

Competition and R&D Financing Decisions: Evidence from the Biopharmaceutical Industry*

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Abstract

How does competition affect innovation and how it is financed in R&D-intensive firms? We study the interaction between competition, R&D investments, and the financing choices of such firms using data on biopharmaceutical firms. Motivated by existing theories, we develop several empirically testable hypotheses. The key predictions are that, as competition increases, R&D-intensive firms will: (1) increase R&D investment relative to 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. We first establish stylized facts using time-series evidence that is consistent with these predictions. To address the endogeneity issue introduced by the fact that a firm's R&D investments and the product-market competition it faces influence each other, we then provide further evidence supporting these predictions through a differences-in-differences analysis.

Keywords: Healthcare Finance; Pharmaceutical Industry; Biotechnology Industry; Capital Structure; R&D Investments; Competition

JEL Classification: G31, G32, L11, L12, L25, L65, O32

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1 Introduction

The idea that innovation is a key to economic growth has a long tradition, dating back at least to Adam Smith, who explicitly recognized the role of technological progress in the production function of the firm. Competition also grows with the economy, and since monopolists are unlikely to perceive the same benefits from innovation that competitive firms perceive (see, for example, Aghion, Bloom, Blundell, and Griffith (2005)), a natural question that arises is: how does competition affect innovation? In addition, investments in R&D that make innovation possible often require large amounts of capital that must be externally financed, so financing frictions and the risk profile of the firm can affect innovation as well (e.g. Hall and Lerner (2010), and Cornaggia, Mao, Tian, and Wolfe (2013)). Since firms can be expected to seek financing through the lowest-cost means, a second important question that arises is: how does product-market competition affect the financing choices and risk profiles of firms through its effect on their innovation incentives? That is, it is important to study how financing and competition interact, and the important role that this interaction plays for R&D-intensive firms, which are crucial drivers of innovation.

The primary goal of this paper is to provide an empirical answer to these questions. While each of the two questions stated above has been studied separately, we are not aware of any paper that has empirically studied the relationship between competition, innovation, financing, and risk in a setting that also overcomes endogeneity concerns. We first describe a simple framework using existing theories to motivate a number of empirically testable hypotheses on the relationship between competition, R&D investment, financing, and the evolution of the firm's risk profile. We then confront these hypotheses with data from the biopharmaceutical (biopharma) industry.

Apart from the fact that the biopharma industry is intimately tied to health care—a sector that is now one-fifth of the U.S. economy—R&D is the lifeblood of biopharma firms, and spending on R&D often dwarfs spending on property, plant, and equipment. Moreover, decisions related to capital budgeting and financing for R&D that these firms make

depart sharply from those made for 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 years. This makes it difficult to simply extrapolate the insights on financing choices for other kinds of firms to R&D-intensive firms like those in biopharma (see Myers and Howe (1997), who lay out these issues for the pharmaceutical industry). Moreover, this industry has become increasingly competitive over time 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 in new products as well as the capital structure choices of these firms.¹ These developments, coupled with the R&D-intensive nature of these firms, make the biopharma industry well suited for the study of the two questions posed above.

We use a combination of existing theories to develop testable hypotheses related to how an R&D-intensive firm makes decisions about investment (how much to invest in R&D and how much to invest in assets in place), capital structure, and cash to carry, and how these decisions are affected by the mediating influence of its competitive environment. Our first hypothesis is that greater product-market competition induces the firm to cut back on investments in assets-in-place and increase investments in R&D. The motivation comes from the “escape-the-competition” effect (e.g. Aghion, Bloom, Blundell, and Griffith (2005))—increased competition erodes margins on existing products, thus making them less attractive relative to new R&D products that are under patent protection.

¹For 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. The implications of these developments are potentially pervasive. For example, see Bloom, Schankerman, and Van Reenen (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.

Our second prediction is that firms will carry more cash and net debt will decline in response to greater product market competition. One reason, which follows from the first prediction, is that greater competition leads to less investment in assets-in-place, which in turn makes debt financing less attractive because it reduces the collateral base that can support debt. A second reason is that the greater investment in R&D requires greater investments in (illiquid) firm-specific human capital by employees, which also makes debt less attractive (see Berk, Stanton, and Zechner (2010) and Jaggia and Thakor (1994)). The reason for carrying extra cash is to avoid having to raise future financing in states of the world in which such financing may be unavailable but is viewed as being valuable by firm insiders. This intuition is similar to the notion of “financing risk” for innovation, as described by Nanda and Rhodes-Kropf (2013, 2016). The relatively large cash balances of R&D-intensive companies are consistent with this implication.

The final prediction follows from the first prediction. Since existing products have systematic risk, whereas (at least early-stage) R&D has mainly idiosyncratic risk (see Pastor and Veronesi (2005)), the reallocation of investments from assets-in-place to R&D that is induced by increased competition 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.

Using data on publicly-traded biopharma companies from 1950 to 2012, we provide empirical support for these predictions. In order to establish stylized facts related to our predictions, we first provide time-series evidence, taking as a given the increase in competition over time which has been documented in previous research. We document that R&D and cash holdings of the firms in the sample are substantial, and have increased over time in response to increasing competition. In particular, for the average biopharma firm, R&D as a percentage of total assets increased from roughly 3% in 1950 to 46% in 2012, whereas cash as a percentage of total assets increased from 22% in 1950 to 55% in 2012. In addition, assets-

in-place and net debt as a percentage of total assets declined for the average biopharma firm as competition increased. Moreover, we show that the betas of a value-weighted portfolio of biopharma firms have declined over time—for example, the market beta of the industry has declined from over 1.0 in 1950 to approximately 0.7 in 2012. Finally, idiosyncratic and total stock return volatility for biopharma firms have increased while competition has increased.

While this time-series evidence is consistent with the predictions of our model, it is also subject to potential endogeneity concerns. In particular, biopharma firms face competition that has both endogenous and exogenous elements. The endogenous competition is affected by how much the firm spends on R&D (the more it spends, the lower the competition *ceteris paribus*). The exogenous nature of competition comes from things like changes in market structure, regulation, and the nature of patent protection—developments that are plausibly exogenous at least at the individual firm level. To deal with these endogeneity concerns and provide causal evidence of the impact of competition on the variables we study, we exploit the quasi-natural experiment represented by a legislative change that induced an exogenous increase in competition in the biopharma industry: the Hatch-Waxman Act of 1984. This legislation made it significantly easier for generic drugs to compete with patented drugs and has been widely regarded as an act that increased competition in the industry (e.g. Grabowski and Vernon (1986, 1992)). Using a differences-in-differences approach, we examine the effect of this legislative change on the biopharma industry by comparing the reaction of their financing characteristics to a propensity-score-matched control group of R&D-intensive firms. We again find strong supporting evidence for the main predictions of the model. The results survive a number of robustness checks, including a falsification test for the year of passage of the Act, and tests that correct for the potential effect of autocorrelation.

Our paper is related to the theoretical industrial organization literature that explores the effect of competition on innovation. For example, a number of papers have shown that innovation may allow the firm to differentiate its products more effectively, thereby

generating an “escape-the-competition” effect (Aghion, Harris, Howitt, and Vickers (2001), and Aghion et. al. (2005)) that implies that competitive firms will tend to innovate more than a monopolist via the so-called “replacement effect” (Tirole (1988)). 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. Aghion, Dewatripont and Rey (1999) reach a similar conclusion based on the logic that competition can stimulate R&D by reducing expected bankruptcy costs. Recently, Aghion, Bechtold, Cassar and Herz (2014) have provided evidence based on lab experiments. They find that higher competition among product-market competitors leads to higher R&D by neck-and-neck firms and lower R&D by laggards.² We rely on this literature for our prediction that an increase in competition will increase innovation (through increased R&D investment). However, we also focus on how competition affects the firm’s choice of funding for innovation and its risk profile. Since a firm’s ability to secure capital is crucial for undertaking R&D, we thus treat competition as an important determinant of innovation by considering its effect on the firm’s interactions with the capital market and its risk characteristics.

Our paper is also related to the literature that explores the financing of R&D.³ Bergemann and Hege (2005) develop a theoretical model in which they examine how the choice of relationship versus arms-length financing by borrowers affects their R&D funding. Brown, Fazzari, and Petersen (2009) empirically document a positive relationship between financing supply and R&D. Hall and Lerner (2010) show that large firms prefer internal funds for financing R&D, whereas small firms experience high external financing costs that are only partially mitigated by venture capital. While these papers focus on issues related to R&D

²Other authors have also made the point that patentable innovation is one way for firms to protect against profit erosion induced by competition. For example, Langinier and Moschini (2002) note that the duration of a patent can affect the length of time the holder can exert monopoly power. See also Grant and Jordan (2015).

³Our work is also related to the vast capital structure literature, 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.

financing, they do not consider the effect of product market competition on how R&D is financed. More recently, a handful of papers have explored how competition affects firms' innovation incentives and cash holdings. Lyandres and Palazzo (2014) show theoretically and empirically that the firms that successfully innovate use cash as a commitment device for implementation of successful innovations. Morellec, Nikolov, and Zucchi (2014) develop a dynamic model and provide empirical support that competition increases corporate cash holdings and equity issues. Begenau and Palazzo (2016) show evidence that the overall increase in firm cash holdings is driven by the entry of more R&D-intensive firms due to more favorable IPO conditions, and provide a model that rationalizes this effect.

Also related is the 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, 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 we also provide additional empirical evidence focused on financial characteristics. Moreover, we focus explicitly on the interaction between competition, R&D spending, and capital structure decisions of biopharma companies which, to our knowledge, has not been considered in previous studies.

In Section 2 we describe the theoretical motivation provided by existing theories and the main empirical predictions that follow. We present the time-series evidence on average trends in Section 3, and the differences-in-differences analysis using the Hatch-Waxman Act

as a source of exogenous variation is described in Section 4. We conclude in Section 5 and provide supplemental results in the Appendix.

2 Formulating Testable Hypotheses

In this section, we provide a sketch of the intuition for the predictions generated by existing theories, to motivate the testable hypotheses we consider in our empirical analysis. Since there is not a single theoretical model that considers all of the interactions we study, we extrapolate based on several theories.⁴

Imagine an R&D-intensive firm, say a biopharmaceutical company, that has assets-in-place as well as an opportunity to invest in R&D. The firm must decide: (i) how much to invest in assets-in-place and how much to invest in R&D; and (ii) the capital structure with which to finance the firm, including how much cash to carry.

The firm faces competition on the products related to its assets-in-place. As competition increases, the firm's profit margins and cash flows from asset-in-place decline.⁵ R&D, when successful, is patent-protected and thus unaffected by competitive entry. 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).⁶

⁴An integrated theoretical model that captures all these interactions in reduced form, and generates the predictions we test, is available upon request.

⁵The notion of competition here is the same as in Bertrand competition, where the two firms will reduce their prices down to their marginal costs. In our model, competition 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 Thakor et. al. (2016)). 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)). Our empirical tests are designed to tackle this potential endogeneity.

⁶This is consistent with the earlier cited literature, e.g. Tirole (1988), Langinier and Moschini (2002), and Grant and Jordan (2015). The specific way we have described competition is not critical to our prediction. All that is needed is that the firm's profit margins on patentable drugs emerging from R&D are higher than

An immediate implication is that an increase in product-market competition induces the firm to invest more in R&D and less in assets-in-place. This is similar to the “escape-the-competition” effect (e.g. Aghion et. al. (2005))—the lower margins on existing products due to increased competition makes these products less attractive relative to new R&D products that are under patent protection.⁷ This is our first testable hypothesis:

- 1) *As product-market competition increases, firms will increase R&D investment and reduce investment in assets-in-place that support existing products.*

The firm also has to determine its capital structure. The firm’s income is taxable and debt interest payments are tax deductible. This makes debt attractive, all else equal. However, raising debt financing at a reasonable cost requires collateralizable assets—the positive correlation between tangible collateralizable assets and debt financing is well-established both theoretically and empirically (see, for example, Rampini and Viswanathan (2010, 2013)). As the firm shifts its investment from assets-in-place to R&D, it has less collateralizable assets, which is one reason why it uses less debt financing in its capital structure.

A second reason why a firm uses less debt as R&D investments increase comes from some of the attributes of R&D. First, R&D often requires employees to make firm-specific human capital investments that may not be completely portable to other firms. Incentivizing employees to make these investments requires long-term contracts that provide insurance against adverse ability-perception shocks, but the effectiveness of these contracts is diminished by the prospect of bankruptcy that can allow these contracts to be renegotiated or undone. Employees will thus respond *ex ante* to higher firm leverage by reducing their investments in R&D-payoff-enhancing firm-specific human capital. This is the essence of the human-capital-based capital structure theories developed by Berk, Stanton, and Zechner (2010) and Jaggia and Thakor (1994). The implication is that the more the firm invests in R&D, the less debt it carries in its capital structure.

those from existing products that do not enjoy patent protection.

⁷In the terminology of Aghion et. al. (2005), we are describing “neck-and-neck” firms competing in the product market.

Finally, R&D can have payoffs that can be contracted upon with outside financiers—such as commercializable products—as well as benefits (such as knowledge generation) for insiders that cannot be contracted upon at reasonable cost. Moreover, R&D may require additional financing. Thus, there may be instances in which, based on non-contractable R&D payoffs, insiders wish to raise additional financing but outsiders are unwilling to provide it at that time. This may limit the firm’s ability to pursue certain innovations. In anticipation of such future stochastic funding needs, the firm may decide to carry large cash balances as insurance against such a value-dissipating liquidity crunch. This can be viewed as precautionary demand for liquidity in anticipation of future states in which there may be a shortfall (see, for example, Bolton, Chen, and Wang (2014)) or to hedge against “financing risk” for innovation, as described by Nanda and Rhodes-Kropf (2013, 2016), and is also similar to the intuition in the theory proposed by Lyandres and Palazzo (2014).

Putting these arguments together leads to our second prediction:

2) *As competition increases, firms will carry more cash and net debt will decline.*

We now turn to the implications for risk. As in Pastor and Veronesi (2009), assume that the risk associated with R&D is idiosyncratic and the risk associated with assets-in-place is systematic. 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 (e.g. Langinier and Moschini (2002)). 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).

Since the firm shifts its investments from assets-in-place (which carry systematic risk) to

R&D (which carries largely idiosyncratic risk) in response to higher competition, an increase in competition also implies that the firm's beta will decline as competition increases. By the same token, the firm's idiosyncratic risk will also increase. Since R&D investments tend to be riskier than other types of investment (e.g. DiMasi, Hansen, Grabowski, and Lasagna (1991)), this also implies that the firm's total stock return volatility will tend to increase. Thus, as competition induces greater investments in R&D, we have our third prediction:

3) As competition increases, firm betas will decline, but idiosyncratic risk will rise. Total stock return volatility may also rise.

3 Time-Series Evidence

To examine our empirical implications on R&D-intensive corporate financial policies, we first establish stylized facts by considering time-series evidence on increasing competition in the biopharma industry and the effect on R&D investments, assets-in-place, capital structure, cash balances, and risk. The time-series evidence is generally consistent with the predictions from the previous section.

This consistency notwithstanding, the time-series evidence 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 follow up the time-series analysis below with a differences-in-differences analysis to provide causal evidence.

3.1 Time-series 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 :

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

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 (1) for $M = 4$ (4-firm Concentration Ratio).⁸ 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). In addition, since the FDA approval process for drugs is lengthy, new competing firms may not have an effect on industry sales until several years after they enter. 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 2. 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-

⁸Our results are also similar when using other sales-based measures of concentration, such as the 8-firm Concentration Ratio (where $M = 8$ in (1)), Herfindahl-Hirschman Index, or the Hannah and Kay (1971) Index. We include these measures in the Appendix.

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

In order to examine Prediction 3 identified in Section 2, 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:

$$R_{i,t} - r_f = \alpha + \beta_{i,t,mkt}(R_{m,t} - r_f) + \beta_{i,t,SMB}R_{SMB,t} + \beta_{i,t,HML}R_{HML,t} + \epsilon_{i,t}. \quad (2)$$

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 (2).

We calculate the total and idiosyncratic volatility of the biopharma industry by taking the standard deviation of a rolling window of the past 360 days of daily returns, consistent with Officer (1973) and others. 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.⁹

Finally, to examine the time-series trend of betas for the biopharma industry, we form

⁹As 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. For robustness, we have also calculated volatility using non-overlapping samples of daily data to construct monthly volatility estimates as in Schwert (1989) and also Bali, Cakici, Yan, and Zhang (2005). These results are available upon request.

a value-weighted portfolio of biopharma firms, and calculate the market factor beta of the portfolio using the Fama-French model (given by (2) above) and a rolling 2-year window of daily portfolio returns.

3.2 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 2830-2836.¹⁰ 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.¹¹ Daily return data for the Fama-French factors and the risk-free rate of return were obtained from Ken French’s web site.¹² 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 a few 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

¹⁰These 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.

¹¹Daily data from 1948 and onwards is used to estimate betas and volatilities for the years 1950 and 1951.

¹²http://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 (1). $(R\&D/TA)_{i,t}$ 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 $\sigma_{i,t}^{idio}$ 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 $\sigma_{P,t}^{idio}$ is idiosyncratic value-weighted portfolio return volatility, calculated from the past 360 daily returns for the value-weighted portfolio of biopharma stocks. $\beta_{t,mkt}$ is the beta of the market factor, 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
$\sigma_{i,t}^{idio}$	0.029	0.014	0.016	0.025	0.039
$\sigma_{P,t}$	0.010	0.004	0.008	0.009	0.011
$\sigma_{P,t}^{idio}$	0.005	0.002	0.004	0.005	0.006
$\beta_{t,mkt}$	0.904	0.173	0.779	0.892	1.060

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% 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.

3.3 Time-Series Evidence on Average Trends

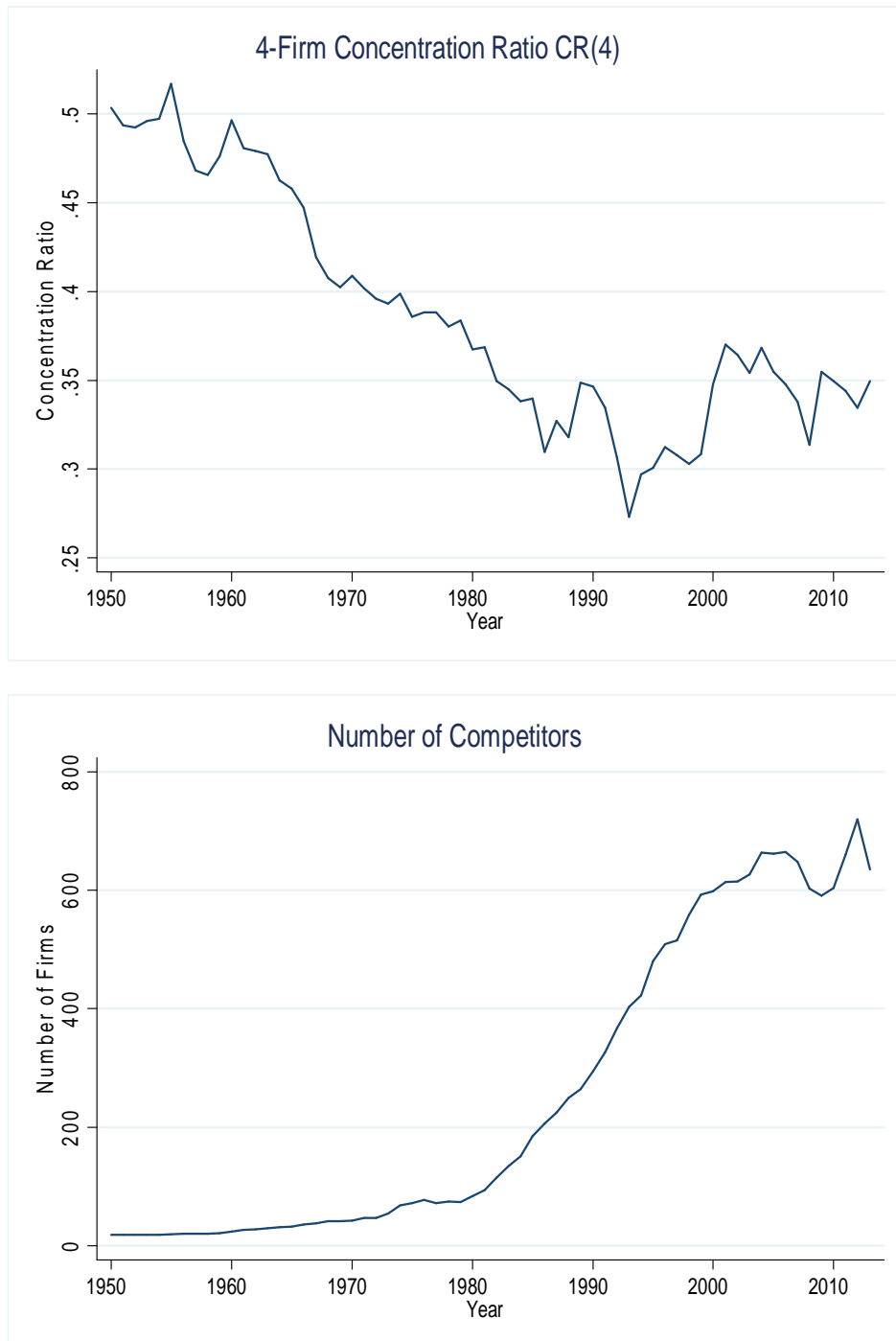
Measures of Competition

The top two graphs of *Figure 1* 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.¹³ 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.

¹³For robustness, in *Figure B1* of the Appendix, we also present the same trends for alternative sales-based competition ratios: the 8-firm Concentration Ratio (where $M = 8$ in (1)), the Herfindahl-Hirschman Index, and the Hannah and Kay (1971) Index. The results are qualitatively similar.

Figure 1: 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 (1), and a higher number indicates increased concentration. The bottom figure gives the number of competitors in the biopharma industry over time.



Financial Characteristics

Taking this increase in competition over time as a given, we now examine the financial characteristics of firms in the biopharma industry. *Figure 2* 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 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 2* are consistent with Predictions 1 and 2 from Section 2. 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.¹⁴ 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.¹⁵

¹⁴The secular increase in mean R&D expenditures understates an interesting cyclicity. One explanation for this cyclicity 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.

¹⁵The trends for R&D, cash, and assets-in-place remain relatively flat until the mid-1970s, while debt

Figure 2: 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.



Stock Return Volatility

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 3*. The evidence is consistent with Prediction 3. 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.¹⁶

Panel (b) of *Figure 3* 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 4*, 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 3* is consistent with Prediction 3. Specifically, total stock return volatility and idiosyncratic volatility have both increased substantially

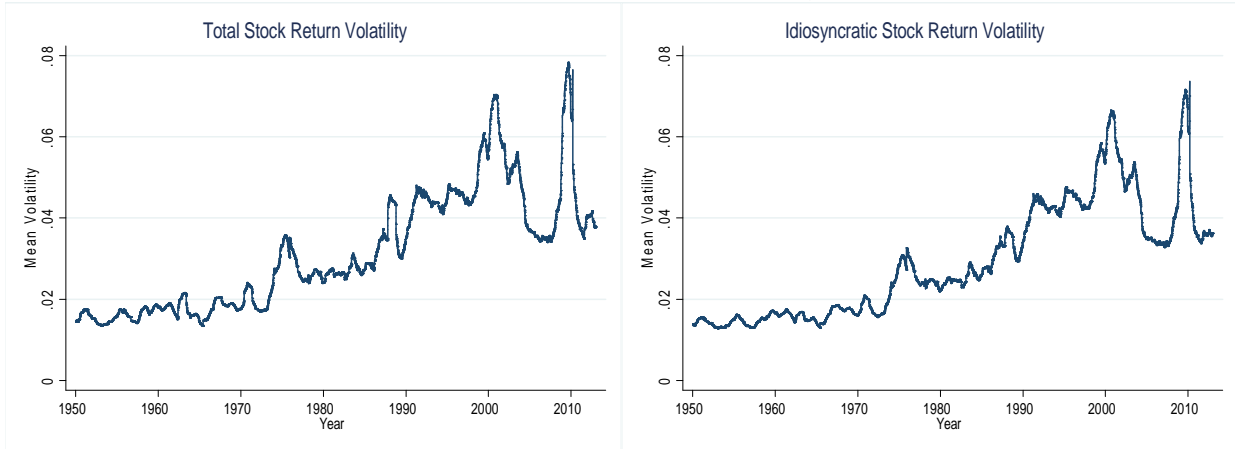
increases during this early time period. While this is in contrast to the reduction in the Concentration Ratio during this time period, this is consistent with the number of competitors (as shown in *Figure 2*) also being relatively flat during this period. As previously discussed, sales-based measures of competition may not be ideal for this industry, and thus these measures may not accurately gauge competition during certain periods.

¹⁶A 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.

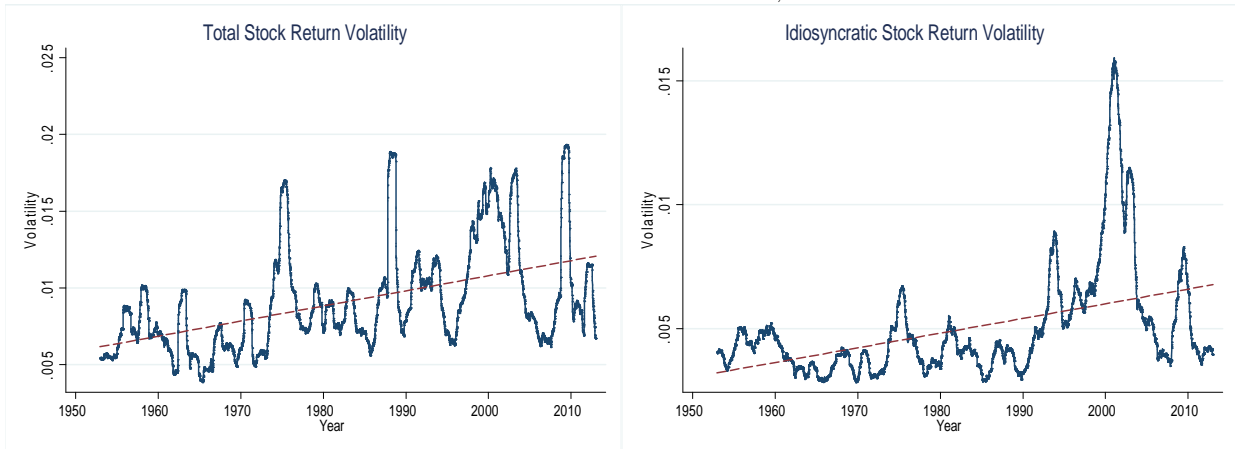
Figure 3: Total and Idiosyncratic Stock Return Volatility

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 (2) 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 (2).

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



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



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.

Betas

The betas of a value-weighted portfolio of biopharma firms are shown in *Figure 4*. The dotted lines represent trend lines for the beta estimates. As can be seen in the figure, the market beta has generally declined from 1950 and onward. In particular, the beta estimate has gone from slightly over 1.0 in the early 1950s to roughly 0.7 in 2012. This downward trend is prominent 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 1*. 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.¹⁷ Overall, the declines in beta over time are consistent with the hypothesis that firms will substitute investments in assets-in-place (which carry systematic risk) with investments in R&D (which carry idiosyncratic risk) when faced with greater competition.¹⁸

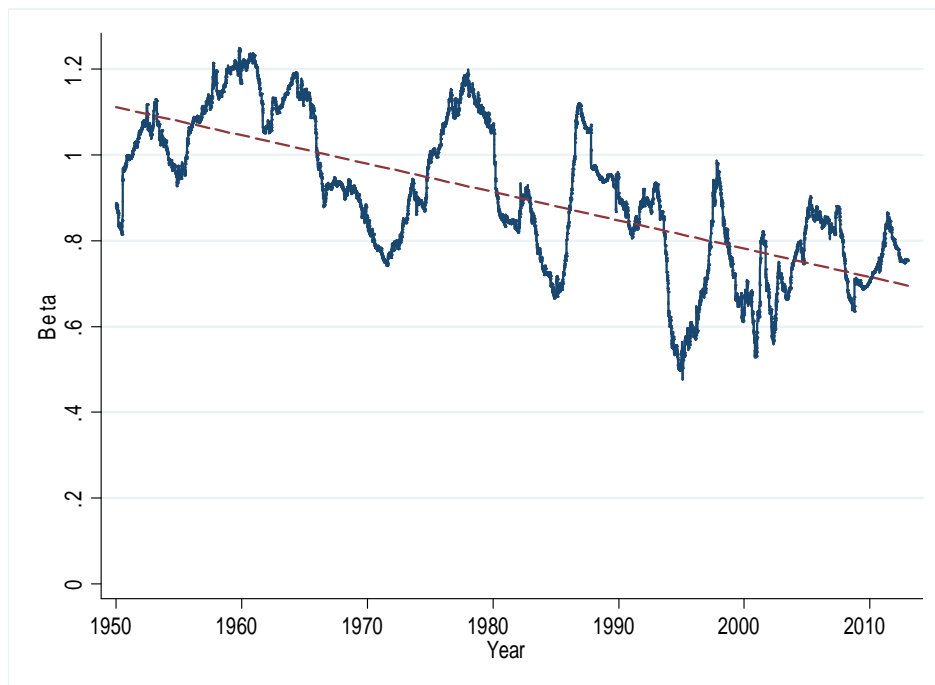
Table A1 of the Appendix summarizes the direction and significance of the relationship between the various financial characteristics and measures of competition through time-series regressions.

¹⁷Results available upon request.

¹⁸We also find similar trends when examining the SMB and HML betas of the Fama-French model; we focus on the market beta because the interpretation of the factor loading over time is clearer. The results for the other betas are available upon request.

Figure 4: Biopharma Industry Value-weighted Betas

This figure shows the market 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 dashed line is a trend line.



4 Differences-in-Differences Analysis

While the previous empirical evidence is consistent with the predictions of the model, a limitation of the evidence is that it treats the increase in competition as exogenous over time. However, this assumption may be violated in practice. 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.

4.1 The Hatch-Waxman Act and its Impact on Competition

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 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, market share, and price data for a sample of drugs after the enactment of the law, as well as Grabowski (2007) for an overview.

Evidence of the effect of the law on competition in the biopharma industry can also be seen empirically through the competition measures. As shown in *Figure 1*, the number of new entrants increases substantially after 1984, although there is an increasing trend in the years prior. The Concentration Ratio experiences a significant drop around 1990. While

this drop occurs a number of years after the passage of the Hatch-Waxman Act, this delay is consistent with the Concentration Ratio being a sales-based competition measure. Since all drugs must first pass the FDA approval process before they can be sold, which takes a number of years, new entrants will not be expected to affect the sales of the industry until several years after their entry. We therefore present an additional indicator of competition in the industry—the number of patent applications filed by biopharma firms. As patent applications can be filed even in the early stage of a drug’s development, the number of patents filed can be viewed as an indicator of the intensity of R&D competition. *Figure 5* graphs the number of whole patent applications filed by U.S. biopharma firms around the introduction of the Hatch-Waxman Act.¹⁹ As can be seen from the figure, the number of new patent applications is flat before 1984, but starting in 1984 the number of applications began to sharply increase. This is consistent with the Hatch-Waxman Act facilitating greater competition amongst biopharma firms.

4.2 Empirical Methodology

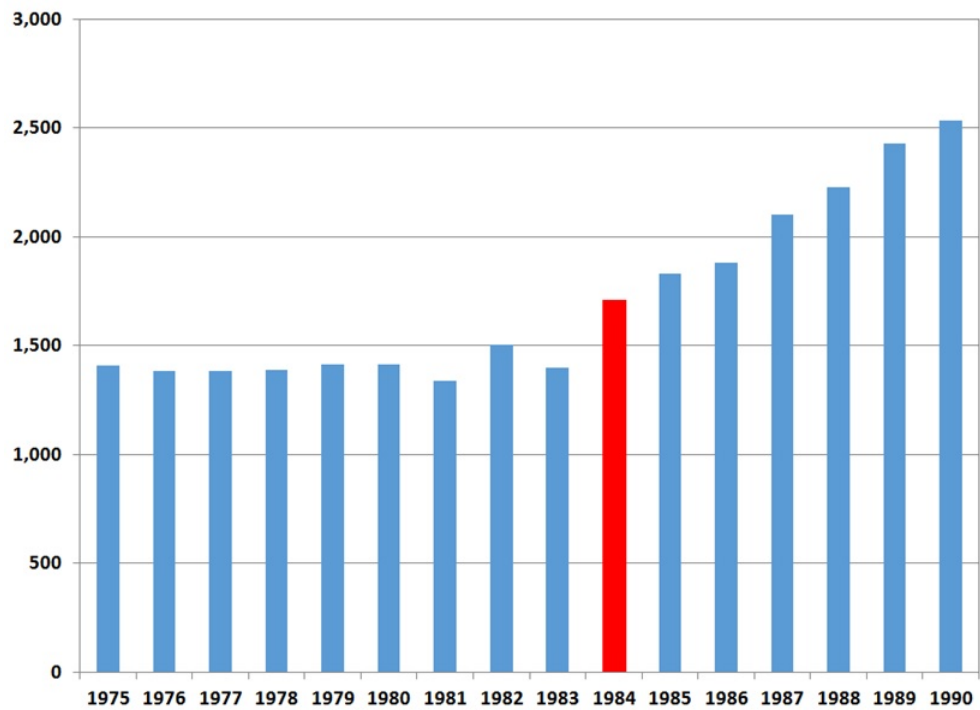
The ideal test is to find two groups of firms with similar characteristics, exogenously change the degree of competition for one group, and then see if the resulting difference conforms to the predictions. We use the Hatch-Waxman Act as a source of exogenous variation in order to conduct a differences-in-differences analysis to provide cleaner empirical support for the predictions identified in Section 2. 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 predictions are 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.²⁰ A concern with such an approach is that the control

¹⁹Data is taken from the U.S. Patent and Trademark Office (USPTO).

²⁰These 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

Figure 5: Biopharma Patent Applications

This figure depicts the number of new whole patent applications from 1975 to 1990 by U.S. firms in the pharmaceutical and medicines industry. Data are taken from the U.S. Patent and Trademark Office.



group has different characteristics and is thus not properly comparable to the biopharma industry. To deal with this, we 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 in the period before the law was passed.²¹

The pre-period is from 1974 to 1983, while the post-period is from 1984 to 1993. The resulting sample consists of 811 firms, for a total of 4,364 firm-years of data for the control group, and a total of 3,259 firm-years of data for the treatment group. We choose a relatively long estimation window to capture any delayed effects of competition on the variables of interest, given the well-documented long gestation periods in the biopharma industry, which will likely drive a slower response in many of the financial characteristics that we examine. However, as noted by Bertrand, Duflo, and Mullainathan (2004), a concern with differences-in-differences estimators with long estimation windows is that they are potentially biased due to autocorrelation. We examine this concern in detail in Section 4.5, including the robustness of our results to a shorter sample window.

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 6* provides graphical evidence for a number of years surrounding the passage of the Hatch-Waxman Act (with an expanded window to show qualitatively patterns before and after the Act), that examines this assumption for the control group. In the left 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

and analyzing equipment (2-digit SIC code 38).

²¹More specifically, we choose firms in the other R&D-intensive industries that match biopharma firms based on observable characteristics in the years between 1974 and 1984. The matching characteristics are: size ($\log(TA)$), profitability ($EBIT/TA$), capital structure ($Net\ Debt/TA$), dividend payout, and investment opportunities as proxied by market-to-book (ME/BE). We allow matches between multiple firms (i.e. we implement matching with replacement, allowing up to three matches), although this assumption does not have a material impact on our results. We further restrict our choice of control firms to the ones which are on a common support in terms of these observable characteristics before the implementation of the law. Our results are also robust to a one-to-one matched biopharma and control group sample over the sample period.

Hatch-Waxman Act was implemented. The right graphs depict the difference between the treatment and control groups for each of the variables. 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, 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 sharply relative to the control group, while debt, net debt, and assets-in-place appear to decrease within a few years after the Act was passed 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.²²

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

$$Y_{i,t} = \gamma_0 + \gamma_1 HW_t \times Biopharma_i + \eta X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}. \quad (3)$$

In (3), $Y_{i,t}$ 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

²²A 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 in order to rule out any sharp changes in competition that may have affected the control group at the same time. *Figure A2* of the Appendix examines changes in competition as measured by the Concentration Ratio (CR(4)) for the biopharma industry and the control group, both graphically and through a differences-in-differences regression. 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 6: Financial Characteristic Trends for Treatment and Control Groups

Trends for financial characteristic variables for R&D expenditures, cash holdings, debt, net debt, and assets-in-place, all scaled by total assets. The graphs on the left represent 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. The graphs on the right depict the differences between the treatment and control groups (treatment minus control). A vertical red line is included in each graph, representing the year that the Hatch-Waxman Act was implemented.

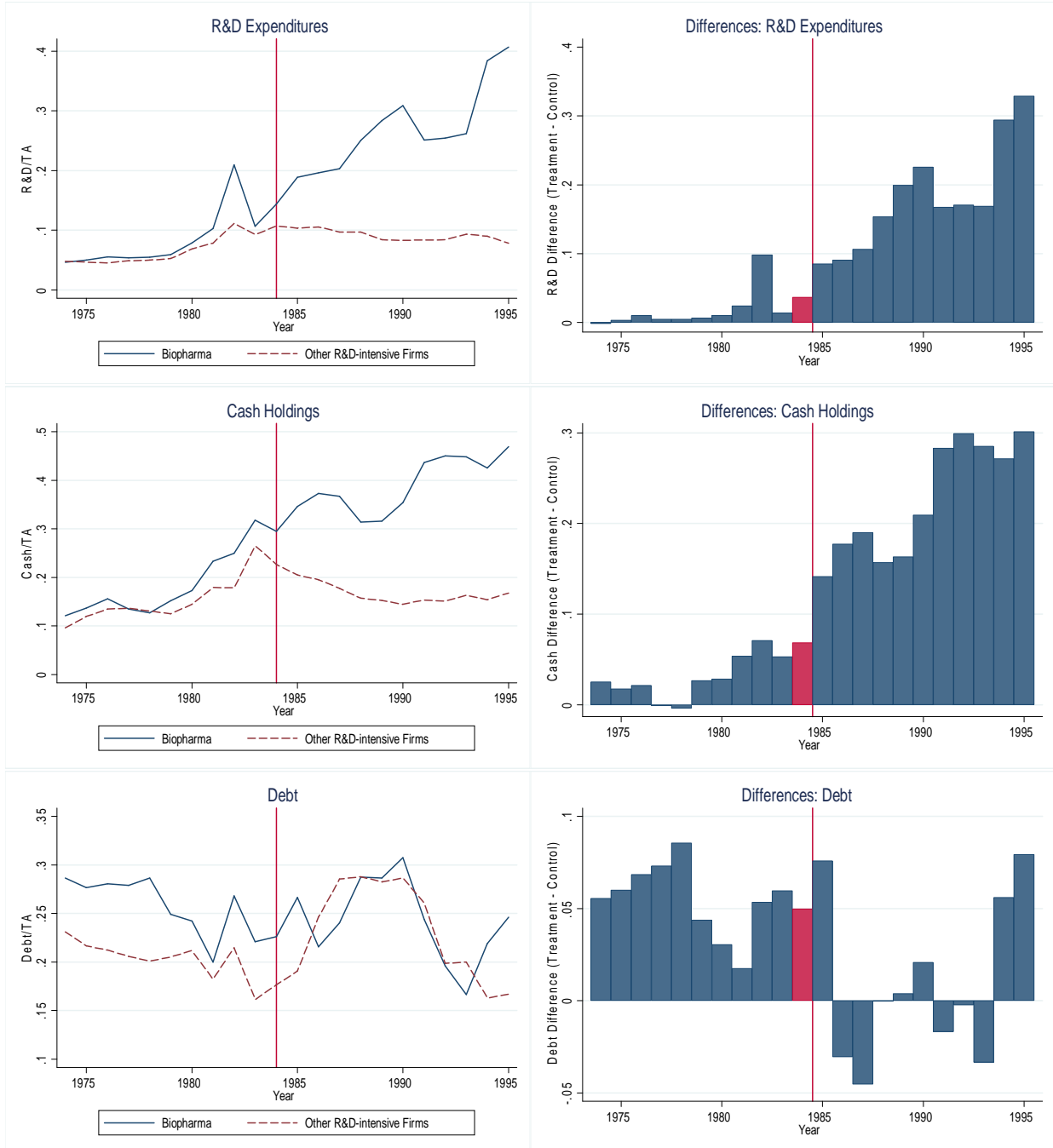
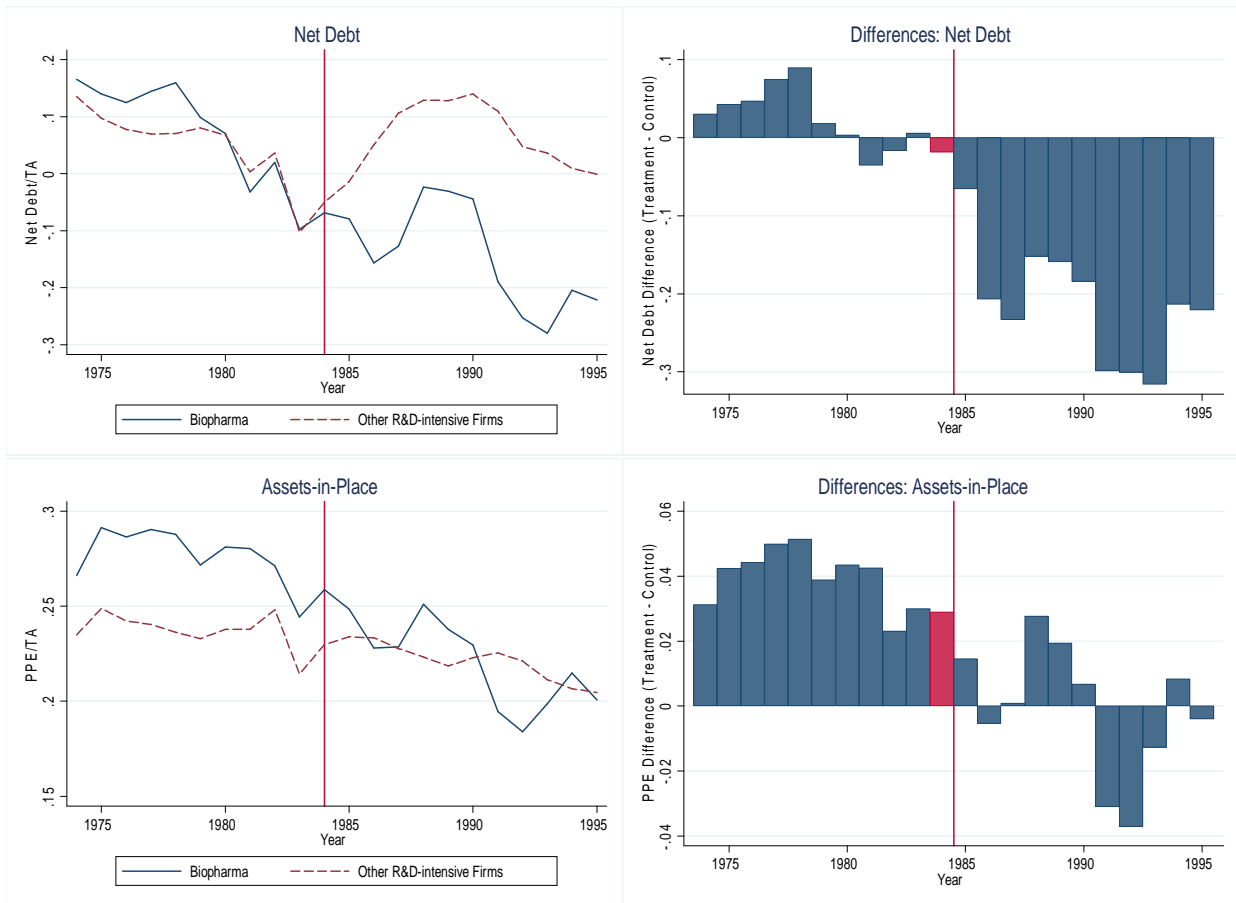


Figure 6 (continued): Financial Characteristic Trends for Treatment and Control Groups



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 regression estimate of γ_1 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 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.²³ Finally, μ_i represents firm fixed effects, to control for time-invariant firm characteristics, and λ_t represents year fixed effects, to control for time-trends. Equation (3) is estimated for the period from 1974 to 1993.

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 1974 to 1993), 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 3.1, 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 $\sigma_{P,t}^{idio}$) 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 (2), using the past 720 days of daily returns.

²³Control variables included in $X_{i,t}$ for the financial characteristic variables include: $\log(NA_{i,t})$ (where $NA = TA - Cash$), $(EBIT/TA)_{i,t}$ (earnings as a fraction of total assets to control for profitability), $(ME/BE)_{i,t}$ (market value of equity to book value of equity). $X_{i,t}$ also includes the following lagged endogenous variables: $(R\&D/TA)_{i,t-1}$, $(PPE/TA)_{i,t-1}$, $(Cash/TA)_{i,t-1}$, $(Debt/TA)_{i,t-1}$, and $(Div/TA)_{i,t-1}$ (the amount of common/ordinary dividends paid). Including these control variables as contemporaneous, rather than lagged values (when they are not the dependent variable of interest), does not change the results.

4.3 Results and Discussion

We begin by examining the effect of the increase in competition caused by the Hatch-Waxman Act on the key financial characteristic variables that were hypothesized earlier, and then examine the impact of Hatch-Waxman on the risk variables for the biopharma industry.

Effect on Financial Characteristics

The estimation results for regression (3) 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 in Section 2. 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. In particular, based on the coefficient from column (2), biopharma firms increased their R&D expenditures as a percentage of total assets relative to the control group by about 2.2%. The differences-in-differences estimator for *PPE* is negative and significant in column (3), which is consistent with the prediction of the model, but while also negative, is insignificant in column (4) when including controls and fixed effects. Thus, 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 relative to the control group as a result of the Hatch-Waxman Act (by roughly 3.5%). The differences-in-differences estimator for *Debt* is negative and significant in column (7), and is also negative though insignificant in column (8), providing some evidence that firms in the biopharma industry decreased their debt as a result of the increase in competition. However, the estimator for *Net Debt* is negative and significant in both columns (9) and (10), indicating that net debt also fell compared to the control group (by roughly 5.5%) as a result of the increase in competition for the biopharma industry.

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

This table estimates the differences-in-differences regression (3) 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 1974 to 1993. 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 $\log(NA_{i,t})$, $(EBIT/TA)_{i,t}$, $(M/B)_{i,t}$, $(PPE/TA)_{i,t-1}$, $(Cash/TA)_{i,t-1}$, $(Debt/TA)_{i,t-1}$, $(R\&D/TA)_{i,t-1}$, and $(Div/TA)_{i,t-1}$. 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	$Cash$	$Cash$	$Debt$	$Debt$	$Net\ Debt$	$Net\ Debt$
$HW_t \times Biopharma_i$	0.125*** (0.017)	0.022** (0.009)	-0.044*** (0.014)	-0.008 (0.008)	0.170*** (0.021)	0.035** (0.015)	-0.055* (0.029)	-0.020 (0.016)	-0.223*** (0.040)	-0.055** (0.025)
$Biopharma_i$	0.023*** (0.011)		0.038*** (0.014)		0.036** (0.019)		0.053*** (0.020)		0.017 (0.030)	
HW_t	0.027*** (0.006)		-0.011 (0.007)		0.018** (0.009)		0.038** (0.018)		0.019 (0.023)	
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	6,709	5,431	7,623	5,471	7,623	5,471	7,615	5,469	7,615	5,469
Number of Firms	756	685	811	689	811	689	811	689	811	689
Adjusted R^2	0.098	0.834	0.012	0.804	0.148	0.818	0.003	0.581	0.035	0.745

Effect on Risk Variables

We now turn to the estimated impact of the Hatch-Waxman Act on the risk variables. *Figure 7* shows the trends over time for total volatility and idiosyncratic volatility for the treatment and control group portfolios (left graphs), and the differences between the two groups (right graphs). For total and idiosyncratic volatility, the treatment and control groups follow parallel trends, with the biopharma firms having slightly lower volatility than the control firms. Within a few years after the enactment of the Hatch-Waxman Act, the volatilities of the biopharma firms increase relative to the control firms, subsequently maintaining a higher volatility than the control firms.

Figure 8 examines the trends for the beta estimates. For the market beta, shown in the top graph, the trends are less clear—the betas of the biopharma and control firms move roughly in parallel until a couple of years prior to the Act, but (apart from a spike in beta around 1986) there does not seem to be any significant divergence after the Act was passed. However, as is well documented in the literature, the market beta is not the only systematic risk factor—as a result, it is possible that the Hatch-Waxman Act affected other risk factors apart from the market beta. In order to explore this, in *Figure 8* we also examine trends for the size (SMB) and value (HML) factors of the Fama and French (1993) model. Both the SMB and HML factor loadings appear to fall for the biopharma firms compared to the control firms, providing suggestive evidence that systematic risk fell for the biopharma industry after the Hatch-Waxman Act came into effect, although this may not be the case for every risk factor.²⁴

The regression 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 more for the biopharma industry than for the control group immediately following the passage of the Hatch-Waxman

²⁴The graph for the SMB beta also indicates that the parallel trends assumption may not hold well for that factor, and thus the results should be interpreted with some caution.

Figure 7: Volatility Trends for Treatment and Control Group

This figure shows trends for the volatility variables. Volatility variables are yearly estimates, calculated using the daily returns over the year of a value-weighted portfolio of biopharma or control firms. In the left graphs, 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. The graphs on the right depict the differences between the treatment and control groups (treatment minus control). A vertical red line is included in each graph, representing the year that the Hatch-Waxman Act was implemented.

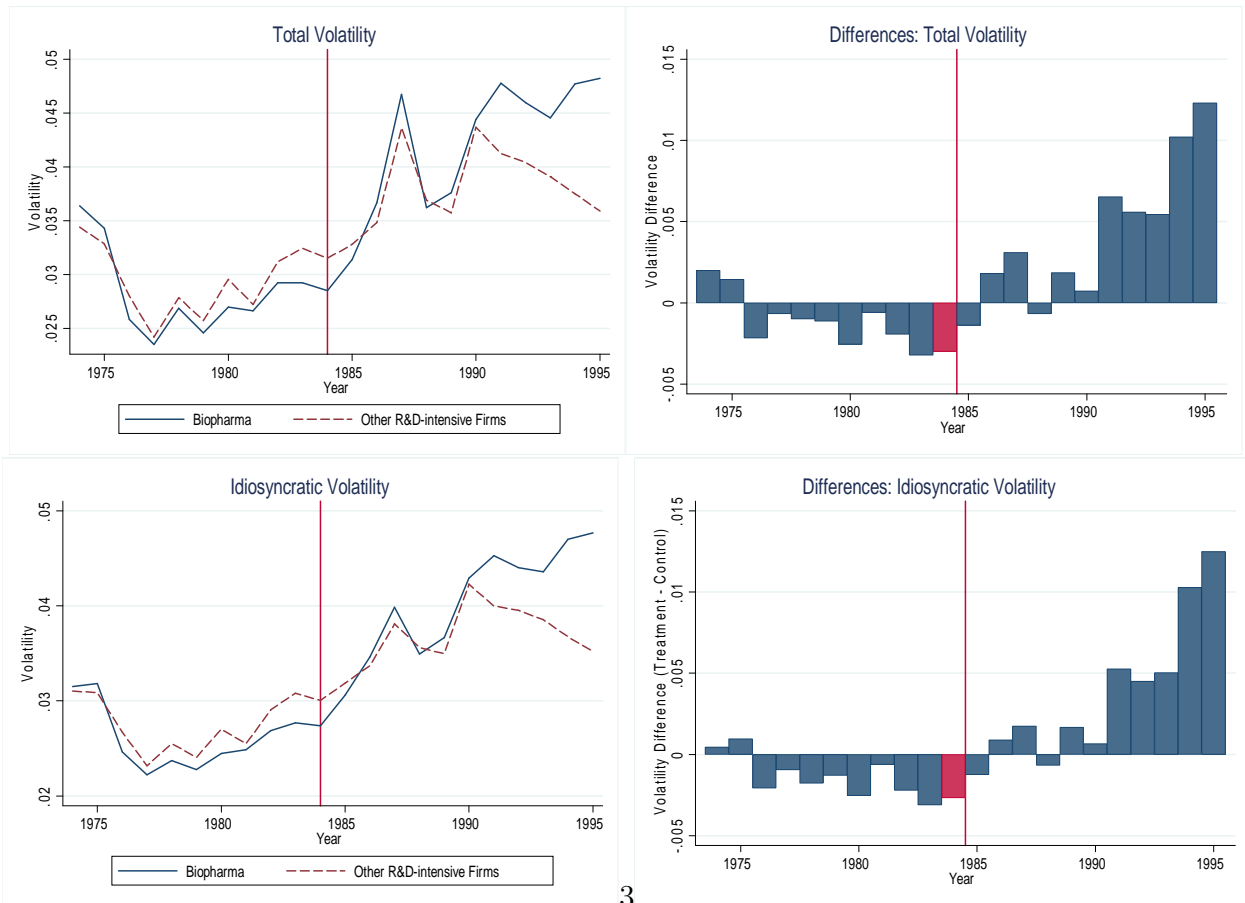
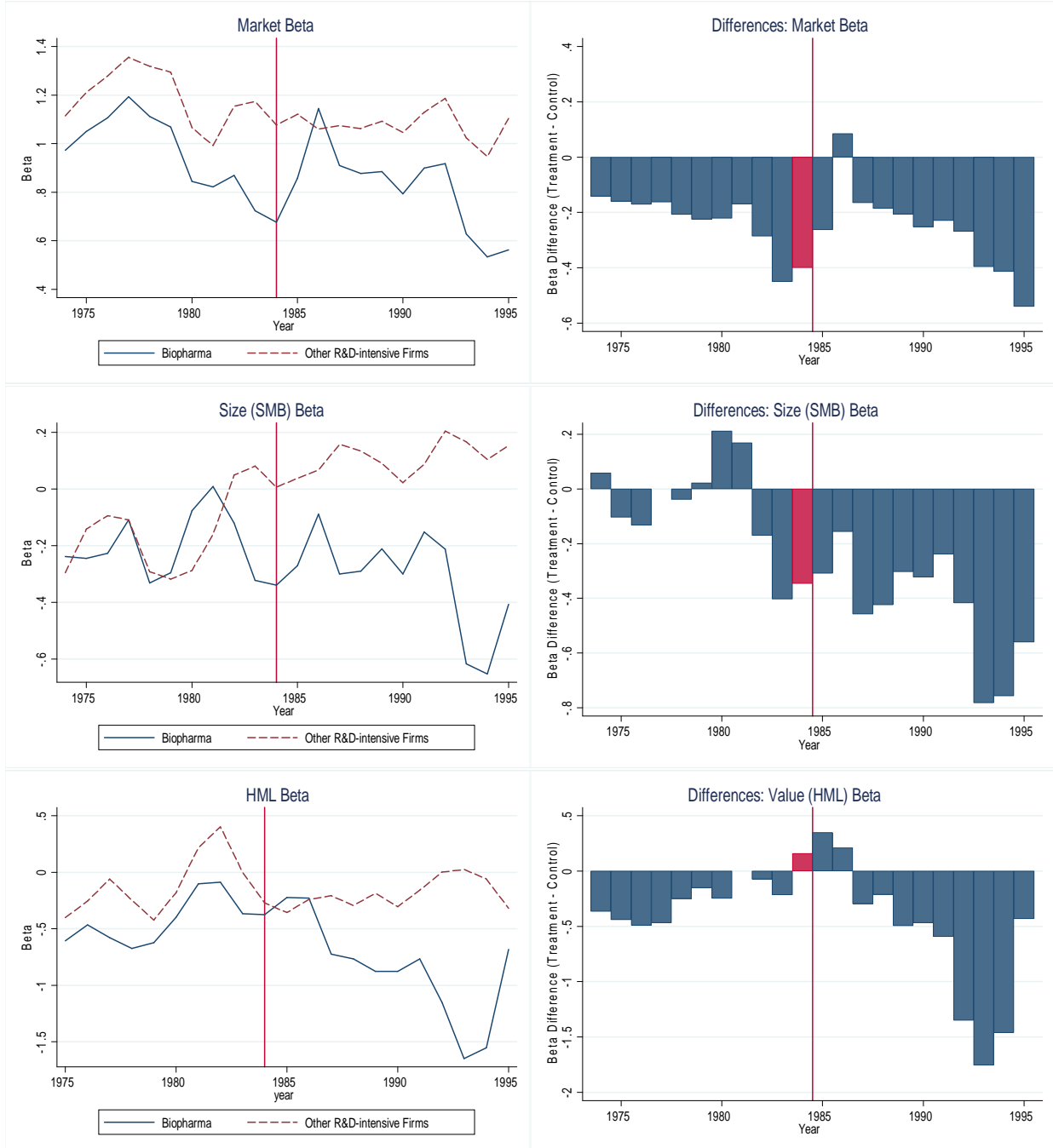


Figure 8: Beta Trends for Treatment and Control Group

This figure shows trends for the beta variables. The 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. The top set of graphs are the market beta estimates, the middle set of graphs are the size (SMB) estimates, and the bottom set of graphs are the value (HML) estimates. In the left graphs of each set, 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. The graphs on the right depict the differences between the treatment and control groups (treatment minus control). A vertical red line is included in each graph, representing the year that the Hatch-Waxman Act was implemented.



Act, which is consistent with the predictions. For the betas, the coefficient for $HW_t \times Biopharma_i$ is negative but insignificant for the market beta, which confirms that there was no statistically significant divergence between the biopharma and control groups. For the SMB factor, the coefficient for $HW_t \times Biopharma_i$ is negative and significant, however, indicating that the systematic risk associated with the size factor reduced for the biopharma industry relative to other R&D-intensive firms after the Hatch-Waxman Act came into effect. Finally, the value (HML) factor also declines for the biopharma industry, although it is not significant.

Overall, the increase in total and idiosyncratic risk are consistent with the hypotheses—an increase in competition leads to an increase in total and idiosyncratic volatility. The evidence for the betas is mixed—the market beta does not show any significant change relative to the control group, and the HML beta declines for the biopharma firms, but the decline is not significant. However, the SMB beta declines significantly for the biopharma group relative to the control group, which is consistent with Prediction 3.

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.

4.4 Robustness: Falsification Test

As a robustness check to account for the possibility that our results are being driven by trends that started before our sample period, we conduct a falsification test for the financial characteristic variables, where we run regression (3) for the sample period from 1964 to 1983, but falsely specify that the Act was implemented in 1974. As before, biopharma firms are our treatment group, and we choose propensity-score matched (based on observable characteristics in the period from 1964 to 1973) R&D-intensive firms as our control group. As indicated in *Figure 2*, there are not as many biopharma firms operating during this period; as a result, the sample consists of a total of 110 firms with 1,002 firm-years of data.

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 1974 to 1993. 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.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	σ	σ^{idio}	β_{mkt}	β_{SMB}	β_{HML}
$HW_t \times Biopharma_i$	0.005*** (0.001)	0.003*** (0.001)	-0.009 (0.052)	-0.337*** (0.078)	-0.175 (0.219)
Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	40	40	40	40	40
R^2	0.969	0.977	0.897	0.794	0.559

The results of the falsification test are included in *Table 4*. R&D, cash, debt, and net debt are all insignificant. However, assets-in-place, as proxied by PPE, is negative and significant. This variable was insignificant in the main regression specification, and thus this falsification test indicates that the results for assets-in-place should be interpreted with caution. Alternatively, it may be that property, plant, and equipment is an imperfect proxy for assets-in-place.

Overall, these results suggest that the results from the previous section are not caused by any long-term trends between the treatment and control groups, as the same results are not found in a different sample period.

4.5 Robustness: Estimation Window and Autocorrelation

A potential concern with our results is that they are biased due to autocorrelation, driven by the long sample window that we use (e.g. Bertrand, Duflo, and Mullainathan (2004)). We choose such a sample window because of the long gestation periods in the biopharma industry. However, we examine the robustness of our results to the length of the estimation window in order to allay potential concerns related to autocorrelation.

Shorter Estimation Window

We first examine how robust our results are to a shorter sample window of 10 years: 5 years for the pre-period from 1979 to 1983, and 5 years for the post-period from 1984 to 1988. The results are given in *Table 5* below.

The overall results are similar to the main results from *Table 2*. In particular, the diff-in-diff estimator for PPE is again negative though insignificant, the estimator for cash is again positive and significant, and the estimator for net debt is again negative and significant. The estimator for debt in this case is negative and significant, which strengthens the result for debt. However, the diff-in-diff estimator is insignificant for R&D, although it is still positive. This may be due to the one-time jump in R&D expenditures for the biopharma group in

Table 4: **Falsification Test for the Differences-in-Differences Analysis**

This table estimates the differences-in-differences regression (3) for financial characteristics, but over the sample period from 1964 to 1983. 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 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 $\log(NA_{i,t})$, $(EBIT/TA)_{i,t}$, $(M/B)_{i,t}$, $(PPE/TA)_{i,t-1}$, $(Cash/TA)_{i,t-1}$, $(Debt/TA)_{i,t-1}$, $(R\&D/TA)_{i,t-1}$, and $(Div/TA)_{i,t-1}$. 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)
	$R\&D$	PPE	$Cash$	$Debt$	$Net\ Debt$
$Act_t \times Biopharma_i$	-0.004 (0.003)	-0.019*** (0.007)	0.005 (0.010)	-0.007 (0.012)	-0.011 (0.018)
Controls	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,002	1,010	1,010	1,007	1,007
Number of Firms	107	110	110	110	110
Adjusted R^2	0.907	0.885	0.820	0.849	0.853

Table 5: **Differences-in-Differences Analysis, Shorter Time Window**

This table estimates the differences-in-differences regression (3) for financial characteristics, but over the sample period from 1979 to 1988. 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. 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 firm i is in the biopharma industry, and a value of 0 otherwise. Control variables include $\log(NA_{i,t})$, $(EBIT/TA)_{i,t}$, $(M/B)_{i,t}$, $(PPE/TA)_{i,t-1}$, $(Cash/TA)_{i,t-1}$, $(Debt/TA)_{i,t-1}$, $(R\&D/TA)_{i,t-1}$, and $(Div/TA)_{i,t-1}$. 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.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	$R\&D$	PPE	$Cash$	$Debt$	$Net\ Debt$
$HW_t \times Biopharma_i$	0.006 (0.001)	-0.011 (0.009)	0.037** (0.017)	-0.035** (0.016)	-0.072*** (0.027)
Controls	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	2,500	2,526	2,527	2,526	2,526
Number of Firms	461	467	467	467	467
Adjusted R^2	0.849	0.813	0.799	0.599	0.739

1982, which is exacerbated by the shorter estimation window.

Thus, these results suggests that our main results are not driven exclusively by the longer estimation window we use, and are robust to a shorter sample window. We now examine other ways to deal with potential autocorrelation in our sample.

Autocorrelation Correction

One direct way to correct for the potential influence of autocorrelation is to correct the standard errors. We therefore re-estimate our results using Newey and West (1987) standard errors. The results are given in *Table 6* below.

The results using Newey-West standard errors are very similar to the main results. As before, R&D is positive and significant, PPE is negative though insignificant, cash is positive and significant, debt is negative but insignificant, and net debt is negative and significant. Thus, our results are robust to explicitly correcting for autocorrelation,

5 Conclusion

In this paper, we explore the interaction between competition, R&D investments, and financing choices, as well as the implications of this interaction for the firm's risk profile. We motivate our empirical hypotheses with the insights of existing theories which, taken together, predict that as competition increases, firms will increase R&D investment, reduce investment in assets-in-place, carry more cash, and have lower levels of net debt. Moreover, firm betas will decline, but idiosyncratic risk and total stock return volatility will rise. We provide time-series evidence on firms in the biopharma industry that is consistent with these predictions. However, since our predictions rely on an exogenous change in competition, whereas in reality competition has both exogenous as well as endogenous elements, 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

Table 6: Differences-in-Differences Analysis, Newey-West Standard Errors

This table estimates the differences-in-differences regression (3) for financial characteristics, correcting for autocorrelation using Newey-West standard errors. 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 $\log(NA_{i,t})$, $(EBIT/TA)_{i,t}$, $(M/B)_{i,t}$, $(PPE/TA)_{i,t-1}$, $(Cash/TA)_{i,t-1}$, $(Debt/TA)_{i,t-1}$, $(R\&D/TA)_{i,t-1}$, and $(Div/TA)_{i,t-1}$. Year and firm fixed effects are included where indicated. Newey-West standard errors are given in parentheses, accounting for autocorrelation of up to 10 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	$R\&D$	PPE	$Cash$	$Debt$	$Net Debt$
$HW_t \times Biopharma_i$	0.022*** (0.007)	-0.008 (0.007)	0.035*** (0.012)	-0.020 (0.013)	-0.055*** (0.020)
Controls	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	5,431	5,471	5,471	5,469	5,469

evidence that strongly supports the model. This approach allows us to overcome the endogeneity concern about competition. Although we have focused on the biopharma industry, our results are also applicable to other R&D-intensive firms.

At a broad level, innovative industries like biopharma have been subject to increased competitive pressures over time, through both regulation and technological breakthroughs that have allowed easier entry (such as the Human Genome Project and increasingly faster and cheaper sequencing technologies). We highlight how these changes in competition may affect important financial characteristics and risk over time, which may, in turn, affect the amount of funding that R&D-intensive firms are able to raise. For example, while increased competition may spur innovation through increased R&D investment, it also increases idiosyncratic and total volatility, potentially affecting the appeal of these firms to investors.

A topic for future research is how potential innovations in the realm of R&D-intensive industries may affect some of the outcomes affected by competition. For example, a recent innovation that has been proposed in the biopharma industry is a portfolio of R&D projects, through the “megafund” idea of Fernandez, Stein and Lo (2012) and Fagnan, Fernandez, Lo, and Stein (2013). One benefit to adopting a portfolio approach is reducing the idiosyncratic risk in R&D due to the diversification provided by a portfolio of projects. Such innovations may change the effects of competition on innovation in important ways.

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Appendix: 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 (1). 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).

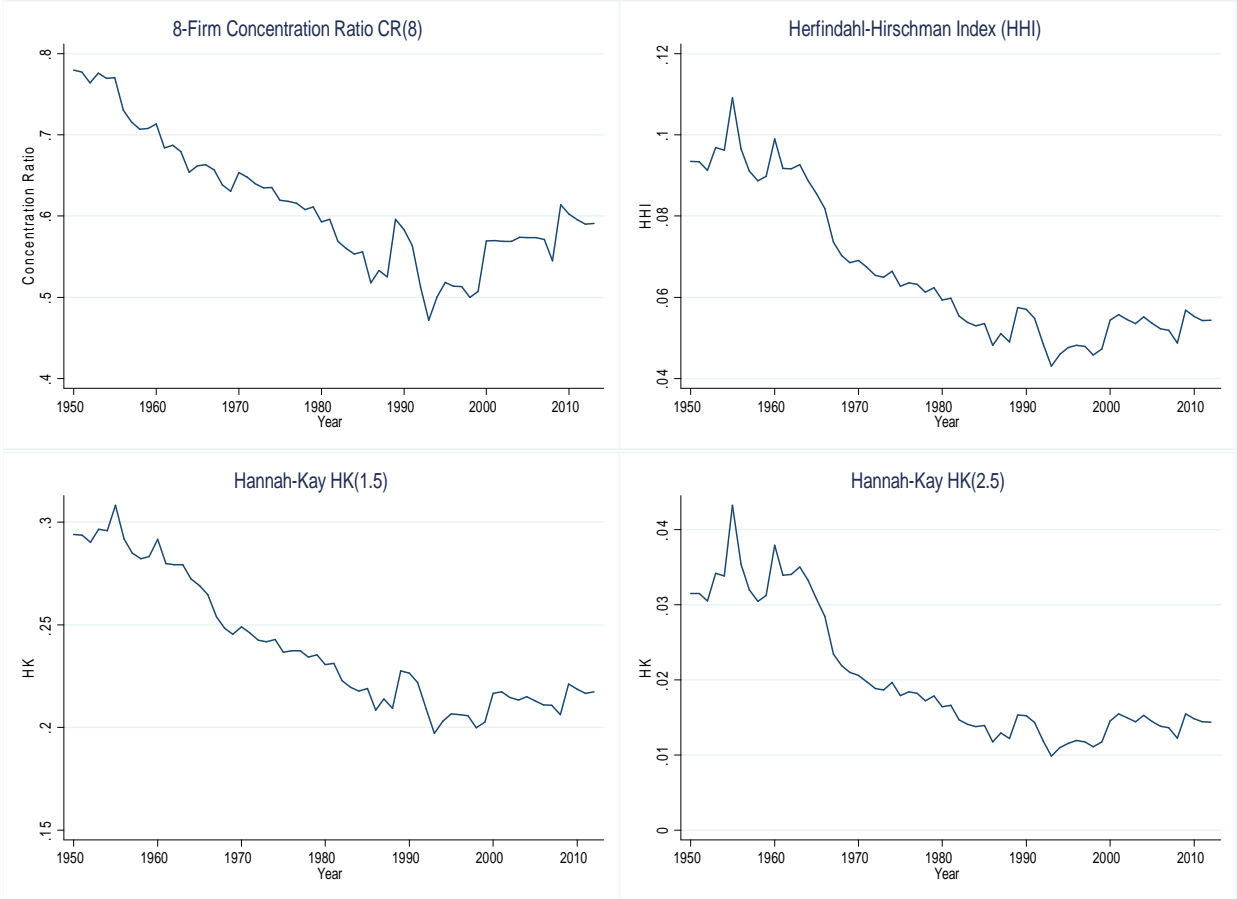
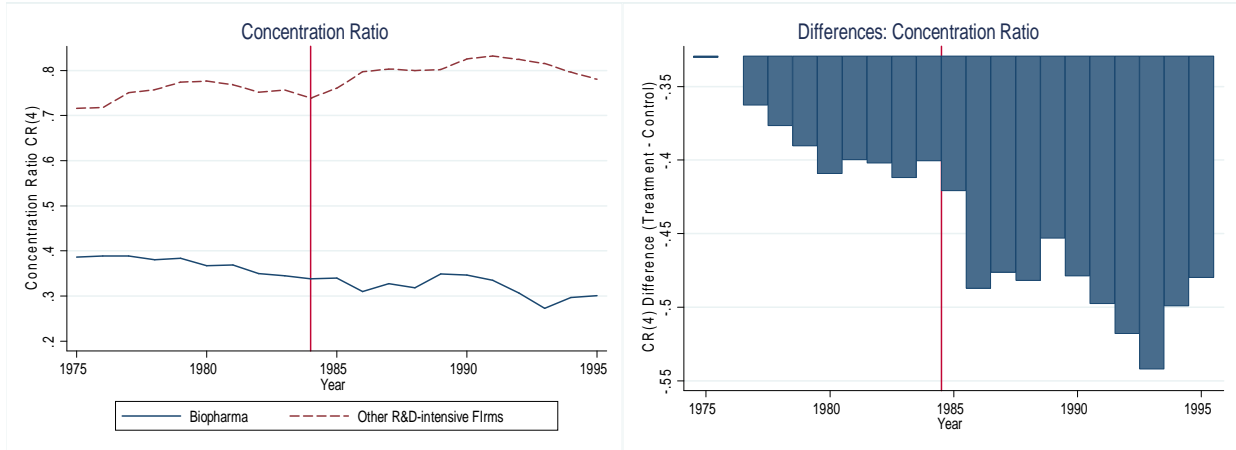


Figure A2: Changes in Competition Around Hatch-Waxman Act

The left graph of Panel (a) depicts the 4-firm Concentration Ratio $CR(4)$ for the biopharma industry (the solid blue line) and the propensity-score matched sample of other R&D-intensive firms (the dashed red line) around the enactment of the Hatch-Waxman Act, and the right graph shows the differences between the two groups. 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 2-digit industry i . 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 are clustered at the 2-digit industry-level. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Each regression includes a constant term (not reported).

(a) Competition Trends for Biopharma and Control Group



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

Dependent Variable: $CR_{i,t}(4)$		
	(1)	(2)
$Biopharma_i \times HW_t$	-0.099** (0.027)	-0.099** (0.030)
$Biopharma_i$	-0.379*** (0.027)	
HW_t	0.046 (0.027)	
Industry Fixed Effects	No	Yes
Year Fixed Effects	No	Yes
Observations	126	126
R^2	0.853	0.960

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. $\beta_{mkt,t}$ is the market beta of a value weighted portfolio of biopharma firms, calculated using (2) 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 Variable	Dependent Variable							
	R&D	Cash	PPE	Debt	Net Debt	σ	σ^{idio}	β_{mkt}
Number	0.0003*** (0.0000)	0.0007*** (0.0000)	-0.0004*** (0.0000)	-0.0001 (0.0001)	-0.0005*** (0.0001)	0.00005*** (0.0000)	0.00005*** (0.0000)	-0.0005*** (0.0001)
Competitors	[0.895]	[0.906]	[0.962]	[0.075]	[0.620]	[0.694]	[0.716]	[0.473]
$CR(4)$	-0.828*** (0.198)	-1.479*** (0.376)	1.011*** (0.173)	-0.271 (0.165)	0.803* (0.432)	-0.170*** (0.021)	-0.167*** (0.021)	1.895*** (0.325)
	[0.393]	[0.311]	[0.513]	[0.075]	[0.100]	[0.585]	[0.606]	[0.478]
$CR(8)$	-0.658*** (0.153)	-1.144*** (0.330)	0.774*** (0.148)	-0.191 (0.137)	0.666* (0.391)	-0.137*** (0.021)	-0.134*** (0.021)	1.454*** (0.330)
	[0.351]	[0.265]	[0.428]	[0.053]	[0.100]	[0.537]	[0.558]	[0.400]
HHI	-2.983*** (0.779)	-5.369*** (1.555)	3.805*** (0.684)	-1.207** (0.568)	2.602 (1.689)	-0.625*** (0.088)	-0.612*** (0.087)	7.087*** (1.175)
	[0.374]	[0.300]	[0.532]	[0.110]	[0.076]	[0.577]	[0.595]	[0.490]
$HK(1.5)$	-1.824*** (0.436)	-3.307*** (0.929)	2.257*** (0.403)	-0.545 (0.343)	1.798* (1.010)	-0.364*** (0.049)	-0.356*** (0.049)	4.049*** (0.695)
	[0.442]	[0.360]	[0.592]	[0.071]	[0.115]	[0.618]	[0.637]	[0.502]
$HK(2.5)$	-5.740*** (1.614)	-10.359*** (3.114)	7.533*** (1.383)	-2.775** (1.105)	4.550 (3.346)	-1.242*** (0.186)	-1.217*** (0.184)	14.378*** (2.263)
	[0.331]	[0.267]	[0.498]	[0.138]	[0.056]	[0.545]	[0.562]	[0.481]