{N}\left[\delta_i \ln\left[1-\exp\left(-\exp\left(x_i(h_i)'\beta+\gamma(h_i)\right)\right)\right]-\sum_{t=1}^{h_i-1}\exp\left(x_i(t)'\beta+\gamma(t)\right)\right]. \tag{6}$$

As this point, although the empirical model can account for observable heterogeneity via the inclusion of $x_i(t)$, it still does not account for unobserved heterogeneity. To address this issue, I once again follow Meyer (1990) and assume that unobserved heterogeneity takes a multiplicative form:

$$\lambda_i(t)=\omega_i\lambda_0(t)\exp\left(x_i(t)'\beta\right).$$

Here ω_i is a random variable that is assumed to be independent of $x_i(t)$. To construct a tractable log-likelihood function, one usually assumes a parametric functional form for the distribution of ω_i. A commonly-used distribution is a gamma with a mean of one. In this case the log-likelihood is

$$\begin{aligned} L(\gamma,\beta) \;=\; & \sum_{i=1}^{N}\ln\left\{\left[1+\sigma^2\sum_{t=1}^{h_i-1}\exp\left(x_i(t)'\beta+\gamma(t)\right)\right]^{-\left(1/\sigma^2\right)}\right. \qquad (7)\\ & \left.-\delta_i\left[1+\sigma^2\sum_{t=1}^{h_i}\exp\left(x_i(t)'\beta+\gamma(t)\right)\right]^{-\left(1/\sigma^2\right)}\right\}, \end{aligned}$$

where σ is the variance of the gamma distribution.[8] The estimation procedure chooses the shape of the hazard to maximize the likelihood of observing the inaction spells in the sample.

My specification of the model allows $x_i(t)$ to contain sales growth, two-digit industry dummies, and year dummies. The year dummies allow the hazard function to be conditioned on aggregate shocks to interest rates and the business cycle. The industry dummies capture several important 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, differ-

[8]It is possible to model heterogeneity as in Cooper, Haltiwanger, and Power (1999) as a discrete number of firm types. Another possibilty 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 these more nonparametric estimation methods have greater data requirements.

ences in the types of capital used across industries could affect depreciation rates, differences in returns to scale, and adjustment costs.

I also need some control for "investment opportunities." Given adjustment costs, the adjustment hazard depends only on the probability of the firm reaching an adjustment trigger, which in turn depends primarily on the expected rate of increase in the marginal product of capital. Therefore, in this model "investment opportunities" is not equivalent to marginal q, but to this speed. Indeed, Caballero and Leahy (1996) show that in the presence of fixed costs of adjustment that occur with each project (as opposed to per unit of time), the relationship between investment and marginal q is not a function but a correspondence. The non-financial determinants of the rate of reaching an adjustment trigger are the mean of the innovation to the z shock, the depreciation rate, and returns to scale. Because technology determines the second two factors, and because technology is likely to vary more across industries than across firms within an industry, the industry dummies control for much of the variation in these components of investment opportunities. I include the ratio of cash flow to assets as an admittedly imperfect proxy for the mean of the innovation to the z shock.

Although the proxy is imperfect, the model *can* shed some light on its quality, and cash flow is, in itself, an easily-measured variable. It is straightforward to show in my model that if the firm invests just enough to replace depreciated capital, expected cash flow is proportional to the population mean of the innovation, and observed cash flow is proportional to the innovation. Therefore, the correlation between z and cash flow will be one. Since optimal behavior implies that firms either remain completely inactive or invest in large spikes, average cash flow will be an imperfect proxy for the mean of the innovation. However, if in a simulation mean cash flow and the innovation mean are highly correlated, the proxy should at least theoretically be of high quality. Using the model of the previous section I simulate 1000 firms, where for each the innovation mean is drawn from a truncated lognormal distribution. The squared cross-sectional correlation between the innovation mean and average sales growth is 0.861. In other words variation in average sales growth accounts for 86.1 percent of the variation in the innovation mean.[9] Because this figure is quite high, I have confidence that the qualitative nature of the following results is unlikely to be an artifact of measurement error. In contrast, the corresponding figure for Tobin's q found by Erickson and Whited (2000) is only approximately 40 percent.

A few further remarks about this proxy are in order. First, with the additional condition of a homogeneous revenue function, expected sales growth is equal to the mean of the innovation to the z shock. Using sales growth as a proxy produces identical qualitative inferences. However, because using both proxies results in insignificant coefficients on sales growth, for brevity, I report only those results obtained by including cash flow. Second, many authors have argued that cash flow contains information about liquidity in addition to information about profitability. However, this ambiguity is *irrelevant* for the problem at hand, because if cash flow does indeed proxy for internal liquidity, any estimated differences in hazard height will not be due to this liquidity effect but to the information in my sample splitting variables on access to external capital markets. Finally, the use of current profits or cash flow as a proxy for investment opportunities also occurs in the Euler equation literature mentioned in the introduction. This similarity is not accidental, since both hazard estimation and Euler equation estimation only need to control for capital productivity in the period *between* investment expenditures. This task is substantially easier than controlling for the expected present value of all future capital productivity, which is required by reduced-form investment regressions.

The question remains as to the justification for this proportional hazards assumption. To approach this issue, I examine the performance of the model 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 100 years of data, using only the last 20 as my "sample." I end up with 3200 "firms" over 20 "years." The

[9] Using actual instead of average cash flow in the estimation produces identical results, since the estimation procedure averages observed cash flow.

estimation results are shown in Figure 4. Here, the solid lines represent theoretical hazards, and the dotted lines represent "estimated" hazards. Note that the model does indeed do 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. Although no guarantee that the duration model will perform well on real data, this result is a necessary condition for the duration model to be able to uncover hazard shape and height.

B. Results

I use this model to compare the estimated hazards of firms and segments categorized along three dimensions: size, diversification, and access to external financial markets. First, however, I examine the importance of controlling for cross-sectional heterogeneity, using my sample of small single-segment firms. I focus on this sample because it is involved in all of the tests that follow. Table 4 presents the results from estimating two models: one that controls for cross-sectional heterogeneity and one that does not. The estimated coefficients on the year and industry dummies are omitted and are almost always significant in all of the results that follow. Each column contains the estimates corresponding to each of the different spike thresholds—1, 1.5, and 2 standard deviations. The log-likelihoods from the no-heterogeneity models on the right are much lower than the log-likelihoods from the models on the left, which do control for heterogeneity. Indeed, standard likelihood ratio tests produce rejections of all of the no-heterogeneity models. Consistent with this result is the significance of the estimates of the heterogeneity variance, which are labeled σ^2. The most interesting aspect of the table is the comparison of the baseline hazards, which are indicated by the entries labeled "$\exp(\gamma_i)$." For example, the estimate of $\exp(\gamma_3)$ is the probability of ending an inaction spell, conditional on the spell lasting at least three years. Note that all of the estimated hazards from the heterogeneity model slope upwards; that is, the estimates of $\exp(\gamma_i)$ increase with i. This result is broadly consistent with one of the predictions from the theoretical model: fixed costs of adjustment result in upward sloping hazards. In contrast, the estimated hazards from the no-heterogeneity model slope downwards. The stark differences in the slopes of the baseline hazards from the two models can be seen in Figure

5, which presents the estimates from the two standard deviation threshold columns. The difference in slope indicates that for the small single-segment firms, the cross-sectional pattern of investment spikes does not match the pattern for any particular firm. The result can be understood as follows: the inclusion of heterogeneity in this hazard model acts loosely as the inclusion of fixed effects in a panel-data model in that both isolate the behavior of an individual over time. Given the superior performance of the heterogeneity model, all results that follow will be from this specification.

Next I examine the hazards from groups of firms categorized by size and diversification. As explained in the previous section, investment by large firms or segments is more likely to be the product of aggregated asynchronous decisions, and hazard estimates from these groups are unlikely to be upward sloping. Table 5 contains hazard model estimates for large single-segment firms and large conglomerates. The most important result in Table 5 is the low flat baseline hazards for both groups. This finding is consistent with the prediction of the theoretical model that aggregation lowers hazards. A related difference is the insignificance of the estimates of the heterogeneity variance. Roughly speaking, for these firms, the cross-sectional distribution of spells is close to the flat individual time-series distribution. Finally, this evidence has an important implication for the empirical investment literature that uses firm size as a proxy for access to external financial markets.[10] Any differences in the behavior of small versus large firms may be due to aggregation issues rather than finance constraints. The evidence in Table 5 does admit, however, a clear alternative interpretation: aggregation issues are unimportant, conglomerates and large single-segment firms face finance constraints, and small single-segment firms do not. Although implausible, this possibility begs for an attempt to disentangle finance effects from aggregation effects.

To do so, I concentrate my analysis on small single-segment firms and small segments of conglomerates, focusing on my central categorization criterion—access to external financial markets. By excluding large stand-alone firms, large segments, and diversified firms from

[10] Studies that use size as a proxy for financing constraints include Gilchrist and Himmelberg (1995), Kaplan and Zingales (1997), and Erickson and Whited (2000). The first claims that small firms appear more constrained than large firms; the second claims that small firms appear less constrained than large firms; and the third finds no evidence of constraints in either.

the analysis, I hope to mitigate the aggregation effects that could contaminate my results. Following much of the literature on external finance constraints, my primary tests of the interaction between finance and investment are based on comparing the behavior of subsamples of firms. The null hypothesis for the three such tests that follow is that the baseline hazard is the same across groups of observations classified by indicators of access to external finance. Note that the rest of the hazard is allowed to vary across groups. This feature is important, since 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 of firms is lower than the baseline hazard for an "unconstrained" group. Structuring the null and alternative hypotheses in this way is crucial, because none of my sample-splitting variables will produce perfect sorting of observations into constrained and unconstrained groups. As emphasized in the introduction, the structure of the null implies that imperfect sorting will only lower the power of the tests but will not affect the size.

The first experiment along this line is a comparison of small single-segment firms who differ in their dividend policies. Because dividend payment is prima facia evidence of the availability of internally generated funds, one can assume that a firm that never distributes cash to its shareholders will be more likely to need external finance than one that does. I group small firms according to whether they have a consistent history of paying dividends or not. Because share repurchases can be thought of as a substitute for dividends, I add repurchases to dividends when splitting the sample. 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. Using lagged distribution behavior as a classification variable mitigates the simultaneity problem that arises because distributions and investment are joint decisions. In other words, this sample splitting variable is at the very least predetermined, if not exogenous. Table 5 shows that the estimated baseline hazards for both groups are upward sloping and that those for the dividend group are higher than those for the no-dividend group. These differences are significant at the five percent level in all but two instances. This difference is illustrated in

Figure 6, which shows the baseline hazards for the two standard deviation threshold.

Second, I split my sample of small firms once again on the basis of size in an identical manner as before. I use firm size in part because it has been used by numerous authors as a measure of financial constraints, in part because it is arguably exogenous to the current investment decision, and in part because I want to determine whether aggregation effects are present in my sample of small firms. One can argue that it is possible for a small firm or segment to be a compilation of even smaller sub-segments. Although the upward sloping hazards for the small firms and segments suggest that this scenario is implausible, I explore this possiblity further by noting that if the sub-segment problem is important (and finance constraints are not), then tiny firms should have higher hazards than the firms that are merely small. Table 6 reveals that this is not the case: the "micro" firms have lower hazards than rest of the small firms. These differences are significant at the five percent level in all but three instances. Illustrated in Figure 7 for the two standard deviation 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.

Third, I run separate hazard models on my group of small single-segment firms and a group of same-sized segments of conglomerates. This experiment is based on the idea that large conglomerates have better relationships 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 7, which shows that the firms have lower hazard rates than the segments. Here, the differences are significant at the five percent level in all but four of the twenty-one instances. The difference in the hazard rates for the two standard deviation threshold is illustrated in Figure 8. To the extent that belonging to a conglomerate is an indicator of easy access to finance, these results also are consistent with the idea that external finance constraints can affect investment. However, although tangentially related to the idea in Williamson (1975) that conglomerates operate internal capital markets, the result says little about the efficiency of internal capital markets, since any test of efficiency needs 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.

It is worth asking whether conglomerate segments and stand-alone firms too fundamentally different to be compared via a simple model. On one hand Maksimovic and Phillips (2002) provide evidence that small peripheral conglomerate segments tend to be less productive than main segments. More importantly for the current results, they find that investment is much more responsive to productivity for single-segment firms than it is for small conglomerate segments. On the other, my model does allow for differential sensitivity of spell length to my measure of investment opportunities. Further, the Maksimovic and Phillips results pertain to a comparison of small segments to all stand-alone firms, whereas my comparison is of small segments to small stand-alones. Finally, my results are not an artifact of the segments belonging to different industries than the firms. I do include industry dummies, and eighty-nine percent of the two-digit industries represented by the sample of small firms are also represented by the sample of small segments, and eighty-eight percent of the two-digit industries represented by the sample of small segments are also represented by the sample of small firms.

Two further issues arise in interpreting all of these results. First, a possible alternative explanation is based on the idea that firms respond to finance constraints by undertaking more often projects that are reduced in size but that still qualify as spikes. 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 policy is only optimal if the firm faces convex adjustment costs, or if the cost of external finance is convex and greater than a nonconvex physical adjustment cost. Since convex costs induce downward sloping hazards, and since all of the subsamples of firms and segments have upward sloping hazards, this explanation is unlikely. Second, it is important to know how much the different groups invest both during an inactivity spell and a spike. For example, suppose that no group is "constrained" and that the groups labeled "constrained" either invest more in the off-spike periods or invest more during the spike periods than the "unconstrained" groups. 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.[11]

As an additional test I include as an explanatory variable lagged net liquid assets: net working capital less inventories, where this quantity is expressed as a fraction of total assets. The intent is to see if accumulation of liquid assets precedes an investment spike. I do not split the sample in this case, since liquid assets are a continuous variable and have no clear break point. As noted in the introduction, liquid assets can have two opposing effects on the height of the hazard. First, small firms with low liquid asset positions may have limited access to debt markets, presumably because they lack the collateral to back their borrowing. Therefore, liquid assets should have a positive coefficient in the hazard model. Further, an accumulation of liquid assets can indicate the presence of financial constraints if the firm needs to save the funds for a large project rather than obtaining them externally. This behavior is also consistent with a positive coefficient. In contrast, Opler, Pinkowitz, Stulz, and Williamson (1999) note that firms with access to external financial markets do not *need* to keep stocks of liquid assets on hand. In this case the coefficient on liquid assets should be negative. An insignificant coefficient could mean one of two things: the above two effects offset one another, or finance and investment are independent. The results from a model that includes liquid assets are in Table 8. As in the other hazard models for the small single-segment firms, the estimated hazards slope upwards. Note the positive estimates of the coefficients on liquid assets, which are significant for the 1 and 1.5 standard deviation thresholds. This result supports the role of liquid assets as a sign of financial health or saving behavior, and it is consistent with the presence of external finance constraints.

Finally, I examine the effect of the lagged (book) debt-to-assets ratio on the hazard. Here, either the debt-overhang problem of Myers (1977), the truncation effect in Hennessy

[11]Two other popular splitting variables include the existence of a corporate bond rating and the index of finacial constraints in Kaplan and Zingales (1997). I cannot use the first because very few of the small firm have bond ratings. I choose not to use the second, because it is endogenously determined with investment, because it contains Tobin's q as a component, and because of evidence that Tobin's q is a very noisy measure of investment opportunities. See Erickson and Whited (2000, 2002).

(2002), or the effects of credit constraints summarized in Gertler (1988) ought to lower the hazard. Although looking at the effect of debt on the hazard cannot distinguish these three effects, doing so is nonetheless interesting in that can provide evidence on the broader question of whether the Modigliani-Miller theorem is empirically important or not. As shown in Table 9, for all three spike thresholds, lagged debt appears with a large negative coefficient. If capital structure were irrelevant, then one would expect to see a positive effect as firms borrow to fund projects. However, the negative effect is at the very least consistent with a view of a world with financial frictions.

VI. 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. One 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 is of this approach deals with measurement issues. I have argued that because my model offers guidance in finding a simple, easily measured control for productivity, the measurement issues are not as severe as those facing regressions of investment on q. Finally, for researchers interested in the interaction between finance and investment, a new angle appears necessary, given the contradictory and inconclusive evidence from a decade and a half of cash-flow sensitivity tests.

Within this framework I use a simple theoretical model 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 an arguably good proxy 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 that aggregation of asynchronous decisions affects investment hazards. As predicted by my fixed-costs model, small single-segment firms have upward sloping hazards; and large single-segment firms and conglomerates have lower hazards than small single-segment firms. This result casts doubt on the common practice of using size as a proxy for access to external capital markets and begs for further research into the widely found "firm size effect" on investment. The most important result is evidence that access to cheap finance lowers investment hazards. Small single-segment firms that distribute cash to shareholders have significantly higher hazards than small single-segment firms that do not. In addition, very small single segment firms have lower hazards than the rest of the small single segment firms; and small segments have significantly higher hazards than their stand-alone counterparts. Finally, lagged stocks of liquid assets raise hazards, and lagged stocks of debt lower hazards.

In sum, the paper has provided a new type of evidence that access to external finance does indeed influence 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 indeed explore other ways to exploit these models. Once avenue consists of looking at plant-level data. Another, more methodological avenue is structural estimation. 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

Production takes place according to

$$\Pi(K, z) = zK^{\theta}. \tag{8}$$

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 follow Cooper and Haltiwanger (2002) and set $\theta = 0.5$.

Next I consider the financing function, whose shape requires considerably more thought. External finance may be more costly than internal finance for several reasons. First, information asymmetries may external investors to require a "lemons" premium. Similarly, external investors may 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 will provide a very conservative estimate of the costs of external finance. To quantify these 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

$$\phi(e) = 0.0341 + 0.0241(e), \tag{9}$$

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 (2002) and set $c = 0.05$. Finally, I set the discount rate equal to 6%, which implies a discount factor $\beta = 0.943$; and I set the depreciation rate equal to the average in my data of depreciation divided by total assets: 0.047. 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,

$$\ln(z') = 0.61 \ln(z) + u', \tag{10}$$

where $u' \sim N(0, 0.11^2)$. I obtain the autoregressive parameter and the error variance from my data by performing a panel autoregression of the variable $\ln\left(\text{Sales}/\text{Assets}^{\theta}\right)$; see Holtz-Eakin, Newey, and Rosen (1988).

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

$$\left[k^*(1-d)^{30}, \ldots, k^*(1-d)^2, k^*(1-d), k^*, k^*/(1-d), \ldots, k^*/(1-d)^{30}\right],$$

where k^* is the steady-state capital stock of a model without any adjustment costs. I let the productivity shock have 61 points of support, transforming (10) into a discrete-state Markov chain using the method in Tauchen (1986).

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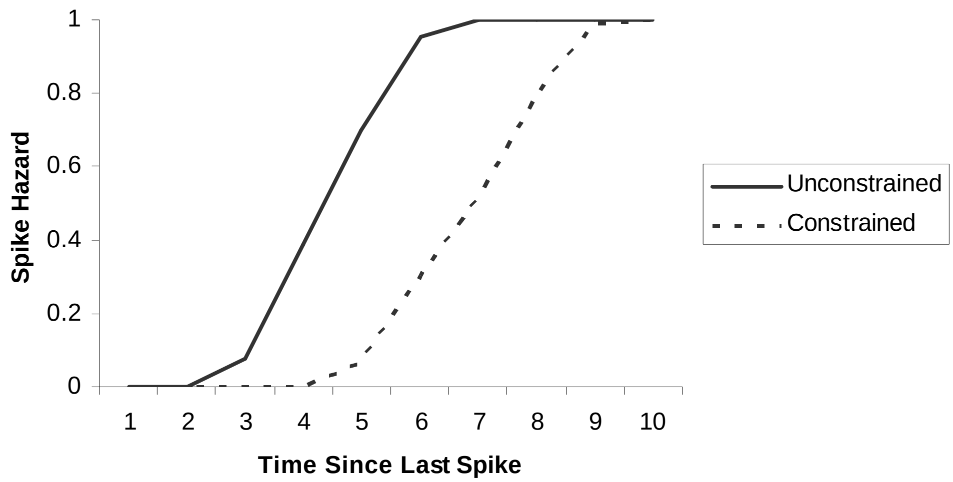
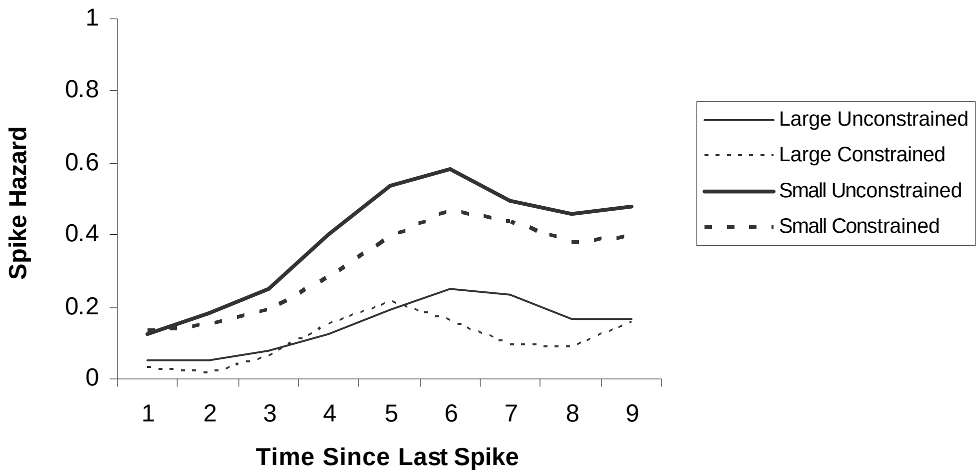
Figure 1
Theoretical Adjustment Hazards
Single Segment Firms



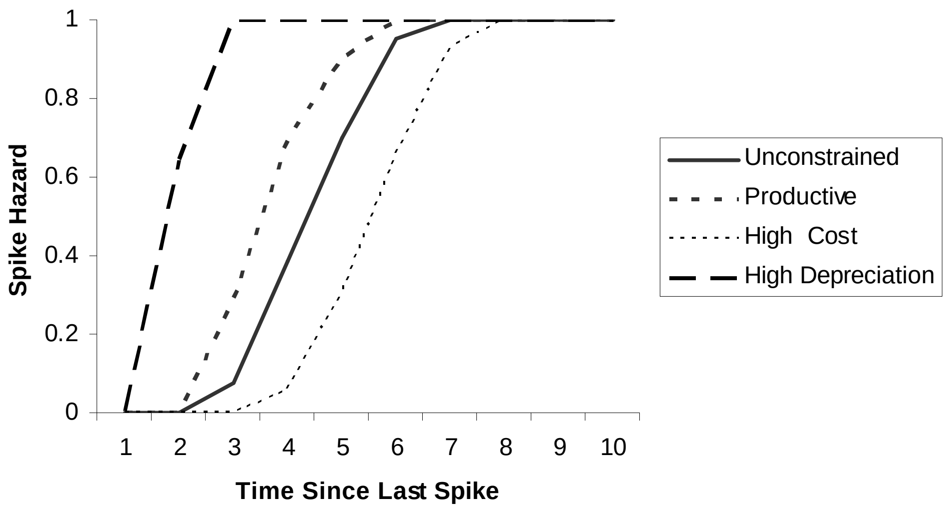
The hazard functions are simulated from the investment model in Section 2. The horizonatal axis measures the length of time since the last investment spike, and the vertical axis measures the probability of a spike, given that the firm has remained inactive up to that time. "Baseline" refers to a firm without costly external finance, and "constrained" refers to a firm with costly external finance.

Figure 2
Theoretical Adjustment Hazards
Conglomerates



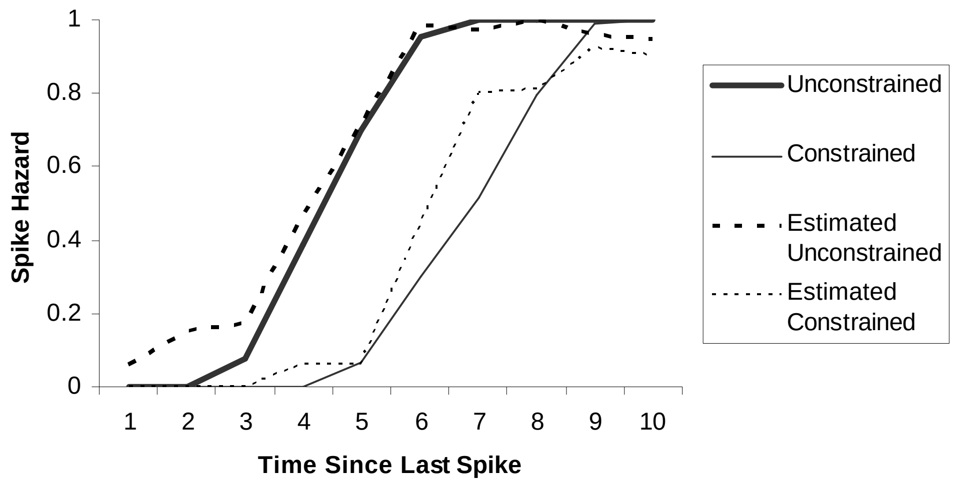
The hazard functions are simulated from the investment model in Section 2. The horizonatal axis measures the length of time since the last investment spike, and the vertical axis measures the probability of a spike, given that the firm has remained inactive up to that time. "Baseline" refers to a firm 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.

Figure 3
Theoretical Adjustment Hazards
Single Segment Firms



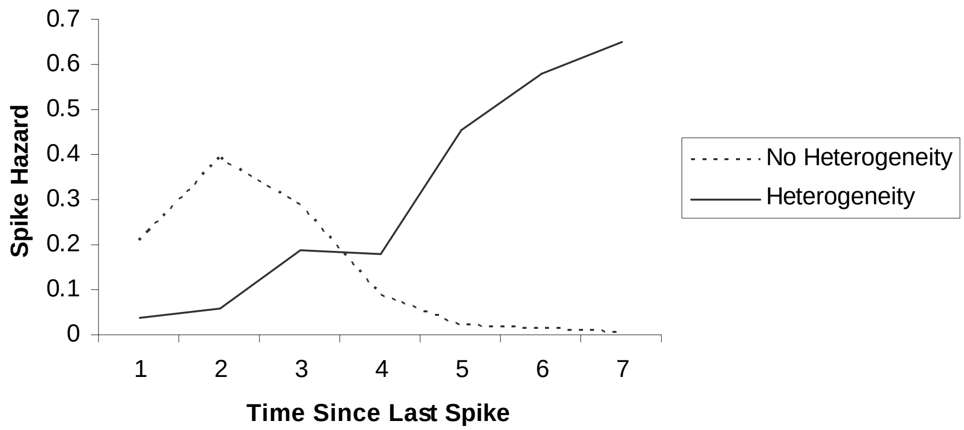
The hazard functions are simulated from the investment model in Section 2. The horizonatal axis measures the length of time since the last investment spike, and the vertical axis measures the probability of a spike, given that the firm has remained inactive up to that time. "Baseline" refers to a firm 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.

Figure 4
Theoretical and "Estimated" Adjustment Hazards



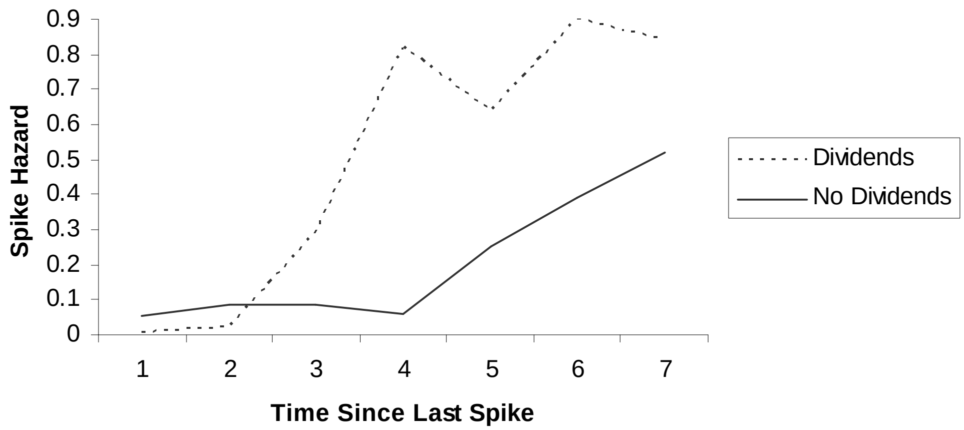
The constrained and unconstrained hazard functions are simulated from the investment model in Section 2. The "estimated" constrained and unconstrained hazard functions are estimated using the methods described in Section 4, with data simulated from the investment model in Section 2 The horizonatal axis 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.

Figure 5
Estimated Hazards
Heterogeneity versus No Heterogeneity



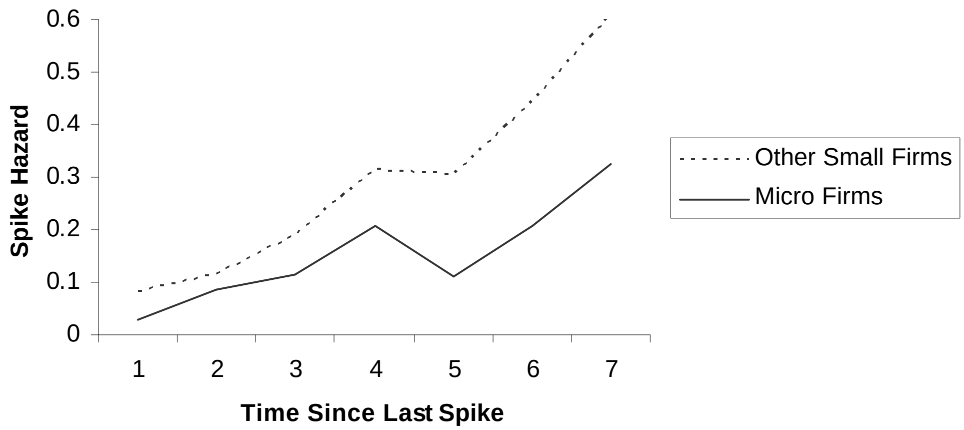
Estimates are from the two-standard-deviation threshold columns of Table 3. “Heterogeneity” refers to estimates from a model that allows for unobservable cross-sectional heterogeneity. “No Heterogeneity” refers to estimates from a model that does not. The horizonatal axis measures the length of time 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. Calculations are based on a sample of single-segment non-financial firms from the combined annual and full coverage 2001 Standard and Poor’s COMPUSTAT industrial files that are also covered by COMPUSTAT’S Business Information File. The sample period is 1983 through 1997.

Figure 6
Estimated Hazards
Dividends versus No Dividends



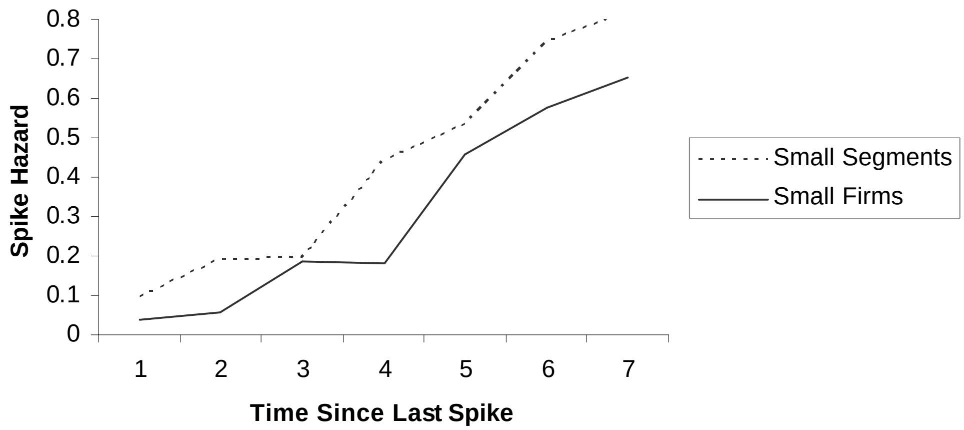
Estimates are from the two-standard-deviation threshold columns columns of Table 5. "No Dividends" refers to estimates from a sample of small single-segment firms that consistently pay no dividends. "Dividends" refers to estimates from a sample of small single-segment firms that does pay dividends. The horizonatal 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. Calculations are based on a sample of single-segment non-financial firms from the combined annual and full coverage 2001 Standard and Poor's COMPUSTAT industrial files that are also covered by COMPUSTAT'S Business Information File. The sample period is 1983 through 1997.

Figure 7
Estimated Hazards
Micro versus Small Firms



Estimates are from the twenty percent threshold columns of Table 6. "Micro Firms" refers 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" refers to estimates from the rest of the sample of small single-segment firms. The horizonatal 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. Calculations are based on a sample of single-segment non-financial firms from the combined annual and full coverage 2001 Standard and Poor's COMPUSTAT industrial files that are also covered by COMPUSTAT'S Business Information File. The sample period is 1983 through 1997.

Figure 8
Estimated Hazards
Small Firms versus Small Segments



Estimates are from the twenty percent threshold columns of Table 7. “Small Firms” refers to estimates from a sample of small single-segment firms. “Small Segments” refers to estimates from a sample of small segments of conglomerates. The horizonatal 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. Calculations are based on a sample of single-segment non-financial firms from the combined annual and full coverage 2001 Standard and Poor’s COMPUSTAT industrial files that are also covered by COMPUSTAT’S Business Information File. The sample period is 1983 through 1997.

Table 1: Summary Statistics

Calculations are based on a sample of non-financial firms and segments of firms from the combined annual and full coverage 2001 Standard and Poor's COMPUSTAT industrial files that are also covered by COMPUSTAT's Business Information File. The sample period is 1983 through 1997. Assets are expressed in millions of 1997 dollars.

	Mean	Median	Standard Deviation
Small Single-Segment Firms			
Investment/Assets	0.071	0.041	0.092
Depreciation/Assets	0.054	0.041	0.055
Cash Flow	0.144	0.168	0.285
Sales Growth	0.103	0.058	0.357
Assets	14.563	9.869	14.988
Large Single-Segment Firms			
Investment/Assets	0.083	0.063	0.076
Depreciation/Assets	0.052	0.044	0.036
Cash Flow	0.177	0.183	0.144
Sales Growth	0.103	0.067	0.260
Assets	1,096	161.2	5,507
Multiple-Segment Firms			
Investment/Assets	0.073	0.059	0.062
Depreciation/Assets	0.048	0.044	0.030
Cash Flow	0.168	0.173	0.107
Sales Growth	0.055	0.043	0.228
Assets	3,655	356.8	12,763
Small Segments			
Investment/Assets	0.074	0.044	0.097
Depreciation/Assets	0.062	0.047	0.065
Cash Flow	0.181	0.169	0.372
Sales Growth	0.070	0.036	0.331
Assets	12.093	8.249	13.101
Large Segments			
Investment/Assets	0.079	0.061	0.088
Depreciation/Assets	0.056	0.049	0.039
Cash Flow	0.187	0.170	0.181
Sales Growth	0.062	0.041	0.246
Assets	1,330	265.6	4,373

Table 2: Investment Spikes and Inaction Spells

Calculations are based on a sample of non-financial firms and segments of firms from the combined annual and full coverage 2001 Standard and Poor's COMPUSTAT industrial files that are also covered by COMPUSTAT's Business Information File. The sample period is 1983 through 1997. SD stands for standard deviation.

Threshold	1 SD	1.5 SD's	2 SD's
Small Single-Segment Firms			
Fraction of Spikes	0.110	0.069	0.046
Number of Spells	634	387	240
Average Length	3.106	3.703	4.283
Fraction Censored	0.383	0.475	0.558
Average Length Censored	5.066	5.549	6.112
Fraction Uncensored	0.617	0.525	0.442
Average Length Uncensored	1.887	2.030	1.972
Large Single-Segment Firms			
Fraction of Spikes	0.107	0.057	0.031
Number of Spells	1541	782	392
Average Length	2.930	3.693	4.541
Fraction Censored	0.356	0.468	0.594
Average Length Censored	5.290	5.844	6.464
Fraction Uncensored	0.644	0.532	0.406
Average Length Uncensored	1.627	1.800	1.723
Multiple-Segment Firms			
Fraction of Spikes	0.069	0.035	0.020
Number of Spells	667	316	174
Average Length	3.724	4.380	4.598
Fraction Censored	0.433	0.528	0.575
Average Length Censored	6.232	6.790	6.690
Fraction Uncensored	0.567	0.472	0.425
Average Length Uncensored	1.807	1.678	1.770
Small Segments			
Fraction of Spikes	0.126	0.083	0.058
Number of Spells	841	550	360
Average Length	2.810	3.236	3.517
Fraction Censored	0.346	0.424	0.464
Average Length Censored	4.715	5.034	5.401
Fraction Uncensored	0.654	0.576	0.536
Average Length Uncensored	1.802	1.915	1.886
Large Segments			
Fraction of Spikes	0.097	0.050	0.028
Number of Spells	1886	921	491
Average Length	2.690	3.130	3.580
Fraction Censored	0.323	0.401	0.473
Average Length Censored	5.039	5.480	5.871
Fraction Uncensored	0.677	0.599	0.527
Average Length Uncensored	1.567	1.560	1.529

Table 3: Semiparametric Hazard Model Estimates: Small Single-Segment Firms

Calculations are based on a sample of non-financial firms from the combined annual and full coverage 2001 Standard and Poor's COMPUSTAT industrial files that are also covered by COMPUSTAT's Business Information File. The sample period is 1983 through 1997. The rows labeled $\exp(\gamma_i)$ contain estimates of the baseline hazard, where the subscript refers to the number of years since the last spike. 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.

	Heterogeneity			No Heterogeneity		
Threshold	1	1.5	2	1	1.5	2
Profit	1.1788	1.1662	1.2082	2.0711	2.2921	2.0842
	(0.1291)	(0.0992)	(0.1874)	(1.5167)	(1.5102)	(1.7173)
$\exp(\gamma_1)$	0.0484	0.0332	0.0360	0.3204	0.3957	0.2079
	(0.0053)	(0.0048)	(0.0074)	(0.0129)	(0.0139)	(0.0388)
$\exp(\gamma_2)$	0.0827	0.0644	0.0568	0.2774	0.3572	0.3921
	(0.0111)	(0.0062)	(0.0052)	(0.0093)	(0.0085)	(0.0271)
$\exp(\gamma_3)$	0.0644	0.1459	0.1861	0.1686	0.1476	0.2875
	(0.0040)	(0.0092)	(0.0143)	(0.0084)	(0.0132)	(0.0174)
$\exp(\gamma_4)$	0.1170	0.2100	0.1796	0.2021	0.2099	0.0880
	(0.0087)	(0.0074)	(0.0078)	(0.0102)	(0.0140)	(0.0059)
$\exp(\gamma_5)$	0.2314	0.3121	0.4553	0.0657	0.0695	0.0202
	(0.0128)	(0.0114)	(0.0171)	(0.0034)	(0.0048)	(0.0010)
$\exp(\gamma_6)$	0.5188	0.4420	0.5776	0.0219	0.0178	0.0107
	(0.0418)	(0.0176)	(0.0289)	(0.0011)	(0.0010)	(0.0007)
$\exp(\gamma_7)$	0.7992	0.6212	0.6513	0.0033	0.0031	0.0025
	(0.0547)	(0.0279)	(0.0660)	(0.0001)	(0.0001)	(0.0001)
σ^2	1.5483	2.1808	2.1476			
	(0.0705)	(0.1203)	(0.1267)			
Log-likelihood	-395.5552	-232.1355	-158.5503	-727.9671	-476.7745	-240.5989
Sample Size	634	387	240	634	387	240

Table 4: Semiparametric Hazard Model Estimates: Firms Grouped by Size and Diversification

Calculations are based on a sample of non-financial 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 1984 through 1997. The rows labeled $\exp(\gamma_i)$ contain estimates of the baseline hazard, where the subscript refers to the number of years since the last spike. 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.

	Large Single-Segment Firms			Conglomerates		
Threshold	1	1.5	2	1	1.5	2
Profit	1.9077	2.1001	2.6044	2.5286	2.1885	2.1008
	(0.0611)	(0.1273)	(0.3050)	(0.0395)	(0.0515)	(0.1508)
$\exp(\gamma_1)$	0.0654	0.0576	0.0478	0.0507	0.0558	0.0294
	(0.0035)	(0.0045)	(0.0067)	(0.0044)	(0.0101)	(0.0066)
$\exp(\gamma_2)$	0.0296	0.0169	0.0253	0.0222	0.0258	0.0319
	(0.0023)	(0.0025)	(0.0055)	(0.0028)	(0.0057)	(0.0088)
$\exp(\gamma_3)$	0.0254	0.0213	0.0106	0.0181	0.0595	0.0616
	(0.0019)	(0.0031)	(0.0031)	(0.0020)	(0.0155)	(0.0196)
$\exp(\gamma_4)$	0.0266	0.0256	0.0183	0.0181	0.0605	0.0373
	(0.0018)	(0.0035)	(0.0051)	(0.0018)	(0.0181)	(0.0096)
$\exp(\gamma_5)$	0.0168	0.0324	0.0145	0.0293	0.0149	0.0243
	(0.0012)	(0.0052)	(0.0028)	(0.0057)	(0.0031)	(0.0104)
$\exp(\gamma_6)$	0.0156	0.0077	0.0193	0.0216	0.0464	0.0972
	(0.0012)	(0.0011)	(0.0036)	(0.0029)	(0.0121)	(0.0254)
$\exp(\gamma_7)$	0.6183	0.4830	0.5427	0.6006	0.9900	0.3012
	(0.0236)	(0.0255)	(0.0787)	(0.0341)	(0.1127)	(0.0151)
σ^2	0.0215	-0.0085	0.1646	0.0530	1.2398	1.3799
	(0.1272)	(0.0323)	(0.3435)	(0.1151)	(0.1366)	(0.1511)
Log-likelihood	-1503.3714	-721.6725	-304.7923	-624.3225	-254.5687	-134.2939
Sample Size	1541	782	392	667	316	174

Table 5: Semiparametric Hazard Model Estimates: Small Single-Segment Firms Grouped by Lagged Dividend Payout

Calculations are based on a sample of non-financial firms from the combined annual and full coverage 2001 Standard and Poor's COMPUSTAT industrial files that are also covered by COMPUSTAT's Business Information File. The sample period is 1983 through 1997. The rows labeled $\exp(\gamma_i)$ contain estimates of the baseline hazard, where the subscript refers to the number of years since the last spike. 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.

	No Dividends			Dividends		
Threshold	1	1.5	2	1	1.5	2
Profit	0.8655	0.1162	1.7650	2.8625	2.4908	1.6925
	(0.1159)	(0.2404)	(0.0743)	(0.0466)	(0.0478)	(0.0490)
$\exp(\gamma_1)$	0.0514	0.0421	0.0530	0.0129	0.0082	0.0053
	(0.0058)	(0.0063)	(0.0113)	(0.0030)	(0.0025)	(0.0023)
$\exp(\gamma_2)$	0.0812	0.0703	0.0873	0.0658	0.0329	0.0196
	(0.0080)	(0.0077)	(0.0161)	(0.0054)	(0.0050)	(0.0045)
$\exp(\gamma_3)$	0.0542	0.0496	0.0831	0.3122	0.3667	0.2875
	(0.0034)	(0.0041)	(0.0058)	(0.0112)	(0.0154)	(0.0137)
$\exp(\gamma_4)$	0.1046	0.1217	0.0574	0.7447	0.8247	0.8192
	(0.0050)	(0.0069)	(0.0070)	(0.0219)	(0.0329)	(0.0911)
$\exp(\gamma_5)$	0.1448	0.1053	0.2540	0.8980	0.5785	0.6390
	(0.0068)	(0.0080)	(0.0091)	(0.0295)	(0.0367)	(0.0220)
$\exp(\gamma_6)$	0.2667	0.4651	0.3907	0.6121	0.7811	0.8983
	(0.0128)	(0.0472)	(0.1208)	(0.0220)	(0.0322)	(0.0597)
$\exp(\gamma_7)$	0.3666	0.4012	0.5189	0.8704	0.7150	0.8430
	(0.0180)	(0.0165)	(0.0219)	(0.0187)	(0.0237)	(0.0388)
σ^2	1.4373	1.5859	1.7377	3.1691	3.9116	4.6803
	(0.0759)	(0.1126)	(0.1555)	(0.1556)	(0.2643)	(0.3730)
Log-likelihood	-219.6960	-112.0266	-93.6215	-199.3434	-114.3573	-83.2705
Sample Size	344	198	121	290	189	119

Table 6: Semiparametric Hazard Model Estimates: Micro versus Small Single-Segment Firms

Calculations are based on a sample of non-financial firms from the combined annual and full coverage 2001 Standard and Poor's COMPUSTAT industrial files that are also covered by COMPUSTAT's Business Information File. The sample period is 1983 through 1997. The rows labeled $\exp(\gamma_i)$ contain estimates of the baseline hazard, where the subscript refers to the number of years since the last spike. 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.

	Micro Firms			Other Small Firms		
Threshold	1	1.5	2	1	1.5	2
Profit	1.1400	1.1979	0.9050	0.7777	1.8894	1.9006
	(0.1225)	(0.1309)	(0.1965)	(0.1169)	(0.0432)	(0.0525)
$\exp(\gamma_1)$	0.0358	0.0263	0.0287	0.0588	0.1064	0.0812
	(0.0050)	(0.0050)	(0.0080)	(0.0064)	(0.0063)	(0.0051)
$\exp(\gamma_2)$	0.0799	0.1301	0.0865	0.0704	0.1472	0.1149
	(0.0123)	(0.0264)	(0.0213)	(0.0114)	(0.0086)	(0.0068)
$\exp(\gamma_3)$	0.1292	0.1134	0.1130	0.1075	0.2523	0.1906
	(0.0085)	(0.0069)	(0.0115)	(0.0086)	(0.0106)	(0.0105)
$\exp(\gamma_4)$	0.1522	0.1846	0.2082	0.2887	0.3185	0.3137
	(0.0068)	(0.0119)	(0.0188)	(0.0141)	(0.0125)	(0.0118)
$\exp(\gamma_5)$	0.1231	0.1229	0.1107	0.8331	0.4632	0.3052
	(0.0055)	(0.0065)	(0.0078)	(0.0907)	(0.0193)	(0.0161)
$\exp(\gamma_6)$	0.2488	0.1813	0.2066	0.8552	0.6044	0.4446
	(0.0226)	(0.0130)	(0.0218)	(0.0501)	(0.0239)	(0.0224)
$\exp(\gamma_7)$	0.3906	0.2965	0.3245	0.8269	0.8187	0.6065
	(0.0129)	(0.0173)	(0.0232)	(0.0407)	(0.0321)	(0.0304)
σ^2	1.7606	2.0963	2.3346	1.7725	2.8410	3.0492
	(0.1211)	(0.1772)	(0.2939)	(0.1031)	(0.1281)	(0.1848)
Log-likelihood	-165.9726	-92.5980	-54.3223	-238.1268	-133.3418	-113.6867
Sample Size	251	152	99	383	235	141

Table 7: Semiparametric Hazard Model Estimates: Small Single-Segment Firms versus Small Segments

Calculations are based on a sample of non-financial 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 1984 through 1997. The rows labeled $\exp(\gamma_i)$ contain estimates of the baseline hazard, where the subscript refers to the number of years since the last spike. 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.

	Single-Segment Firms			Segments		
Threshold	1	1.5	2	1	1.5	2
Profit	1.1788	1.1662	1.2082	1.0793	0.9003	0.7572
	(0.1291)	(0.0992)	(0.1874)	(0.0385)	(0.0331)	(0.0398)
$\exp(\gamma_1)$	0.0484	0.0332	0.0360	0.1033	0.0974	0.0937
	(0.0053)	(0.0048)	(0.0074)	(0.0095)	(0.0118)	(0.0148)
$\exp(\gamma_2)$	0.0827	0.0644	0.0568	0.1723	0.1808	0.1912
	(0.0111)	(0.0062)	(0.0052)	(0.0048)	(0.0063)	(0.0078)
$\exp(\gamma_3)$	0.0644	0.1459	0.1861	0.2850	0.2524	0.1956
	(0.0040)	(0.0092)	(0.0143)	(0.0075)	(0.0077)	(0.0085)
$\exp(\gamma_4)$	0.1170	0.2100	0.1796	0.4813	0.4493	0.4422
	(0.0087)	(0.0074)	(0.0078)	(0.0112)	(0.0129)	(0.0158)
$\exp(\gamma_5)$	0.2314	0.3121	0.4553	0.6258	0.5531	0.5355
	(0.0128)	(0.0114)	(0.0171)	(0.0147)	(0.0160)	(0.0190)
$\exp(\gamma_6)$	0.5188	0.4420	0.5776	0.9252	0.9223	0.7437
	(0.0418)	(0.0176)	(0.0289)	(0.0215)	(0.0283)	(0.0263)
$\exp(\gamma_7)$	0.7992	0.6212	0.6513	0.7458	0.7336	0.8185
	(0.0547)	(0.0279)	(0.0660)	(0.0181)	(0.0212)	(0.0273)
σ^2	1.5483	2.1808	2.1476	1.8406	2.0691	2.2292
	(0.0705)	(0.1203)	(0.1267)	(0.0489)	(0.0891)	(0.1186)
Log-likelihood	-395.5552	-232.1355	-158.5503	-660.5470	-383.9469	-231.8074
Sample Size	634	387	240	841	550	360

Table 8: Semiparametric Hazard Model Estimates: Liquid Asset and Debt Models

Calculations are based on a sample of non-financial firms and segments of conglomerates from the combined annual and full coverage 2001 Standard and Poor's COMPUSTAT industrial files that are also covered by COMPUSTAT's Business Information File. The sample period is 1983 through 1997. The rows labeled $\exp(\gamma_i)$ contain estimates of the baseline hazard, where the subscript refers to the number of years since the last spike. The row labeled σ^2 contain estimates of the variance of cross-sectional heterogeneity of the hazards. The "financial variable" for the first model is the ratio of liquid assets to total assets, and the "financial variable" for the second model is the book value of total long-term debt divided by total assets. Standard errors are in parentheses under the parameter estimates.

	Liquid Asset Model			Debt Model		
Threshold	1	1.5	2	1	1.5	2
Profit	1.2831	1.0291	1.2446	1.1782	0.8086	1.0788
	(0.0661)	(0.1014)	(0.1465)	(0.1134)	(0.1214)	(0.1837)
Financial Variable	0.1077	0.0626	0.0512	-0.7021	-0.6190	-1.4434
	(0.0257)	(0.0344)	(0.0397)	(0.0490)	(0.0582)	(0.1245)
$\exp(\gamma_1)$	0.0918	0.0737	0.0788	0.0388	0.0293	0.0348
	(0.0086)	(0.0097)	(0.0131)	(0.0035)	(0.0039)	(0.0067)
$\exp(\gamma_2)$	0.0865	0.0902	0.0617	0.0399	0.0366	0.0644
	(0.0026)	(0.0039)	(0.0137)	(0.0019)	(0.0027)	(0.0137)
$\exp(\gamma_3)$	0.0766	0.0828	0.1365	0.0487	0.0807	0.0774
	(0.0023)	(0.0041)	(0.0108)	(0.0022)	(0.0047)	(0.0130)
$\exp(\gamma_4)$	0.1125	0.1130	0.1365	0.0910	0.1162	0.1185
	(0.0034)	(0.0045)	(0.0058)	(0.0035)	(0.0045)	(0.0110)
$\exp(\gamma_5)$	0.1685	0.1763	0.0663	0.1536	0.1795	0.0464
	(0.0052)	(0.0058)	(0.0052)	(0.0048)	(0.0064)	(0.0054)
$\exp(\gamma_6)$	0.3160	0.2463	0.2728	0.3523	0.2568	0.2882
	(0.0059)	(0.0056)	(0.0113)	(0.0128)	(0.0095)	(0.0281)
$\exp(\gamma_7)$	0.4813	0.4571	0.5351	0.5195	0.4103	0.5730
	(0.0145)	(0.0175)	(0.0325)	(0.0242)	(0.0199)	(0.0438)
σ^2	1.1924	1.3702	1.3911	1.4001	1.8898	1.8273
	(0.0667)	(0.0987)	(0.1080)	(0.0690)	(0.1061)	(0.1294)
Log-likelihood	-372.3053	-230.0274	-143.0770	-327.4210	-214.6607	-134.9850
Sample Size	634	387	240	634	387	240