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

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Abstract

How does competition affect innovation investment 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 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 (3) maintain less net debt. We provide evidence supporting these predictions by exploiting differences between the biopharma industry and other industries, as well as heterogeneity within the biopharma industry, in response to an exogenous change in competition.

Keywords: Healthcare Finance; Pharmaceutical Industry; Biotechnology Industry; Capital Structure; R&D Investments; Cash Holdings; 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 investment in innovation?

In addition, investments in R&D that fuel innovation often require large amounts of capital that must be externally sourced, so financing frictions 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 arises: how does product-market competition affect the financing choices of firms through its effect on their innovation incentives?

These questions underscore the important role that interactions between financing and competition play 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 previously each of these questions has been studied separately, we are unaware of any prior research that has empirically examined the interactive relationship between competition, innovation and financing in a setting that overcomes endogeneity concerns. The interactive effects and endogeneity concerns are especially important because theory suggests that competition affects innovation incentives but innovation can affect competition as well, generating an endogenous effect in addition to the exogenous drivers of changes in competition. 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, and financing. 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

\(^1\)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. 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.
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.

Our second prediction is that firms will carry more cash in response to greater competition. One 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). Another reason for carrying additional cash is to minimize the inadvertent revelation of valuable project information to competitors through the act of raising capital (e.g. Kamien and Schwartz (1978)). The relatively large cash balances of R&D-intensive companies are consistent with these implications.

Our final prediction is that net debt will decline in response to greater 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)).

Using data on publicly-traded biopharma companies, we provide empirical support for these predictions. In order to uncover some relevant empirical regularities, 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 addition, assets-in-place and net debt as a percentage of total assets declined for the average biopharma firm as competition increased.

While these stylized facts are consistent with our predictions, they do not address endogeneity concerns. In particular, biopharma firms face competition that has both endogenous
and exogenous elements. Endogenous competition is affected by how much the firm spends on R&D. Exogenous competition is affected by 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. Specifically, we compare the reaction of financial characteristics of biopharma firms to a propensity-score-matched control group of R&D-intensive firms in other industries which were not affected by the legislation. We find strong supporting evidence for the main predictions. The results survive a number of robustness checks, including a falsification test for the year of passage of the Act, tests that correct for the potential effect of serial correlation, and restricting our sample to account for changes in sample composition.

A potential concern with our approach is that, by using a control group of firms in other industries, we may not be able to fully account for unobservable characteristics or structural changes that may drive differences between the treatment and control groups. We therefore conduct a second test by exploiting variation within the biopharma industry. Specifically, we use the Hatch-Waxman Act in order to compare the reaction of generic drug manufacturers in the pharma sector—firms for which the hypotheses are less applicable—to other pharma firms in a differences-in-differences approach. We again find supporting evidence for the main predictions.

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 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. More recently, Aghion, Bechtold, Cassar and Herz (2014) have provided evidence based on lab experiments. 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. 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.

Our paper is also related to the literature that explores the financing of R&D. 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 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’

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2 Other 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). And Lie and Yang (2017) empirically shows that the increase in import penetration by Chinese firms boosted innovation by US firms, and also prompted them to reduce their capital expenditures.

3 Our 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.
innovation incentives and cash holdings. Morellec, Nikolov, and Zucchi (2014) develop a
dynamic model and provide empirical support that competition increases corporate cash
holdings and equity issues. Lyandres and Palazzo (2016) show theoretically and empirically
that the firms that successfully innovate use cash as a commitment device for implementation
of successful innovations.

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
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 inter-
action 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 describe our data and time-series statistics in
Section 3. In Section 4, we describe our main empirical methodology. Section 5 provides
our main results and robustness tests. In Section 6, we provide an additional test of our
main predictions by exploiting heterogeneity within the biopharma industry. We conclude
in Section 7.
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 biopharma 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 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. (2001, 2005))—the lower margins on existing products due to increased competition

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

5 The notion of competition here is 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 in 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. 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.

6 This 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 those from existing products that do not enjoy patent protection.
makes these products less attractive relative to new R&D products that are under patent protection.\textsuperscript{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 how to fund its R&D investments. 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 and associated spillover effects) for insiders that cannot be contracted upon at reasonable cost. Thus, there may be instances in which, based on non-contractable R&D payoffs, insiders wish to raise additional financing in the future 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 (2016).

Furthermore, R&D-intensive firms operate in an environment in which information about the prospect of R&D success is valuable, and may be damaging to the firm if conveyed to its competitors. Because the firm knows more relative to the market, the very act of going to the capital market to raise financing may reveal information to competitors. As a result, an R&D-intensive firm has more of an incentive to finance investments through internal funds as competitive pressures increase (see Kamien and Schwartz (1978) and Thakor and

\textsuperscript{7}In the Aghion et al. (2001, 2005) terminology, we are describing “neck-and-neck” firms competing in the product market. Aghion et al. (2005) also note that at high levels of competition, an increase in competition may in fact decrease innovation. As we will show in Section 3, the level of competition in the biopharma sector continued to increase even after our period of focus, indicating that it is likely not especially high during our period of focus. We thus note that our empirical setting matches more closely the former “escape-the-competition” effect.
Lo (2017)). Putting these arguments together leads to our second prediction:

2) As competition increases, firms will carry more cash.

Finally, the firm has to determine its capital structure beyond its cash holdings. 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, e.g., Rampini and Viswanathan (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). These arguments lead to our final prediction:

3) As competition increases, debt and net debt will decline.

3 Data and Stylized Facts

In this section, we describe the data on the biopharma sector that we use in our empirical tests. We also present stylized facts using this data by considering the evolution of the characteristics of the biopharma industry over time, as a first step in examining the predictions in the previous section.
3.1 Data and Summary Statistics

Our main data come from Compustat. The focus of our empirical analysis is the biopharma industry, which we take to be all firms that are comprised of Global Industry Classification Standard (GICS) codes 352020 (pharmaceuticals) and 352010 (biotechnology). We use GICS codes to identify biopharma firms because it is a newer and more accurate classification system widely used by analysts, and is thus less exposed to the shortcomings of other classifications (such as SIC and NAICS) in identifying biopharma firms that have been noted by others (e.g. Carlson (2016) and Thakor et al. (forthcoming)).

However, our results are also robust to identifying biopharma firms using classifications such as SIC codes. We focus on firms that are incorporated in the U.S., as our main empirical analysis involves a change in legislation that occurs in the U.S. This provides us with a broad initial sample of 1,266 biopharma firms from 1950 to 2016, which we compare to other firms in Compustat.

We construct the following variables at the firm-year level in order to examine the predictions from Section 2. R&D investment is measured by \( \frac{R&D}{TA} \), which is R&D expenditures scaled by total assets. Assets-in-place are measured by \( \frac{PPE}{TA} \), which is property, plant, and equipment scaled by total assets. Cash is represented by \( \frac{Cash}{TA} \), which is measured by cash and short-term investments scaled by total assets. Debt is represented by \( \frac{Debt}{TA} \), which is the sum of total long-term debt and short-term debt (debt in current liabilities). Net debt is represented by \( \frac{Net\ Debt}{TA} \), where \( Net\ Debt = Debt - Cash \).

Summary statistics for these variables for the biopharma sector are given in Table 1. The entries in Table 1 show that R&D spending is substantial for the industry, averaging roughly 39% of total assets over the sample period. In addition, cash holdings are also substantial.

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8As an example, the standard way to identify biopharma firms via SIC codes is to use: 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. However, given that SIC is an older classification system and the nature of the biopharma industry has evolved over time, there are newer biotech firms which do not cleanly fit into SIC industries in a way that makes it difficult to distinguish them from non-drug firms.

9Variables are winsorized at the 1% level across all firms in order to reduce the impact of extreme outliers.
averaging 52% of total assets. While the mean level of debt is somewhat high at 30% 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. However, accounting for the substantial cash holdings and computing net debt that reflects these holdings, we see that the mean firm as well as the median firm in the industry hold negative net debt.

[Table 1 Here]

### 3.2 Time-Series Stylized Facts

To document how the competitive environment in the biopharma industry has changed over time, we take a simple approach and focus on the increase in the number of firms operating in the biopharma sector. We do so because typical measures of industry competition, such as the Herfindahl-Hirschman Index or concentration ratio, are likely to present a distorted view of competition since they are sales-based measures. For the biopharma industry in particular, 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 or 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. Thus, sales-based metrics and other traditional measures of competition are unlikely to accurately capture changes in competition for the biopharma industry.

*Figure 1* shows that the number of competitors in the industry has increased steadily until the mid-1990s, after which it has remained relatively flat. This suggests a substantial increase in competition over time from the 1950s, with the largest increase starting in the 1980s and continuing until the late 1990s, when it began to taper off. This is consistent with existing papers (e.g. Caves, Whinston, and Hurwitz (1991), Grabowski and Vernon (1990,
1992), and others) that have shown that the industry has become more competitive over time.

[Figure 1 Here]

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. The mean and median values of $R&D/TA$, $PPE/TA$, $Cash/TA$, $Debt/TA$, and $Net Debt/TA$ 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.

[Figure 2 Here]

The graphs presented in Figure 2 are consistent with the predictions from Section 2. In particular, as competition has increased over time, both mean and median R&D expenditures have increased, while assets-in-place (measured by PPE) have decreased sharply.\textsuperscript{10} Moreover, cash holdings have increased substantially.\textsuperscript{11} 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. The changes in these variables are the largest in the 1980s and 1990s, which

\textsuperscript{10}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.

\textsuperscript{11}The cash trends for biopharma compared to other industries are also in line with the findings of Begenau and Palazzo (2016), who show evidence that the overall increase in firm cash holdings is driven by the entry of more R&D-intensive firms.
mirrors the trend in the number of firms over the sample 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.

4 Empirical Methodology

While the previous stylized facts are generally consistent with the predictions of the model, they of course do not account for endogeneity—that R&D is affected by competition, but competition is also affected by R&D. 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 therefore now turn to describing our main empirical strategy—exploiting 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

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 express 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.

While evidence of the effect of the law on competition in the biopharma industry has been established in the studies mentioned above, it can also be seen empirically. As shown in Figure 1, the number of new entrants increases substantially after 1984, although there is an increasing trend in the years prior. An additional indicator of the effect of the legislation on the industry is 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 loosely viewed as an indicator of the intensity of R&D competition. Figure 3 graphs the number of whole patent applications filed by U.S. biopharma firms around the introduction of the Hatch-Waxman Act. 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 increase sharply. This is consistent with the Hatch-Waxman Act facilitating greater competition amongst biopharma firms.

[Figure 3 Here]

4.2 Empirical Methodology: Inter-Industry Variation

We first use the Hatch-Waxman Act as a source of exogenous inter-industry variation to conduct a differences-in-differences analysis which can provide clearer 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. 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.  

\footnote{Data is taken from the U.S. Patent and Trademark Office (USPTO).}

\footnote{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).}
A concern with such an approach is that the control group has different characteristics and is thus not properly comparable to the biopharma industry. To deal with this, we construct the control group by using propensity-score matching to choose firms from the other R&D-intensive industries that are comparable to biopharma firms based on observable characteristics in the sample period before the law was passed. More specifically, we choose firms in the other R&D-intensive industries that match biopharma firms based on their mean observable characteristics in the years between 1977 and 1983. The matching characteristics are: size (log (Net Assets)), profitability (EBIT/TA), capital structure (Net Debt/TA), cash holdings (Cash/TA), R&D (R&D/TA), assets-in-place (PPE/TA) and investment opportunities as proxied by market-to-book (ME/BE).14 We show in Section 5.1 that the parallel trends assumption holds for the treatment and control groups.

Using these treatment and control groups, we estimate the following regression:

\[ Y_{i,t} = \gamma_0 + \gamma_1 HW_t \times Biopharma_i + \eta X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}. \]  

(1)

In (1), \( Y_{i,t} \) 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, and 0 if it is in the control group. It follows that the regression estimate of \( \gamma_1 \) is the differences-in-differences (diff-in-diff) 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 hypotheses. Specifically, for the financial characteristics, we examine \( R&D/TA, PPE/TA, Cash/TA, Debt/TA, \) and \( Net Debt/TA \) as choices for \( Y_{i,t} \). To control for the possibility of differential trends between the control and treatment groups that are

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14We implement the propensity score matching using one-to-one logit matching without replacement, and restrict observations to a common support.
not accounted for by the matching procedure, $X_{i,t}$ is a vector of contemporaneous and lagged control variables that may also covary with the dependent variable.\textsuperscript{15} Finally, $\mu_i$ represents firm fixed effects, to control for time-invariant firm characteristics, and $\lambda_t$ represents year fixed effects, to control for time-trends.

Equation (1) is estimated for the period from 1977 to 1991, which includes the seven years prior to and seven years subsequent to the passage of the law. 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.\textsuperscript{16} 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 and other robustness issues in Section 5.

## 5 Results and Robustness

In this section, we present our main results, followed by various robustness checks.

### 5.1 Parallel Trends

A critical assumption of the diff-in-diff framework is that the treatment and control groups exhibit parallel trends in terms of the outcome variables prior to the event in question. Figure 4 provides graphical evidence of this assumption for the years surrounding the passage of the Hatch-Waxman Act. 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

\textsuperscript{15}Control variables included in $X_{i,t}$ for the financial characteristic variables include: $\log (NA)$ (where $NA = TA - Cash$), $EBIT/TA$ (earnings as a fraction of total assets to control for profitability), $ME/BE$ (market value of equity to book value of equity), and $Div/TA$ (the amount of common/ordinary dividends paid). Since the dependent variables are also simultaneously determined, we also include the following lagged endogenous variables: $R&D/TA$, $PPE/TA$, $Cash/TA$, $Debt/TA$.

\textsuperscript{16}DiMasi & Grabowski (2007) document that the mean project length across the pharma and biotech sectors is approximately 8 years.
R&D-intensive firms. Vertical red lines are include in 1983, the final year of the pre-period, and thus all years to the right of the line are when the Hatch-Waxman Act is in effect. The right graphs depict the differences between the treatment and control groups for each of the variables.

[Figure 4 Here]

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

5.2 Regression Results

The estimation results for regression (1) are included in Table 2. Results both with and without control variables and fixed effects are included.

[Table 2 Here]

Overall, the results from the differences-in-differences analysis are consistent with the predictions in Section 2. The diff-in-diff 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 in the biopharma industry, firms in that
industry increased their R&D relative to the control group. 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 diff-in-diff 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. The diff-in-diff 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 6.7%). The diff-in-diff estimator for Debt is negative but insignificant in both columns (7) and (8)), providing mixed evidence that firms in the biopharma industry decreased their debt as a result of the increase in competition. This may be due to the noisy pre-trends shown earlier. 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 8.4%) as a result of increased competition in the biopharma industry.

5.3 Robustness: A 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, where we estimate regression (1) for the pre-Act sample period from 1969 to 1983, but falsely specify that the Act was implemented in 1976. As before, biopharma firms are our treatment group, and we choose propensity-score matched (based on observable characteristics in the period from 1969 to 1975) R&D-intensive firms as our control group.

The results of this falsification test are included in Table 3. When run over this time period, all of the variables are insignificant. Overall, this suggests that the results from the previous sections are not caused by any long-term trends between the treatment and control groups, as the same results are not replicated in sample period preceding the Act.

[Table 3 Here]
5.4 Robustness: Serial Correlation

A potential concern with our results is that they are biased due to serial correlation, driven by the relatively 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 accounting for serial correlation to address these concerns.

One direct way to correct for the potential influence of serial correlation is to perform an adjustment of the standard errors. We therefore re-estimate our results using Newey and West (1987) standard errors. The results are given in Table 4 below.

(Table 4 Here)

The results using Newey-West standard errors are very similar to the previous results. As before, in comparing biopharma to other R&D-intensive firms, 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. The results for generic compared to other pharma firms are also similar to the earlier results—R&D and cash are negative and significant, PPE and net debt are positive and significant, and debt is positive but insignificant. Thus, our results are robust to explicitly correcting for serial correlation.

A potentially improved way to account for autocorrelation is suggested by Bertrand, Duflo, and Mullainathan (2004), and involves collapsing the sample into two datapoints—one for the pre-period and one for the post-period—for each cross-sectional unit by taking means across time. We perform this analysis in Table 5.17

(Table 5 Here)

The results are similar to those in Table 2. The diff-in-diff estimator for PPE is negative and significant, the estimator for cash is again positive and significant, the estimator for R&D is again positive and significant, and the estimator for net debt is again negative and

17The regression specifications include year and treatment group fixed effects.
significant. The estimator for debt in this case is negative though insignificant, as in earlier results.

Put together, these results suggests that our main results are not driven by serial correlation induced by our longer estimation window.

5.5 Robustness: Incumbent Firms

Another concern is that our results could be driven by changes in the sample composition over time. In particular, if the characteristics of newly-listed biopharma firms entering our sample are systematically different from those of existing firms, this could drive some of our results. We note that our predictions are applicable for these new entrants as well, and not just for incumbent firms—for example, a private or venture capital-backed firm should still respond to a change in competition in the way predicted in Section 2, and then this would be (correctly) reflected in our sample when that firm goes public. Nevertheless, we examine whether our main results hold by restricting our sample to just incumbents that were operating before the law was enacted.

Figure 5 shows the parallel trends for this sample. Overall, the trends are very similar to those for the main results in Figure 4. While the pre-period trend line for R&D slopes downward, this is due to the drop in R&D for the treatment group in 1983; the treatment and control groups move closely together through 1982, indicating that the parallel trends assumption is still reasonable in this case. After this, the treatment group drops for a few years relative to the control group until subsequently increasing in line with the predictions. 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. As with our main results, cash and net debt exhibit strong parallel trends before the Hatch-Waxman Act was implemented, while the trends are slightly noisier for debt and assets-in-place. Together, these graphs indicate the appropriateness of the diff-in-diff framework for the restricted sample.
Table 6 estimates regression (1) for the restricted sample of incumbents. The results—in terms of significance, sign, and magnitude—are all very similar to those for the full sample presented in Table 2. Relative to the control group, incumbent biopharma firms increase their R&D and cash significantly in response to the Hatch-Waxman Act. The also decrease their net debt significantly, and decrease their assets-in-place and debt (albeit the effect is not significant). This provides evidence that our main results are not due to a sample composition effect.

6 An Additional Test Using Intra-industry Variation

A potential concern with the previous methodology is that, even after performing matching and controlling for fixed effects and other observables, the control group may be different in unobservable ways from the treatment group. A related concern is that any results may be due to contemporaneous structural changes occurring in the control group industries that are unrelated to the Hatch-Waxman Act. Therefore, in this section, we conduct an additional test by exploiting variation within the biopharma industry.

6.1 Empirical Methodology

We compare the reaction to the law by pharma firms that are focused on generic drug manufacturing to that of other pharma firms. The logic is that, since the Hatch-Waxman Act increased competition by facilitating the entry of generic drugs into the market place, the predictions in Section 2 should apply less to the firms that were already primarily generic manufacturers prior to the passage of the law. In other words, generic pharma firms should reduce their R&D and cash, and increase their debt, net debt, and assets-in-place relative to other pharma firms after the Act was passed.
To identify generic drug manufacturers, we use data from the FDA’s Approved Drug Products with Therapeutic Equivalence Evaluations (also known as the Orange Book), which contains historical information on every drug approved by the FDA and who the applicant is. Using this data, we identify all applications for the approval of generic drugs, and construct a measure for each firm of the proportion of total drug applications prior to 1984 that consists of generic drugs.\(^{18}\) We construct our treatment group in this setting as firms for which at least 15% of their (pre-Act) drug portfolios are comprised of generic drugs.\(^{19}\) One disadvantage of this approach is that there are relatively few generic drug manufacturers in our sample—21 firms operated in the treatment group prior to the enactment of the law. This has the potential to reduce the power of our analysis, but also makes it critical to select appropriate firms for the control group.\(^{20}\) We therefore construct our control group of pharma firms using propensity-score matching in the same way as described in Section 4.2.

Using these treatment and control groups, we estimate the same diff-in-diff specification as (1), replacing Biopharma with Generic as the indicator for our treatment group.

\[\text{6.2 Parallel Trends}\]

Figure 6 depicts the parallel trends for the treatment and control groups. For R&D and cash, the levels of the treatment and control groups are very similar prior to the enactment of the Hatch-Waxman Act, and exhibit parallel trends in the pre-period. Subsequently, the control group increases relative to the treatment group, consistent with the predictions. In contrast, debt and net debt appear to only move in parallel in the two or three years before to the passage of the law; prior to that, they appear to move in opposite directions. While the trends for net debt then diverge in ways consistent with the predictions, the trends for debt are noisy throughout. Thus, the parallel trends assumption for these variables is less likely to hold, and their results should be interpreted with caution. Finally, the trends assets-in-place

\(^{18}\)A generic drug application is classified as an Abbreviated New Drug Application (ANDA).

\(^{19}\)Among firms in the sample, this corresponds to the top quartile in terms of the proportion of drugs which are generics.

\(^{20}\)These reasons also make it infeasible to run our treatment as a continuous variable.
are also noisy, though to a lesser extent—the treatment and control group move roughly in parallel for the first four years of the sample, but then begin to diverge in the years prior to the law change. However, the divergence then widens in a manner consistent with the predictions.


6.3 Regression Results

The regression results are included in Table 7. These results are broadly consistent with the predictions from Section 2. The diff-in-diff estimator for R&D is negative and significant without control variables and fixed effects (columns (1)), but is marginally insignificant (p-value of 0.16) when controls and fixed effects are included. This indicates that, as the Hatch-Waxman Act increased competition for the industry, generic manufacturers did not increase their R&D by as much as other pharma firms. The diff-in-diff estimator for PPE is positive and significant in column (3), which is consistent with the prediction of the model—this shows that generic firms increased their assets-in-place relative to other pharma firms in response to the Hatch-Waxman Act. The diff-in-diff estimator for Cash is negative and significant in both columns (5) and (6), indicating that generic pharma firms decreased their cash holdings relative to the control group as a result of the Hatch-Waxman Act. The diff-in-diff estimator for Debt is positive but insignificant in both columns (7) and (8)), and Net Debt is positive in columns (9) and (10), but is significant only without controls and fixed effects. This provides some evidence that generic firms increased their (net) debt as a result of the increase in competition, but should be interpreted with caution due to the noisy pre-trends and potentially low power owing to the small sample size.


Overall, these results, in combination with the previous inter-industry results, provide strong evidence for the hypotheses laid out in Section 2.
Conclusion

In this paper, we explore the interaction between competition, R&D investments, and financing choices. We motivate our empirical hypotheses with the insights of existing theories which, viewed collectively, 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. We provide time-series evidence on firms in the biopharma industry that are consistent with these predictions. To overcome endogeneity concerns, we use the Hatch-Waxman Act of 1984 as a source of exogenous variation that increased competition in the biopharma industry, and conduct a differences-in-differences test. We find strong supporting evidence for our predictions, which survive various robustness tests as well as an additional test which exploits within-industry variation. 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 facilitated 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, 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 may also increase the reliance of these firms on funding through equity markets. This, in turn, could slow innovation down during “cold” markets, or alter the types of investments these firms make due to adverse selection in the capital markets.

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), Fagnan, Fernandez, Lo, and Stein (2013), and Hull, Lo, and Stein (2017). Such financial innovations may change
the effects of competition on innovation in important ways.
References


Figure 1: Competition in the Biopharma Industry
This figure presents the number of competitors in the biopharma industry over time.
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.
Figure 3: 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.
Figure 4: Main Results: Trends for Treatment and Control Groups

Inter-industry trends 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. A vertical red line is included, representing the year that the Hatch-Waxman Act was implemented. The graphs on the right depict the differences between the treatment and control groups (treatment minus control), with pre- and post-period trend lines added.
Figure 4 (continued): Main Results: Trends for Treatment and Control Groups

- **Net Debt/TA**
  - Biopharma and other R&D-intensive firms show trends over the years 1977 to 1991.

- **Differences: Net Debt**
  - Differences between treatment and control groups are depicted over the same years.

- **Assets-in-Place**
  - Similar trends for Biopharma and other R&D-intensive firms are observed over the same period.

- **Differences: Assets-in-Place**
  - Differences in assets-in-place for the treatment and control groups are illustrated over the years.
Figure 5: Incumbent Firms: Trends for Treatment and Control Groups
This table shows inter-industry trends for incumbent firms 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. A vertical red line is included, representing the year that the Hatch-Waxman Act was implemented. The graphs on the right depict the differences between the treatment and control groups (treatment minus control), with pre- and post-period trend lines added.
Figure 5 (continued): Incumbent Firms: Trends for Treatment and Control Groups
Figure 6: Generic and Other Pharma Firms: Trends for Treatment and Control Groups

Intra-industry 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 treatment group of generic-focused pharma firms, while the red dashed lines give averages for the control group of other matched pharma firms. A vertical red line is included, representing the year that the Hatch-Waxman Act was implemented. The graphs on the right depict the differences between the treatment and control groups (treatment minus control), with pre- and post-period trend lines added.
Figure 6 (continued): Generic and Other Pharma Firms: Trends for Treatment and Control Groups
**Table 1: Summary Statistics**

This table provides summary statistics for biopharma firms from 1950 to 2016. $R\&D/TA$ is R&D expenditures scaled by total assets. $PPE/TA$ is property, plant, and equipment scaled by total assets. $Cash/TA$ is cash and short-term investments scaled by total assets. $Debt/TA$ is debt, which is the sum of total long-term debt and short-term debt (debt in current liabilities), scaled by total assets. $Net\ Debt/TA$ is net debt scaled by total assets, where $Net\ Debt = Debt - Cash$. All variables run from 1950 to 2012. All variables are at the firm-year level, and are winsorized at the 1% level.

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### Table 2: The Effect of the Hatch-Waxman Act on Biopharma and R&D-Intensive Firms

This table estimates the differences-in-differences regression (1) for financial characteristics. The sample consists of biopharma firms and a control group consisting of propensity-score matched R&D-intensive firms. The sample period spans from 1977 to 1991. 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 if it is in the control group. Control variables include $\log(NA)$, $EBIT/TA$, $M/B$, $Div/TA$, and lagged values of $PPE/TA$, $Cash/TA$, $Debt/TA$, and $R&D/TA$. 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.

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</table>
Table 3: Falsification Test

This table estimates the differences-in-differences regression (1), but over the sample period from 1969 to 1983. 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 1976 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 if it is in the propensity-score matched control group of other R&D-intensive firms. Control variables include $\log (NA)$, $EBIT/TA$, $M/B$, $Div/TA$, and lagged values of $PPE/TA$, $Cash/TA$, $Debt/TA$, and $R&D/TA$. Year and firm fixed effects are included, as 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.

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Act_t \times Biopharma_i$</td>
<td>0.002</td>
<td>0.014</td>
<td>$-0.010$</td>
<td>0.009</td>
<td>0.019</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Firm Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>852</td>
<td>858</td>
<td>858</td>
<td>857</td>
<td>857</td>
</tr>
<tr>
<td>Number of Firms</td>
<td>114</td>
<td>114</td>
<td>114</td>
<td>114</td>
<td>114</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.924</td>
<td>0.879</td>
<td>0.846</td>
<td>0.855</td>
<td>0.876</td>
</tr>
</tbody>
</table>
Table 4: Differences-in-Differences Regressions, Newey-West Standard Errors

This table estimates the differences-in-differences regression (1) for financial characteristics, correcting for autocorrelation using Newey-West standard errors. The dependent variables consist of $R&D$, $PPE$, $Cash$, $Debt$, and $NetDebt$, each scaled by total assets. $Act_i$ 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 if it is in the propensity-score matched control group of other R&D-intensive firms. Control variables include log $(NA)$, $EBIT/TA$, $M/B$, $Div/TA$, and lagged values of $PPE/TA$, $Cash/TA$, $Debt/TA$, and $R&D/TA$. Year and firm fixed effects are included. Newey-West standard errors are given in parentheses, with 10 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(1) $R&amp;D$</th>
<th>(2) $PPE$</th>
<th>(3) $Cash$</th>
<th>(4) $Debt$</th>
<th>(5) $NetDebt$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Act_i \times Biopharma_i$</td>
<td>0.022**</td>
<td>−0.005</td>
<td>0.067***</td>
<td>−0.019</td>
<td>−0.084**</td>
</tr>
<tr>
<td>(0.011)</td>
<td>(0.010)</td>
<td>(0.018)</td>
<td>(0.024)</td>
<td>(0.034)</td>
<td></td>
</tr>
</tbody>
</table>

| | Controls | Firm Fixed Effects | Year Fixed Effects | Observations |
| | Yes | Yes | Yes | 2,063 |
| | Yes | Yes | Yes | 2,080 |
| | Yes | Yes | Yes | 2,080 |
| | Yes | Yes | Yes | 2,078 |
| | Yes | Yes | Yes | 2,078 |
Table 5: Differences-in-Differences Regressions, Collapsed Sample

This table estimates the differences-in-differences regression (1) for financial characteristics, collapsing the samples into pre- and post-periods following the procedure of Bertrand, Duflo, and Mullainathan (2004). 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 if it is in the propensity-score matched control group of R&D-intensive firms. Year and treatment group fixed effects are included. Robust standard errors are given in parentheses, and are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(1) (R&amp;D)</th>
<th>(2) (PPE)</th>
<th>(3) (Cash)</th>
<th>(4) (Debt)</th>
<th>(5) (Net Debt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Act_t \times Biopharma_i)</td>
<td>0.169***</td>
<td>-0.044**</td>
<td>0.212***</td>
<td>0.012</td>
<td>-0.195***</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.017)</td>
<td>(0.034)</td>
<td>(0.048)</td>
<td>(0.070)</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>551</td>
<td>589</td>
<td>589</td>
<td>589</td>
<td>589</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.101</td>
<td>0.023</td>
<td>0.095</td>
<td>0.007</td>
<td>0.017</td>
</tr>
</tbody>
</table>
Table 6: Differences-in-Differences Regressions, Restricted Incumbent Sample

This table estimates the differences-in-differences regression (1) for financial characteristics using the restricted sample of incumbent firms. The sample consists of biopharma firms and a control group consisting of propensity-score matched R&D-intensive firms. The sample period spans from 1977 to 1991. 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 if it is in the control group. Control variables include log ($NA$), $EBIT/TA$, $M/B$, $Div/TA$, and lagged values of $PPE/TA$, $Cash/TA$, $Debt/TA$, and $R&D/TA$. 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.

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Act_t \times Biopharma_i$</td>
<td>0.021*</td>
<td>−0.004</td>
<td>0.058***</td>
<td>−0.013</td>
<td>−0.070**</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.011)</td>
<td>(0.019)</td>
<td>(0.025)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Firm Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>1,568</td>
<td>1,581</td>
<td>1,581</td>
<td>1,579</td>
<td>1,579</td>
</tr>
<tr>
<td>Number of Firms</td>
<td>177</td>
<td>178</td>
<td>178</td>
<td>179</td>
<td>178</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.854</td>
<td>0.824</td>
<td>0.793</td>
<td>0.677</td>
<td>0.778</td>
</tr>
</tbody>
</table>
Table 7: The Effect of the Hatch-Waxman Act on Generic and Other Pharma Firms

This table estimates the differences-in-differences regression (1) for financial characteristics. The sample consists of generic-focused pharma firms and a control group consisting of propensity-score matched pharma firms. The sample period spans from 1977 to 1991. 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. Generic\(_i\) is a dummy variable which takes a value of 1 if firm \(i\) is focused on generic drugs, and a value of 0 if it is in the control group. Control variables include log (NA), EBIT/TA, M/B, Div/TA, and lagged values of PPE/TA, Cash/TA, Debt/TA, and R&D/TA. 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.

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HW(_t) × Generic(_i)</td>
<td>-0.035***</td>
<td>-0.008</td>
<td>0.024</td>
<td>0.018*</td>
<td>-0.124**</td>
<td>-0.057**</td>
<td>0.066</td>
<td>0.008</td>
<td>0.187**</td>
<td>0.064</td>
</tr>
<tr>
<td>(0.012)</td>
<td>(0.006)</td>
<td>(0.033)</td>
<td>(0.011)</td>
<td>(0.054)</td>
<td>(0.027)</td>
<td>(0.048)</td>
<td>(0.030)</td>
<td>(0.082)</td>
<td>(0.044)</td>
<td></td>
</tr>
<tr>
<td>Generic(_i)</td>
<td>0.004</td>
<td>0.007</td>
<td>0.001</td>
<td>-0.048</td>
<td>-0.046</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.010)</td>
<td>(0.036)</td>
<td>(0.047)</td>
<td>(0.042)</td>
<td>(0.078)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HW(_t)</td>
<td>0.045***</td>
<td>-0.027</td>
<td>0.128**</td>
<td>-0.044</td>
<td>-0.171**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.010)</td>
<td>(0.028)</td>
<td>(0.050)</td>
<td>(0.040)</td>
<td>(0.072)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 | 487 | 417 | 494 | 419 | 494 | 419 | 487 | 418 | 487 | 418 |
Number of Firms | 42 | 41 | 42 | 41 | 42 | 41 | 42 | 41 | 42 | 41 |
\(R^2\) | 0.119 | 0.823 | 0.012 | 0.879 | 0.079 | 0.733 | 0.013 | 0.733 | 0.044 | 0.796 |