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ABSTRACT

R&D-intensive firms such as biotechnology and pharmaceutical companies follow very different corporate financial policies from firms in less R&D-intensive industries. To account for these differences, we propose an equilibrium model for such firms in which their capital structure, amount of R&D investment, and information disclosure policy are all endogenously determined in response to the degree of competition in the industry. The key results are that, as competition increases, such firms will: (1) increase R&D investment and reduce investment in assets-in-place that support existing products; (2) carry more cash and maintain less net debt; and (3) experience declining betas but greater total stock return volatility due to higher idiosyncratic risk. While the focus is on the biopharmaceutical industry, the results are broadly applicable to other R&D-intensive industries as well. We confirm the model's empirical implications using historical data from the biopharmaceutical industry, and our tests also deal with the endogeneity issue introduced by the fact that a firm's R&D investments and the product-market competition it faces influence each other.

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1 Introduction

R&D-intensive firms such as biopharmaceutical firms, which operate in an increasingly competitive and risky environment, are essential to the continued development of new drugs and therapeutics. They make large investments, and the outcomes of these investments (new drugs) are often a significant driver of economic growth and welfare. It is therefore important to understand the investment and financing decisions of these firms, the evolution of their risk characteristics, and the impact of competition on these. The goal of this paper is to theoretically and empirically examine these issues.

While existing theories of the corporation make numerous well-developed predictions of broad application to many industries, R&D-intensive firms have special characteristics that make the application of these theories unclear. For these firms, spending on R&D often dwarfs spending on property, plant, and equipment, while capital budgeting and financing for R&D can be quite different compared to other capital projects, due to the high-risk, staged nature of R&D investment and the absence of observable post-investment cash flows for many periods (see Myers and Howe (1997), who lay out these issues for the pharmaceutical industry). Additionally, competition in R&D-intensive industries affects the likelihood of winning a patent race associated with a given R&D investment as well as the profits following patent expiration. The biopharmaceutical (biopharma) industry provides a good example of the effect of competition between R&D-intensive firms. This industry has become increasingly competitive for a variety of reasons, including regulation, lower costs of entry due to improvements in technology, and the expiration of patents combined with high development costs of new therapeutics (e.g. Caves, Whinston, and Hurwitz (1991), Grabowski and Vernon (1992), and others). These factors have squeezed margins from existing products associated with assets-in-place, with marked implications for R&D investments into new products as well as the capital structure choices of these firms.[1]

[1]For example, the expiration of a patent and the subsequent entry of a generic drug in the marketplace. Another factor is the rapid improvement in technology in the past decades, which has allowed many competitors to enter the marketplace and offer products that directly compete with many long-established firms.

Like other firms, R&D-intensive firms make decisions within the context of the information environment in which they operate. In the standard analysis of investment and financing decisions, the firm's information environment is taken as given.[2] However, in practice, firms decide how much information to disclose, so that the informational gap between the firm's insiders and outside investors becomes partly *endogenous*. Decisions on information disclosure are made simultaneously with decisions on how much to invest in R&D, how much to invest in assets-in-place, and what capital structure to use. As the "two-audience" signaling literature (e.g. Bhattacharya and Ritter (1983)) has shown, disclosing information is a double-edged sword for the firm: it can reduce adverse selection problems and improve both the cost of and access to external finance, but it also reveals information to the firm's competitors, who can then free-ride on the firm's new ideas and introduce competing products that depress the firm's profits. However, it has not been recognized thus far that the tradeoff between the costs and benefits of disclosure depends on the firm's capital structure, and also influences it. For example, if the firm is largely dependent on debt financing, it is likely to withhold information about the upside potential of its project—information that is of limited value to its creditors, but potentially costly to disclose for competitive reasons. On the other hand, if the firm is largely reliant on equity, disclosing information about the upside is critical to lowering the share of ownership it must give up to obtain financing. These issues are central in R&D-intensive firms such as those in the biopharma industry, where testing and development of proprietary therapeutics is vital to survival and success.[3] Consequently, the cost-benefit tradeoff involved in information disclosure, and the effects of

The implications of these developments are potentially pervasive. For example, see Bloom, Schankerman, and Van Reenan (2013), who examine the effects of R&D spillovers, which may be either positive (due to improvements in knowledge and technology) or negative (due to business competition). Also, see Kogan and Papanikolaou (2010, 2014), who model the effects technology shocks on assets-in-place and growth opportunities, and derive macroeconomic and asset pricing implications. And Haddad, Ho, and Loualiche (2014) explore the impact of disagreement about the details of R&D on competition, which can lead to innovation booms.

[2]The exceptions to this are signaling models, in which the firm's debt choice signals information about its value, i.e., the firm consciously influences the information investors have about the firm (see Ross (1977) and Gibbons, Gertner, and Scharfstein (1988)).

[3]See Jones (2007), for example, for empirical evidence on the costs and benefits of information disclosure for R&D-intensive industries.

this tradeoff on the firm's investment and financing decisions, are likely to be significantly different for biopharma firms compared to other firms.

How does an R&D-intensive firm make decisions about investment, capital structure, and information disclosure, and how are these decisions affected by its competitive environment? In order to address this question, in this paper we develop a theory which endogenizes the firm's information disclosure decision and its investment decision (R&D and assets-in-place). While the theory is developed with biotechnology and pharmaceutical firms in mind, with empirical tests of the theory presented for those firms, the theory is applicable to other R&D-intensive firms as well. An important goal of the theory is to determine how competition interacts with and affects the firm's decisions. Our theory shows that greater product-market competition induces the firm to cut back on investments in assets-in-place. By the same token, it also places greater pressure on the firm to develop new patentable products that can support profit margins for some time. A key result in our analysis is that competition increases the importance of R&D relative to investments in existing property, plant, and equipment (PP&E), causing the firm to make greater investments in R&D and invest less in existing products and PP&E. Since existing products have systematic risk, whereas (at least early-stage) R&D has mainly idiosyncratic risk (see Pastor and Veronesi (2005)), this reallocation of investments causes systematic risk in the firm to decline. Moreover, competition causes idiosyncratic risk in R&D to *increase* over time, so the shift in stock returns from systematic to idiosyncratic risk is accompanied by an *increase* in total stock return volatility.

Next we turn to the firm's capital structure and cash accumulation decisions. In our model, there are two distinct stages in R&D investment, a stylized version of the multi-stage drug development process in the pharmaceutical industry, but applicable to any industry in which information about a candidate product's safety and efficacy is revealed over time. In the first stage of our model, the major investment is made, but the only knowledge the firm possesses is how profitable this investment will be in the event of a success. In the second

stage, the firm acquires private information about whether the R&D effort is successful. If so, the firm will invest more in the second stage.

In the first stage, when the firm is deciding how much financing to raise, it will also have to decide how much information to reveal about its proprietary investment project. The two-audience signaling problem implies that the more information the firm discloses, the lower will be the cost of raising external capital, but the higher will be the probability of competitive entry, which will reduce the firm's expected R&D payoff. However, the more the firm knows *privately*, the greater will be the adverse selection cost of *not* disclosing this information, and hence the greater the need for more disclosure, implying larger competitive-entry losses. This effect has the important consequence that it is better for the firm to raise financing when it knows *less* privately than when it knows more. This in turn implies that the firm should raise financing for its second-stage R&D investment up front when it is raising financing for its first-stage R&D investment rather than waiting. The relatively large cash balances of R&D-intensive companies are consistent with this implication.

Our model also implies that the R&D-intensive firm will issue debt such that bondholders have no *ex post* incentive to force the firm to repay debt early. The reason is that the firm's assets-in-place have systematic risk, so bondholders have an incentive to force the firm to settle its debt obligation in bad states of the economy, when the expected value of waiting to be repaid will fall short of what the bondholders could collect by forcing immediate repayment. This implies that whatever cash the firm is carrying for its second-stage R&D investment would be jeopardized by the threat of having to use it to pay off the bondholders, forcing the firm to raise external financing to fund its second-stage R&D. Raising external financing at this stage would require information disclosure when the firm has much more private information about the prospects of its R&D investment than it did in the first stage, which can be very costly. Therefore, our model implies that the firm will attempt to choose a capital structure that avoids this outcome. This also produces a rationale for the large cash holdings and low leverage of R&D-intensive firms that is distinct from previous theories,

such as precautionary motives or distress costs.[4]

With regard to investment, while the majority of the analysis focuses on the choice between investing in assets-in-place versus new early-stage in-house R&D, in reality, an R&D-intensive firm may also be able to choose a later-stage R&D investment outside of the firm, through acquisition or collaboration. For example, it is common for a pharmaceutical company to acquire a smaller biotech company in order to gain access to its portfolio of R&D projects that are in the later stages of development. In order to incorporate this aspect into the analysis, we include a simple extension of the main model in which the biopharma firm has a choice of R&D projects: either do R&D in-house ("internal" R&D) or acquire a biotech company with an R&D project that has already succeeded ("external" R&D). While there is a large theoretical and empirical literature on the R&D boundaries of the firm related to the choice between internal and external R&D, our goal is to simply connect this R&D choice to the analysis in this paper, and to demonstrate how the analysis may change when such a choice is open to firms.[5]

Overall, our model produces the following main predictions about the effects of increased product market competition:

1. The firm will increase R&D investment and reduce investment in assets-in-place that support existing products.

2. Firms will carry more cash and net debt will decline.

3. Firm betas will decline, but total risk and idiosyncratic stock return volatility will rise.

Using data on publicly traded biopharma companies from 1950 to 2012, we provide empirical support for these predictions, taking as a given the increase in competition over time which has been documented in previous research. We find that average cash holdings and R&D expenditures have contemporaneously increased, while PP&E and net debt have decreased

[4]See Tirole (2010) for a review of these theories.

[5]See Bhattacharya and Guriev (2004), Bhattacharya, Glazer, and Sappington (1990), Pisano (1990), Gans and Stern (1997), and Cassiman and Veugelers (2006), among others.

over this time period. Moreover, we show that the beta of a value-weighted portfolio of biopharma firms has declined over time, while idiosyncratic and total stock return volatility have increased While this time-series evidence is consistent with the predictions of our model, it is also subject to potential endogeneity concerns. To overcome these concerns, we further test the predictions of our model by exploiting a legislative change that induced an exogenous increase in competition in the biopharma industry. Using a differences-in-differences approach, we again find supporting evidence for the main predictions of the model.

Our paper is related to the theoretical industrial organization literature that explores the effect of competition on innovation. For example, Aghion et. al. (2005) build a model where firms facing large competitive pressures may innovate in order to regain lost profit margins, but this effect may be reversed in industries where competition is less intense and laggard firms face large costs to catch up to industry leaders. While our paper also predicts an increase in competition will increase innovation (through increased R&D investment), our model differs from Aghion et. al. (2005) and other studies in that we also focus on how competition affects the firm's funding of innovation. As a firm's ability to secure capital is crucial for undertaking R&D, we thus tie competition in with an important determinant of innovation through considering its effect on the firm's interactions with the capital market and risk characteristics.[6]

Since our analysis relies on the idea that the firm's communication to the financial market has spillover effects on its product-market payoffs, our paper is related to two important contributions to the "two-audience" signaling literature. One is Bhattacharya and Ritter (1983), in which the firm engages in directly verifiable information disclosure—as in our analysis—that impacts its cash flows. We differ from that paper in our focus on capital structure and its interaction with R&D choice. The other contribution is Gibbons, Gertner, and Scharfstein (1988), in which firms do not directly disclose verifiable information but rather signal with capital structure. In contrast to that paper, capital structure conveys

[6]See Hall and Lerner (2010) and Brown, Fazzari, and Petersen (2009) for empirical evidence on the link between the availability of financing and R&D.

no information in our analysis beyond that conveyed by direct and verifiable disclosure. Moreover, unlike both papers, we analyze the impact of competition on the firm's investment and cash accumulation decisions and also provide empirical evidence for our theory.[7]

Our analysis is also related to the very large theoretical literature on capital structure, e.g. Jensen and Meckling (1976), Myers and Majluf (1984), Stulz (1990), Zwiebel (1996), Abel (2014); see Graham and Leary (2011) and Myers (2001) for comprehensive reviews. The key difference between these papers and ours is that through our focus on R&D-intensive firms, we assign a key role to the endogenous information disclosure decision that is made simultaneously with the decision of how much to invest in R&D versus existing products and the capital structure decision. Moreover, we also provide several empirical tests of the predictions of our model, all of which are found to have empirical support. While our analysis is related to many empirical investigations of capital structure (e.g. Welch (2004)), our narrower focus on R&D-intensive firms yields predictions that go beyond capital structure, allowing us to test our model along multiple dimensions.

Finally, our results are also related to an empirical literature that examines the R&D costs, returns, and risks in the pharmaceutical industry. For example, Grabowski and Vernon (1990) and DiMasi, Grabowski, and Vernon (1995) examine a selection of drugs introduced in the U.S. and show a substantial increase in competition and a skewed distribution of sales returns from the drugs. DiMasi, Hansen, and Grabowski (2003) examine the cost of new drug development. Ellison, Cockburn, Griliches, and Hausman (1997) model the demand for pharmaceutical products and compute price elasticities. Myers and Howe (1997) build a Monte Carlo life-cycle model of drug R&D development for the pharmaceutical industry, and examine the model's estimates of risk, return, NPV, and cost of capital. Gans, Hsu, and Stern (2002) and Gans and Stern (2003) look more generally at R&D-intensive firms,

[7]Some alternative sources of funding that may partly avoid disclosure to competitors are bank financing and venture capital funding (see Bhattacharya and Chiesa (1995) for an examination of these). While R&D-intensive firms do rely on these sources as well, the large investment outlays by many of these firms necessitate external financing (see Lerner, Shane and Tsai (2003) and DiMasi, Hansen, and Grabowski (2003))—we therefore focus on these firms' interactions with the capital market.

and examine how their R&D strategies are affected by competition and cooperation. Our paper is complementary to some of the evidence provided in these studies, but also provides additional empirical evidence focused on financial characteristics as well as formal theoretical foundations for this evidence. Moreover, we focus explicitly on the capital structure decision of biopharma companies which, to our knowledge, has not been considered in previous studies of this industry.

In Section 2 we describe our theoretical framework, and in Section 3 we present derive its main implications and predictions. Section 4 contains a description of the data and empirical analysis, and we conclude in Section 5. Formal proofs of the results in Section 3 as well as supplemental figures and results appear in the Appendix.

2 The Model

We begin by introducing the model setup, preferences, and main assumptions, and then proceed to describe the structure of the model.

2.1 Actors, Preferences, and Asset Pricing

Consider a biopharmaceutical firm that faces a decision to undertake a staged R&D investment. There are 2-periods with three dates: $t = 0$, $t = 1$, and $t = 2$. At $t = 0$, the firm chooses an amount to invest in either assets-in-place (such as existing products) or in R&D (for new products). If it chooses to invest in an R&D project, the project has two stages. At $t = 0$, the first-stage investment is made. At $t = 1$, the second-stage investment is made.

At both of these dates, the firm may need to raise capital and can choose between issuing equity and debt. The financing decision also involves a decision of how much information to disclose to investors while raising funds. A certain amount of information disclosure is necessary to convince outsiders to invest in the project. However, this disclosure imposes a cost because of the "two-audience" signaling problem, which is that any information disclosed

$t = 0$	$t = 1$	$t = 2$
• Firm determines its capital structure as well as scale, i.e., how much to invest in assets-in-place (or existing products) and how much to invest in R&D. • Firm determines how much information to disclose to investors while raising funds. • Firm makes its investment in existing products and its first-stage investment in R&D	• The state of the economy (which will determine date-2 payoffs of assets that covary with the economy) is revealed. • Bondholders can demand repayment on debt. • Firm may need to raise additional financing to fund its second-stage R&D, in which case it will also need to determine how much additional information to disclose	All payoffs are realized. Shareholders and bondholders are paid off

Figure 1: Time-line of Decisions

to the financial market is also unavoidably disclosed to (existing and potential) product-market competitors, producing real cash-flow/value losses (e.g. Bhattacharya and Ritter (1983)).

At the final date, $t = 2$, all payoffs are realized, and shareholders and bondholders are paid off. A timeline of these events is given below.

The expected rate of return on an asset with systematic risk loading β is $K(\beta)$. The riskfree rate for a single period is $r > 0$ and is intertemporally constant. Systematic risk is priced, and idiosyncratic risk is not. For example, assume that there is a linear factor model for returns:

$$R_i = r + \beta_i \mathbf{\Gamma} + \varepsilon_i \tag{1}$$

where $\mathbf{\Gamma}$ represents a vector of returns of systematic factors, β_i is a vector of loadings on those factors for asset i, r is the riskless rate of return, and ε_i is a mean-zero error term that represents the idiosyncratic portion of the return. The expected return on any such asset is

thus given by:

$$K(\beta) \equiv \mathbb{E}[R_i] = r + \beta_i \mathbb{E}[\mathbf{\Gamma}]. \tag{2}$$

The CAPM or Fama-French 3-factor model would be an example of such a model.

2.2 Investing in Existing Products/Assets vs. R&D

For simplicity, the existing products/assets of the firm have only systematic risk, with $\beta = 1$, whereas R&D has only idiosyncratic risk with $\beta = 0$. This can be justified along the same lines as Pastor and Veronesi (2009): by definition, R&D involves new projects that are one-off stand-alone investments by individual firms, and hence uncorrelated with the economy. Existing products involve similar investments by many other firms, and hence contain systematic risk. For example, in the biopharma industry, new drugs have patent protection and are thus less affected by investments by other firms due to the monopoly that patents confer on the specific drug. In contrast, existing products include generic drugs that no longer enjoy patent protection and are sensitive to the investments of other firms. This is also consistent with previous studies that have established that greater monopoly power is associated with a lower degree of systematic risk (e.g. Subrahmanyam and Thomadkis (1980), Lee, Liaw, and Rahman (1990), and others).

There are two states of the macroeconomy: an "up" state and a "down" state. The up state occurs with probability p and the down state occurs with probability $1 - p$. When the up state occurs, the firm's existing products pay off x_H, and when the down state occurs they pay off x_L. That is, the payoff from existing products is perfectly correlated with the state of the economy, so the single-period discount rate applicable to these payoffs is $K(1) \equiv K$. More specifically, if the firm invests an amount $A > 0$ in assets-in-place or existing products, and the degree of competition is $\theta \in \left[\underline{\theta}, \overline{\theta}\right]$, then the existing products will generate a payoff of $x_H(A, \theta)$ with probability $p \in (0, 1)$ at $t = 2$ and a payoff of $x_L(A)$ with probability $1 - p$ at $t = 2$. Here a higher θ means greater product-market competition for the firm, and

$x_H > x_L \; \forall \, A > 0$ and $\forall \, \theta \in \left[\underline{\theta}, \overline{\theta}\right]$.[8] We impose the standard assumptions on the production function $x_H(A, \theta)$:

$$\partial x_H / \partial A > \partial x_L / \partial A > 0, \quad \partial^2 x_H / \partial A^2 < 0,$$

$$\partial^2 x_L / \partial A^2 < 0, \quad \left|\partial^2 x_H / \partial A^2\right| > \left|\partial^2 x_L / \partial A^2\right|, \tag{3}$$

and

$$\partial^2 x_H / \partial A \partial \theta < 0. \tag{4}$$

Note that $\partial^2 x_H / \partial A \partial \theta < 0$ implies that investments in existing products become less productive at the margin when competition increases, which is economically intuitive.[9]

Investment in R&D involves two phases. At $t = 0$, the firm makes its first-stage R&D investment R. Then, if it observes at $t = 1$ that the successful state has occurred for R&D, it must invest an additional $\hat{\omega} R$, $\hat{\omega} \in (0, 1)$, in order to realize the payoff conditional on success. Absent this second-stage investment, the R&D payoff at $t = 2$ is zero. Such a setup captures the staged drug R&D investment in biopharma firms in which a drug is considered a "success" if it passes Phases 1–3 of clinical trials, where each phase requires an additional investment.

If the firm invests R in R&D, it privately observes at $t = 1$ whether the R&D is successful or not—the probability of success is q. Conditional on R&D success, the payoff at $t = 2$ is

[8] In our model, changes in competition θ can be interpreted as structural changes in the industry or other changes in competition that are exogenous to the individual firm. Important drivers of competition to industries such as biopharma are exogenous technology or regulatory shocks that lower entry costs. For example, the Human Genome Project represented a technology shock that was plausibly exogenous to any individual firm's decision, and it led to the entry of numerous small biotech firms into the industry (see Anaya et. al. (2014)). Another example is the Hatch-Waxman Act, which was a source of exogenous variation in competition for the biopharma industry, and something we use for identification purposes later in our analysis. However, since R&D by incumbents can also affect the degree of competition, some portion of the degree of competition is endogenous (e.g. Gans and Stern (2000)). While our empirical tests are designed to tackle this potential endogeneity, we account for it in our model through the information disclosure decision for the firm, which we discuss later. The theory thus has both exogenous and endogenous determinants of competition.

[9] In other words, changes in θ affect the profitability of existing assets (which have largely exhausted their patent protection and are thus vulnerable to competitive pressures) relative to new, patent-protected drugs that have greater immunity to competitive pressures.

$\tilde{y}$ which is unconditionally distributed as follows at $t = 0$:

$$\tilde{y} = \begin{cases} y_+(R, \theta) & \text{with probability } \delta \\ y_-(R) & \text{with probability } 1 - \delta \end{cases}. \tag{5}$$

Let $y_+ > y_-$, so that the project yields a high payoff with probability δ and a low payoff with probability $1 - \delta$. We assume that:

$$\partial y_+ / \partial R > 0, \quad \partial y_- / \partial R > 0,$$

$$\partial^2 y_+ / \partial R^2 < 0, \quad \partial^2 y_- / \partial R^2 < 0, \tag{6}$$

and

$$\partial^2 y_+ / \partial R \partial \theta > 0. \tag{7}$$

If the R&D effort fails at $t = 1$, the payoff is zero with probability 1. Assumption (7) states that the marginal productivity of investing in R&D increases with the degree of competition in the firm's market for *existing* products. That is, the more competitive that market is, the bigger is the marginal benefit of investing capital in R&D. The idea is that new products enable the firm to escape the pressure of competition in the market for existing products, so the marginal benefit of innovation is greater when competition is greater. For example, one of the reasons why firms in the biopharma industry engage in R&D is to replace old drugs (many of which may be off-patent and thus face competitive pressures) with new drugs (which are patent-protected and insulated from competition). The R&D payoff distribution is given in *Figure 2*.

We assume that the R&D investment creates value (and thus is positive NPV at $t = 0$), so:

$$[\delta y_+ + [1 - \delta]\, y_-]\, [1 + r]^{-2} > R + \hat{\omega} R\, [1 + r]^{-1} \tag{8}$$

Note that, since R&D contains only idiosyncratic risk (hence $\beta = 0.$) each side is discounted

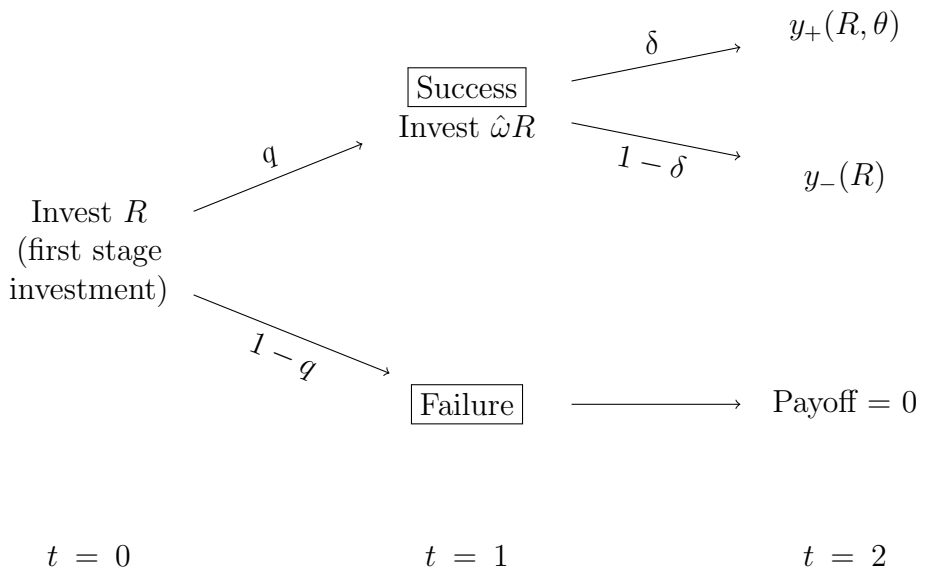


Figure 2: R&D Payoff Distribution Over Time

by the riskfree rate $1 + r$.

2.3 Informational Assumptions

Suppose there are two types of firms: good firms and lemons. The common prior is that the probability of a randomly-chosen firm being good is $g \in [0.5, 1)$ and being a lemon is $1 - g$.[10] The lemons are fly-by-night operators who raise financing at $t = 0$ and abscond with the money. The good firms are described above. The firm *privately* knows at $t = 0$ whether they are good or lemons. Given this private information, we will model their interactions as a game in which the informed firm moves first with its capital structure decision and how much financing to raise for R&D (and when to raise it). The uninformed capital market reacts to the firm's choice and makes Bayesian rational inferences about the firm's payoffs, which then results in prices for the firm's securities.

At $t = 0$, each firm can determine how much information about its R&D project it reveals to investors, and hence to its competitors. Let ξ represent the amount of disclosure, with

[10]The lower bound on g is to avoid a corner solution by ensuring that there are sufficiently many good firms to allow financing to be raised.

$\xi \in \left[0, \bar{\xi}\right]$. There is a two-audience signaling problem in that any disclosure to the market is also a disclosure to R&D competitors. This effect is captured as follows. The more the firm discloses, the higher is the posterior probability that the firm is good, conditional on the firm's true type being good (the positive effect of disclosure in the financial market), but the higher also is the probability of competitive entry that reduces q, the probability of R&D success. The effect of disclosure on q captures the idea that the super-normal profits from innovation can be captured by the firm only if it wins the R&D race, and the probability of winning goes down as competitive entry increases.[11] Thus, if τ is the firm's type, with $\tau \in \{good, lemon\}$, and $\hat{g}(\xi \mid \tau)$ is the posterior belief the firm is good when its true type is τ and it has chosen disclosure ξ (higher values of ξ mean higher disclosure), then

$$\frac{\partial \hat{g}(\xi \mid good)}{\partial \xi} > 0, \quad \frac{\partial^2 \hat{g}(\xi \mid good)}{\partial \xi^2} < 0, \tag{9}$$

$$\frac{\partial \hat{g}(\xi \mid lemon)}{\partial \xi} < 0, \tag{10}$$

and the Inada-type conditions hold:

$$\lim_{\xi \to 0} \frac{\partial \hat{g}(\xi \mid good)}{\partial \xi} = \infty, \quad \lim_{\xi \to \bar{\xi}} \frac{\partial \hat{g}(\xi \mid good)}{\partial \xi} = 0. \tag{11}$$

Moreover,

$$\hat{g}(0 \mid good) = \hat{g}(0 \mid lemon) = g, \quad \hat{g}\left(\bar{\xi} \mid good\right) = g^{+} \in (0, 1). \tag{12}$$

The product-market effect of disclosure is captured as follows:

$$\frac{\partial q(\theta, \xi)}{\partial \xi} < 0, \quad \frac{\partial^2 q(\theta, \xi)}{\partial \xi^2} < 0 \ \forall \theta, \tag{13}$$

[11] Thus, in contrast to θ, which represents changes to competition that are *exogenous* to an individual firm's decisions, ξ can be interpreted as spurring *endogenous* changes to competition that are influenced by an individual firm's actions. In other words, the amount of information disclosure ξ is controlled by each individual firm, and an increase in information disclosure by an individual firm will increase competition for that firm's products.

$$q(\theta,0)=\bar{q}(\theta)\in(0,1),\quad q\left(\theta,\bar{\xi}\right)=\underline{q}(\theta)\in(0,\bar{q}(\theta))\,. \tag{14}$$

At $t=1$, the firm can choose to hide whether its R&D was successful or not, but if it raises external financing for the second-stage R&D, then everybody will know that success was encountered. In this case, competitive entry causes δ to drop to $\delta_0<\delta$ for the good firm. It will be assumed throughout that this drop is large enough to guarantee:

$$\underline{q}(\theta)\left[y_+-y_-\right]\left[\delta-\delta_0\right]>\hat{\omega}R[1+r]\;\forall\theta. \tag{15}$$

Whether a firm is a lemon or a good firm cannot be unambiguously determined by outsiders until payoffs are observed at $t=2$.

2.4 Financing Choices and Structure of the Game

The firm has no internal funds available at $t=0$. Therefore, it raises all the necessary financing by issuing debt and equity, which then determines its capital structure. Equity holders will be paid off at $t=2$. The bondholders can choose to demand repayment at $t=1$ or wait until $t=2$ to be paid. The face value of debt to be repaid at $t=2$ is F, and if repayment occurs at $t=1$ the bondholders are paid $F_1<F$. The initial debt financing raised is D.

The firm's initial shareholders must give up ownership $\alpha\in(0,1)$ in order to raise the necessary equity, along with debt, to finance the existing product line and R&D. The variables D, F, F_1, and α will all be endogenously determined.

Since this is a game in which the informed firm moves first with its decisions and the uninformed investors move second, the appropriate notion of equilibrium is sequential equilibrium (Kreps and Wilson (1982)) and its subsequent refinements.

3 Equilibrium Implications and Predictions

We now analyze the equilibrium in the model. Proofs of all results are included in Section A of the Appendix.

The following lemma characterizes the equilibrium decision of the firm with respect to when to raise financing for its second-stage R&D investment.

Lemma 1: *There is a sequential equilibrium in pure strategies in which all firms prefer to raise at* $t = 0$ *the present value of the second-stage R&D financing that will be needed at* $t = 1$ *and invest this in the riskless asset, rather than wait until* $t = 1$ *to raise this financing. This equilibrium satisfies the Cho and Kreps (1987) Intuitive Criterion refinement.*[12]

The intuition for this is as follows. At $t = 0$ there is the least information asymmetry and hence the least for the firm to lose, from a competitive standpoint, from disclosing what it knows. Disclosure at a later date is more costly. Thus, the firm prefers to disclose the necessary information and raise the financing it needs, not only for investment at $t = 0$ but also for its future investment. The cash it does not need for investment at $t = 0$ is then invested in the riskless asset for future use. We now turn to the analysis at $t = 0$. At $t = 0$, the firm is making a number of decisions: (i) how much information to disclose; (ii) how much to invest in the existing product or assets-in-place; and (iii) its capital structure (or the mix of debt and equity to use in raising financing).

3.1 The Information Disclosure Decision

For the information disclosure decision, we take as a given the optimal choices of A and R (denoted as A^* and R^*, respectively) and the firm's capital structure, and solve for ξ.

Suppose we conjecture that

$$F = x_L(A^*), \quad F_1 = x_L(A^*)[1+r]^{-1}, \tag{16}$$

[12]Note that it can be shown that this equilibrium also survives the universal divinity refinement of Banks and Sobel (1987).

so that competitive capital market pricing of debt implies that:

$$D = F\left[1+r\right]^{-2}. \tag{17}$$

Note that we discount the date-2 debt repayment of F at the riskless rate since $x_L\left(A^*\right)$ is the lowest possible cash flow at $t=2$, so debt is essentially riskless if the face value is set as in (16).

Let V_E be the value of equity at $t=0$. Then with the assumed debt level, we have:

$$\begin{aligned} V_E &= \left\{p\left[x_H(A,\theta)-F\right]+\left[1-p\right]\left[x_L(A)-F\right]\right\}\left[1+K\right]^{-2} \\ &\quad +q(\xi)\left\{\delta y_+(R,\theta)+\left[1-\delta\right]y_-(R)\right\}\left[1+r\right]^{-2}+\left[1-q(\xi)\right]\hat{\omega}R\left[1+r\right]\left[1+r\right]^{-2}. \end{aligned} \tag{18}$$

To understand V_E, note that F is the debt repayment at $t=2$, so the first term in the braces in (18) consists of the expected payoff to shareholders from existing products (assets-in-place), given investment A and level of competition θ. This date-2 payoff is discounted back to $t=0$ for two periods using the equity cost of capital K, which accounts for the systematic risk associated with this payoff. The second term in braces is multiplied by the probability of success of the R&D in the first phase, $q(\xi)$, given a level of disclosure ξ. The term in the braces is simply the expected R&D payoff, which is discounted at the riskless rate because the R&D risk is purely idiosyncratic. The third term represents the payoff from *not* investing the money raised for second-stage R&D because it becomes known to the firm at $t=1$ that the R&D has failed. So $\hat{\omega}R$ is invested for a second period in the riskless asset to obtain $\hat{\omega}R\left[1+r\right]$ at $t=2$, which is discounted back to $t=0$ at the riskless rate r.[13] This present value is multiplied by the probability of failure of the R&D, $1-q(\xi)$.[14]

[13]The firm raises $\hat{\omega}R\left[1+r\right]^{-1}$ at $t=0$, and invests it in the riskless asset to have $\hat{\omega}R$ to invest at $t=1$.

[14]Note that bondholders do not have any incentive to demand repayment at date 2. Thus setting $F_1>0$ is an off-equilibrium path possibility, and so F_1 does not enter into (18).

Substituting for F from (16) into (18) gives us:

$$\begin{aligned} V_E &= \{p\left[x_H(A,\theta) - x_L(A)\right]\}\left[1+K\right]^{-2} \\ &\quad + q(\xi)\left\{\delta y_+(R,\theta) + \left[1-\delta\right] y_-(R)\right\}\left[1+r\right]^{-2} + \left[1-q(\xi)\right]\omega R, \end{aligned} \tag{19}$$

where

$$\hat{\omega}\left[1+r\right]^{-1} \equiv \omega. \tag{20}$$

Note that V_E above is the value of the good firm's equity, as assessed by the initial shareholders who know that the firm is good. The *outside* shareholders who buy the firm's equity cannot distinguish noiselessly between good firms and lemons, so they price the firm at:

$$V_E^e = \hat{g}(\xi,\tau)V_E \;\forall \tau \in \{good \mid lemon\}. \tag{21}$$

The total amount of financing raised by the firm is $A + R[1+\omega]$, of which D comes from debt. So the equity financing raised is $A + R[1+\omega] - D$. The equilibrium pricing condition gives us:

$$\alpha V_E^e = A + R[1+\omega] - D. \tag{22}$$

The net wealth of the initial shareholder is $[1-\alpha]V_E$. Thus, given A, R, and the capital structure choice, the firm chooses ξ to solve:

$$\xi \in \arg\max_{[0,\bar{\xi}]} [1-\alpha]V_E. \tag{23}$$

We now have the following result:

Proposition 1: *There is a unique interior optimal level of disclosure $\xi^* \in \left(0,\bar{\xi}\right)$ chosen by every firm in a sequential equilibrium. This choice of ξ^* is a solution to (23).*

The economic intuition can be seen by considering the opposite effects that information

disclosure has on the firm's probability of success from its R&D and its cost of raising financing. The more the firm discloses, the greater is the cost that it incurs in terms of a lower probability that it has of winning the R&D race, but the higher also is the benefit that it experiences in terms of more favorable financing terms. This trade-off produces an interior optimal level of information disclosure.

3.2 The Investment Decision

Next we examine how the firm determines A^* and R^*, taking as a given the optimal capital structure assumed, and recognizing that ξ^* is determined simultaneously with A^* and R^*. That is, the firm solves:

$$(A, R) \in \arg\max_{\mathbb{R}^2} [1 - \alpha] V_E, \tag{24}$$

where $\mathbb{R}$ is the real line. The following result can be proved:

Proposition 2: *There is a unique optimal level of investment in assets-in-place, A^*, and a unique optimal level of investment in R&D, R^* at $t = 0$, with $dA^*/d\theta < 0$ and $dR^*/d\theta > 0$.*

This proposition shows that as competition increases, the firm invests more in R&D and less in assets-in-place that are used to support and expand existing products. The economic intuition is that investing in coming up with proprietary new products/knowledge becomes more valuable *relative to* investing more in the existing business as competition compresses margins in existing products.

Since existing products have systematic risk, whereas R&D has only idiosyncratic risk, one implication of this result is that higher competition will lead to declining betas and increasing idiosyncratic risk for firms.[15] The volatility of payoffs associated with R&D is

[15] As argued by Myers and Howe (1997), an increase in R&D may also generate an "R&D leverage" effect, which can increase systematic risk in a way similar to a financial leverage effect, by creating a series of fixed obligations (R&D investments) that must be paid in the future. In our analysis, the additional R&D investments are discretionary (i.e. the firm has no obligation to undertake them), and therefore the effect is not applicable in our setting.

typically higher than that associated with well-established existing products, so we should expect an increase in the total volatility of stock returns as firms substitute investments in existing products with investments in R&D. Moreover, higher competition typically introduces greater uncertainty about a firm's prospects in any industry, leading to higher total stock return volatility. Because the higher investment in R&D is caused by higher competition, we have another channel through which R&D investments end up being positively correlated with total stock return volatility.

We can formally derive the conditions under which a shift in investment from assets-in-place to R&D increases the total volatility of the firm's returns. For this, define $S_x \equiv x_H - x_L$ as the "spread" between the low and high payoffs for the assets in place and $S_y \equiv y_+ - y_-$ as the "spread" for the payoffs of R&D conditional on first-stage success. Then $\partial S_x/\partial A > 0$ is the marginal impact of investment in assets-in-place on the spread S_x and $\partial S_y/\partial R > 0$ is the marginal impact of R&D investment on the spread S_y. Then we have the following result:

Corollary 1: *If S_y is sufficiently greater than S_x and $\partial S_y/\partial R$ is sufficiently greater than $\partial S_x/\partial A$, then the marginal impact of an increase in R&D investment accompanied by an equal decrease in investment in assets-in-place is to increase the variance of firm value.*

Thus, if the spread between the payoffs conditional on success is much larger for R&D than for assets-in-place, and investment has a bigger marginal impact on this spread for R&D, we should expect higher R&D spending to induce an increase in total volatility. A large spread of payoffs conditional on success for R&D is consistent with the empirical evidence for pharmaceuticals of Grabowski and Vernon (1990), who document a skewed distribution of returns for drugs in the marketplace, with "blockbuster" drugs achieving much higher returns than other drugs.

3.3 The Capital Structure Decision at $t = 0$

Finally, we consider the firm's initial capital structure decision, and how it changes with respect to competition.

Proposition 3: *The firm will wish to issue debt with the face values indicated in (16), and it will result in the raising at $t = 0$ of debt D in the amount indicated in (17). An increase in competition will lead to a decrease in debt in the firm's capital structure, and an increase in the amount of cash carried on the balance sheet.*

The intuition for why debt is not exposed to systematic risk is that if debt is exposed to such risk it creates an incentive for the bondholders to demand early payment (at $t = 1$) if the down systematic risk state occurs. This then forces the firm to have to raise additional financing at $t = 1$, with the accompanying losses due to information disclosure, or carry extra financing from $t = 0$ onward to meet the bondholders' early repayment request and thereby incur additional adverse selection costs. This explains why the face value of debt is chosen to satisfy (16). The intuition for why debt declines as competition increases is that the firm invests less in assets-in-place, thereby reducing the asset base available to insulate the bondholders against systematic risk. However, both first-stage and second-stage R&D investments increase with competition, and the financing for the second-stage R&D is raised at the beginning and carried as cash, so higher R&D outlays imply higher cash balances.

3.4 Model Extension: An Acquisition as an Alternative to R&D

A realistic alternative that a biopharma firm has to investing in R&D in-house is to purchase another firm (such as a biotech firm) that has already successfully developed the R&D. To consider this possibility, suppose that the biopharma firm has the choice to acquire a biotech firm whose only asset is one R&D project that has successfully completed the first stage of R&D investment. Thus the biopharma firm, when it chooses to invest in R&D, may either invest in "internal" R&D, by investing in the R&D project described previously, or

"external" R&D, by acquiring the biotech firm. Acquisition occurs at $t = 0$, in which case the acquiring biopharma firm would identify a biotech firm that has successfully developed the R&D.

Let $\overline{V}_{external}$ be the value of the target (assumed to be unlevered, for simplicity) if it is not acquired:

$$\overline{V}_{external} = \left[\delta \overline{y}_{+}\left(\overline{R}, \theta\right) + \left[1-\delta\right] \overline{y}_{-}\left(\overline{R}\right)\right] \left[1+r\right]^{-2}, \tag{25}$$

which is conditional on investment of $\overline{R}$ in the R&D, and $\overline{y}_{+}$, $\overline{y}_{-}$, and $\overline{R}$ correspond to the target's R&D payoffs and investment. We assume that the target does not have access to financing. If the target is purchased by the acquirer, then there is a synergy gain of $\triangle$, so the value of the target (the external R&D project) to the acquirer is:

$$V_{external} = \left[\triangle + \delta \overline{y}_{+}\left(\overline{R}, \theta\right) + \left[1-\delta\right] \overline{y}_{-}(\overline{R})\right] \left[1+r\right]^{-2}. \tag{26}$$

(26) can be compared to the value of doing an internal R&D project:

$$V_{internal} \equiv q(\xi) \left\{\delta y_{+}(R, \theta) + \left[1-\delta\right] y_{-}(R)\right\} \left[1+r\right]^{-2} + \left[1-q(\xi)\right] \omega R. \tag{27}$$

For simplicity, we assume that the target sells at a price that is exactly equal to $\overline{V}_{External}$, so that the target receives the expected value of what it would have received if it had the funds to invest in second-stage R&D, and the acquirer captures the entire synergy gain.[16]

Since the target's R&D has already succeeded, information disclosure by the acquirer cannot reduce the value of the target.[17] Thus, the good firm will choose the maximum level of disclosure in order to finance the acquisition: $\xi = \overline{\xi}$. When the good firm raises the financing it needs for its assets in place and to buy the target, outside shareholders will price

[16] Alternative assumptions about the possible sharing of the synergy between the acquirer and the target do not affect our analysis qualitatively.

[17] Put differently, since the biotech firm is a target for acquisition in the marketplace, disclosing additional information will not reduce its value since all of that information is already public.

the firm at:

$$\hat{V}_E^e = g^+ \hat{V}_E, \tag{28}$$

where

$$\hat{V}_E = \left\{ p \left[x_H \left(\hat{A}, \theta \right) - x_L \left(\hat{A} \right) \right] \right\} [1+K]^{-2} + V_{external}, \tag{29}$$

where $\hat{A}$ is the investment in assets-in-place made by the acquiring firm. The analog of (22) is:

$$\hat{\alpha} \hat{V}_E = \hat{A} + \overline{V}_{external} - \hat{D}, \tag{30}$$

where $\overline{V}_{external}$ is the price paid for the target and $\hat{D}$ is the debt level. As before,

$$\hat{D} = \hat{F} [1+r]^{-2} = x_L \left(\hat{A} \right) [1+r]^{-2}. \tag{31}$$

Whether the firm prefers to invest in internal R&D or external R&D (via acquiring another firm) depends on whether

$$[1-\alpha] V_E (A^*, R^*, \xi^*) \geq [1-\hat{\alpha}] \hat{V}_E \left(\hat{A}, \overline{\xi} \right) \tag{32}$$

holds. If (32) holds, the firm will invest in internal R&D. If (32) does not hold, the firm will prefer to acquire.

Now, using (14), we can express $q(\theta, \xi)$ as:

$$q(\theta, \xi) = \underline{q}(\theta) + \tilde{q}(\theta, \xi), \tag{33}$$

where

$$\tilde{q}(\theta, \xi) = \begin{cases} \overline{q}(\theta) - \underline{q}(\theta) & \text{for } \xi = 0 \\ 0 & \text{for } \xi = \overline{\xi} \end{cases} \tag{34}$$

and $\tilde{q}(\theta, \xi)$ is decreasing and concave in ξ. Suppose $\underline{q}(\theta)$ varies in the cross-section of firms.

For simplicity, consider two types of firms that vary in how likely their first-stage R&D is to succeed: types 1 and 2, with $\underline{q}^1(\theta) < \underline{q}^2(\theta)$. We can then see that the value of internal R&D is higher for the firm with $q = \underline{q}^1(\theta)$. The following result is then straightforward to show:

Proposition 4: *If the good firm with $\underline{q}^1(\theta)$ invests in internal R&D, so does the good firm with $\underline{q}^2(\theta)$. If the good firm with $\underline{q}^2(\theta)$ acquires another firm to obtain external R&D, so does the good firm with $\underline{q}^1(\theta)$. There are exogenous parameter values for which the good firm with $\underline{q}^1(\theta)$ acquires and the good firm with $\underline{q}^2(\theta)$ invests internally in R&D.*

The basic idea is simple. A firm with a higher probability of success with internal R&D is more likely to invest in R&D, whereas a firm with a sufficiently low R&D success rate will prefer to engage in external R&D by acquiring a firm that has already successfully harvested the result of investing in R&D.

Following from the analysis in the previous sections, it follows that an increase in competition will induce more firms to engage in external R&D via acquisitions. These will be the firms which have a lower probability of internal R&D success. Moreover, since external R&D involves less risk than internal R&D, one would expect acquiring firms' stock returns to have lower idiosyncratic risk than the stock returns of firms that engage in internal R&D. We leave tests of these predictions to future research.

3.5 Empirical Implications

Our model has implications for how the characteristics of R&D-intensive biopharma firms change in response to changes in competition. A number of studies have documented increased competition in the biopharma industry, brought about by a combination of improvements in technology and entry of generic drugs. For example, the Drug Price Competition and Patent Term Restoration Act of 1984 (informally known as the Hatch-Waxman Act) and the Generic Initiative for Value and Efficiency of 2007 were designed to increase the entry of generic drugs into the market place in order to spur competition (see Caves, Whin-

ston, and Hurwitz (1991), Grabowski and Vernon (1990, 1992), and others for more details). Consistent with this evidence, we also document in the empirical results an increase in competition over time, as viewed through various measures. Based on the model, as competition increases, the following is predicted for biopharma firms:

1. The firm will increase R&D investment and reduce investment in assets-in-place that support existing products.

2. Firms will carry more cash and net debt will decline. This follows from the result that firms raise enough financing initially and then carry cash for second-stage R&D and the result that higher competition leads to less debt in the firm's capital structure.

3. Firm betas will decline, but idiosyncratic risk and total stock return volatility will rise.

4 Data and Empirical Evidence

To test the empirical implications of our model of R&D-intensive corporate financial policies, we first consider time-series evidence on increasing competition in the biopharma industry and then turn to the predictions of the model for R&D investments, assets-in-place, capital structure, cash balances, and risk. The empirical evidence is generally consistent with the theory's predictions.

While the time-series evidence is suggestive of the effects documented by our model, it is subject to endogeneity concerns, as its interpretation implicitly requires competition in the biopharma industry to be exogenous. However, this assumption is unlikely to hold for the biopharma industry. For example, R&D outlays by incumbent firms can act as a competitive entry barrier—in other words, R&D is affected by competition, but competition is also affected by R&D. To overcome this endogeneity problem, we exploit the exogenous variation introduced by the passage of the Drug Price Competition and Patent Term Restoration Act of 1984 and conduct a differences-in-differences analysis to provide a cleaner empirical test of the model.

4.1 Empirical Methodology

We begin by documenting evidence of how competition in the biopharma industry has increased over time, consistent with the results of other studies. We first measure competition through the Concentration Ratio, which is defined as the market share of the largest firms in the industry. It is defined as follows for each year t:

$$CR_t(M) = \sum_{i=1}^{M} s_{i,t}, \tag{35}$$

where s_i is the market share of firm i, defined as the proportion of the industry's sales that are attributable to firm i. A lower value of $CR_t(M)$ in a given year indicates less concentration, and thus greater competition, in the industry. As is common, we calculate (35) for $M = 4$ (4-firm Concentration Ratio).[18] However, for the biopharma industry, many small biotech firms compete with larger firms through their R&D efforts, even though they may not have products that are commercialized (and therefore have little to no sales). Therefore, sales-based measures of competition such as the Concentration Ratio may not fully capture changes in competition for the biopharma industry. As a result, we also measure competition in a more simple manner as a robustness check, using the number of competitors in the industry over time.

We next document the financial characteristics of interest that are related to predictions 1 and 2 in Section 3.4. They are defined as follows. R&D investment is measured by $(R\&D/TA)_{i,t}$, which is R&D expenditures scaled by total assets for firm i in year t. Assets-in-place are measured by $(PPE/TA)_{i,t}$, which is property, plant, and equipment scaled by total assets. Cash is represented by $(Cash/TA)_{i,t}$, which is measured by cash and short-term investments scaled by total assets. Debt is represented by $(Debt/TA)_{i,t}$, which is the sum of total long-term debt and short-term debt (debt in current liabilities). Net debt is

[18] Our results are also similar when using other sales-based measures of concentration, such as the 8-firm Concentration Ratio (where $M = 8$ in (35)), Herfindahl-Hirschman Index, or the Hannah and Kay (1971) Index. We include these measures in the Appendix.

represented by $(Net\,Debt/TA)_{i,t}$, where $Net\,Debt_{i,t} = Debt_{i,t} - Cash_{i,t}$. The mean values of these variables are calculated for each year in the sample.

In order to examine prediction 3 of the theoretical model, we construct time-series estimates of stock return volatility and betas for the biopharma industry. To examine stock return volatility, we compute both the total stock return volatility and the idiosyncratic stock return volatility of firms in the biopharma industry. The calculation of idiosyncratic stock return volatility requires a measure of the idiosyncratic component of total stock returns, which we calculate in the following way. First, the betas for the Fama and French (1993) three-factor model are calculated using a rolling two-year window of daily returns:

$$R_{i,t} - r_f = \alpha + \beta_{i,t,mkt}\left(R_{m,t} - r_f\right) + \beta_{i,t,SMB}R_{SMB,t} + \beta_{i,t,HML}R_{HML,t} + \epsilon_{i,t}. \tag{36}$$

Second, once the betas have been calculated for each day, the idiosyncratic portion of the return ($\epsilon_{i,t}$) is estimated using the beta estimates and (36).

We take two simple approaches to calculating the total and idiosyncratic volatility of the biopharma industry. The first approach, which is consistent with Officer (1973) and others, is to calculate volatility by taking the standard deviation of a rolling window of the past 360 days of daily returns. We calculate these rolling volatilities at the individual stock level and then average the volatilities at each date across all stocks, and we also consider the rolling return volatilities of a value-weighted portfolio of biopharma firms. This is done for both total stock returns and for idiosyncratic returns. We let $\sigma_{i,t}$ represent total stock return volatility for firm i, $\sigma_{P,t}$ represent portfolio return volatility, $\sigma_{i,t}^{idio}$ represent idiosyncratic return volatility for firm i, and $\sigma_{P,t}^{idio}$ represent idiosyncratic portfolio return volatility.

As noted by Schwert (1989) and French, Schwert, and Stambaugh (1987), a potential concern of the above procedure is autocorrelation in the return series, which may bias the volatility estimates. Therefore, our second approach to calculating volatility is to use non-overlapping samples of daily data to construct monthly volatility estimates. Specifically, we

follow Bali, Cakici, Yan, and Zhang (2005) and calculate a measure of average stock variance. We first calculate the monthly variance of a stock i within a month T as the sum of the squared daily returns of that stock within the month. These monthly variance estimates are then averaged across all stocks, to create an average stock variance for month T:

$$\left(\hat{\sigma}_T\right)^2 = \frac{1}{N_T}\sum_{i=1}^{N_T}\left[\sum_{t=1}^{D_T} R_{i,t}^2\right], \tag{37}$$

where D_T is the number of days in month T, $R_{i,t}$ is the return of stock i on day t, and N_T is the total number of stocks that exist in month T.[19] The average stock standard deviation (volatility) is given by the square root of the variance, i.e. $\hat{\sigma}_T = \sqrt{\left(\hat{\sigma}_T\right)^2}$. Similarly, average idiosyncratic return variance for month T is given by:

$$\left(\hat{\sigma}_T^{idio}\right)^2 = \frac{1}{N_T}\sum_{i=1}^{N_T}\left[\sum_{t=1}^{D_T} \epsilon_{i,t}^2\right], \tag{38}$$

and the average idiosyncratic volatility is given by $\hat{\sigma}_T^{idio} = \sqrt{\left(\hat{\sigma}_T^{idio}\right)^2}$. For robustness, we also calculate monthly volatilities as in Schwert (1989). We include these estimates in the Appendix.

Finally, to examine the time-series trend of betas for the biopharma industry, we form a value-weighted portfolio of biopharma firms, and calculate the Fama-French factor betas (given by (36) above) of the portfolio using a rolling 2-year window of daily portfolio returns.

[19] This calculation of stock variance differs slightly from Bali et. al. (2005) in that they include a term that includes the cross-product of adjacent returns within the month, as in French, Schwert and Stambaugh (1987). The calculation of the monthly variance in (37) follows from Schwert (1989), who notes that including cross-products of returns may lead to negative volatility estimates. One could also make an adjustment for the mean return in the calculation of the monthly variance, but Schwert (1989) notes that the differences in the estimates are very small.

4.2 Data and Summary Statistics

The focus of the empirical results is on the biopharma industry, which we take to be comprised of 4-digit Standard Industry Classification (SIC) codes 2830-2836.[20] The sample period is from 1950 to 2012. For our financial characteristic data, we include all biopharma firms that are listed in the Compustat database. The data encompass a total of 15,366 firm-year observations. For stock return data, we take all biopharma firms from the CRSP database for which daily data is available, which encompass 2,356,868 daily return observations.[21] Daily return data for the Fama-French factors and the risk-free rate of return were obtained from Ken French's web site.[22] All variables except for those formed from stock returns are winsorized at the 1% level in order to reduce the impact of extreme outliers.

Summary statistics for all of the variables are given in *Table 1*. The entries in *Table 1* show that R&D spending is substantial for the industry, averaging roughly 32% of total assets over the sample period. In addition, cash holdings are also substantial, averaging 45% of total assets. While the mean level of debt is somewhat high at 26% of total assets, the much lower median and 25th percentile values (as well as high standard deviation) indicate that the distribution is skewed—there are firms with substantial amounts of debt on their balance sheet that drive the mean up. However, accounting for cash holdings and computing net debt, the mean firm in the industry as well as the median firm hold substantially negative net debt as a result of their cash holdings.

Table 1 also contains summary statistics for the volatility and beta estimates. The mean volatility of daily returns, calculated from rolling 360-day windows, is 3.1% for total volatility and 2.9% for idiosyncratic volatility. Consistent with portfolio diversification benefits, the numbers are lower when considering rolling volatilities of daily portfolio returns, 1% and 0.5%

[20]These are made up of Drugs (2830), Biological Products (2831), Medicinal Chemical and Botanical Products (2833), Pharmaceutical Preparations (2834), In Vitro and In Vivo Diagnostic Substances (2835), and Biological Products except diagnostics (2836). These are the same SIC codes that comprise the Fama and French (1993) "Drugs" industry.

[21]Daily data from 1948 and onwards is used to estimate betas and volatilities for the years 1950 and 1951.

[22]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 1: Summary Statistics

This table provides summary statistics for all variables. $CR_t(4)$ is the 4-firm concentration ratio for year t, defined by equation (35). $(R\&D/TA)_{i,t}$ is R&D expenditures scaled by total assets. $(PPE/TA)_{i,t}$ is property, plant, and equipment scaled by total assets. $(Cash/TA)_{i,t}$ is cash and short-term investments scaled by total assets. $(Debt/TA)_{i,t}$ is debt, which is the sum of total long-term debt and short-term debt (debt in current liabilities), scaled by total assets. $(Net\,Debt/TA)_{i,t}$ is net debt scaled by total assets, where $Net\,Debt_{i,t} = Debt_{i,t} - Cash_{i,t}$. $\sigma_{i,t}$ is individual stock return volatility, and $\sigma^{idio}_{i,t}$ is individual idiosyncratic return volatility, both calculated from a rolling window of the past 360 daily returns for each stock. $\sigma_{P,t}$ is value-weighted portfolio return volatility and $\sigma^{idio}_{P,t}$ is idiosyncratic value-weighted portfolio return volatility, calculated from the past 360 daily returns for the value-weighted portfolio of biopharma stocks. $\hat{\sigma}_T$ is the monthly estimate of average stock volatility, given by (37), and $\hat{\sigma}^{idio}_T$ is the monthly estimate of average idiosyncratic volatility given by (38). $\beta_{t,mkt}$, $\beta_{t,SMB}$, and $\beta_{t,HML}$ are the betas of the market, size, and value Fama-French factors, estimated using a rolling 2-year window of daily value-weighted portfolio returns. All variables run from 1950 to 2012. All financial characteristic variables are winsorized at the 1% level.

Variable	Mean	SD	p25	Median	p75
$CR_t(4)$	0.387	0.066	0.339	0.368	0.453
$(R\&D/TA)_{i,t}$	0.317	0.354	0.066	0.183	0.426
$(PPE/TA)_{i,t}$	0.173	0.165	0.039	0.125	0.267
$(Cash/TA)_{i,t}$	0.447	0.324	0.131	0.420	0.765
$(Debt/TA)_{i,t}$	0.258	0.465	0.0003	0.087	0.286
$(Net\,Debt/TA)_{i,t}$	-0.185	0.635	-0.679	-0.248	0.104
$\sigma_{i,t}$	0.031	0.015	0.018	0.027	0.043
$\sigma^{idio}_{i,t}$	0.029	0.014	0.016	0.025	0.039
$\sigma_{P,t}$	0.010	0.004	0.008	0.009	0.011
$\sigma^{idio}_{P,t}$	0.005	0.002	0.004	0.005	0.006
$\hat{\sigma}_T$	0.166	0.086	0.090	0.160	0.217
$\hat{\sigma}^{idio}_T$	0.141	0.077	0.076	0.127	0.186
$\beta_{t,mkt}$	0.904	0.173	0.779	0.892	1.060
$\beta_{t,SMB}$	-0.087	0.258	-0.247	-0.130	0.086
$\beta_{t,HML}$	-0.362	0.339	-0.578	-0.298	-0.144

for total and idiosyncratic volatility, respectively. The monthly average volatility estimates are higher, at roughly 17% for total volatility and 14.1% for idiosyncratic volatility. Finally, for the beta estimates, the mean market beta for the industry is roughly 0.90, indicating that the biopharma industry co-moves less than one-for-one with the market. The mean of the SMB beta is slightly less than 0; however the standard deviation and 75th percentile indicate that it is also positive for a number of years. The mean of the HML beta is negative, and while the standard deviation indicates substantial variability, the negative percentile values also indicate that it is negative for most years.

4.3 Time-Series Evidence on Average Trends

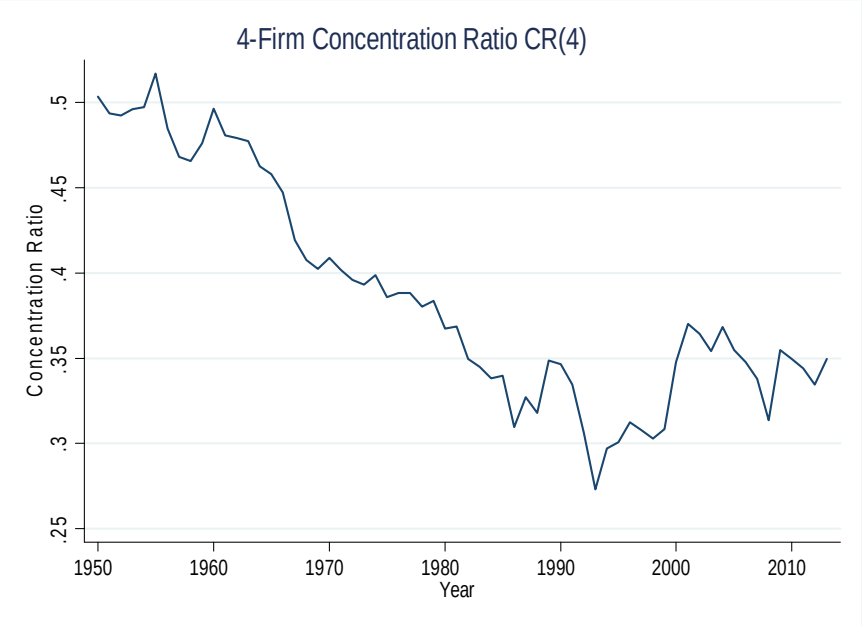
The top two graphs of *Figure 3* show the value of of the Concentration Ratio for the biopharma industry over time. As can be seen from the graphs, the Concentration Ratio has shown a steady decline over time from 1950 until the mid 1990s, and then has exhibited a slight upward trend.[23] Similarly, the number of competitors in the industry has steady increased until the mid-1990s, after which it has remained relatively flat. Overall, both the Concentration Ratio and the number of competitors in the industry indicate that concentration in the biopharma industry has gone down (and thus that competition has gone up) substantially over time from 1950. This is consistent with existing papers (e.g. Caves, Whinston, and Hurwitz (1991), Grabowski and Vernon (1990, 1992), and others), who have shown that the industry has become more competitive over time.

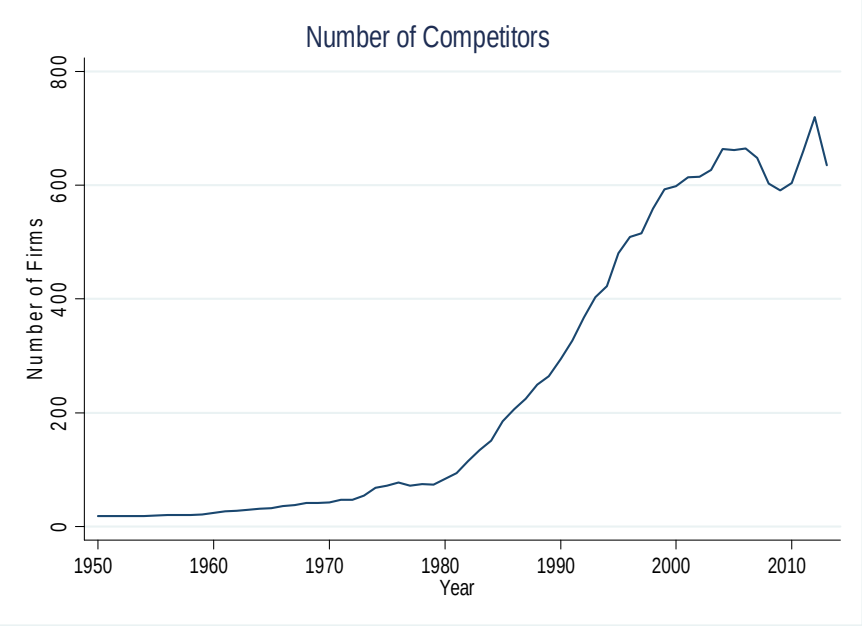
Taking this increase in competition over time as a given, we now examine the financial characteristics of firms in the biopharma industry. *Figure 4* shows how the financial characteristics of the biopharma industry have evolved over time. The mean and median values of $(R\&D/TA)_{i,t}$, $(PPE/TA)_{i,t}$, $(Cash/TA)_{i,t}$, $(Debt/TA)_{i,t}$, and $(Net\,Debt/TA)_{i,t}$ are calculated for each year. In order to distinguish these trends from larger trends that may also be

[23]For robustness, in Section B of the Appendix, we also present the same trends for alternative sales-based competition ratios: the 8-firm Concentration Ratio (where $M = 8$ in (35)), the Herfindahl-Hirschman Index, and the Hannah and Kay (1971) Index. The results are qualitatively similar.

Figure 3: Competition in the Biopharma Industry

These figures present estimates of competition over time for the biopharma industry. The top figure gives the 4-firm Concentration Ratio. The ratio is calculated for each year using equation (35), and a higher number indicates increased concentration. The bottom figure gives the number of competitors in the biopharma industry over time.





taking place in other industries, the mean values of these variables are also included for all other industries apart from the biopharma industry.

The graphs presented in *Figure 4* are consistent with predictions 1 and 2 of the theoretical model. In particular, as competition has increased over this time period, both mean and median R&D expenditures have increased, while assets-in-place (measured by PPE) have decreased sharply.[24] Moreover, cash holdings have increased substantially over this time period. Finally, while the mean level of debt has increased over time (mostly in the 1970s and the 2000s), the median level of debt has declined consistently from the mid-1970s. As the summary statistics also indicated, the debt levels are cross-sectionally skewed across firms, with some firms holding very large amounts of debt—this drives the mean values upwards. But the median debt levels indicate that the majority of firms have decreased their debt levels in the industry. Net debt shows a similar trend, although the decline in both mean and median values are more marked until the late-1990s. While the mean level increases after that point (concurrent with the increase in debt), the median level of net debt stays relatively flat, consistent with how the competition measures behaved over this period. For all of the variables, the trends for the biopharma industry are more striking than those for other industries, suggesting that the trends we observe for the biopharma industry are not driven by aggregate trends affecting all industries.[25]

For the volatility time-series trends of the biopharma industry, we begin by examining the rolling total and idiosyncratic stock return volatility of individual stocks in the biopharma industry, averaged at each date—i.e. the mean levels of $\sigma_{i,t}$ and $\sigma_{i,t}^{idio}$ at each date. The results are shown in panel (a) of *Figure 5*. The evidence is consistent with the predictions

[24]The secular increase in mean R&D expenditures understates an interesting cyclicality. One explanation for this cyclicality is a change in profitability each year, which partly determines how much firms are able to spend on R&D—and which in turn is partly dependent on the overall state of the economy. A graph of R&D expenditures scaled by earnings reveals a smoother trend over time.

[25]The trends for R&D, cash, and assets-in-place remain relatively flat until the mid-1970s, while debt increases during this early time period. While this is in contrast to the reduction in the Concentration Ratio during this time period, this is consistent with the number of competitors (as shown in *Figure 3*) also being relatively flat during this period. As previously discussed, sales-based measures of competition may not be ideal for this industry, and thus these measures may not accurately gauge competition during certain periods.

Figure 4: Financial Characteristics over Time

These graphs show the mean (solid blue line) and median (dashed red line) values of financial characteristics for the biopharma industry in each year. The green dotted lines represent the mean values of financial characteristics for all other industries.

of the model. Specifically, total stock return volatility and idiosyncratic volatility have both increased substantially over time, as competition has also increased. This effect is the most striking for the post-1960s time period, when the number of firms increases substantially.

Panel (b) of *Figure 5* depicts the rolling total and idiosyncratic stock return volatility of a value-weighted portfolio of biopharma firms over time (represented by $\sigma_{P,t}$ and $\sigma_{P,t}^{idio}$). The dotted red lines represent trend lines. In general, the level of volatility is lower for the portfolio, as a result of diversification. While not as striking as the results in panel (a) of *Figure 5*, both total and idiosyncratic volatility have trended upwards (as shown by the dotted red trend lines). Total stock return volatility exhibits a number of periods of large spikes in volatility, especially after the mid-1980s. The same is true for idiosyncratic stock return volatility after the 1970s, which in addition also has a very large spike around 2001, which may be attributable to the September 11th attacks and also the bursting of the private equity bubble. While there is a substantial decline in volatility in the years following that, both graphs generally show an increased number of periods of high volatility over time.

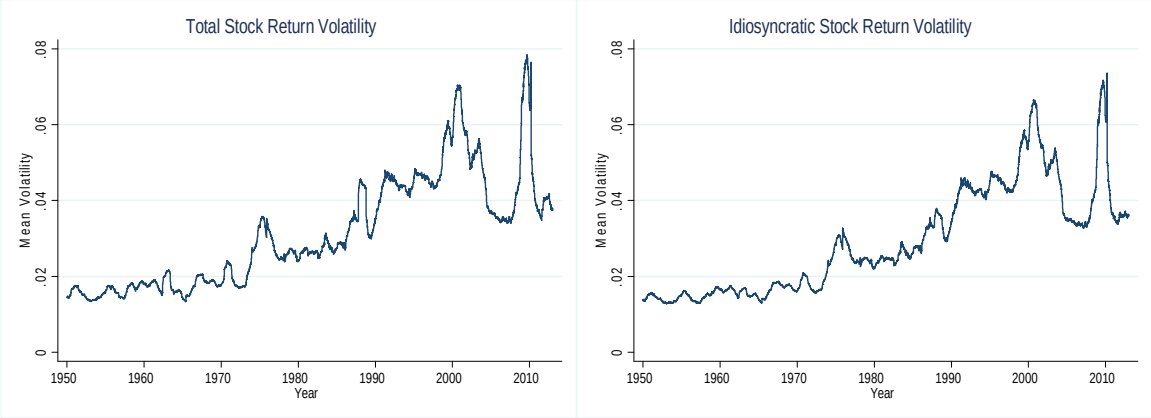
The evidence in both panels of *Figure 5* is consistent with the predictions of the model. Specifically, total stock return volatility and idiosyncratic volatility have both increased substantially over time, as competition has also increased. This effect is the most striking for the post-1960s time period, when the number of firms increases substantially. These results are also consistent with the findings of Irvine and Pontiff (2009), who argue that an increase in idiosyncratic volatility of the average stock is attributable to more intense economy-wide competition.

We next examine the volatility of the biopharma industry using non-overlapping monthly volatilities. *Figure 6* depicts average monthly stock volatility as in Bali et al. (2005), as described in equations (37)–(38). In panel (a) of *Figure 6*, the left graph shows total stock volatility (described by equation (37)), while the right graphs shows idiosyncratic stock volatility (described by equation (38)). Panel (b) of *Figure 6* illustrates a simple 12-month moving average of the graphs in Panel (a). Overall, the graphs illustrate a clear trend of

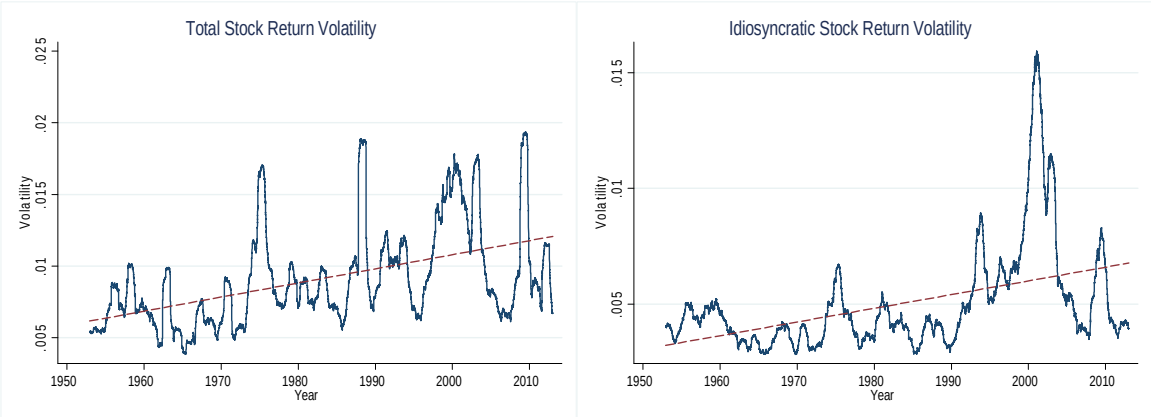
Figure 5: Total and Idiosyncratic Stock Return Volatility

Panel (a) shows total and idiosyncratic volatility for the biopharma industry, calculated as the average, at each date, of total and idiosyncratic stock return volatility of individual stocks. The left figure of panel (a) shows total stock return volatility for the biopharma industry, while the right figure of panel (a) shows mean idiosyncratic stock return volatility for the biopharma industry. Total stock return volatility is calculated using the rolling standard deviation of the past 360 days of daily returns and then averaged across all firms each day, while idiosyncratic volatility is calculated using the rolling standard deviation of the past 360 days of individual daily idiosyncratic returns from (36) and then averaged across all firms each day. Panel (b) shows total (left figure) and idiosyncratic (right figure) volatility for a value-weighted portfolio of firms in the biopharma industry. Total stock return volatility is calculated using the rolling standard deviation of the past 360 days of daily value-weighted portfolio returns, while idiosyncratic volatility is calculated using the rolling standard deviation of the past 360 days of daily idiosyncratic portfolio returns from (36).

(a) Mean Levels of $\sigma_{i,t}$ and $\sigma_{i,t}^{idio}$



(b) Levels of $\sigma_{P,t}$ and $\sigma_{P,t}^{idio}$



increasing volatility over time, consistent with the predictions of the model as competition has increased.[26] For further robustness, the Appendix gives additional monthly estimates of value-weighted portfolio volatility.

The betas of a value-weighted portfolio of biopharma firms are shown in *Figure 7*. The dotted lines represent trend lines for the different beta estimates. As can be seen in the figure, the beta estimates for all three factors have generally declined from 1950 and onward. The market beta exhibits a somewhat gradual decline over the time period, from slightly over 1.0 in 1950 to roughly 0.7 in 2012. However, the decline over time is more striking for the SMB and HML factor betas. The SMB factor beta shows a clear downward trend from 1950 until 2000, though it has trended upward since 2000. The HML factor beta also exhibits a striking downward trend from 1950 through the mid-to-late 1990s. While this trend does not continue after the late 1990s, this coincides with the slight increase in concentration in the industry around the same time, as depicted in *Figure 3*. In addition, the two large spikes during this period may be attributable to the bursting of the dot com bubble in the late 1990s and the September 11th terrorist attacks in 2001/bursting of the private equity bubble. The beta estimates may be affected by the changes in debt and cash levels over time; hence, we re-ran our analysis using *unlevered* stock returns—constructed using a simple unlevering formula—and our results and main findings are unchanged.[27] Overall, the declines in beta over time are consistent with the predictions of the model that firms will substitute investments in assets-in-place (which carry systematic risk) for investments in R&D (which carry idiosyncratic risk).

Table A1 of the Appendix summarizes the direction and significance of the relationship between the various financial characteristics and measures of competition through time-series regressions.

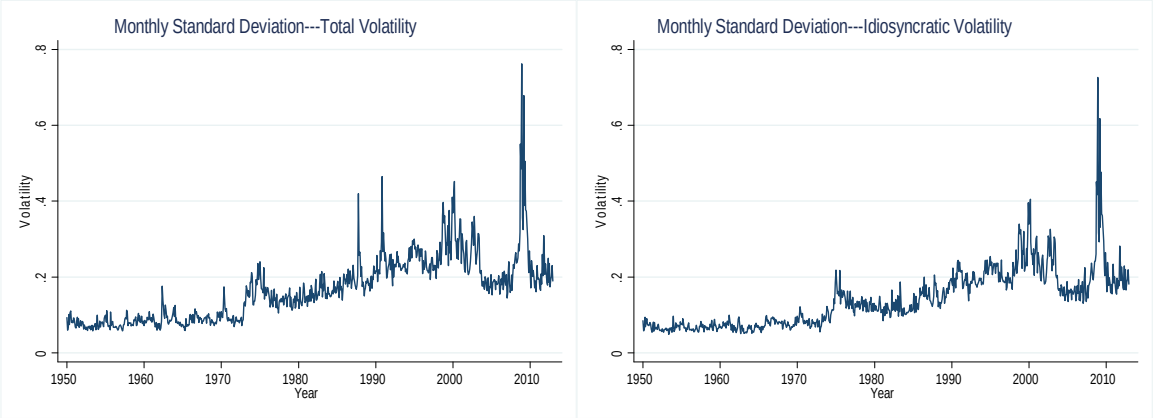
[26] A possible concern is that the upward trend in volatility is stochastic rather than deterministic in nature. To examine this, we also run Augmented Dickey-Fuller tests on the monthly series to test for the presence of a unit root. For both total volatility and idiosyncratic volatility, Augmented Dickey-Fuller tests reject the presence of a unit root at at least the 5% level when up to 5 lags are included, regardless of whether a trend is included.

[27] Results available upon request.

Figure 6: Total and Idiosyncratic Stock Return Volatility

Monthly estimates of total return volatility and idiosyncratic volatility. Panel (a) depicts of monthly estimates of average (across all firms in a given month) total and idiosyncratic stock volatility, as in Bali et. al. (2005). The left graph of panel (a) is total stock volatility, as described by equation (37). The right graph of panel (a) is idiosyncratic stock volatility, as described by equation (38). Panel (b) gives 12-month simple moving averages of the graphs in panel (a).

(a) Levels of $\hat{\sigma}_T$ and $\hat{\sigma}_T^{idio}$



(b) Moving Average of $\hat{\sigma}_T$ and $\hat{\sigma}_T^{idio}$

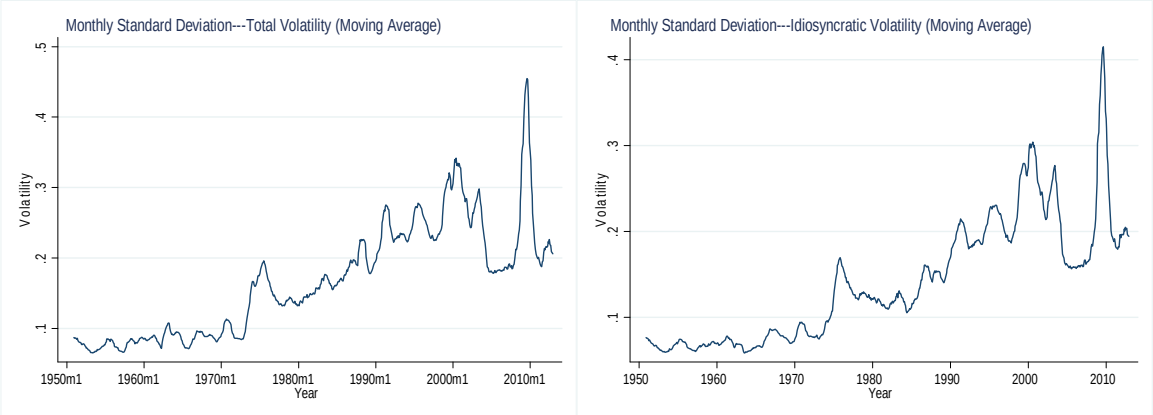
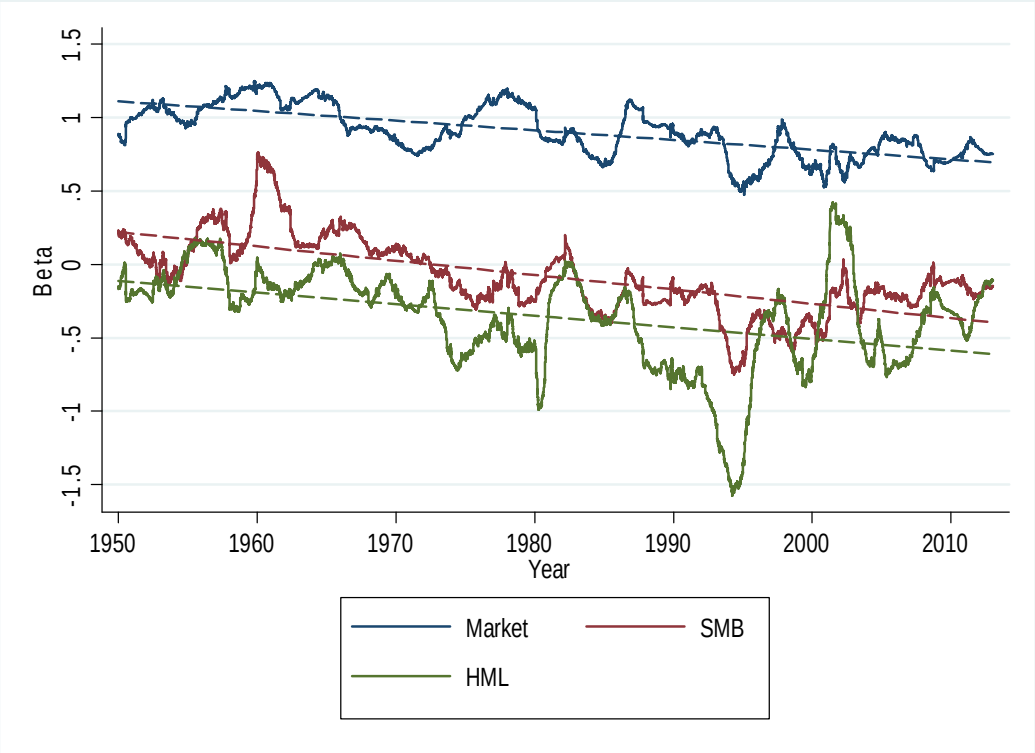


Figure 7: Biopharma Industry Value-weighted Betas

This figure shows the betas of a value-weighted portfolio of biopharma stocks, calculated via the Fama-French 3-factor model using a rolling 2-year window of daily stock returns. The blue line represents the market factor, the green line represents the market-to-book factor (HML), and the red line represents the size factor (SMB). The dotted lines are trend lines for the factors.



4.4 An Empirical Test Using the 1984 Hatch-Waxman Drug Act

4.4.1 Motivation and Empirical Strategy

While the previous empirical evidence is consistent with the predictions of the model, a weakness of the evidence is that it treats the increase in competition as exogenous over time. However, there is an endogeneity problem associated with competition and the outcome variables predicted by the model. For example, R&D outlays by incumbent firms can act as a competitive entry barrier, thus creating an endogeneity problem—R&D is affected by competition, but competition is also affected by R&D. In order to overcome this, we exploit the exogenous variation in competition introduced by the passage of the Drug Price Competition and Patent Term Restoration Act of 1984.

The Drug Price Competition and Patent Term Restoration Act of 1984 (informally known as the Hatch-Waxman Act, and henceforth referred to as such) was introduced for the expressed purpose of increasing competition in the drug marketplace, by facilitating the entry of generic drugs after the expiration of a patent. Prior to the passage of the Hatch-Waxman Act, onerous Food and Drug Administration requirements made it necessary for generic drugs to replicate many of the original drug's tests in order to gain market approval. However, once the law was passed, generic drugs only needed to prove bioequivalence to the original drug, thus greatly decreasing the barriers to competitive entry. A number of papers have argued and provided evidence that the Hatch-Waxman Act did indeed increase competition and facilitate the entry of generic drugs (see, for example, analysis and evidence by Grabowski and Vernon (1986, 1992), who look at entry and price data for a sample of drugs after the enactment of the law).

The ideal test is to find two groups of firms with similar characteristics (as defined by the theory), exogenously change the degree of competition for one group, and then see if the resulting difference conforms to the predictions of the theory. We use the Hatch-Waxman Act as a source of exogenous variation in order to conduct a differences-in-differences analysis to

provide cleaner empirical support for the predictions of the theory. As the Hatch-Waxman Act specifically influenced the biopharma industry through an increase in competition, the treatment group consists of biopharma firms (SIC codes 2830-2836). Since the theory is applicable for firms in R&D-intensive industries, we choose firms from the five top R&D-intensive industries other than biopharma as our control group.[28] A concern is that the control group has different characteristics and is thus not properly comparable to the biopharma industry. To account for this, we therefore use propensity score matching to choose firms from the other R&D-intensive industries that are comparable to the firms in our biopharma sample based on observable characteristics.[29] The pre-period is from 1975 to 1983, while the post-period is from 1984 to 1995. The resulting sample for the control group consists of a total of 827 firms and 10,277 firm-years of data, while the treatment group consists of a total of 315 firms and 2,689 firm-years of data.

A critical assumption of the differences-in-differences framework is that the treatment and control groups exhibit parallel trends in terms of the outcome variables prior to the event in question. For the financial characteristic variables, *Figure 8* provides graphical evidence for the 20 years surrounding the passage of the Hatch-Waxman Act, that examines this assumption for the control group. In these graphs, the solid blue lines represent average values for the biopharma industry, while the dashed red lines represent average values for other R&D-intensive firms. The vertical red lines represent the year that the Hatch-Waxman Act was implemented. The levels of R&D expenditures, cash holdings, debt, net debt, and assets-in-place are all similar for both biopharma and the control group in the pre-period,

[28]These industries are identified by the NSF (National Science Foundation (1999)) as being the top R&D-intensive industries, and include: Industrial and other chemicals (2-digit SIC code 28, excluding 3-digit code 283), industrial and commercial machinery and computers (2-digit SIC code 35), electrical equipment (2-digit SIC code 36), transportation equipment including aircraft and missiles (2-digit SIC code 37), and measuring and analyzing equipment (2-digit SIC code 38).

[29]More specifically, we choose firms in the other industries that match biopharma firms based on size ($\log(TA)$), profitability ($EBIT/TA$), capital structure ($Debt/TA$), and investment opportunities as proxied by market-to-book (ME/BE). We allow matches between multiple firms (i.e. we implement matching with replacement), although this assumption does not have a material impact on our results. We further restrict the sample to biopharma and control firms which are on a common support in terms of these observable characteristics. Our results are also robust to not matching the control group and biopharma firms; these are available upon request.

showing that these two industries are similar in terms of these financial characteristics. Moreover, these characteristics exhibit strong parallel trends before the Hatch-Waxman Act was implemented. After the Act was implemented, the values for the two groups diverge in a way consistent with the predictions of the model. Specifically, in the period following the enactment of the law, R&D expenditures and cash holdings for biopharma firms appear to increase, while debt, net debt, and assets-in-place appear to decrease relative to the trend for the control group. Overall, the graphs provide evidence supporting the appropriateness of the differences-in-differences analysis in this setting, and also provide suggestive evidence for the effect of the Hatch-Waxman Act on the financial characteristics of the biopharma industry.[30]

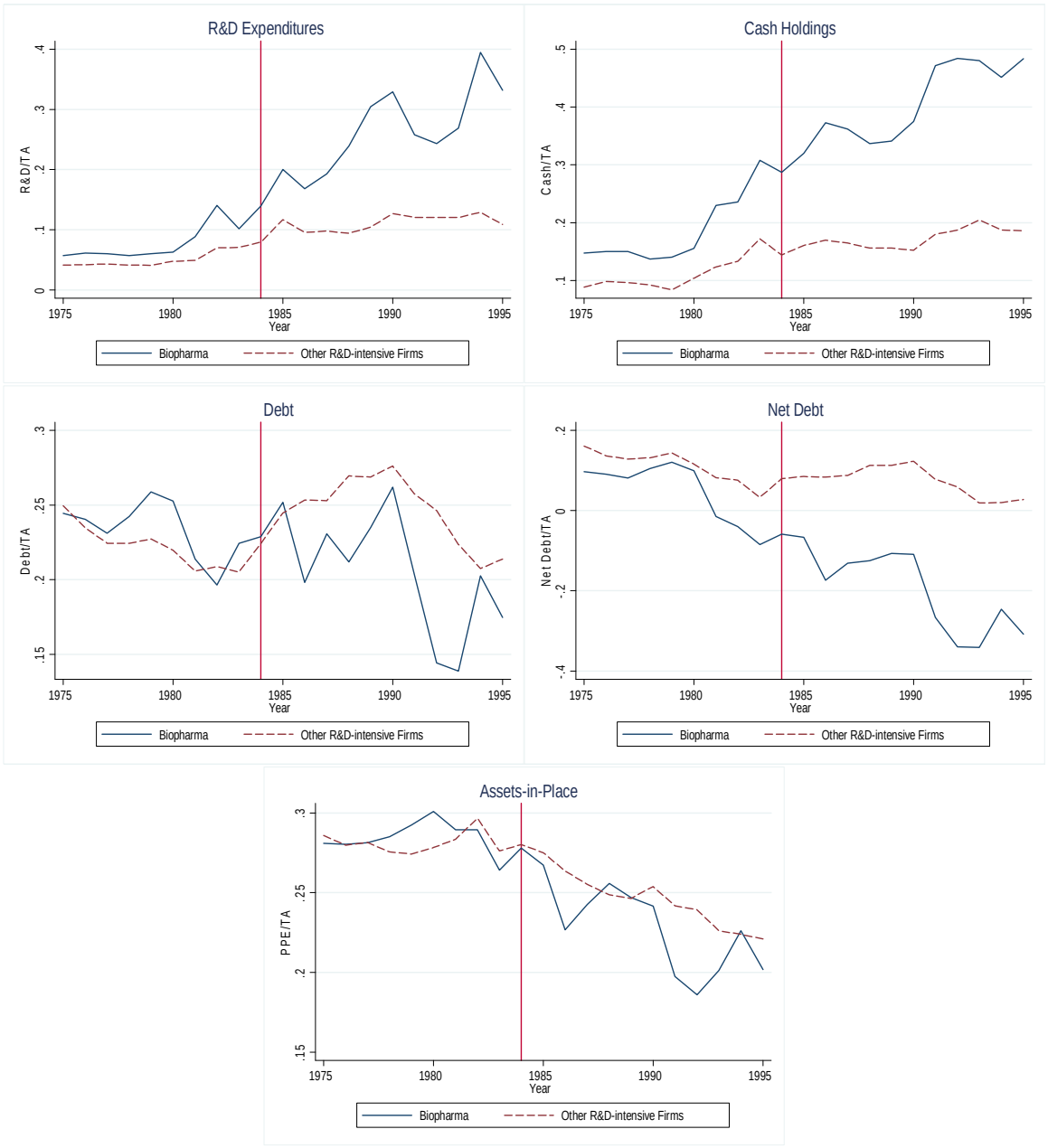
For a more formal analysis, we estimate the following regression for the financial characteristic predictions:

$$Y_{i,t} = \gamma_0 + \gamma_1 HW_t + \gamma_2 Biopharma_i + \gamma_3 HW_t \times Biopharma_i + \eta X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}. \quad (39)$$

In (39), $Y_{i,t}$ represents the dependent variable of interest for firm i in year t, predicted to vary as a function of competition by the theoretical model. HW_t is an indicator variable which takes a value of 1 if the year is 1984 or later, which is the period after the Act was enacted into law. $Biopharma_i$ is an indicator variable which takes a value of 1 if firm i is in the biopharma industry. It follows that the that the regression estimate of γ_3 is the differences-in-differences estimator—the effect of the increase in competition stemming from the Hatch-Waxman Act on $Y_{i,t}$. For the financial characteristics, the dependent variable $Y_{i,t}$ represents the variable of interest for firm i in year t, as predicted by the theoretical model. Specifically, for the financial

[30] A further assumption of the differences-in-differences framework in this setting is that the event (i.e. the Hatch-Waxman Act) increased competition for the biopharma industry relative to the control group. While the Hatch-Waxman Act dealt with drug development and thus was targeted specifically toward the biopharma industry, we explicitly test this assumption graphically and through a differences-in-differences regression in *Figure A3* of the Appendix through changes in competition as measured by the Concentration Ratio (CR(4)). While the Concentration Ratio and other sales-based measures of concentration are likely imperfect measures of competition for the biopharma industry, as we previously argued, the results show that the Concentration Ratio dropped for the biopharma industry relative to the control group after the Hatch-Waxman Act, which is consistent with it increasing competition for the biopharma sector.

Figure 8: Financial Characteristic Trends for Treatment and Control Group
Trends for financial characteristic variables for R&D expenditures, cash holdings, debt, net debt, and assets-in-place, all scaled by total assets. All variables are averages for each group. The solid blue lines give averages for the biopharma industry, while the red dashed lines give averages for the propensity-score-matched sample of R&D-intensive firms. A vertical red line is included in each graph, representing the year that the Hatch-Waxman Act was implemented.



characteristics, we examine $(R\&D/TA)_{i,t}$, $(PPE/TA)_{i,t}$, $(Cash/TA)_{i,t}$, $(Debt/TA)_{i,t}$, and $(Net\,Debt/TA)_{i,t}$ as choices for $Y_{i,t}$. In order to control for the possibility of differential trends between the control and treatment groups, $X_{i,t}$ is a vector of contemporaneous and lagged control variables that may also covary with the dependent variable.[31] Finally, μ_i represents firm fixed effects and λ_t represents year fixed effects. Equation (39) is estimated for the period from 1975 to 1995.

We also examine the effect of the Hatch-Waxman Act on the stock return risk variables. Specifically, we estimate a differences-in-differences regression for the period surrounding the implementation of the Act (from 1975 to 1995), in order to examine how the volatility and betas of biopharma and control R&D-intensive firms changed after the Act was put into law. Consistent with the approach in Section 4.1, the volatility and beta variables which we use as dependent variables are calculated for value-weighted portfolios of biopharma firms and control R&D-intensive firms. For the volatility variables, we calculate yearly values of total and idiosyncratic volatility ($\sigma_{P,t}$ and $\sigma^{idio}_{P,t}$) for value-weighted portfolios of both groups of firms using the standard deviation of each portfolio's daily total or idiosyncratic returns over the year. For the beta variables, we calculate yearly beta estimates of value-weighted portfolios of biopharma and control firms via equation (36), using the past 720 days of daily returns.[32]

[31] Control variables included in $X_{i,t}$ for the financial characteristic variables include: $\log(NA_{i,t})$ (where $NA = TA - Cash$), $(PPE/TA)_{i,t}$, $(Cash/TA)_{i,t}$, $(EBIT/TA)_{i,t}$ (earnings as a fraction of total assets to control for profitability), $(ME/BE)_{i,t}$ (market value of equity to book value of equity), and $(Div/TA)_{i,t}$ (the amount of common/ordinary dividends paid in the previous period). Cash and PPE are excluded as control variables in the cases when they are the dependent variables of interest.

[32] *Figure A4* of the Appendix graphs trends for the risk variables and the control group surrounding the passage of the law. All three beta estimates drop by more for the biopharma industry than the control group following passage of the law, while total and idiosyncratic volatility increase more for the biopharma industry than for the control group. However, while the HML and SMB betas show roughly parallel trends prior to the passage of the law, the parallel trend assumption may not hold well for the market beta and volatility variables.

4.4.2 Results and Discussion

We begin by examining the effect of the increase in competition caused by the Hatch-Waxman Act on the financial characteristic variables predicted by the theory. The estimation results for regression (39) are included in *Table 2*. Results both with and without control variables and fixed effects are included.

Overall, the results from the differences-in-differences analysis are consistent with the predictions of the model. The differences-in-differences estimator for $R\&D$ is positive and significant with or without control variables and fixed effects (columns (1) and (2)). This indicates that, as the Hatch-Waxman Act increased competition for the biopharma industry, firms in the industry increased their R&D relative to the control group. The differences-in-differences estimator for PPE is insignificant and has a different sign across the two specifications, showing that the evidence for assets-in-place in this setting is mixed. The differences-in-differences estimator for $Cash$ is positive and significant whether controls are included or not, indicating that firms in the biopharma industry increased their cash holdings as a result of the Hatch-Waxman Act. The differences-in-differences estimator for *Debt* is negative and significant whether controls are included or not, providing evidence that firms in the biopharma industry decreased their debt as a result of the increase in competition. Finally, the estimator for *Net Debt* is negative and significant in both columns (9) and (10), indicating that net debt also fell as a result of the increase in competition for the biopharma industry.[33]

We next examine the effect of the Hatch-Waxman Act on the risk variables for the biopharma industry. The estimation results are given in *Table 3*. For both total and idiosyncratic stock return volatility, the differences-in-differences estimator is positive and significant, indicating that both total and idiosyncratic return volatility increased significantly

[33]As a robustness check to account for the possibility that our results are being driven by trends that started before our sample period, we do a falsification test where we run regression (39) for the sample period from 1965 to 1985, falsely specifying that the Act was implemented in 1974. These results are included in *Table A2* of the Appendix, and show that the sign and significance of our main results do not hold for the falsification sample.

Table 2: The Effect of the Hatch-Waxman Act on Financial Characteristics

This table estimates the differences-in-differences regression (39) for financial characteristics. The sample consists of biopharma firms and a control group consisting of propensity-score matched R&D-intensive firms, matched on size, profitability, capital structure, and market-to-book. The sample period spans from 1975 to 1995. The dependent variables consist of $R\&D$, PPE, $Cash$, $Debt$, and $Net\,Debt$, each scaled by total assets. HW_t is a dummy variable which takes a value of 1 if the year is 1984 or later, and a value of zero otherwise. $Biopharma_i$ is a dummy variable which takes a value of 1 if firm i is in the biopharma industry, and a value of 0 otherwise. Control variables include $\log(NA_{i,t})$, $(PPE/TA)_{i,t}$, $(Cash/TA)_{i,t}$, $(EBIT/TA)_{i,t}$, $(M/B)_{i,t}$, and $(Div/TA)_{i,t}$. Controls for cash and PPE are excluded when they are the dependent variable of interest. Year and firm fixed effects are included where indicated. Robust standard errors are given in parentheses, and standard errors are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable:									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$R\&D$	$R\&D$	PPE	PPE	$Cash$	$Cash$	$Debt$	$Debt$	$Net\,Debt$	$Net\,Debt$
$HW_t \times Biopharma_i$	0.132***	0.018**	-0.025	0.016	0.162***	0.034**	-0.055***	-0.034*	-0.216***	-0.080***
	(0.018)	(0.009)	(0.016)	(0.016)	(0.025)	(0.015)	(0.021)	(0.019)	(0.039)	(0.030)
$Biopharma_i$	0.032***		0.002		0.084***		0.010		-0.074**	
	(0.010)		(0.017)		(0.023)		(0.020)		(0.035)	
HW_t	0.060***		-0.035***		0.059***		0.023**		-0.036***	
	(0.006)		(0.006)		(0.006)		(0.010)		(0.013)	
Constant	0.051***	0.143***	0.281***	0.295***	0.113***	0.492***	0.221***	0.222***	0.108***	-0.386***
	(0.003)	(0.016)	(0.006)	(0.020)	(0.005)	(0.020)	(0.007)	(0.048)	(0.010)	(0.040)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	10,409	8,199	12,381	9,675	12,392	9,675	12,373	9,675	12,373	9,675
Number of Firms	1,040	958	1,141	1,063	1,142	1,063	1,142	1,063	1,142	1,063
Adjusted R^2	0.110	0.852	0.018	0.791	0.182	0.847	0.003	0.548	0.070	0.748

more for the biopharma industry than for the control group immediately following the passage of the Hatch-Waxman Act, which is consistent with the predictions of the theory. For the betas, the coefficient for $HW_t \times Pharma_i$ is negative though marginally insignificant for the beta of the market factor, but is negative and significant for the betas of the size (SMB) and value (HML) factors. This decline in betas compared to the control group immediately following the Hatch-Waxman Act is consistent with the predictions of the theory. Thus, overall the empirical results for the risk variables support the predictions of the theory and suggest that the increase in competition brought by the Hatch-Waxman Act led to increased volatility but reduced betas for biopharma firms.

Table 3: The Effect of Competition on Risk Variables

This table estimates the change in the stock return risk variables for biopharma firms versus control group firms as a result of the Hatch-Waxman Act. The control group is a propensity-score matched sample of R&D-intensive firms, matched on size, profitability, capital structure, and market-to-book. The sample spans from 1975 to 1995. The dependent variables in columns (1) and (2) consist of the total and idiosyncratic stock return volatilities of value-weighted portfolios of biopharma or control firms (σ_t and σ_t^{idio}), calculated at the end of each year using daily returns. The dependent variables in columns (3)–(5) consist of the betas of value-weighted portfolios of biopharma or control firms, calculated as of the end of year t—the market beta$\beta_{mkt,t}$, size beta $\beta_{SMB,t}$, and value beta$\beta_{HML,t}$. HW_t is a dummy variable which takes a value of 1 if the year is after 1984, and a value of zero otherwise. $Biopharma_i$ is a dummy variable which takes a value of 1 if sector i is the biopharma industry, and 0 otherwise. Robust standard errors are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable:				
	(1)	(2)	(3)	(4)	(5)
	σ	σ^{idio}	β_{mkt}	β_{SMB}	β_{HML}
$HW_t \times Pharma_i$	0.007**	0.007***	-0.143	-0.224***	-0.390**
	(0.003)	(0.003)	(0.086)	(0.083)	(0.152)
$Biopharma_i$	-0.002	-0.003**	-0.128*	-0.035	-0.190**
	(0.001)	(0.001)	(0.065)	(0.060)	(0.085)
HW_t	0.009***	0.009***	-0.034	0.039	-0.017
	(0.002)	(0.002)	(0.040)	(0.047)	(0.069)
Constant	0.027***	0.025***	1.094***	-0.165***	-0.194***
	(0.001)	(0.001)	(0.038)	(0.041)	(0.056)
Observations	42	42	41	41	41
R^2	0.662	0.683	0.471	0.409	0.506

5 Conclusion

In this paper, we develop a parsimonious model that captures the effects of competition on R&D-intensive firms in an environment where capital structure, information disclosure policy, and R&D investment are all simultaneously determined as endogenous choice variables. While the focus has been on the biopharma industry, the results are also applicable to other R&D-intensive industries. The model predicts that, as competition increases, firms will increase R&D investment, reduce investment in assets-in-place, carry more cash, and have a lower level of net debt. Moreover, firm betas will decline, but idiosyncratic risk and total stock return volatility will rise. We also develop a simple extension of the model where we introduce a choice between developing R&D in-house versus externally via an acquisition. We provide time-series evidence about firms in the biopharma industry that is consistent with all of these predictions. Moreover, we have used the Hatch-Waxman Act of 1984 as an exogenous variation that increased competition in the biopharma industry, and conducted a differences-in-differences test that produces evidence that strongly supports the model. This is important because investments in R&D and the degree of competition influence each other, so an endogeneity problem arises. Our approach allows us to overcome this endogeneity concern.

On a broad level, we highlight the importance of some unique features of R&D-intensive firms, and how these features may explain some interesting secular trends in financial characteristics and risk over time. We do not view this as a complete characterization of the financial characteristics of important R&D-intensive industries such as the biopharma industry, but rather as a starting point for analyzing them. For example, the nature of R&D projects may change over time as a result of the discovery of new technology—this would affect the risk characteristics of R&D-intensive industries in ways that are not explicitly considered in the model. Another interesting direction to explore in future research is optimal patent regulation in the context of the frictions of this model. Because of the "two-audience" signaling costs of information disclosure, R&D firms wish to limit disclosure, which then raises

the cost of (external) financing, and may discourage some R&D investments. This suggests that patent protection should be provided to offset some of these disclosure costs. However, our analysis also implies that greater competition related to the firm's assets-in-place leads to higher R&D investments, suggesting that patent protection should be terminated when the products resulting from the R&D have become a part of the firm's ongoing business portfolio. It would be interesting to examine how this additional tradeoff affects the choice of optimal patent regulation from private and social-welfare perspectives.

A final interesting extension would be to consider a portfolio of R&D projects, rather than the single R&D project in our analysis. In the context of our analysis, adopting a portfolio approach has two benefits. The first is that the idiosyncratic risk in R&D is reduced due to the diversification provided by a portfolio of projects. The other is that information disclosure about a portfolio may entail lower two-audience signaling costs because it may tell product-market competitors less about the technical aspects of any individual projects. While a number of advantages of creating a portfolio of R&D projects have been pointed out through the "megafund" idea of Fernandez, Stein and Lo (2012) and Fagnan, Fernandez, Lo, and Stein (2013), our analysis suggests that there may be additional benefits beyond those explicitly considered in previous studies. Future work could extend our framework to evaluate these effects as well as the impact of additional frictions related to moral hazard or information asymmetries, and the new empirical predictions they generate.

Appendix

A Proofs of Results

Proof of Lemma 1: Note first that the lemons will always pool with the good firms at any date in any sequential equilibrium because adopting a different strategy would unambiguously reveal them as lemons, and they would then be unable to raise financing. Therefore we can focus on the strategies of the good firms. Consider the conjectured equilibrium in which all firms pool by raising at $t = 0$ the funding for the second-stage R&D investment that will occur at $t = 1$ if the R&D is successful, i.e. raising $\hat{\omega}R$ at $t = 0$. Without loss of generality, we can view the firm as being all-equity financed and this financing as being raised through an equity issue in which the initial shareholders give up ownership $\hat{\alpha}$ in exchange for $\hat{\omega}R\left[1+r\right]^{-1}$ of funding. The equilibrium pricing constraint is:

$$\hat{\alpha}gV_T = \hat{\omega}R\left[1+r\right]^{-1}, \tag{A.1}$$

where V_T is the total value of the good firm at $t = 0$. Because the equilibrium is pooling, the financing leaves the investors' posterior belief about the firm's type at the prior belief g. The actual value surrendered by the initial shareholders of the good firm to raise the financing is $\hat{\alpha}V_T$, so the net post-financing wealth of the shareholders of the good firm is

$$\left[1-\hat{\alpha}\right]V_T, \tag{A.2}$$

where $\hat{\alpha}$ satisfies (A.1).

Now, conditional on all the other firms staying with their equilibrium strategies, suppose a firm decides to deviate and raise second-stage R&D financing at $t = 1$ instead of $t = 0$. Let V_T^0 be the total value of the good firm in this case, reflecting the fact that revealing the R&D has been successful reduces δ to δ_0. Thus, clearly $V_T^0 < V_T$. Let α^0 be the ownership fraction the shareholders will have to give up in order to raise the financing. The pricing constraint is:

$$\alpha^0 g^0 V_T^0 = \hat{\omega}R\left[1+r\right]^{-1}, \tag{A.3}$$

where g^0 is the firm's posterior belief investors have about the firm's type, conditional on observing the deviation at $t = 1$. Suppose we conjecture the posterior belief most favorable to the firm: $g^0 = 1$. Then (A.3) becomes:

$$\alpha^0 V_T^0 = \hat{\omega}R\left[1+r\right]^{-1}, \tag{A.4}$$

and the net post-financing wealth of the firm's shareholders is:

$$\left[1-\alpha^0\right]V_T^0. \tag{A.5}$$

We want to show that the expression in (A.2) exceeds that in (A.5), for any given A, R, and ξ. That is, we ask whether:

$$[1-\hat{\alpha}]\,V_T > \left[1-\alpha^0\right]V_T^0,$$

or

$$V_T - V_T^0 > \hat{\alpha}V_T - \alpha^0 V_T^0. \tag{A.6}$$

Using (A.1) and (A.4), recognizing that $V_T = \{px_H + [1-p]x_L\}\,[1+K]^{-2} + q\,\{\delta y_+ + [1-\delta]y_-\}\,[1+r]^{-2} + [1-q]\hat{\omega}R[1+r]^{-1}$ andV_T^0 is defined similarly to V_T except that δ is replaced by δ_0, (A.6) requires:

$$q\,[y_+ - y_-]\,[\delta - \delta_0]\,[1+r]^{-2} > \hat{\omega}R[1+r]^{-1}\left[\frac{1}{g} - 1\right]. \tag{A.7}$$

Since $g \in [0.5, 1)$, this inequality holds, given (15). Note that the riskless rate of return, r, is used for discounting because the R&D payoff risk is purely idiosyncratic. This proves that the firm does not have an incentive to deviate from the pooling equilibrium of raising second-stage R&D financing at $t = 0$ even if it anticipates investors believing almost surely that its type is good if it waits until $t = 1$ to raise financing. This means the pooling equilibrium is sequential. Moreover, since the good firm has no incentive to deviate from the equilibrium, regardless of the out-of-equilibrium beliefs of investors upon observing a deviation, we have also proved that both types can be eliminated as potential deviators in step 1 of the Cho and Kreps (1987) Intuitive Criterion. Hence, the sequential equilibrium satisfies the Intuitive Criterion. ■

Proof of Proposition 1: The first order condition for a maximum, using (23), is:

$$\left[\frac{\partial V_E}{\partial \xi}\right][1-\alpha] - \left[\frac{\partial \alpha}{\partial \xi}\right]V_E = 0, \tag{A.8}$$

where

$$\begin{aligned}\frac{\partial V_E}{\partial \xi} &= \left[\frac{\partial q}{\partial \xi}\right]\{\delta y_+ + [1-\delta]\,y_-\}\,[1+r]^{-2} - \left[\frac{\partial q}{\partial \xi}\right]\omega R \\ &= \left[\frac{\partial q}{\partial \xi}\right]\left[\{\delta y_+ + [1-\delta]\,y_-\}\,[1+r]^{-2} - \omega R\right] \\ &< 0\end{aligned} \tag{A.9}$$

since $\partial q/\partial \xi < 0$ by (11) and the rest of the expression is positive by (8). Next,

$$\frac{\partial \alpha}{\partial \xi} = \frac{-\left[A + R[1+\omega] - D\right]}{\left[V_E^e\right]^2}\left[\frac{\partial V_E^e}{\partial \xi}\right], \tag{A.10}$$

from (20), where

$$\frac{\partial V_E^e}{\partial \xi} = \hat{g}\left[\frac{\partial V_E}{\partial \xi}\right] + V_E\left[\frac{\partial \hat{g}}{\partial \xi}\right]. \tag{A.11}$$

Now, $\partial V_E/\partial\xi < 0$ by (A.9) and $\partial\hat{g}/\partial\xi > 0$ by (9). However, given the Inada-type condition on $\hat{g}$ that $\lim_{\xi\to 0}[\partial\hat{g}/\partial\xi] = \infty$, we know that $\exists\ \xi \in \left(0, \bar{\xi}\right)$ small enough such that $\partial\hat{g}/\partial\xi > |\partial V_E/\partial\xi|$. Consequently, for $\xi \in \left(0, \bar{\xi}\right)$ small enough, we have $\partial V_E^e/\partial\xi > 0$, and thus $\partial\alpha/\partial\xi < 0$.

Now, the second-order condition for a unique maximum is

$$\left[\frac{\partial^2 V_E}{\partial\xi^2}\right][1-\alpha] - 2\left[\frac{\partial V_E}{\partial\xi}\right]\left[\frac{\partial\alpha}{\partial\xi}\right] - V_E\left[\frac{\partial^2\alpha}{\partial\xi^2}\right] < 0. \tag{A.12}$$

Note that

$$\frac{\partial^2 V_E}{\partial\xi^2} = \left[\frac{\partial^2 q}{\partial\xi^2}\right]\left[\{\delta y_+ + [1-\delta]\, y_-\}\,[1+r]^{-2} - \omega R\right] < 0, \tag{A.13}$$

from (A.9), and $\partial V_E/\partial\xi < 0$, and $\partial\alpha/\partial\xi < 0$ for ξ small enough. Moreover,

$$\frac{\partial^2\alpha}{\partial\xi^2} = \frac{[A + R[1-\omega] - D]}{\left[V_E^e\right]^3}\left[\frac{\partial V_E^e}{\partial\xi}\right]^2 - \frac{[A + R[1-\omega] - D]}{\left[V_E^e\right]^2}\left[\frac{\partial^2 V_E^e}{\partial\xi^2}\right]. \tag{A.14}$$

Note that

$$\frac{\partial^2 V_E^e}{\partial\xi^2} = \hat{g}\left[\frac{\partial^2 V_E}{\partial\xi^2}\right] + 2\left[\frac{\partial V_E}{\partial\xi}\right]\left[\frac{\partial\hat{g}}{\partial\xi}\right] + \frac{\partial^2\hat{g}}{\partial\xi^2}V_E < 0, \tag{A.15}$$

since $\partial^2 V_E/\partial\xi^2 < 0$, $\partial V_E/\partial\xi < 0$, $\partial\hat{g}/\partial\xi > 0$, and $\partial^2\hat{g}/\partial\xi^2 < 0$. Thus, from (A.14) we see that:

$$\frac{\partial^2\alpha}{\partial\xi^2} > 0. \tag{A.16}$$

Going back to (A.12), we have now shown that $\partial^2 V_E/\partial\xi^2 < 0$, $\partial V_E/\partial\xi < 0$, $\partial\alpha/\partial\xi < 0$ for ξ small enough, and $\partial^2\alpha/\partial\xi^2 > 0$. Thus, we see that (A.12) is satisfied, and a unique optimal value of ξ, call it ξ^*, exists. Uniqueness of ξ^* follows from the Inada-type conditions. ■

Proof of Proposition 2: Substituting (21) and (22) into (23) gives us:

$$(A, R) \in \arg\max_{\mathbb{R}^2}\left\{V_E - \frac{A + R[1+\omega] - D}{g}\right\}. \tag{A.17}$$

The first-order condition for an optimal A is:

$$\left[\frac{\partial V_E}{\partial A}\right] - \frac{1}{g} = 0, \tag{A.18}$$

where $\partial V_E/\partial A = p\,[1+K]^{-2}\{[\partial x_H/\partial A] - [\partial x_L/\partial A]\} + [1+K]^{-2}[\partial x_L/\partial A] > 0$ by (3). The second-order condition is:

$$SOC \equiv p\,[1+K]^{-2}\left\{\left[\frac{\partial^2 x_H}{\partial A^2}\right] - \left[\frac{\partial^2 x_L}{\partial A^2}\right]\right\} + [1+K]^{-2}\frac{\partial^2 x_L}{\partial A^2} < 0, \tag{A.19}$$

which is also satisfied by (3).

To show that $dA^*/d\theta < 0$, totally differentiate the first-order condition:

$$SOC\left[\frac{dA^*}{d\theta}\right] + \left[\frac{\partial^2 V_E}{\partial A \partial \theta}\right] = 0, \tag{A.20}$$

where $\partial^2 V_E/\partial A\partial\theta = p\left[1+K\right]^{-2}\left\{\partial^2 x_H/\partial A\partial\theta\right\} < 0$ by (4). Thus,

$$\begin{aligned}\frac{dA^*}{d\theta} &= \frac{-\partial^2 V_E/\partial A\partial\theta}{SOC} \\ &< 0.\end{aligned} \tag{A.21}$$

Next, consider the first-order condition for R using (A.17):

$$\frac{\partial V_E}{\partial R} - [1+\omega]g^{-1} = 0, \tag{A.22}$$

where $\partial V_E/\partial R = q\left[1+r\right]^{-2}\left\{\delta\left[\partial y_+/\partial R\right] + \left[1-\delta\right]\left[\partial y_-/\partial R\right]\right\} + \left[1-q\right]\left[1+r\right]^{-1}\omega > 0$. The second-order condition is:

$$SOC_R \equiv \frac{\partial^2 V_E^2}{\partial R^2} < 0, \tag{A.23}$$

where $\partial^2 V_E/\partial R\partial\theta = q[1+r]^{-2}\delta\left[\partial^2 y_+/\partial R\partial\theta\right] > 0$ by (7). Thus, taking the total derivative,

$$\begin{aligned}\frac{dR^*}{d\theta} &= \frac{-\left[\partial^2 V_E/\partial R\partial\theta\right]}{SOC_R} \\ &> 0.\end{aligned} \tag{A.24}$$

■

Proof of Corollary 1: The expected value of the firm at $t=2$ is:

$$\begin{aligned}\mathbb{E}\left[V\right] &= \left\{p\left[x_H - x_L\right] + x_L\right\} + q\left\{\delta\left[y_+ - y_-\right] + y_-\right\} + \left[1-q\right]\hat{\omega}R[1+r] \\ &= pS_x + q\delta S_y + \left[1-q\right]\hat{\omega}R\left[1+r\right] + x_L + qy_-\end{aligned} \tag{A.25}$$

Thus, the variance of firm value is:

$$\begin{aligned}
\sigma_V^2 &= \mathbb{E}\left\{V - \mathbb{E}\left[V\right]\right\}^2 \\
&= pq\delta\left\{x_H + y_+ - \mathbb{E}\left[V\right]\right\}^2 + pq[1-\delta]\left\{x_H + y_- - \mathbb{E}\left[V\right]\right\}^2 + p[1-q]\left\{x_H + \hat{\omega}R[1+r] - \mathbb{E}\left[V\right]\right\}^2 \\
&\quad +[1-p]q\delta\left\{x_L + y_+ - \mathbb{E}\left[V\right]\right\}^2 + [1-p]q[1-\delta]\left\{x_L + y_- - \mathbb{E}\left[V\right]\right\}^2 \\
&\quad +[1-p][1-q]\left\{x_L + \hat{\omega}R[1+r] - \mathbb{E}\left[V\right]\right\}^2 \\
&= pq\delta\left\{[1-p]S_x - q\delta S_y + y_+ - qy_- - [1-q]\hat{\omega}R[1+r]\right\}^2 \\
&\quad +pq[1-\delta]\left\{[1-p]S_x - q\delta S_y + (1-q)y_- - [1-q]\hat{\omega}R[1+r]\right\}^2 \\
&\quad +p[1-q]\left\{[1-p]S_x - q\delta S_y - qy_- + q\hat{\omega}R[1+r]\right\}^2 \\
&\quad +[1-p]q\delta\left\{y_+ - qy_- - pS_x - q\delta S_y - [1-q]\hat{\omega}R\left[1+r\right]\right\}^2 \\
&\quad +[1-p]q[1-\delta]\left\{[1-q]y_- - pS_x - q\delta S_y - [1-q]\hat{\omega}R\left[1+r\right]\right\}^2 \\
&\quad +[1-p][1-q]\left\{q\hat{\omega}R\left[1+r\right] - pS_x - q\delta S_y - qy_-\right\}^2
\end{aligned} \tag{A.26}$$

Now, consider a small increase in investment R in R&D, accompanied by an equal decrease in investment A in assets-in-place. Thus we want to evaluate $\left[\partial\sigma_V^2/\partial R\right] - \left[\partial\sigma_V^2/\partial A\right]$. For notational convenience, let:

$$J_1 \equiv [1-p]S_x + [1-q\delta]S_y + [1-q]y_- - [1-q]\hat{\omega}R[1+r], \tag{A.27}$$

$$J_2 \equiv [1-p]S_x + [1-q]y_- - q\delta S_y - [1-q]\hat{\omega}R[1+r], \tag{A.28}$$

$$J_3 \equiv [1-p]S_x + \hat{\omega}R[1+r] - q\delta S_y - [1-q]\hat{\omega}R[1+r] - qy_-, \tag{A.29}$$

$$J_4 \equiv [1-q\delta]S_y - pS_x + [1-q]y_- - [1-q]\hat{\omega}R[1+r], \tag{A.30}$$

$$J_5 \equiv [1-q]y_- - pS_x - q\delta S_y - [1-q]\hat{\omega}R[1+r], \tag{A.31}$$

and

$$J_6 \equiv \hat{\omega}R[1+r] - pS_x - q\delta S_y - [1-q]\hat{\omega}R[1+r] - qy_-. \tag{A.32}$$

Note that $J_1 > 0$, $J_2 < 0$ for S_y large enough, $J_3 < 0$ for S_y large enough, $J_4 > 0$ for S_y large enough, $J_5 < 0$ for S_y large enough, and $J_6 < 0$ for S_y large enough. With this notation in hand,

we can now evaluate $\left[\partial\sigma_V^2/\partial R\right] - \left[\partial\sigma_V^2/\partial A\right]$:

$$\begin{aligned}
\frac{\partial\sigma_V^2}{\partial R} - \frac{\partial\sigma_V^2}{\partial A} &= 2pq\delta J_1\left\{[1-q\delta]\left[\frac{\partial S_y}{\partial R}\right] - [1-p]\left[\frac{\partial S_x}{\partial A}\right] + [1-q]\left[\frac{\partial y_-}{\partial R}\right]\right\} \\
&\quad +2pq[1-\delta]J_2\left\{[1-q]\left[\frac{\partial y_-}{\partial R}\right] - q\delta\left[\frac{\partial S_y}{\partial R}\right] - [1-p]\left[\frac{\partial S_x}{\partial A}\right]\right\} \\
&\quad +2p[1-\delta]J_3\left\{-q\delta\left[\frac{\partial S_y}{\partial R}\right] - [1-p]\left[\frac{\partial S_x}{\partial A}\right] - q\left[\frac{\partial y_-}{\partial R}\right]\right\} \\
&\quad +2[1-p]q\delta J_4\left\{[1-q]\left[\frac{\partial S_y}{\partial R}\right] + p\left[\frac{\partial S_x}{\partial A}\right] + [1-q]\left[\frac{\partial y_-}{\partial R}\right]\right\} \\
&\quad +2[1-p]q[1-\delta]J_5\left\{[1-q]\left[\frac{\partial y_-}{\partial R}\right] + p\left[\frac{\partial S_x}{\partial A}\right] - q\delta\left[\frac{\partial S_y}{\partial R}\right]\right\} \\
&\quad +2[1-p][1-q]J_6\left\{p\left[\frac{\partial S_x}{\partial A}\right] - q\delta\left[\frac{\partial S_y}{\partial R}\right] - q\left[\frac{\partial y_-}{\partial R}\right]\right\}. \qquad \text{(A.33)}
\end{aligned}$$

The above expression has six terms. For $\partial S_y/\partial R$ sufficiently large, we see that in the first term, the quantity in the braces multiplying $2pq\delta J_1$ is positive. Since $J_1 > 0$, the first term is positive. Similarly, the quantity inside the braces in the second term is negative, and since $J_2 < 0$, the second term is positive. The quantity inside the braces in the third term is negative. Since $J_3 < 0$, the third term is positive. In the fourth term, the quantity inside the braces is clearly positive. Since $J_4 > 0$, the fourth term is positive. In the fifth term, the quantity inside the braces is negative for $\partial S_y/\partial R$ large enough. Since $J_5 < 0$, the fifth term is positive. In the sixth term, the quantity inside the braces is negative for S_y large enough. Since $J_6 < 0$, the sixth term is positive. Thus, we have proved that $\left[\partial\sigma_V^2/\partial R\right] - \left[\partial\sigma_V^2/\partial A\right] > 0$. ■

Proof of Proposition 3: Suppose counter-factually that it is not true and the firm issues debt with a face value $F^\varepsilon = x_L(A^*) + \varepsilon$, $\varepsilon > 0$, and $F_1^\varepsilon = [x_L(A^*) + \varepsilon][1+r]^{-1}$, and $D^\varepsilon = F^\varepsilon[1+r]^{-2}$. This will reduce the amount of outside equity the firm will have to raise, but since both debt and equity are subject to the same degree of adverse selection, this substitution of equity with debt has no impact on the wealth of the shareholders. However, in this case, if the down state of the economy occurs, bondholders will demand to be repaid F_1^ε at $t = 1$. If the firm is carrying exactly the amount of cash needed to fund its second-stage R&D, $\hat{\omega}R$, then it will need to raise additional financing at $t = 1$ if it encounters R&D success at $t = 1$. But this will reveal R&D success to product-market competitors and reduce the value of R&D. Alternatively, if the firm decides to raise at $t = 0$ the additional payment, ε, it may need to make to bondholders at $t = 1$, then it will suffer the cost of adverse selection at $t = 0$ ($\hat{g} < 1$ even though the firm is good). This too will reduce firm value. Hence, raising the debt face value by ε above $y_-(R)$ will reduce the wealth of the initial shareholders of the firm. It is clear that setting $F < y_-(R)$ may work as well, but the shareholders cannot do better with such a debt choice than with $F = y_-(R)$.

Next, note that (16) states that $F = x_L(A^*)$. From Proposition 2, we know that $dA^*/d\theta < 0$. Moreover, $\partial x_L(A^*)/\partial A^* > 0$. Thus, it follows that in (16), $dF/d\theta^* < 0$ and $dF_1/d\theta^* < 0$. Finally,

since $dR^*/d\theta > 0$ and the second-stage R&D, $\hat{\omega}R^*$ cost, is raised at the outset and carried as cash, higher competition leads to higher cash balances. ■

Proof of Proposition 4: It is straightforward to see that $V_E(A^*, R^*, \xi^*)$ is higher for the firm with $\underline{q}^2(\theta)$ than for the firm with $\underline{q}^1(\theta)$, which means α is lower. Hence, the left-hand-side of (32) is larger for the firm with $\underline{q}^2(\theta)$ than for the firm with $\underline{q}^1(\theta)$. However, the right-hand-side of (32) is the same for both types of firms. Thus, internal R&D relative to external R&D is always higher for the firm with $\underline{q}^2(\theta)$ than for the firm with $\underline{q}^1(\theta)$. This means we can always find exogenous parameters such that the firm with $\underline{q}^2(\theta)$ invests in internal R&D and the firm with $\underline{q}^1(\theta)$ acquires. ■

B Supplemental Empirical Results

Figure A1: Additional Competition Measures

These figures present additional estimates of sales-based competition over time for the biopharma industry. The top-left figure gives the 4-firm Concentration Ratio, calculated using equation (35). The top-right figure gives the value of the Herfindahl-Hirschman Index (HHI) over time, which is calculated as: $HHI_t = \sum_{i=1}^{N} s_{i,t}^2$, where s_i is the sales market share of firm i in year t. The bottom figures give the value of the Hannah-Kay Index over time, which is defined as: $HK_t(\alpha) = \sum_{i=1}^{N} s_{i,t}^{\alpha}$. A higher α represents a higher weight attached to larger firms in terms of sales. The bottom right figure gives results for $\alpha = 1.5$ (relatively more weight to smaller firms in terms of sales), while the bottom right figure gives results for $\alpha = 2.5$ (relatively more weight to larger firms in terms of sales). For all measures, a higher value indicates more concentration (i.e. less competition).

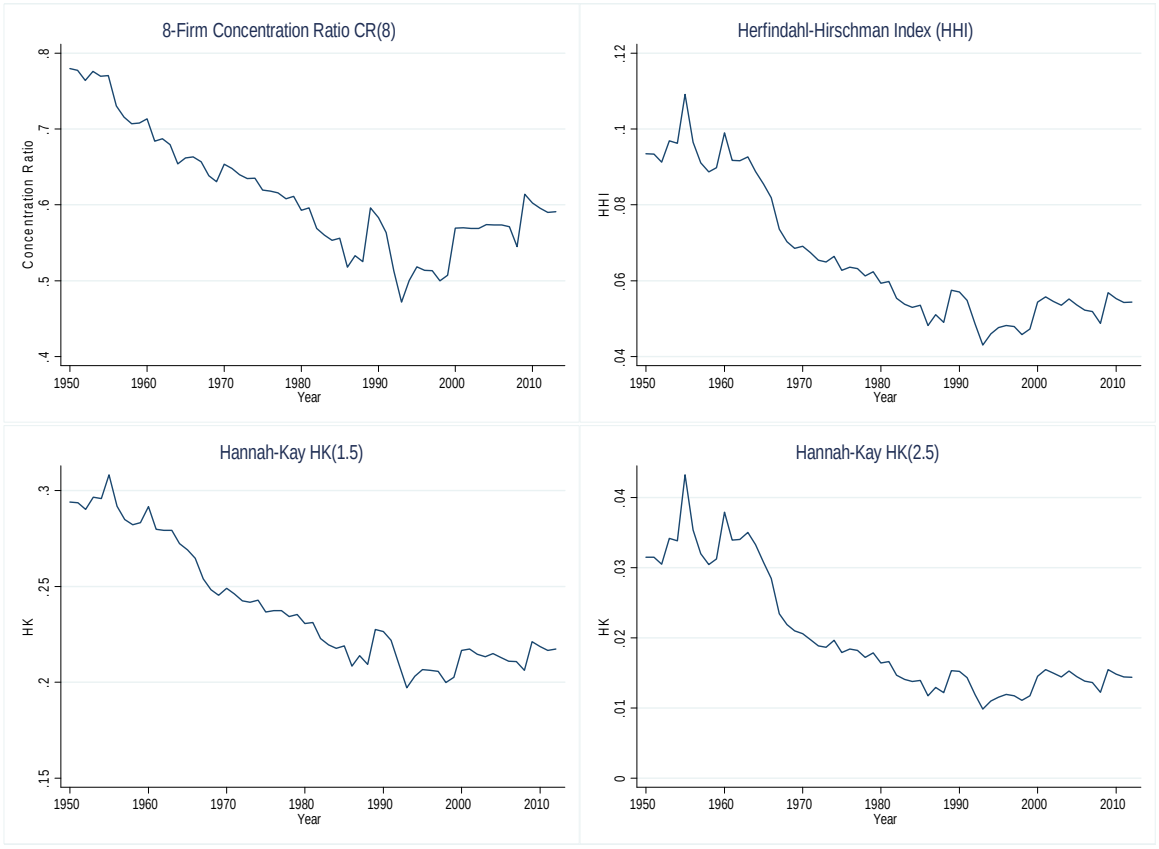
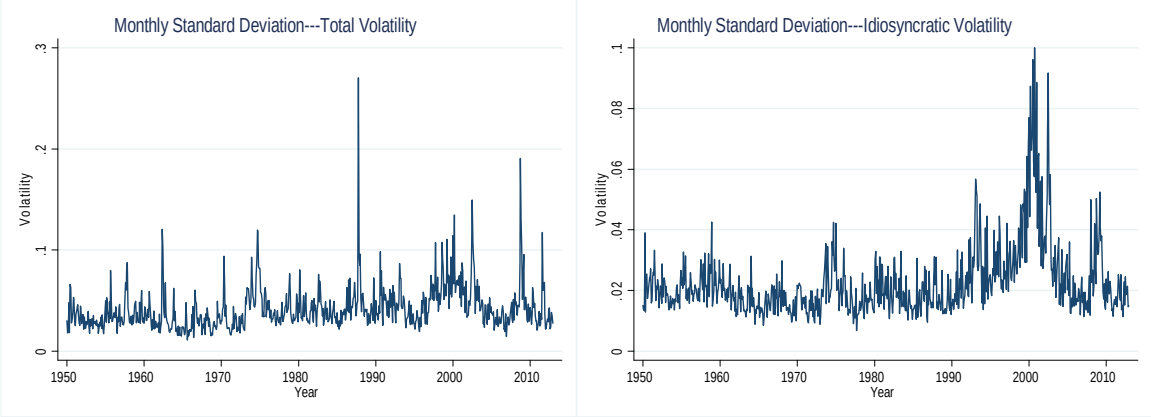


Figure A2: Total and Idiosyncratic Stock Return Volatility

This figure shows the monthly estimates of value-weighted portfolio volatility, following Schwert (1989). In panel (a), the left graph depicts total stock return volatility, calculated by forming a value-weighted portfolio of biopharma stocks, and then estimate the monthly standard deviation of the total portfolio as the square root of the sum of the squared daily excess (over the mean daily return in the month) returns over the month: $\hat{\sigma}_{P,T} = \sqrt{\sum_{t=1}^{D_T} (R_{P,t} - \mu_T)^2}$, where $R_{P,t}$ is the daily portfolio return for date t and μ_T is the mean daily portfolio return for month T. In a similar way, the right graph in panel (a) depicts idiosyncratic volatility, which is given by: $\hat{\sigma}^{idio}_{P,T} = \sqrt{\sum_{t=1}^{D_T} \left(\epsilon_{P,t} - \mu^{idio}_T\right)^2}$, where $\epsilon_{P,t}$ is the idiosyncratic return of the value-weighted portfolio for day t and μ^{idio}_T is the mean idiosyncratic return in month T. Augmented Dickey-Fuller tests were also run on these monthly series to test for the presence of a unit root. For both total volatility and idiosyncratic volatility, Augmented Dickey-Fuller tests reject the presence of a unit root at at least the 5% level when up to 5 lags are included, regardless of whether a trend is included.

(a) Levels of $\hat{\sigma}_{P,T}$ and $\hat{\sigma}^{idio}_{P,T}$



(b) Moving Average of $\hat{\sigma}_{P,T}$ and $\hat{\sigma}^{idio}_{P,T}$

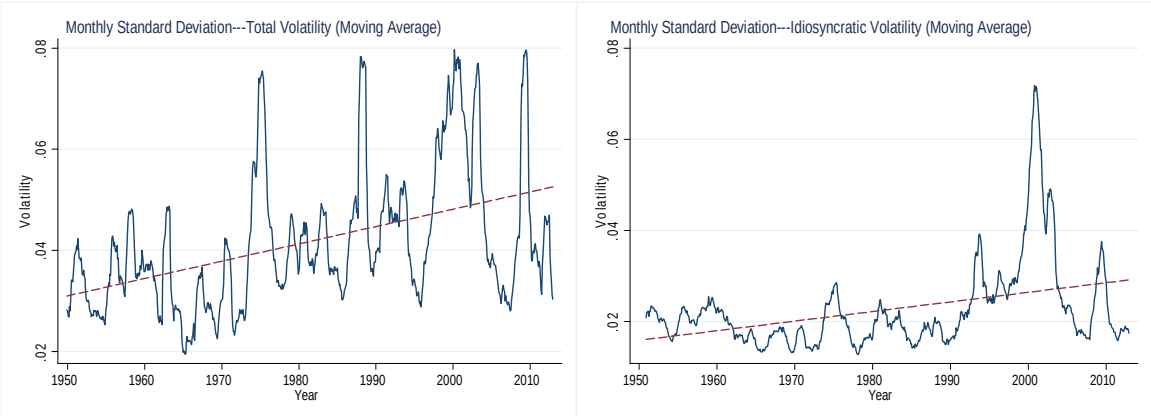
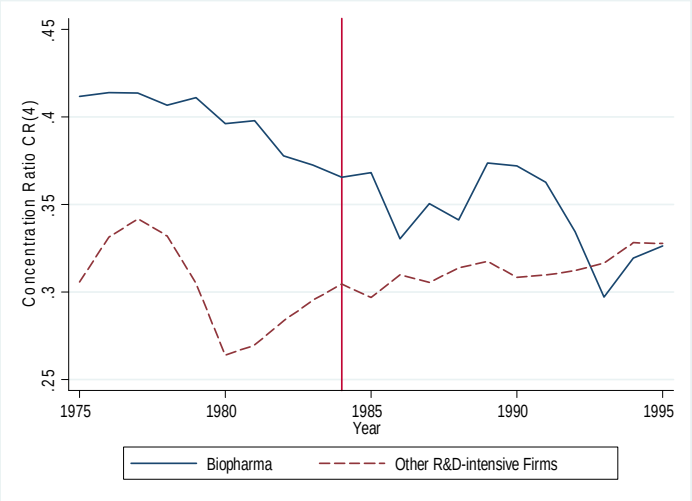


Figure A3: Changes in Competition Around Hatch-Waxman Act

Panel (a) depicts the 4-firm Concentration Ratio CR(4) for the biopharma industry (the solid blue line) and other R&D-intensive firms (the dashed red line) around the enactment of the Hatch-Waxman Act. Panel (b) estimates a differences-in-differences regression for the effect of the Hatch-Waxman Act on the Concentration Ratio CR(4) of the biopharma industry versus other R&D-intensive firms. The regression is run at the industry-year level. $CR_{i,t}(4)$ is the value of the 4-firm concentration ratio for group i, either the biopharma industry or other R&D-intensive industries. HW_t is a dummy variable which takes a value of 1 if the year is 1984 or later, and a value of zero otherwise. $Biopharma_i$ is a dummy variable which takes a value of 1 for the biopharma industry, and a value of 0 otherwise. Robust standard errors are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

(a) Competition Trends for Biopharma and Control Group



(b) Differences-in-Differences Estimation for Changes in Competition

Dependent Variable:	$CR_{i,t}(4)$
$Biopharma_i \times HW_t$	-0.065***
	(0.013)
$Biopharma_i$	0.097***
	(0.011)
HW_t	0.009
	(0.010)
Constant	0.303***
	(0.009)
Observations	42
R^2	0.776

Figure A4: Risk Variable Trends for Treatment and Control Group

Trends for risk variables. Beta variables are yearly estimates, calculated from a value-weighted portfolio of biopharma or propensity-score matched R&D-intensive firms using the previous 2 years of daily portfolio returns as of the end of each year. Volatility variables are yearly estimates, calculated using the daily returns over the year of a value-weighted portfolio of biopharma or control firms. The solid blue lines give estimates for the biopharma industry, while the red dashed lines give estimates for the propensity-score-matched sample of R&D-intensive firms. A vertical red line is included in each graph, representing the year that the Hatch-Waxman Act was implemented.

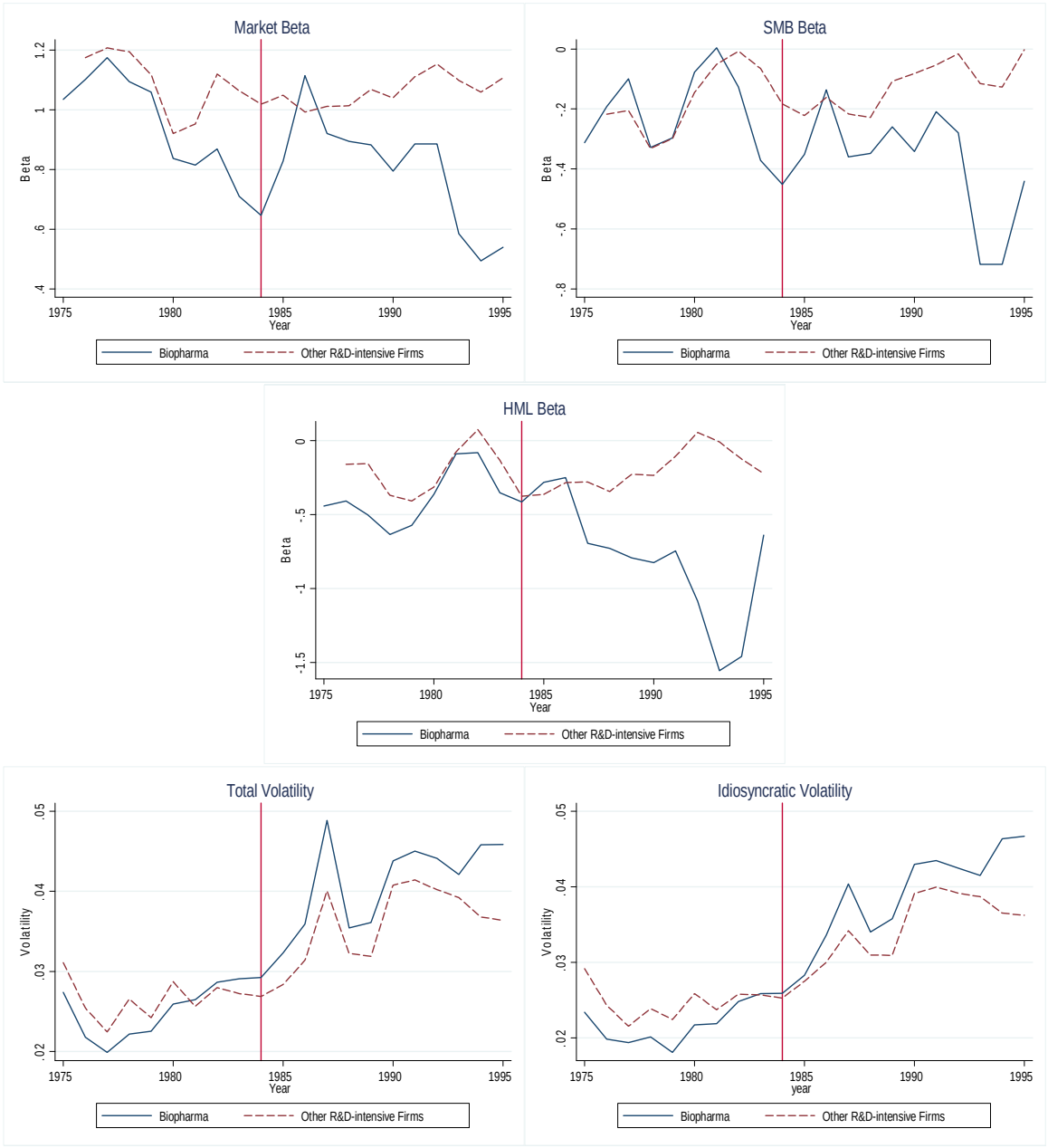


Table A1: Time-series Regressions

Time-series regressions of the effect of competition on levels of financial characteristics. Each entry in the table is a univariate regression of the effect of the indicated measure of competition on the indicated financial characteristics for the biopharma industry. All variables are yearly estimates, yielding 63 observations per regression. For the competition measures, Number Competitors is the number of firms in the biopharma industry each year, $CR(M)$ is the M-firm Concentration Ratio, HHI is the Herfindahl-Hirschman Index, and $HK(\alpha)$ is the Hannah-Kay Index with weight α. An increase in the concentration index measures indicates a decrease in competition. $R\&D$, PPE, $Cash$, $Debt$, and $Net\,Debt$ are median estimates, calculated by first scaling each variable by total assets at the firm-year level, and then taking the median across all firms (other than debt, which has a skewed distribution as previously explained, results are robust to using mean levels of these variables). σ is mean total stock return volatility, while σ^{idio} is mean idiosyncratic stock return volatility, each calculated by taking the standard deviation of the past 360 days of daily total or idiosyncratic returns as of the last day of each year for each firm, and then averaging across all firms. $\beta_{mkt,t}$, $\beta_{SMB,t}$, and $\beta_{HML,t}$ are betas of a value weighted portfolio of biopharma firms, calculated using (36) for the past 2 years of daily returns as of the last day of each year. Autocorrelation-adjusted (for up to 5 lags) standard errors are in parentheses, calculated following Newey and West (1987), while R-squared estimates are given in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Independent	Dependent Variable									
Variable	R&D	Cash	PPE	Debt	Net Debt	σ	σ^{idio}	β_{mkt}	β_{SMB}	β_{HML}
Number	0.0003***	0.0007***	-0.0004***	-0.0001	-0.0005***	0.00005***	0.00005***	-0.0005***	-0.0006***	-0.0004*
Competitors	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0002)	(0.0002)
	[0.895]	[0.906]	[0.962]	[0.075]	[0.620]	[0.694]	[0.716]	[0.473]	[0.365]	[0.105]
$CR(4)$	-0.828***	-1.479***	1.011***	-0.271	0.803*	-0.170***	-0.167***	1.895***	3.285***	3.212***
	(0.198)	(0.376)	(0.173)	(0.165)	(0.432)	(0.021)	(0.021)	(0.325)	(0.600)	(0.761)
	[0.393]	[0.311]	[0.513]	[0.075]	[0.100]	[0.585]	[0.606]	[0.478]	[0.663]	[0.408]
$CR(8)$	-0.658***	-1.144***	0.774***	-0.191	0.666*	-0.137***	-0.134***	1.454***	2.551***	2.573***
	(0.153)	(0.330)	(0.148)	(0.137)	(0.391)	(0.021)	(0.021)	(0.330)	(0.641)	(0.696)
	[0.351]	[0.265]	[0.428]	[0.053]	[0.100]	[0.537]	[0.558]	[0.400]	[0.569]	[0.372]
HHI	-2.983***	-5.369***	3.805***	-1.207**	2.602	-0.625***	-0.612***	7.087***	12.165***	11.176***
	(0.779)	(1.555)	(0.684)	(0.568)	(1.689)	(0.088)	(0.087)	(1.175)	(2.231)	(2.599)
	[0.374]	[0.300]	[0.532]	[0.110]	[0.076]	[0.577]	[0.595]	[0.490]	[0.666]	[0.362]
$HK(1.5)$	-1.824***	-3.307***	2.257***	-0.545	1.798*	-0.364***	-0.356***	4.049***	6.743***	6.110***
	(0.436)	(0.929)	(0.403)	(0.343)	(1.010)	(0.049)	(0.049)	(0.695)	(1.390)	(1.507)
	[0.442]	[0.360]	[0.592]	[0.071]	[0.115]	[0.618]	[0.637]	[0.502]	[0.646]	[0.342]
$HK(2.5)$	-5.740***	-10.359***	7.533***	-2.775**	4.550	-1.242***	-1.217***	14.378***	24.994***	22.869***
	(1.614)	(3.114)	(1.383)	(1.105)	(3.346)	(0.186)	(0.184)	(2.263)	(4.047)	(5.152)
	[0.331]	[0.267]	[0.498]	[0.138]	[0.056]	[0.545]	[0.562]	[0.481]	[0.671]	[0.362]

Table A2: Falsification Test for the Differences-in-Differences Analysis

This table estimates the differences-in-differences regression (39) for financial characteristics, but over the sample period from 1965 to 1985. The sample consists of biopharma firms and a control group consisting of propensity-score matched R&D-intensive firms, matched on size, profitability, capital structure, and market-to-book. The dependent variables consist of $R\&D$, PPE, $Cash$, $Debt$, and $Net\,Debt$, each scaled by total assets. Act_t is a dummy variable which falsely specifies the passage of the Hatch-Waxman Act—it takes a value of 1 if the year is 1974 or later, and a value of zero otherwise. $Biopharma_i$ is a dummy variable which takes a value of 1 if firm i is in the biopharma industry, and a value of 0 otherwise. Control variables include $\log(NA_{i,t})$, $(PPE/TA)_{i,t}$, $(Cash/TA)_{i,t}$, $(EBIT/TA)_{i,t}$, $(M/B)_{i,t}$, and $(Div/TA)_{i,t}$. Controls for cash and PPE are excluded when they are the dependent variable of interest. Year and firm fixed effects are included where indicated. Robust standard errors are given in parentheses, and standard errors are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable:									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$R\&D$	$R\&D$	PPE	PPE	$Cash$	$Cash$	$Debt$	$Debt$	$Net\,Debt$	$Net\,Debt$
$Act_t \times Biopharma_i$	0.006	0.003	0.000	-0.009	0.034	0.012	0.070***	0.025	0.038	0.013
	(0.011)	(0.004)	(0.019)	(0.017)	(0.021)	(0.009)	(0.024)	(0.019)	(0.038)	(0.025)
$Biopharma_i$	0.030***		0.002		0.048***		-0.053**		-0.101***	
	(0.006)		(0.020)		(0.016)		(0.023)		(0.033)	
Act_t	0.011***		-0.019***		0.010*		0.007		-0.004	
	(0.003)		(0.006)		(0.006)		(0.008)		(0.011)	
Constant	0.039***	0.122***	0.310***	0.274***	0.092***	0.386***	0.211***	0.165***	0.120***	-0.308***
	(0.003)	(0.015)	(0.008)	(0.027)	(0.005)	(0.028)	(0.009)	(0.042)	(0.011)	(0.054)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	4,506	4,166	6,510	5,873	6,510	5,873	6,469	5,873	6,469	5,873
Number of Firms	412	410	456	456	456	456	456	456	456	456
Adjusted R^2	0.028	0.848	0.005	0.823	0.042	0.722	0.006	0.670	0.011	0.718

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