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The Growth Opportunity Channel of Debt Structure*

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Abstract

This paper studies the importance of growth opportunities for debt structure decisions. High growth firms use more unsecured debt to preserve financial flexibility (in the form of untapped secured debt capacity) in connection with future growth opportunities: the growth opportunity channel of debt structure. Our base regression results establish a strong positive relation between growth opportunities and unsecured debt. To better identify this relation, we examine the effects of the Biologics Price Competition and Innovation Act (BPCIA) of 2010 on the debt structure of the pharmaceutical industry. We show that pharmaceutical firms responded to the positive BPCIA-induced growth shock by shifting their debt structures towards more unsecured debt. Our large sample tests indicate that although unsecured debt has a direct negative effect on leverage, that effect is strongly mitigated for high growth firms. High growth firms may attract more unsecured funds because their greater growth opportunities are more likely to generate cash flows in excess of secured debt repayments. Our posited growth opportunity channel of debt structure is complementary to, but conceptually distinct from, more classic explanations of debt structure based on collateral and adverse selection.

Key words: Growth opportunities, unsecured debt, debt structure, financial flexibility.
JEL classification: G31, G32.

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Introduction

Lemmon, Roberts, and Zender (2008) show that established drivers of capital structure variation explain a smaller portion of that variation than initially thought. In response, studies by Colla, Ippolito, and Li, (2012) and Choi, Hackbarth, and Zechner (2012) or earlier studies by Johnson (2003) and Billet, King, Mauer (2007) find that much can be learned from other aspects of the financing process, such as debt-specialization, debt-maturity, or covenant structure. We contribute to this growing literature by studying what drives high growth firms to use relatively more unsecured debt: *the growth opportunity channel of debt structure*. Unsecured debt preserves financial flexibility in the form of untapped secured debt capacity that can be used to fund future investment prospects. This flexibility is especially valuable to high growth firms, who recognize that some of their growth opportunities will need to be funded under tightened credit conditions.

How does the growth opportunity channel of debt structure affect firms' financing? A high growth firm could maintain flexibility by funding assets with equity, but at the cost of forgone tax or monitoring benefits of debt. Unsecured debt provides some of the flexibility of equity but at a premium rate compared to secured debt. That premium covers lenders' costs to determine the likelihood that the firm will exercise its option to issue secured debt during the term of the loan, plus the expected loss of collateral backing the unsecured debt if secured debt is issued. Unsecured lenders could be willing to lend more at smaller premiums to relatively high growth firms, because those firms may be more likely to delay exercising their options to maintain flexibility as they grow, or because the firms' many growth opportunities will provide more than enough cash to cover possible secured debt payments (Stulz and Johnson, 1985; Tirole, 2006; Hackbarth and Mauer, 2012).[1]

The headline result of our paper is that we find a strong positive relation between firm growth opportunities and unsecured debt. We establish this relation using a large sample of non-financial firms from COMPUSTAT (1981-2010). A complement to that result is that we find that leverage is higher for high-growth high-unsecured debt firms. Therefore, we show that the growth opportunity channel drives unsecured-secured debt structure, which in turn feeds into leverage.

Our large sample regression tests use Tobin's Q as a proxy for growth opportunities. To show that the positive growth-unsecured debt relation does not rely on the validity of that

[1] The rationale for the growth opportunity channel of debt structure is discussed in more detail in section 1.

proxy, we study an exogenous regulatory shock to the growth opportunities of pharmaceutical firms. The Biologics Price Competition and Innovation Act (BPCIA) of 2010 established the regulatory pathway for U.S. generic biological drugs, a large new market in which pharmaceutical firms planned to compete. Consistent with our growth opportunity channel argument, we find that pharmaceutical firms adjusted their debt structures towards more unsecured debt following the BPCIA passage. Importantly, this adjustment to debt structure is not likely to be related to any concomitant changes in pharmaceutical firms' cash flows or the value of collateral.

The first step in our empirical analysis is to provide basic evidence on the composition of debt structure for a large sample of non-financial firms from COMPUSTAT covering the period from 1981 through 2010. We find that unsecured debt (as proportion of total debt) for the average (median) firm is 63% (75%). This finding is surprising because unsecured debt is generally thought to be more expensive than secured debt, hence, firms could be expected to use less unsecured debt. But the average firm in our sample also has a Tobin's Q of 1.939, suggesting that it has significant growth opportunities. We propose that growth helps explain firms' reliance on unsecured debt. We further establish that there is significant variation in firms' unsecured-secured debt structures to warrant more in-depth analysis.

We perform a series of formal tests to identify the effect of growth opportunities on unsecured debt. In the first set of tests, we regress unsecured debt on Q and standard control variables. This analysis shows that Q has a positive, significant, and economically sizable effect on unsecured debt. These regression results could be biased because of possible endogeniety or problems related to the use of Q as a proxy for growth opportunities (Erickson and Whited, 2000). To mitigate these concerns, we supplement these regression-based tests with evidence from a quasi-natural experiment: Passage of the Biologics Price Competition and Innovation Act (BPCIA) of 2010 [Public Law 111-148].

The BPCIA authorized the Food and Drug Administration (FDA) to approve generic biologic drugs (also called biosimilars), much like the Hatch-Waxman Act did for generic pharmaceutical drugs in 1984. Pharmaceutical firms, like Merck and Pfizer, view biosimilars as a substantial growth opportunity. Indeed, the Federal Trade Commission estimates that the biosimilar market will be worth $100 billion by the end of 2015. Our analysis of the stock price reaction for pharmaceutical firms around the BPCIA passage shows that pharmaceutical firms experienced positive Cumulative Average Abnormal Returns (CAARs) of 7.83% in the 20 days surrounding the passage of the BPCIA.

Next, we study whether pharmaceutical firms adjusted their debt structures towards more unsecured debt (and related financial flexibility) following the positive BPCIA-induced growth shock, as predicted by the growth opportunity channel. To test this prediction, rather than simply comparing unsecured debt for pharmaceutical firms in the pre- and post-Act period, we use a difference-in-differences estimation approach that is designed to measure the change in unsecured debt for pharmaceutical firms relative to control firms from the same one digit SIC ("control group") while controlling for industry-wide effects and firm heterogeneity. Results show that pharmaceutical firms increased unsecured debt (by 10.4% or 11.3% depending on the model specification). Importantly, this adjustment to debt structure is not likely to be related to any concomitant changes in cash flows or the value of collateral. These difference-in-differences estimation results are new to the literature and are consistent with the logic of a growth opportunity channel of debt structure.

To assess the robustness of our base difference-in-differences estimation results, we consider a number of alternative specifications to our base approach and perform a series of falsification tests. We start by assessing the robustness of our findings to a possible violation of the "parallel-trend" assumption. In our setting, this is a requirement that unsecured debt for "treated" and "control" firms were moving in parallel prior to the passage of the BPCIA. This is important to assure that our difference-in-differences estimate is measuring a pharmaceutical-only jump caused by the Act rather than a trend effect in the data. We find that our difference-in-differences estimate remains positive and sizable after we control for a possible violation of the "parallel trend" assumption. Next, we re-estimate our difference-in-differences model *as if* the treated units were firms in industry segments in the same one digit SIC as pharmaceutical firms but not directly affected by the passage of the BPCIA ("placebo treated"). We find that our difference-in-differences estimates are never positive and significant in these placebo tests, supporting the validity of our identification strategy.

We also analyze the covenant structure of unsecured debt to assess its implications for financial flexibility. Evidence based on data from the Mergent-FISD and the DealScan databases shows only limited use of restrictive covenants on secured debt or total leverage in the pharmaceutical industry in the post-BPCIA period. Hence, most new unsecured debt did not contain covenants that would limit financial flexibility. Additional robustness tests consistently support the robustness of our primary estimation results and the validity of our identification strategy.

Our paper adds to the current debate on what explains capital structure variation. Lem-

mon, Roberts, and Zender (2008) find that traditional determinants of capital structure lose about 60% of their explanatory power when firm-fixed effects are accounted for. Choi, Hackbarth, Zechner (2012), Colla, Ippolito, and Li (2012), and Giambona, Mello, and Riddiough (2012) show that features of debt structure like granularity of debt maturity, debt specialization, and collateral quality, can help explain corporate financing.[2] Consistent with our debt structure results, Erel et al. (2012) show that firms rely more on secured debt during recessions, when credit quality becomes more important to lenders. This fits our claim that firms use unsecured debt because it preserves flexibility to issue secured debt when credit is tight. We go further to show that this is particularly true for growth firms who likely suffer most from foregone or delayed growth opportunities.

Our paper also contributes to research on the role of financial flexibility. Graham and Harvey (2001) use survey data to show that about 60% of CFOs in the U.S. identify financial flexibility as the primary determinant of their debt policy. In a multi-period setting, Acharya, Almeida, and Campello (2007) show that spare debt capacity plays an important role in firms' anticipation of future investments. Gamba and Triantis (2008) show that firms use cash holdings to boost financial flexibility in the presence of financing frictions. Denis and McKeon (2012) find that firms have long-run conservative target leverage ratios to preserve financial flexibility. Nash, Netter, and Poulsen (2003) focus on covenants and find that firms that expect to make large investments include fewer dividend and debt issuance covenant restrictions in their bond contracts. Murfin (2012) shows, however, that only borrowers that have access to multiple lenders have the ability to limit the use of strict covenants. Our paper adds to these studies by characterizing how debt – if structured as unsecured debt – can preserve the financial flexibility that firms need in connection with growth opportunities.

The rest of the paper proceeds as follows. The next section develops the conceptual framework for the growth opportunity channel of debt structure and explains our main predictions. Section 2 describes the base sample and provides preliminary evidence on debt structure variation. Section 3 presents base regression results on the effects of growth opportunities on unsecured debt. Section 4 develops our BPCIA-based identification strategy and presents related evidence. Section 5 shows how the growth opportunity channel of debt structure affects leverage. Section 6 is a conclusion.

[2]Rauh and Sufi (2010) focus on a random sample of rated firms and show that they use more than two different types of debt instruments.

1 The Growth Opportunity Channel of Debt Structure: Conceptual Framework and Empirical Predictions

This section presents a rationale for the growth opportunity channel of debt structure. The firm's market value is the sum of the value of its assets in place plus the value of its growth opportunities. We propose that, all else equal, high growth firms prefer a debt structure characterized by proportionally more unsecured debt. Hereafter, when we refer to unsecured debt we mean the ratio of unsecured debt to total debt. We assume that the firm prefers a capital structure with some debt because of the tax shields or monitoring benefits of debt financing. This preference is an expedient used to shift the focus from capital structure (the combination of debt and equity) to debt structure (the combination of secured and unsecured debt). We also assume no debt covenants.[3]

In this setting, high growth firms prefer unsecured debt because (relative to secured debt) it offers greater financial flexibility. Unsecured debt preserves the firm's option to subsequently issue secured debt on unencumbered assets (Stulz and Johnson, 1985; Tirole, 2006; and more recently, Hackbarth and Mauer, 2012). This flexibility is especially valuable to high growth firms, who recognize that some of their growth opportunities will need to be funded in periods when access to the unsecured debt market could be rationed (e.g., a period of credit tightening).[4] In these periods, they will be able to tap the safer-secured debt market by pledging unencumbered assets and finance their investment activities.[5]

An intuitive prediction follows from this discussion: high growth firms use more unsecured debt to preserve financing flexibility (in the form of untapped secured debt capacity) in connection with future growth prospects, all else equal. We characterize this relation as *the growth opportunity channel of debt structure*.[6]

[3]It is important that unsecured debt is not issued with covenants that limit the firm's ability to issue secured debt on unencumbered assets going forward. We analyze the covenant structure of unsecured debt issuances in the empirical section of the paper.

[4]This explanation of debt structure is consistent with Myers' (1977) classic explanation that firms with more growth prospects use more equity financing. We extend this framework to debt structure by arguing that conditional on issuing debt, high growth firms prefer unsecured debt (over secured debt) because of its "equity-like" form.

[5]We assume that all firms can be rationed ex post in the unsecured debt market depending on the severity of the credit squeeze in the macro economy. As a result, firms value the financial flexibility of unsecured debt in connection with growth opportunities independently from whether they are ex ante financially constrained. In this sense, our approach is different from the approach in Hackbarth and Mauer (2012) who focus on the financial flexibility of debt priority based on whether firms are ex ante financially constrained.

[6]We note that our growth opportunity channel of debt structure does not conflict with more standard explanations of debt type selection like the pecking order theory. In the pecking order framework, financing is a one shot game and firms prefer secured debt over unsecured debt because secured debt is less information

By comparison, firms with limited growth prospects rely more on (cheaper) secured debt financing. This occurs because future investment prospects are limited for low growth firms, and as a result, there is limited value in the financial flexibility option embedded in unsecured debt. Furthermore, the limited benefits are less likely to cover the premium cost of unsecured debt. That premium covers the lender's costs to verify a borrower's growth prospects, and the lender's expected loss in loan value due to subsequent secured debt issuance. An unsecured lender must determine the value of all unencumbered collateral plus the likelihood that those assets could become encumbered, whereas a secured lender only needs to determine the value of the loan collateral.

Although we focus on the unsecured-secured debt decision, the growth channel of debt structure has implications for leverage. Firms prefer the financial flexibility of unsecured debt, but it costs them more than secured debt, hence, all else equal, firms using proportionately more unsecured debt financing will have less leverage.

But for high growth firms, it is more likely that at least some of their many growth opportunities will generate cash flows that exceed associated secured debt payments, reducing the expected loss to unsecured lenders. High growth firms may also be less likely to exercise their option to issue secured debt in order to maintain their financial flexibility as they grow. As a result, lenders could provide more unsecured lending to high growth firms (relative to low growth firms), all else equal. Hence, we predict that high-growth high-unsecured debt firms will also have higher leverage.[7]

2 Base Analysis

2.1 Sample Selection and Variables Construction

Our base sample includes all non-financial firms from COMPUSTAT covering the period from 1981 through 2010. We start the sample in 1981 because our focus is on how variation in debt structure relates to growth opportunities and COMPUSTAT does not report information on secured debt prior to 1981.[8] The raw sample includes all firms with non-missing information

sensitive. In our framework, the firm's preference for unsecured debt arises intertemporally in connection with growth opportunities. With limited growth opportunities, firms prefer cheaper secured debt.

[7] We assume that firms' relatively fixed production technologies and reputation effects on future borrowing limit their incentives to over-issue cheaper secured debt and shift risk to unsecured debt holders.

[8] Using COMPUSTAT allows us to use a large sample to study unsecured-secured debt structure, but does not allow us to extend our results to other related forms of debt heterogeneity. For example, debt priority could also be used to further differentiate between debt, and different levels of priority could offer different levels of financial flexibility. Unfortunately, COMPUSTAT does not report detailed data on debt priority.

on item *"dm:" debt mortgages & other secured* in COMPUSTAT.[9] We exclude firm-year observations for which the value of total assets is less than $1 million. To avoid undue influence of outliers, we winsorize all variables at the 5^{th} and 95^{th} percentiles of their distributions.

We combine the COMPUSTAT sample with information obtained from several other data sources, including return data from the Center for Research in Security Prices (CRSP), M&A information from Thomson One, capital structure data from Capital IQ, and covenant data from the Mergent – Fixed Income Securities Database (FISD) and the Thomson-Reuters LPC DealScan database. We use this additional information to design a quasi-natural experiment that contributes to the identification of our growth opportunity channel of debt structure. For brevity, we devote the remaining part of this section to describing variable constructions, sample statistics, and simple correlations. We discuss our base regression results and identification strategy in sections 3 and 4, respectively.

We define our focus variable, *UnsecuredDebt*, as the ratio of unsecured debt (COMPUSTAT items $dlc + dltt - dm$) to total debt ($dlc + dltt$). There are 16,534 firms for which COMPUSTAT reports information on item *dm* during our sample period and up to 152,926 firm-year observations.[10] However, our final sample includes 15,937 firms (or 130,921 firm-year observations) because *UnsecuredDebt* is undefined for zero-debt firms (i.e., firms for which $dlc + dltt$ is equal to zero).[11] The other variables are defined following standard practice in corporate finance established in capital structure studies published over the last two decades.[12] Q is defined as the ratio of the market value of total assets ($at - ceq + prcc\_c \times csho$) to the book value of total assets (at). *MarketLeverage* is the ratio of total debt to the market value of total assets. *BookLeverage* is the ratio of total debt to the book value of total assets. *Size* is total sales (*sale* – measured in millions of 2010 dollars using the Producer Price Index

[9] Barclay and Smith (1995) and Rajan and Winton (1995) are among the first to our knowledge to use item *dm* (formerly item #241) from COMPUSTAT. More recent studies include Carpenter and Petersen (2002), Bryan, Tyras, and Wheatley (2002), and Aivazian and Zhou (2012).

[10] The coverage of item *dm* in COMPUSTAT is comparable to the coverage of other items in the database. For instance, information on item *at* – arguably one of the items with the highest coverage in the database – is available for 17,775 firms over our sample period (or 177,619 firm-year observations). Over the same sample period information on item *dm* is available for 16,534 firms (or 93% of the firms for which item *at* is available in COMPUSTAT). The coverage is 86% if one considers the number of firm-year observations. Item *dm* is available for 152,926 firm-year observations relative to 177,610 firm-year observations for item *at*.

[11] This definition of *UnsecuredDebt* is consistent with the logic of our theoretical argument, where we focus on how firms choose the combination of secured and unsecured debt conditional on them having access to debt financing.

[12] These studies include Barclay and Smith (1995), Rajan and Zingales (1995), Graham (2000), Baker and Wurgler (2002), Frank and Goyal (2003), Johnson (2003), Faulkender and Petersen (2006), Flannery and Rangan (2006), Billett, King, and Mauer (2007), Lemmon, Roberts, and Zender (2008), Byoun (2008), and Sibilkov (2009).

(PPI) published by the U.S. Department of Labor as the deflator). *Tangibility* is defined as the ratio of tangible assets (*ppent*) to the book value of total assets. *DebtRating* is a dummy variable that equals 1 if the firm has either a bond rating (*splticrm*) or a commercial paper rating (*spsticrm*), and 0 otherwise. *Profitability* is the ratio of earnings before interest, taxes, depreciation and amortization (*oibdp*) to book value of total assets. *EarningsVolatility* is the ratio of the standard deviation of earnings before interest, taxes, depreciation and amortization using 4 years of consecutive observations to the average book value of total assets estimated over the same time horizon.

2.2 Descriptive Statistics and Correlations

Table 1 lists the descriptive statistics for the variables used in our main empirical models. A new trait of our study is the focus on debt structure. Table 1 shows that unsecured debt is a key component of total debt. The mean and median *UnsecuredDebt* are 63.0% and 75.2%, respectively. Notably, the median value implies that half of all public firms in the U.S. use mostly unsecured debt. Furthermore, the 75^{th} percentile of the distribution for *UnsecuredDebt* is equal to 100%, which suggests that 25% of the firm-year observations in the sample use exclusively unsecured debt.

To our knowledge, ours is the first study to identify and highlight this salient feature of debt structure for a large sample of publicly listed firms in the U.S. The *UnsecuredDebt* distribution is noteworthy especially in combination with the observation that average Q equals 1.939, and that *UnsecuredDebt* and Q are positively correlated (see Table 2). Hence, the univariate evidence is in line with the growth opportunity channel of debt structure.

TABLE 1 ABOUT HERE

We briefly describe the other variables used as controls. The statistics for these variables resemble those of earlier studies. For example, the average market leverage of 21% for our sample matches Johnson's (2003) and is very similar to the 19.9% reported by Faulkender and Petersen (2006). Similarly, the average *Tangibility* of 0.306 for our sample is comparable to the 0.322 reported in Flannery and Rangan (2006) or the 0.327 in Sibilkov (2009). The average *EarningsVolatility* of 0.100 for our sample coincides with the corresponding figure in Lemmon, Roberts, and Zender (2008). All the other variables' statistics reported in Table 1 are close to what earlier studies find.

Table 2 reports simple correlation coefficients between some of our focus variables. All

correlation coefficients are statistically significant at the 1% level or higher. We start by noting that *UnsecuredDebt* is negatively correlated with both *MarketLeverage* and *BookLeverage*. This suggests that debt capacity of unsecured debt is lower compared to raising debt financing by issuing secured debt on assets in place. Relatedly, this evidence also suggests that with unsecured debt, firms may preserve their flexibility to expand leverage by issuing secured debt in the future on untapped collateral. Arguably, the flexibility embedded in unsecured debt is particularly valuable to high growth firms (growth opportunity channel of debt structure). In line with this expectation, *UnsecuredDebt* and Q are positively correlated. Similarly, growth firms can preserve future debt capacity by issuing more equity, which could help explain the negative correlation between *MarketLeverage* (*BookLeverage*) and Q.

TABLE 2 ABOUT HERE

The correlation between *UnsecuredDebt* and *Tangibility* equals -0.167, and by definition, the correlation between secured debt and *Tangibility* is +0.167. This positive correlation is no surprise, but its magnitude is. If firms fully exploited their tangible assets to issue cheaper secured debt, one would expect a correlation closer to +1. Even if some tangible assets offer less than dollar for dollar collateral capacity,[13] this relatively low correlation is consistent with the notion that firms preserve secured debt capacity by keeping some of their collateral untapped. Similarly, the correlations of *MarketLeverage* and *BookLeverage* with *Tangibility* are positive, but relatively small.

2.3 Dynamics and Composition of Unsecured Debt Variation

Over time, our growth opportunity channel of debt structure implies that firms adjust their debt structure towards more unsecured debt in response to positive growth shocks. Hence, we expect to observe substantial variation in firms' unsecured debt over our sample period.

Table 3 reports the number of transitions of individual firms across the quartiles of *UnsecuredDebt*. The first step in the analysis is to assign firms to four different quartiles based on the 25^{th}, 50^{th}, and 75^{th} percentiles of the distribution for *UnsecuredDebt* (which are respectively equal to 28%, 75%, and 100%). Firm-year observations with *UnsecuredDebt* less than 28% are assigned to the first quartile of the *UnsecuredDebt* distribution. Firms with *UnsecuredDebt*

[13] For instance, Campello and Giambona (2012) find that land and buildings, which arguably are more easily redeployable, sustain a higher debt capacity than tangible assets that are more firm specific, such as machines or equipment.

larger than or equal to 28% but less than 75% are assigned to the second quartile. Firms with *UnsecuredDebt* larger than or equal to 75% but less than 100% are allocated to the third quartile. Finally, firms with *UnsecuredDebt* equal to 100% are assigned to the fourth quartile of the *UnsecuredDebt* distribution. We explore the frequency with which firms move among the quartiles of the *UnsecuredDebt* distribution during the sample period.

Column 1 reports the number of firm-year observations by *UnsecuredDebt* quartile. For our purposes, the most important findings are reported in columns 2-5, which show the number of firm-year observations within each *UnsecuredDebt* quartile that move across the other quartiles of the distribution during the sample period. Consider the partition of firms in quartile 1. The figure in the first row of column 3 indicates that 24,726 firm-year observations out of 32,731 [or 76%] in quartile 1 moved to the adjacent quartile 2 during the sample period. Similarly, the evidence in columns 4 and 5 shows that 17,831 [or 55%] and 14,990 [or 46%] of firm-year observations moved from quartile 1 to quartiles 3 and 4, respectively, during the sample period. Only 3,828 [or 12%] firm-year observations were intransient and remained in the first quartile during the entire sample period (column 6). Table 3 also documents substantial movement between the other quartiles of the *UnsecuredDebt* distribution.

TABLE 3 ABOUT HERE

To recap, the evidence in Table 3 points to significant variation in *UnsecuredDebt*. This evidence is consistent with findings in Rauh and Sufi (2010) who identify significant heterogeneity in corporate debt and highlight how this heterogeneity relates to firm incentives.

Next, we decompose debt structure variation into industry-related and firm-specific components. We regress *UnsecuredDebt* on lagged *IndustryUnsecuredDebt*,[14] measured as the firm's 4-digit SIC industry-year average *UnsecuredDebt* (own-firm excluded). Regression results are reported in Table 4. The model is estimated through OLS and includes year-fixed effects. In all our estimations, standard errors reported in parentheses are based on heteroskedastic consistent errors adjusted for clustering across observations of a given firm (Petersen, 2009).

In column 1, the coefficient estimate on *IndustryUnsecuredDebt* suggests that firms increase *UnsecuredDebt* by about 23 basis points in response to a 1 percent increase in unsecured debt from their industry peers. However, the *Adj.-*R^2 reported at the bottom on Table 4 is only 1.1%.[15] In column 2, we rerun the regression but add firm dummies to it (estimates not

[14] The use of lags and the way we define *IndustryUnsecuredDebt* are responsible for the decrease in the number of observations from 130,921 in Table 3 to 109,397 in Table 4.

[15] Including a trend variable in the regression specification increases the *Adj.-*R^2 only modestly to 1.8%.

reported). Note that the estimate on *IndustryUnsecuredDebt* drops significantly (from 0.232 in column 1 to 0.038 in column 2) suggesting that there is minimal industry-related variation in *UnsecuredDebt*. However, the *Adj.*-R^2 increases sharply to 45.9%, implying that 44.8% (=45.9% – 1.1%) of the variation in *UnsecuredDebt* is related to variation across firms within industry. Importantly, the remaining 54.1% (=100% – 45.9%) of the variation in *UnsecuredDebt* is accounted for by within-firm variation over time.[16]

TABLE 4 ABOUT HERE

3 The Relation Between Unsecured Debt and Growth Opportunities: Base Regression Analysis

In this section we examine how debt structure relates to growth opportunities with a base regression of *UnsecuredDebt* on the traditional Tobin's Q (used as a proxy for growth opportunities). In the following section, we present the core of our identification strategy, where we explore how regulatory changes introduced by the Biologics Price Competition and Innovation Act (BPCIA) of 2010 drive growth opportunity and debt structure changes for pharmaceutical firms. Our base-regression model is:

$$UnsecuredDebt_{i,t} = \alpha + \beta Q_{i,t-1} + \boldsymbol{\gamma UDControls}_{i,t-1} + \varepsilon_{i,t-1}, \tag{1}$$

where i denotes a firm, t denotes a year, and α a constant. Our focus is on the importance and robustness of the estimate on Q, which we expect to be positive. The regressions also include a set of control variables – ***UDControls*** – including *Leverage* (market or book), *LogSize*, *Tangibility*, *DebtRating*, *Profitability*, and *EarningsVolatility* (as defined above) to account for firm heterogeneity. All regressions also include year dummies to absorb time-specific effects.

The unsecured debt regression results are reported in Table 5. The model is estimated with simple OLS and IV-GMM for the base sample of non-financial firms over the period from 1981 through 2010. In the IV-GMM specification, all variables are first differenced and instrumented by their own lags in levels (to mitigate concerns about endogeneity and measurement problems with Q (Erickson and Whited, 2000)). All of our regressions are estimated with heteroskedasticity-consistent errors clustered by firm (Petersen, 2009).

[16] Similarly, MacKay and Phillips (2005) and Graham and Leary (2011) find that most of the variation in leverage occurs within industries or within firm (split almost evenly). Graham and Leary (2011) document that a similar pattern also occurs for debt maturity.

The key finding in Table 5 is that the coefficient estimates for Q are positive and highly statistically significant. In line with our growth opportunity channel of debt structure, firms with more growth prospects rely significantly more on unsecured debt. The effect is also economically large. Consider the IV-GMM estimates reported in column 4 (specification with book leverage). Because variables are defined in changes, the focus is on how *UnsecuredDebt* varies (within firm) in relation to a corresponding change in Q. The coefficient estimate on Q is 0.057. This suggests that a one standard deviation increase in Q generates a change in *UnsecuredDebt* equal to 0.083 (=0.057 $\times$ 1.463), or a 13% increase relative to the sample average *UnsecuredDebt* of 0.630. The effect is qualitatively similar but smaller in the OLS specifications, where we do not instrument the independent variables to account for measurement problems or endogeneity.

To recap, these findings are consistent with our growth opportunity channel of debt structure. Firms appear to adjust their debt structure towards more unsecured debt in response to positive changes to their growth prospects.

TABLE 5 ABOUT HERE

The estimates on the control variables have the expected signs. Both *MarketLeverage* and *BookLeverage* enter the unsecured debt regression with a negative coefficient estimate, which suggests that the debt capacity of unsecured debt is lower compared to debt secured by assets in place. *LogSize* and *DebtRating* have positive and significant effects on unsecured debt. If larger firms and firms with access to the bond market are more transparent (Faulkender and Petersen, 2006), then this could explain why lenders are more willing to provide more unsecured credit to them.

The estimate on *Tangibility* is negative. Firms with more tangible assets can support more secured debt, all else equal, hence, they have proportionately less unsecured debt. Notably, the estimate on *Tangibility* is relatively small (ranging from -0.197 to -0.214), consistent with the small simple correlation coefficient of -0.167 shown in Table 2.

Profitability has a negative and significant effect on unsecured debt. Profitable firms can increase their financial flexibility by retaining some of their internal cash flows to expand their equity cushion. Paying a price for the financial flexibility associated with unsecured debt becomes less attractive to them, all else equal. Somewhat surprisingly, the estimate on *EarningsVolatility* is positive and significant in the OLS estimations, although it alternates in sign and becomes insignificant in the IV-GMM estimations.

The diagnostic statistics for our IV-GMM unsecured debt regression estimations are reported at the bottom of Table 5. The high p-values for the Hansen J-test of over-identifying restrictions indicate that we never reject the joint null hypothesis that our instruments are uncorrelated with the error term in the unsecured debt regressions and the models are well specified. Furthermore, the low p-values associated with the first-stage F-test of excluded instruments suggest that our instruments are relevant. Finally, we reject the null hypothesis that the error terms display autocorrelation of order-2 or higher using the Arellano-Bond test for serial-correlation (p-values of 0.360 and 0.412, respectively for the estimations in column 3 and 4), which suggests that lagged variables are valid instruments.

Summing up our results, evidence from regression-based analysis (OLS and IV-GMM) suggests that firms shift their debt structures toward more unsecured debt in response to positive changes to their growth opportunity set. This evidence is new to the literature and supports the argument that firms issue unsecured debt to preserve their flexibility to issue secured debt in the future on untapped collateral. This flexibility is especially valuable to firms with substantial growth opportunities.

While these regression results are consistent with the logic of a growth opportunity channel of debt structure, they may still not fully satisfy endogeneity concerns or more generally the use of Q as a proxy for growth opportunities. In the next section, we offer evidence from a natural experiment designed to mitigate the limitations of our regression-based analysis.

4 Evidence from a Natural Experiment: The Biologics Price Competition and Innovation Act

Our regression-based analysis supports a strong positive relation between growth opportunities and unsecured debt. To better identify this relation, we examine the effects of the Biologics Price Competition and Innovation Act of 2010 (the BPCIA or the Act) on the debt structure of pharmaceutical firms. The Act provides the regulatory pathway for the development and commercialization of generic versions of biological drugs, so-called biosimilars or follow-on biologics. We argue that although biosimilars have positive effects on the growth prospects of pharmaceutical firms, they have little immediate impact on the value of firms' collateral and cash flows. This offers an ideal setting to isolate and identify the effects of growth opportunities on debt structure. We describe our strategy in detail in this section.

4.1 Institutional Setting

The drug industry broadly defined is characterized by two main segments, the traditional pharmaceutical segment and the younger biotechnology segment (also known as biological or biotech segment). Roughly speaking, pharmaceutical firms manufacture drugs using chemical science to produce small molecule drugs. Compared to biologics, pharmaceuticals have relatively simple well-defined structures and easily characterized properties, and are usually dispensed as pills. In contrast, biotech firms use microorganisms, animals, or humans to produce complex large molecule biologic drugs, which are usually dispensed by injection or infusion.

Prior to the BPCIA, generic drug approval was regulated exclusively by the Drug Price Competition and Patent Term Restoration Act of 1984, colloquially known as the Hatch-Waxman Act [Public Law 98-417]. The 1984 Act requires a generic to be essentially identical to its reference brand-name drug. This is an extremely difficult and costly hurdle for generic biologics to clear because even slight differences in manufacturing can generate large differences in biologic drug properties (Mody, Varshney, and Patankar, 2010). Without low-cost generics, biologic drug prices can stay high for long periods of time, even after patents expire. On the other hand, because of their relatively simple structure, generic versions of pharmaceutical drugs – such as the aspirin[17] – have been around since the 1980's.[18]

Figure 1 provides a visual example to help illustrate why few generic biological drugs have been approved under the Hatch-Waxman Act of 1984. It shows the magnified images of the molecular structures of aspirin (a pharmaceutical drug) and Factor VIII (a biological blood-clotting protein used to treat Hemophilia A). Clearly, the structure of aspirin is simpler. Its molecular weight (MW) is only 0.2 kda's (units of molecular mass) compared to Factor VIII with an MW of about 330 kda's and 2330 Amino Acids (AA).

The complex structure of biological molecules means that biosimilar copies will inevitably have missing or extra atoms, whereas generic copies of pharmaceuticals do not. The molecular imperfections have been important enough to the Food and Drug Administration (FDA) that

[17] The aspirin was the first pharmaceutical drug to be patented in the U.S., with Patent No. 644,077 in 1900, and is considered to be the beginning of the modern drug industry. Another recent emblematic pharmaceutical is Lipitor (manufactured by Pfizer), one of the best-selling drug in history with nearly $11B in revenues in 2011, whose patent expired at the end of 2011.

[18] Generic pharmaceutical drugs can sell for up to 80% below the original price of the brand-name drugs (Grabowski, Ridley, and Schulman, 2007; and Barclays Capital, 2011). The main source of this price reduction is the reduced number of clinical trials. This is possible because generic drugs are exact copies of brand-name drugs, and therefore, the FDA accepts most of the clinical results of the brand-name drug to support the generic. It does not require the extensive number of clinical and preclinical trials that are necessary to prove the efficacy of a new brand-name drug.

in almost all cases, they have treated biosimilars in the same way that they treat any proposed new drug, requiring a full series of clinical trials.

FIGURE 1 ABOUT HERE

The FDA made it clear that it believed that Hatch-Waxman did not give it the authority for an abbreviated approval process for biosimilars. That authority came when the Biologics Price Competition and Innovation Act (BPCIA) of 2010 [H.R. 3590] was attached to the Patient Protection and Affordable Care Act (PPACA) and signed by the president on March 23, 2010 [Public Law 111-148]. The new law authorizes the FDA to approve generic biologics based on a "principle of biosimilarity." Manufacturers of generic biological drugs no longer have to prove that generic biologics are identical to innovator drugs, they only need to show sufficient similarity. This greatly reduces the number of clinical trials and accelerates the approval process for generic biologics.

The passage of the BPCIA was not a foregone conclusion. Political pressure to allow generic biologics has been around since the first blockbuster biologics (recombinant insulin) came to the market in 1982. A bill crafted by Senator Edward Kennedy in the early 2000's never came up for a vote under the 2000-2008 Republican administrations. Strong bipartisan opposition to the bill suggests that its passage would not have been obvious even under the more recent Democrat administration. The BPCIA only passed the Senate on December 24, 2009 after it was attached to the PPACA, and Democrats mustered a super-majority to break a Republican filibuster.[19] Passage of the BPCIA was uncertain because passage of the PPACA in the Senate was uncertain. Final passage of the PPACA by the Democrat-controlled House of Representatives was relatively certain and occurred on March 21, 2010. President Obama signed the bill into law on March 23, 2010.

4.1.1 The BPCIA and Growth Opportunities for the Pharmaceutical Industry

The BPCIA can be viewed as a positive growth shock for traditional pharmaceutical firms. We test whether pharmaceutical firms increased their unsecured debt in response to this shock.

We argue that the BPCIA generated *synergies* between pharmaceutical and biotech firms (especially small and medium-sized firms), providing an opportunity for pharmaceutical firms to enter the biosimilar segment. The complex molecular structure of biosimilars, combined

[19] Democrats were able to muster all of their own members to break the filibuster because some who previously had voted against the PPACA bill were voted out of office or were retiring, hence, were willing to vote for the bill even though their state's constituents would not look favorably on such a vote.

with the fact that they are predominantly used to treat life threatening diseases (like cancer) means that substantial marketing and organizational resources are required to convince patients, doctors, hospitals and benefit managers to switch from the associated innovator biologic to the biosimilar (e.g., Jelkmann, 2007; Voet, 2011).[20] Most innovator biotech firms are small or medium-sized firms focused mostly on research and development. They lack the deep marketing, financial,[21] and clinical resources of established pharmaceutical firms,[22] which are crucial to successfully navigating the FDA approval process, marketing the biosimilar to customers, and defending its intellectual property.

In line with this synergy-related argument, we find an increase in different forms of collaboration between pharmaceutical and biotech firms following the passage of the BPCIA. M&A data from the Thomson One database (formerly, SDC) show a significant increase in M&A activity between pharmaceutical and biotech firms in the year following the passage of the Act. M&A transactions increased to 31 or by 63% in 2010, relative to 19 transactions in either 2008 or 2009 (with an average of about 15 transactions per year from 2000 to 2007).[23]

More recent data from Current Partnering (an industry consultant and data provider) shows that at least 30 biotech-related deals have been structured between pharmaceutical and biotech firms since early 2011. In several instances, the language of the press releases makes it clear that the objective of the deal is to exploit operational synergies with the biotech developing the biosimilar, and the pharmaceutical firm contributing financial, marketing, and clinical resources. In early June 2012, for instance, Dr. Reddy's Laboratories and Merck & Co. (a pharmaceutical firm) announced a deal to develop, seek FDA approval for, and market biosimilar-cancer drugs. In late 2011, Merck also created Merck-BioVentures with plans to

[20] The European experience shows a price reduction for generic biologics in the range of 20% to 40% of the innovator drug price, compared to a price reduction of up to 80% for traditional pharmaceutical drugs. The significant lower price reduction for biosimilars depends on the more complex structure of biological drugs compared to chemical drugs, which requires significantly more trials and tests before they can be made available to the public (Grabowski, Ridley, and Schulman, 2007; and Barclays Capital, 2011).

[21] Lerner, Shan, and Tsai (2003) and more recently Garcia (2008) have documented that limited access to finance has implications for the ability of biotech firms to maintain their bargaining position in relation to pharmaceutical firms. Relatedly, Li (2011) shows that restricted external financing can cause firms to discontinue R&D projects.

[22] The complex molecular structure that characterizes biosimilar drugs implies development costs that are generally prohibitive for smaller biotech firms. Myshko (2012) notes that it would cost up to $200 million to develop a biosimilar drug and the development process can take 6 to 8 years. By comparison, an average pharmaceutical generic drug takes four years and $5 million to develop and seldom requires clinical trials.

[23] Pharmaceutical firms' ability to leverage their regulatory, marketing, and intellectual property defense resources could explain why Higgins and Rodriguez (2006) find that pharmaceutical firm acquisitions have earned abnormal returns of about 4 percent compared to negative returns reported for most other acquisitions.

invest $1.5 billion in order to have several biosimilars in late-stage trials in the near future.[24] Similar deals have been structured by other pharmaceutical firms such as Pfizer (Bourgoin, 2011).

To recap, biotech firms have the expertise and research capacity necessary to develop biosimilars, but often lack the preferential access to customers and experience with tight FDA scrutiny to successfully commercialize new drugs. Pharmaceutical firms can contribute these capabilities.[25]

4.2 Market Reaction for Pharmaceutical Firms around the Passage of the BPCIA

The growth opportunities associated with biosimilars are large enough that the surprise passage of the BPCIA is likely to have impacted pharmaceutical firms' stock prices. There is a large near-term bulge in the pipeline of biologics available to be copied. Many top-selling biologics have lost patent protection but have not been subject to biosimilar competition in the U.S. The Federal Trade Commission (2009) reports that of the $112 billion biologic sales in 2009, 87% came from biologics that have already lost or that will lose patent protection between 2010 and 2015, with the majority of the remaining market going off patent by 2020. Perhaps more important, biosimilars offer pharmaceutical firms opportunities to enter or expand into the biotech segment. The biologics industry is widely viewed as the future of the drug industry because biologics make up the majority of the breakthroughs in the treatment of cancer or other forms of life-threatening diseases, where treatments can cost $100,000 or more per year per patient (Malik, 2009).[26]

To analyze the reaction of pharmaceutical stock prices to the BPCIA event, we identify

[24] These outcomes were anticipated in the language of the firm's annual report for 2010, where the firm describes its intention to diversify its product line into biosimilars through Merck-BioVentures division and exploit merger synergies to maintain its late-stage product pipeline and expand its access to worldwide external science (which is largely biologic science as opposed to chemical science).

[25] Bourgoin (2011) analyzes how joint ventures, license agreements, and similar forms of collaboration contributed to the success of Teva Pharmaceuticals Ltd. in the follow-on biological market in Europe. Garcia (2008) describes the different organizational and financial aspects that characterize the structure of strategic alliances and partnerships between pharmaceutical and biotech firms.

[26] According to a 2010 consensus-sale forecast report by Thomson Reuters (Hirschler, 2010), 8 out of the 10 best selling drugs by 2014 will be biologics (relative to 5 out of 10 in 2010). This trend is paralleled by evidence that hospital spending in traditional pharmaceutical drugs is declining in favor of biologics (Aitken, Berndt, and Cutler, 2009). These authors also show that the number of new blockbusters is growing faster in the biologic segment, and so are sales (biologics represented 10 (17) percent of the combined drug market in 2002 (2007)). Bourgoin (2011) expects that trend to continue because early-stage clinical trials involving biologics has gone from three percent of all drug trials in 2005, to 15 percent in 2010.

December 24, 2009 as the "event-date." Its passage by the Senate on that date was unexpected because Democrats mustered a supermajority necessary to break a Republican filibuster after many failures to do so. The approval of the bill by the House on March 21, 2010 where Democrats held a majority, was generally perceived as a foregone conclusion, as was the president's signing on March 23, 2010.

We start by analyzing how Tobin's Q changed for pharmaceutical firms in the period following the passage of the BPCIA. Our evidence shows that Q increased from an average of 3.2 in 2009 Q3 to 3.4 in 2009 Q4, and again to 3.7 by the end of 2010 Q1. The increases in Q are consistent with the argument that the BPCIA induced a positive growth shock for pharmaceutical firms. There are caveats, however, when one relies on Q as a proxy for growth opportunities. For this reason, we complement these results with evidence from a standard event study, which also accounts for possible changes in systematic risk and is more closely centered around the event.

Table 6 reports the event study evidence. Results are reported for pharmaceutical firms (SIC 2834) – "treated firms" – as well as firms operating in the same one digit SIC as pharmaceutical firms (SICs 2000 – 2999), which serve as "control firms." The control group results are useful to evaluate the extent of industry-wide events unrelated to the effects induced by the passage of the BPCIA. We exclude from the control group firms operating in the same two digit SIC as pharmaceutical firms (SICs 2800 – 2899), such as biotech firms and generic pharmaceutical firms. Those firms' lines of business are close to pharmaceuticals, therefore, they could be affected by passage of the Act. Abnormal stock returns are estimated using standard event-study methods, with the market portfolio proxied by the CRSP Value-Weighted stock index return.[27]

The Cumulative Average Abnormal Returns (CAARs) for the pharmaceutical group and the comparison group are computed over various trade-day windows around December 24, 2009, along with a standardized cross-sectional test to assess statistical significance. We use these different windows to capture possible information leakage, which could happen because of daily vote counts by Senate leaders (concerning the PPACA), and negotiations on final bill language that takes place around votes.

Over the five trading days starting two weeks before the passage of the Act, denoted [-10; -5], both groups show no significant CAARs. We find positive and significant CAARs for all

[27] Results are similar if we use the CRSP Equally Weighted or the S&P 500 Index or if we calculate CAARs using the Fama-French model plus momentum.

other time windows in Table 6, but only for pharmaceutical firms. CAARs for pharmaceutical firms over five trading days after the event date [+1; +5] equal 1.12% and are statistically significant. In the time window [-5; +5], pharmaceutical firms experienced significant positive CAARs of 2.82%. The combined evidence from these two-time windows suggests possible information leakage around the event. CAARs increased further for pharmaceutical firms over longer-time horizons, reaching 7.83% over the time window [-5; +15]. By comparison, CAARs are always economically very small and statistically insignificant for the sample of control firms over any of the time windows in Table 6.

TABLE 6 ABOUT HERE

4.3 Identification Strategy

Passage of the BPCIA appears to have had positive effects on the growth opportunities of pharmaceutical firms. But did pharmaceutical firms respond by increasing unsecured debt? Before answering this question, we note that our strategy to identify the growth-unsecured debt relation could be weakened if BPCIA passage affected pharmaceutical firms through effects on collateral value or cash flows. We address these concerns first. Tests of whether pharmaceutical firms adjusted their debt structure following the Act are discussed in the next section.

Biologic production involves different science, know-how, research, and production facilities than pharmaceutical production. For these reasons, pharmaceutical firms are mostly entering the biosimilar segment by establishing partnerships, joint ventures, and related forms of collaboration with existing biotech firms. This is important for our identification strategy because it means that the passage of the Act was unlikely to have affected the value of pharmaceutical firms' assets in place or their collateral value.[28]

Near term cash flows were also unlikely to be affected by the BPCIA. The first new biosimilar drugs approved under the BPCIA will not appear quickly. FDA guidelines on biosimilars have been released only on February 9, 2012 (nearly two years after the Act was approved). According to a 2011 report by Thomson–Reuters, it takes about 6 to 8 years to develop a biosimilar and get it to market (which is very similar to the time it takes to develop an in-

[28] The logic of our identification strategy motivates our choice of pharmaceutical firms rather than biotech firms in designing our empirical strategy. While arguably the passage of the Act has a direct effect on growth opportunities for biotech firms, the Act also likely affected their assets' collateral value or cash flows. This occurs because the production technology and assets-in-place dedicated to brand-name biological drugs can be rededicated to the production of biosimilar drugs. Pharmaceutical production and R&D facilities cannot be easily converted.

novator pharmaceutical drug (FDA, 2002)). Overall, this suggests that the introduction of biosimilars is unlikely to have any near term effect on cash flows for pharmaceutical firms.

Furthermore, pharmaceutical firms are unlikely to change their debt structures toward more unsecured debt because they anticipate that biosimilar investments will be more R&D intensive than their typical investments. Grabowski, Ridley, and Schulman (2007) note that compared to branded pharmaceutical investments, biosimilar investments on "copycat-versions" of branded-biological drugs are relatively less R&D intensive and more CAPEX intensive. If biosimilar investments were more R&D intensive and less CAPEX intensive, then firms might use more unsecured debt because biosimilar investment will provide less collateral to support secured debt.

Is it possible that there are other effects related to the passage of the Act that could weaken our identification strategy? One possibility is that the BPCIA was passed as part of the Patient Protection and Affordable Care Act (PPACA), which includes other potentially confounding statutes. The centerpiece of the PPACA is the "individual mandate,"[29] a requirement that everyone have health insurance. This implies that more individuals will be insured, increasing prescription-drug sales once the mandate is implemented in 2014. However, the legislation also introduces a nondeductible-annual fee on brand-name pharmaceutical firms. It is expected that the fee will generate resources for the Federal Government in the order of $4.1 billion by 2018. The fee will be calculated annually by the Department of the Treasury and partitioned among pharmaceutical entities in proportion of each firm's branded prescription drug sales (excluding biosimilars and pharmaceutical generics) to the Government in the previous year (Cf., Pricewaterhouse Coopers, 2010).

The fee was negotiated under a "principle of neutralization" between the Obama administration and representatives from the pharmaceutical industry with the objective of offsetting reform-induced increases in pharmaceutical firm cash flows. This aspect of the healthcare reform is crucial for our identification strategy because it helps mitigate concerns that there might be cash flow effects (related to the broader healthcare reform) concomitant to the growth opportunity effects that we intend to identify.

To summarize, our identification works because the Act has direct positive effects on growth opportunities for pharmaceutical firms through the biosimilar channel, while being fairly or-

[29] Twenty six states have challenged the constitutionality of the mandate to the Supreme Court on the grounds that the Government should not force individuals to buy a product against their will. In a ruling on June 28, 2012, the Court upheld the law arguing that the individual mandate is in effect a tax and does not interfere with people's free will.

thogonal to the value of their collateral and cash flows.

4.4 Experimental Design

We now describe the empirical strategy that we use to test whether pharmaceutical firms adjusted their debt structure following the BPCIA. Our prediction is that pharmaceutical firms (SIC 2834) – "treated firms" – should adjust their debt structure towards more unsecured debt following the Act-induced shock to their growth opportunities: the growth opportunity channel of debt structure. To isolate the growth opportunities effects from other industry-wide effects, rather than simply measuring unsecured debt for pharmaceutical firms in the pre- and post-Act period, we use a difference-in-differences estimation approach. It is designed to compare the adjustment in unsecured debt by pharmaceutical firms to the corresponding adjustment in unsecured debt by "control firms" (firms in the same one digit SIC as pharmaceutical firms: SICs 2000 – 2999).[30] We perform our tests by estimating the following regression model:

$$\begin{aligned} UnsecuredDebt_{i,t} = \alpha + \beta_1 Pharmaceutical \times PostBiosimilarAct + \beta_2 Pharmaceutical \\ + \beta_3 PostBiosimilarAct + \boldsymbol{\gamma UDControls}_{i,t-1} + \varepsilon_{i,t-1}, \end{aligned} \tag{2}$$

where i denotes a firm, t denotes a year, and α is a constant. Our focus is on the importance and robustness of the estimate on $Pharmaceutical \times PostBiosimilarAct$: the difference-in-differences estimator. This variable is defined as the interaction between the dummy variable *Pharmaceutical*, which equals 1 for firms operating in SIC 2834, and 0 for control firms (i.e., firms in SICs 2000 – 2999), and the dummy variable *PostBiosimilarAct*, which equals 1 for 2010 (the year following the passage of the Act by the Senate on December 24, 2009), and 0 otherwise. By design, the interaction term measures the change in unsecured debt for pharmaceutical firms in the year following the passage of the Act relative to the change for control firms.

In the regression, we also include the *Pharmaceutical* dummy on its own to control for possible differences in the level of unsecured debt between pharmaceutical firms and the control group. Likewise, the *PostBiosimilarAct* dummy is included to control for secular trends in unsecured debt that are common to both the pharmaceutical firms and the control firms. The regression also includes a set of control variables, ***UDControls***, defined earlier in Equation (1) to account for possible sources of heterogeneity between the groups of treated and control firms. The purpose of this empirical design is to ensure that treated firms are comparable to

[30] We exclude from the sample, firms operating in the same two digit SIC as pharmaceutical firms (SICs 2800 – 2899) because of their "closeness" to the pharmaceutical segment. We note however that all our findings are robust if we do not exclude these firms from our analysis.

control firms along many observable dimensions, with the only difference being the extent to which the passage of the Act has caused a shock to the growth opportunities of pharmaceutical firms, and a related adjustment in their debt structure.

The model is estimated by OLS over the period from 1981 through 2010. Our final sample consists of 11,317 firm-year observations. It includes 1,336 firms in the specification with market leverage as a control, of which 2,068 firm-year observations (or 310 firms) are from pharmaceutical firms and the remaining 9,249 (or 1,026 firms) are from the control group. There are 11,659 firm-year observations (or 1,349 firms) in the specification with book leverage as a control. All of our regressions are estimated with heteroskedasticity-consistent errors clustered by firm (Petersen, 2009).

Table 7 reports the regression estimates. The estimate on the *Pharmaceutical* dummy is positive, but economically small and statistically insignificant in both specifications. This suggests that the level of unsecured debt for pharmaceutical firms is not significantly different from that of the control group. The coefficient estimate on the *PostBiosimilarAct* dummy is negative and statistically significant, implying a common negative secular trends in unsecured debt for both groups.

Our variable of interest is the interaction between the two dummy variables. The estimate on *Pharmaceutical*×*PostBiosimilarAct* is positive and highly significant. Consistent with our growth opportunity channel of debt structure, this finding implies that, following the BPCIA-induced growth shock, pharmaceutical firms increased unsecured debt relative to control firms. This debt structure adjustment is also economically large. Consider the estimate in column 1. It implies that pharmaceutical firms increased unsecured debt by 10.4% (=0.201 – 0.097) relative to control firms in the post-Act period, after accounting for the negative trend in unsecured debt. Evidence reported in column 2 leads to a similar conclusion, with an increase in unsecured debt equal to 11.2% (=0.197 – 0.085).

TABLE 7 ABOUT HERE

All of the estimates on the control variables, with the exception of the estimate on earnings volatility (which is insignificant in Table 7) have the same signs and statistical significance observed for the larger sample of non-financial firms reported in Table 5. This is important for our empirical design because it suggests that our experimental sample is comparable to the larger sample of non-financial firms in terms of basic-fundamental determinants of debt structure.

To recap, the results in Table 7 show that pharmaceutical firms responded to the BPCIA-induced shock to growth prospects by increasing unsecured debt. The results are novel and reveal a strong relation between growth opportunities and the financial flexibility provided by unsecured debt.

4.5 Robustness Analysis and Falsification Tests

In this section, we assess the robustness of our empirical model specifications and estimation results. Although they are designed to account for firm heterogeneity and secular trends in both groups, a trend in unsecured debt specific to pharmaceutical firms could bias the results. This would constitute a violation of the parallel-trend assumption, which requires that the outcome variable for the treated and control groups moves in parallel before the treatment takes place. This violation could be problematic for our identification because it would suggest that the difference-in-differences estimate in Table 7 could be capturing a pharmaceutical-specific trend rather than the Act-induced shock to growth opportunities and the associated increase in unsecured debt.

In Table 8, we re-estimate the models using an empirical design that allows us to control for possible pharmaceutical-specific trends in unsecured debt. This is achieved by including in our regressions the interaction variable *Pharmaceutical*×*Trend*, where *Trend* is a time trend (Cf., Angrist and Pischke, 2009).

Table 8 shows that the coefficient estimate on *Pharmaceutical*×*Trend* is positive and significant, but economically very small (0.005 and 0.004 in columns 1 and 2, respectively). This suggests that while a pharmaceutical-specific trend in unsecured debt could be present in the data, its effect is too small to have any significant influence on our results. In line with this expectation, the estimates on *Pharmaceutical*×*PostBiosimilarAct* decrease just slightly in Table 8, but are still very sizable at 0.183 or 0.180 (relative to 0.201 and 0.197 reported in Table 7).

TABLE 8 ABOUT HERE

The sample period for the estimations reported in Table 7 covers 1981 to 2010. To check whether our results are unduly influenced by any specific year in the sample, we re-estimate the model in Table 7 by shortening the sample period gradually by one year at a time up to when only 2009 and 2010 are left in the sample. In every estimation (unreported), the coefficient on the interaction term (our variable of interest) is positive, significant, and economically large.

Overall, these robustness tests suggest that our results are robust to the length of the sample period used in the analysis.

If our identification strategy is valid, firms operating outside of the pharmaceutical industry should not make adjustments to their unsecured debt like pharmaceutical firms did following the passage of the Act. This provides an opportunity to construct a series of falsification tests that we can use to assess the validity of our identification approach.

We perform the falsification tests by estimating the models in Table 7 for each subsector in the same one digit SIC as the pharmaceutical group, one at a time. Because the firms in the other subsectors are not affected by the passage of the BPCIA ("false treated"), estimates on the interaction variable between *FalsePharmaceutical* (a dummy identifying one of these false-treated groups) and *PostBiosimilarAct* should not be positive and significant. Our results (unreported) show that for any of these false-treated groups the estimates alternate in sign between positive or negative, with all of them small and insignificant.

Finally, we check the robustness of our findings to the role of convertible debt. Because convertible debt can be characterized as an equity-like instrument, firms can rely on this source of financing to maintain financial flexibility. Therefore, it is important to assess the extent to which our results are driven by the role of convertible debt as opposed to "non-convertible" unsecured debt.

We start by noting that convertible debt is 4.7% of total debt for our sample of non-financial firms. This means that the average unsecured debt reported in Table 1 decreases, but remains a sizable 58% of total debt if we subtract convertible debt from our main measure of unsecured debt. More importantly, our regression results are largely unchanged if we exclude convertible debt from our measure of unsecured debt or if we exclude from our estimations the sub-sample of firms with access to the bond market.

Overall, these additional tests make it less likely that possible confounding effects – and not the experimental treatment we designed – can explain the results in Table 7. In the next section, we discuss other aspects of the growth opportunity channel for debt structure and provide additional tests.

4.6 Capital Structure Adjustments and Debt Covenants

Our growth opportunity channel of debt structure implies that pharmaceutical firms *actively* adjusted their capital structure towards more unsecured debt in response to the Act-induced shock to growth opportunities for the purpose of increasing their financial flexibility going

forward. Therefore, it is important to analyze the debt structure adjustment of pharmaceutical firms following the BPCIA to mitigate concerns that our findings are the outcome of a passive approach to capital structure.

Table 9 provides evidence on the capital structure adjustment for pharmaceutical firms in 2010. The evidence shows that pharmaceutical firms increased unsecured debt (as a percentage of total debt) by 6.2% in 2010 relative to 2009 (from 72.2% to 78.4%), while leverage decreased by 1.6% (from 25.2% to 23.6%). These results are reassuring. First, firms did not increase their leverage in 2010 but they increased the proportion of debt that was unsecured. Second, the decrease in leverage is consistent with Myers' (1977) expectation that growth opportunities and leverage should be negatively related. If pharmaceutical firms sought financial flexibility after the BPCIA passage, increasing unsecured debt and equity are two ways to do so.

We also find that pharmaceutical firms actively rebalanced their capital structure towards more unsecured debt and equity. New issuances of long-term debt in 2010 were equal to 5.7% of total assets. Using information from COMPUSTAT in combination with data from annual reports and Capital IQ (when available), we separate long-term debt issuances into unsecured and secured portions of 3.1% and 2.6% of total assets, respectively. Debt reductions (long-term and short-term) due to buybacks and maturity were equal to 4.3% (=4.2% + 0.1%) in the same year and consist of unsecured and secured portions of 1.3% and 2.9% of total assets, respectively.

Overall, total debt increased by 1.4% in 2010 as a result of new debt issuances and reductions (=5.7% - 4.3%). Notably, firms replaced maturing secured debt with more unsecured debt, with the consequence that unsecured debt (as a percentage of total debt) increased by 6.2% in the same year.[31] Table 9 also shows that net equity (equity issuance – equity reduction) increased by 3% (=3.9% - 0.9%) in 2010. The relatively large expansion in equity compared to debt accounts for the 1.6% decrease in leverage reported in the second row of Table 9. Pharmaceutical firms made debt structure and capital structure adjustments that increased their financial flexibility in the year following the BPCIA.

TABLE 9 ABOUT HERE

Finally, we study the covenant structure of unsecured debt issuances in 2010. Our growth opportunity channel of debt structure implies that pharmaceutical firms issue unsecured debt

[31] In line with this finding, data from the Mergent – Fixed Income Securities Database (FISD) shows that unsecured debt issuances increased to 97% of total issuances in 2010 relative to 92% of total in 2009.

in order to preserve secured debt capacity and achieve greater financial flexibility. This claim would be weakened if unsecured debt issued in 2010 came with covenants limiting these firms' ability to increase leverage or issue secured debt.[32] It is, therefore, important that we study the covenant structure of unsecured-debt issuances of pharmaceutical firms in 2010.

We collect covenant information from the Mergent – Fixed Income Securities Database (FISD) on unsecured debt issuances for our sample of pharmaceutical firms with access to the bond market. We find that only 12% of these issuances have a covenant restricting firms' future leverage, while 33% of them include a "negative pledge agreement," which limits a firm's ability to pledge unencumbered assets in the future. None of the debt issuances in 2010 included a coverage ratio covenant restriction.

We complement this information with covenant data on bank lending from the Thomson-Reuters LPC DealScan database. Covenant information in DealScan is provided at the "package" level (where a package is defined as a collection of facilities including term loans, lines of credit, or similar). We match covenant data with our sample of pharmaceutical firms from COMPUSTAT using the link-file made available by Chava and Roberts (2008).[33] For our purposes, we focus on packages that include only unsecured debt facilities, which we categorize as "unsecured packages." DealScan contains data on several financial covenants, but unfortunately does not report information on negative pledge agreements. Our analysis of available data shows that only 11% of the unsecured debt packages in 2010 included a covenant provision restricting pharmaceutical firms' ability to increase leverage, while an additional 4% includes a coverage ratio covenant restriction. Altogether, these findings further confirm our claim that pharmaceutical firms actively adjusted their debt structure and associated covenants to increase their financial flexibility in connection with a positive shock to growth opportunities induced by the BPCIA.

In the last part of the paper, we study whether our growth opportunity channel of debt structure has economically significant implications for firm leverage.

[32] Gârleanu and Zwiebel (2009) show that lenders require tighter covenants when information asymmetry is higher. We argue that intertemporally (and conditional on information asymmetry), firms with more growth prospects could opt for looser covenants to maintain financial flexibility.

[33] We are grateful to Chava and Roberts (2008) for making their DealScan-COMPUSTAT link-file available through the WRDS platform. We refer the reader to Chava and Roberts (2008) for a complete account and analysis of the covenant information in the DealScan database.

5 The Implications of the Growth Opportunity Channel of Debt Structure for Leverage

Our prediction in accordance with the growth opportunity channel of debt is that lenders will offer high growth firms more unsecured credit, all else equal. Lenders will do this because they recognize that it is more likely that high growth firms will have some projects that generate cash flows that exceed any associated secured debt payments that might be required if the firm subsequently issues secured debt. To test this prediction, we estimate the following leverage regression model:

$$\begin{aligned} Leverage_{i,t} = \alpha + \beta_1 UnsecuredDebt_{i,t-1} \times Q_{i,t-1} + \beta_2 UnsecuredDebt_{i,t-1} + \beta_3 Q_{i,t-1} \\ + \boldsymbol{\gamma LControls}_{i,t-1} + \varepsilon_{i,t-1}, \end{aligned} \tag{3}$$

where i denotes a firm, t denotes a year, and α is a constant. Our focus is on the estimate on $UnsecuredDebt \times Q$, which we expect to be positive. We also include *UnsecuredDebt* and Q separately to assess the standalone effects of unsecured debt and growth opportunities on leverage.

The regressions also include a set of control variables, ***LControls***, including *LogSize*, *Tangibility*, *DebtRating*, *Profitability*, *EarningsVolatility* (from the *UnsecuredDebt* regressions), and *InvestmentTaxCredit*, *LossCarryForwards*, and *AbnormalEarnings* (which are specific to the leverage regressions). *InvestmentTaxCredit* is a dummy variable that takes a value of 1 if the firm has positive investment tax credits (COMPUSTAT's item *itcb*), and 0 otherwise. *LossCarryForwards* is a dummy variable that takes a value of 1 if the firm has positive tax loss carry forwards (*tlcf*), and 0 otherwise. The purpose of the two dummy variables is to capture the effects of taxes on capital structure. *AbnormalEarnings* is the ratio of the change in operating income per share from year t to year $t+1$ (*oibdp/csho*) to the share price in year t (*prcc_c*). *AbnormalEarnings* is used to capture the prediction in Ross (1977), that high quality firms take on more debt at time t to signal that they expect to perform well enough at time $t+1$ to repay the debt. Low quality firms cannot match the signal because they know that they face a greater chance of bankruptcy if they take on debt and subsequently perform poorly.[34] All regressions include year dummies to absorb time-specific effects.

The leverage regression results are reported in Table 10. The model is estimated by simple OLS and IV-GMM for the entire sample of non-financial firms over the sample period from 1981 through 2010. In the IV-GMM specification, all variables are first differenced and instrumented

[34]The control variables specific to the leverage regression come from Johnson (2003), Billet, King, and Mauer (2007), and Saretto and Tookes (2013).

by their own lags. We report results separately for the market and book leverage regressions. All our regressions are estimated with heteroskedasticity-consistent errors clustered by firm (Petersen, 2009).

The estimates on *UnsecuredDebt* in all of the regressions are negative and highly statistically significant. This means that, unconditionally, firms borrow less (more) when the debt is unsecured (secured). The estimates on Q are also negative and highly statistically significant, consistent with Myers' (1977) theoretical argument and many empirical capital structure studies that find significant negative relations. High growth firms borrow less to maintain financial flexibility.

The unconditional effects of *UnsecuredDebt* and Q are both negative. However, we find that their combined effect is positive. The estimate on *UnsecuredDebt*$\times Q$ in all of the leverage regressions is positive and highly statistically significant. The positive estimate supports our prediction that lenders offer high-growth high-unsecured debt firms more credit, all else equal.

The conditional combined effect is also economically large. Consider the IV-GMM estimation of the book leverage regression in column 4. For a firm that relies completely on unsecured debt financing (a shift of 0.370 from the average *UnsecuredDebt* of 0.630), the stand-alone estimate on *UnsecuredDebt* implies that its leverage would be 0.030 (=-0.081 $\times$ 0.370) lower than the average firm in the sample, or 0.271 (=0.301 – 0.030). However, this direct negative effect of unsecured debt is significantly mitigated for growth firms. At the average level of Q (=1.939), the estimate of 0.038 on *UnsecuredDebt*$\times Q$ implies an offsetting effect on leverage of 0.027 (=1.939 $\times$ 0.370 $\times$ 0.038), and combined produce leverage of 0.298 (=0.301 – 0.030 + 0.027). The hypothetical all-unsecured debt firm has leverage just 0.003 below the sample average of 0.301 because of its growth opportunities.

TABLE 10 ABOUT HERE

The estimates on the control variables generally have the expected signs. The estimates on *LogSize* is negative. Larger firms face less information asymmetry and can raise capital more easily through the equity market (Myers and Majluf, 1984). The estimates on *Tangibility* are positive. The *DebtRating* dummy enters all regressions with a positively significant coefficient, consistent with the argument in Faulkender and Petersen (2006) that firms with access to the bond market are less opaque and can borrow more. *Profitability* has a strong negative effect on leverage, a result that is usually linked with Myers's (1984) pecking order hypothesis. *EarningsVolatility* has a negative effect on leverage, consistent with the expectation that the

probability of financial distress increases with cash flow volatility.

Firms with tax credits from investment and losses carry forward need to rely less on leverage to shield their tax income. Consistent with this notion, the estimates on *InvestmentTaxCredit* are negative. However, the estimates on *LossCarryForwards* are positive (Johnson, 2003, also finds positive estimates). Finally, the estimates on *AbnormalEarnings* alternate in sign, hence, support for Ross's (1977) signaling hypothesis is mixed.

The diagnostic statistics for the IV-GMM leverage regression estimations are reported at the bottom of Table 10. The high p-values for the Hansen J-test of over-identifying restrictions indicate that we never reject the joint null hypothesis that our instruments are uncorrelated with the error term in the leverage regressions and the models are well specified. Furthermore, the low p-values associated with the first-stage F-test of excluded instruments suggest that our instruments are relevant. Additionally, the Arellano-Bond test for serial-correlation (p-values of 0.642 and 0.554, respectively for the estimations in column 3 and 4) suggests that lagged variables are valid instruments.

Finally, we check the robustness of the findings in Table 10 to the inclusion of the effects of short-term debt. Johnson (2003) finds effects of short-term debt on leverage that are similar to what we find for unsecured debt. To determine whether the effects of short-term debt and unsecured debt are separate effects, we re-estimate the leverage regressions in Table 10 after adding a short-term debt variable (percentage of debt maturing within 3 years) and a variable to capture the interaction between short-term debt and Q. Our estimation results (not reported) confirm the evidence in Johnson (2003). We find that the estimate on short-term debt is negative, while the estimate on the interaction variable is positive; both are statistically significant. The positive estimates on our focus variable $UnsecuredDebt \times Q$ remain positive, significant, and economically large. Therefore, the effect of the growth opportunity channel of debt structure on leverage is robust to the effects of short-term debt.

6 Conclusion

This paper considers the role of growth opportunities in explaining debt structure variation. High growth firms use more unsecured debt to preserve financial flexibility (in the form of untapped secured debt capacity) in anticipation of future investment prospects. In contrast, firms with limited growth prospects rely more on (cheaper) secured debt financing because they place less value on the financial flexibility that comes with unsecured debt.

The evidence suggests that growth opportunities play a key role in explaining debt structure variation. Using data for a large sample of non-financial firms in COMPUSTAT over the period from 1981 through 2010, we document significant variation in debt structure and show that this variation occurs mainly between firms within an industry or within firm over time. Furthermore, using a standard regression approach, we find that there is a strong positive relation between unsecured debt and growth opportunities (as proxied by Tobin's Q). To help identify this relation, we supplement regression-based results with evidence from a quasi-natural experiment from the pharmaceutical industry: The Biologics Price Competition and Innovation Act (BPCIA) of 2010. Consistent with a BPCIA-induced positive shock to growth opportunities, we find that pharmaceutical firms responded by significantly adjusting their debt structures towards more unsecured debt and greater financial flexibility.

We also analyze the implications of the growth opportunity channel of debt structure for leverage. We find that although unsecured debt has a direct negative effect on leverage, this effect is strongly mitigated for high growth firms. These findings are consistent with our growth opportunity argument: high growth firms are able to attract more unsecured debt because lenders recognize that growth opportunities will generate cash flows in excess of their secured debt repayments.

Our paper identifies a well-defined channel – the growth-opportunity channel of debt structure – to help explain the dynamics of firms' unsecured versus secured debt choices. Future research could consider additional implications of debt-security design for innovation and growth. It should recognize that firms need to *intertemporally* balance trade-offs between current and future frictions in the financial markets. The importance of financial flexibility and the drawbacks of high leverage and secured debt for growth have come to the forefront of economic debate during the recent financial and sovereign debt crises in the U.S. and Europe. This suggests that better understanding of the subject could benefit borrowers, lenders and regulators.

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Table 1 - Sample Descriptive Statistics

This table reports summary statistics for the main variables used in the paper. All firm level data are obtained from the COMPUSTAT industrial database. The sample includes all non-financial firms over the period 1981-2010. $UnsecuredDebt$ is the ratio of total unsecured debt (COMPUSTAT's items $dlc+dltt-dm$) to total debt ($dlc+dltt$). Q is the ratio of market value of total assets ($at-ceq+prcc\_c \times csho$) to book value of total assets (at). $MarketLeverage$ is the ratio of total debt to market value of total assets. $BookLeverage$ is the ratio of total debt to book value of total assets. $Size$ is total sales ($sale$ - measured in millions of 2010 dollars using the Producer Price Index (PPI) published by the U.S. Department of Labor as the deflator). $Tangibility$ is the ratio of property, plants, & equipments ($ppent$) to book value of total assets. $DebtRating$ is a dummy variable that takes a value of 1 if the firm has either a bond rating ($splticrm$) or a commercial paper rating ($spsticrm$), and zero otherwise. $Profitability$ is the ratio of earnings before interest, taxes, depreciation and amortization ($oibdp$) to book value of total assets. $EarningsVolatility$ is the ratio of the standard deviation of earnings before interest, taxes, depreciation and amortization using 4 years of consecutive observations to the average book value of total assets estimated over the same time horizon.

Variables	Sample Statistics					
	Mean	Median	St. Dev.	25th Pct.	75th Pct.	Obs.
$UnsecuredDebt$	0.630	0.752	0.371	0.280	1.000	130,921
Q	1.939	1.401	1.463	1.049	2.166	112,507
$MarketLeverage$	0.210	0.164	0.183	0.050	0.330	109,263
$BookLeverage$	0.301	0.258	0.236	0.105	0.441	130,921
$Size$ ($\$Billions$)	1.479	0.122	8.130	0.022	0.615	130,525
$Tangibility$	0.306	0.243	0.235	0.114	0.450	130,677
$DebtRating$	0.180	0.000	0.384	0.000	0.000	130,921
$Profitability$	0.035	0.101	0.228	0.000	0.166	130,208
$EarningsVolatility$	0.100	0.060	0.108	0.030	0.123	121,730

Table 2 - Correlations between Unsecured Debt, Leverage, Q, and Tangibility

This table reports correlation coefficients between $UnsecuredDebt$, $MarketLeverage$, $BookLeverage$, Q, and $Tangibility$. The sample includes all non-financial firms from COMPUSTAT over the period 1981-2010. Refer to Table 1 for detailed variable definitions.

	$UnsecuredDebt$	$MarketLeverage$	$BookLeverage$	Q	$Tangibility$
$UnsecuredDebt$	1.000				
$MarketLeverage$	-0.103***	1.000			
$BookLeverage$	-0.054***	0.818***	1.000		
Q	0.069***	-0.418***	-0.061***	1.000	
$Tangibility$	-0.167***	0.278***	0.217***	-0.161***	1.000

Note: ***, ** and * indicate statistical significance at the 1%, 5%, and 10% (two-tail) test levels, respectively.

Table 3 - Transition of Firms Across Unsecured Debt Quartiles

This table reports a transition matrix of firms across unsecured debt quartiles. Column 1 reports the number of firm-year observations by unsecured debt quartile. Quartile 1 includes firm-year observations with unsecured debt less than 28% of total debt. Quartile 2 includes firm-year observations with unsecured debt greater than or equal to 28% of total debt but less 75%. Quartile 3 includes firm-year observations with unsecured debt greater than or equal to 75% of total debt but less 100%. Quartile 4 includes firm-year observations with unsecured debt equal to 100% of total debt. The table also reports the number of firm-year observations within each unsecured debt quartile that have transitioned across the remaining unsecured debt quartiles (columns 2-5). For example, the figure in the first row of column 3 means that 24,726 firm-year observations out of 32,731 [or 76%] in quartile 1 have transitioned to quartile 2 during our sample period. Column 6 reports the number of firm-year observations for firms that have never transitioned to other quartiles. The sample includes all non-financial firms from COMPUSTAT over the period 1981-2010. Refer to Table 1 for detailed variable definitions.

	Firm-Year Obs.	Transitions to UnsecuredDebt Qtle 1 [%]	Transitions to UnsecuredDebt Qtle 2 [%]	Transitions to UnsecuredDebt Qtle 3 [%]	Transitions to UnsecuredDebt Qtle 4 [%]	Number of Intransient Firms [%]
	(1)	(2)	(3)	(4)	(5)	(6)
Obs. in UnsecuredDebt Qtle 1	32,731	N.A.	24,726 [76%]	17,839 [55%]	14,990 [46%]	3,828 [12%]
Obs. in UnsecuredDebt Qtle 2	32,729	22,085 [67%]	N.A.	22,390 [68%]	15,974 [49%]	2,278 [7%]
Obs. in UnsecuredDebt Qtle 3	32,730	16,488 [50%]	23,144 [71%]	N.A.	18,512 [57%]	3,278 [10%]
Obs. in UnsecuredDebt Qtle 4	32,731	14,448 [44%]	17,680 [54%]	20,153 [62%]	N.A.	6,268 [19%]
Obs. in UnsecuredDebt (Firms)	130,921 (15,931)	53,021	65,550	60,382	49,476	15,652

Table 4 - Sources of Unsecured Debt Variation

This table reports OLS estimation results from unsecured debt regressions. In column 1, we regress each firm's *UnsecuredDebt* on its *IndustryUnsecuredDebt*, which we measure as the firm's lagged 4-digit SIC industry-year mean unsecured debt (own-firm excluded). In column 2, we regress *UnsecuredDebt* on *IndustryUnsecuredDebt* along with firm dummies (unreported coefficients). The sample includes all non-financial firms from COMPUSTAT over the period 1981-2010. Refer to Table 1 for detailed variable definitions. Standard errors reported in parentheses are based on heteroskedastic consistent errors adjusted for clustering across observations of a given firm (Petersen, 2009).

	Between Industry Variation	Between and Within Industry Variation
	(1)	(2)
IndustryUnsecuredDebt	0.232***	0.038***
	(0.017)	(0.014)
Intercept	0.607***	0.635***
	(0.117)	(0.011)
Firm-Fixed Effects	No	Yes
Year-Fixed Effects	Yes	Yes
Adj.-R^2 Including Year-Fixed Effects	0.011	
Adj.-R^2 Including Firm and Year-Fixed Effects		0.459
Obs.	109,397	109,397

Note: ***, ** and * indicate statistical significance at the 1%, 5%, and 10% (two-tail) test levels, respectively.

Table 5 - The Relation between Unsecured Debt and Q

This table reports OLS and IV-GMM estimation results from unsecured debt regressions (Eq. (1) in the text). In the IV-GMM estimations, all variables are in first-difference. Estimations also include year dummies. All firm level data are from the COMPUSTAT industrial database. The sample includes all non-financial firms over the period 1981-2010. Refer to Table 1 for detailed variable definitions. Standard errors reported in parentheses are based on heteroskedastic consistent errors adjusted for clustering across observations of a given firm (Petersen, 2009).

	OLS		IV-GMM	
	(1)	(2)	(3)	(4)
Q	0.006***	0.016***	0.037***	0.057***
	(0.002)	(0.001)	(0.012)	(0.017)
$MarketLeverage$	-0.240***		-0.546***	
	(0.014)		(0.056)	
$BookLeverage$		-0.127***		-0.235***
		(0.010)		(0.025)
$LogSize$	0.038***	0.038***	0.038***	0.044***
	(0.002)	(0.002)	(0.007)	(0.007)
$Tangibility$	-0.197***	-0.214**	-0.205***	-0.199***
	(0.012)	(0.012)	(0.032)	(0.046)
$DebtRating$	0.145***	0.141**	0.227***	0.138***
	(0.007)	(0.007)	(0.038)	(0.047)
$Profitability$	-0.252***	-0.244***	-0.386***	-0.277***
	(0.011)	(0.011)	(0.075)	(0.077)
$EarningsVolatility$	0.062***	0.076***	-0.023	0.031
	(0.021)	(0.021)	(0.082)	(0.075)
Obs.	97,929	100,918	88,871	92,917
Adj.-R^2	0.099	0.097	0.107	0.105
Hansen's J (p-value)			0.771	0.363
F-test (p-value) (Excluded Instruments)			<0.001	<0.001

Note: ***, ** and * indicate statistical significance at the 1%, 5%, and 10% (two-tail) test levels, respectively.

Table 6 - Cumulative Average Abnormal Returns for Pharmaceutical and Comparison Firms Following the Passage of the Biologics Price Competition and Innovation Act (BPCIA)

This table reports Cumulative Average Abnormal Returns (CAARs) around the passage by the U.S. Senate of the Biologics Price Competition and Innovation Act (BPCIA) on December 24, 2009 ("event date"). Pharmaceutical firms are those operating in the industry with SIC code 2834. Comparison firms are those operating in industries with SIC codes 2000 - 2999, but excluding firms operating in industries with SIC codes 2800 - 2899 (*Chemical & Related Products*), because their activities are related to the pharmaceutical industry and therefore could be indirectly affected by the Act. Abnormal returns are estimated using standard event-study methodology and CRSP Value-Weighted Index. *t*-statistics (cross-sectional adjusted) are reported in parentheses.

Cumulative Average Abnormal Returns - CAARs [time window in days]	Pharmaceutical Firms	Comparison Firms
[-10;-5]	-0.51%	-0.03%
	(-0.44)	(-0.42)
[+1;+5]	1.12%	0.29%
	(2.17)**	(0.96)
[-5;+5]	2.82%	0.34%
	(2.86)***	(1.40)
[-5;+10]	5.38%	-0.06%
	(2.83)***	(-0.25)
[-5;+15]	7.83%	0.02%
	(3.64)**	(0.37)

Note: ***, ** and * indicate statistical significance at the 1%, 5%, and 10% (two-tail) test levels, respectively.

Table 7 - Change in Unsecured Debt for Pharmaceutical Firms Following the Passage of the Biologics Price Competition and Innovation Act (BPCIA)

This table reports OLS estimation results from unsecured debt regressions (Eq. (2) in the text). All firm level data are from the COMPUSTAT industrial database. The sample includes firms with SIC codes 2000 - 2999 over the period 1981-2010. Refer to Table 1 for detailed variable definitions. *Pharmaceutical* is a dummy variable that takes a value of 1 for firms operating in the industry with SIC code 2834, and zero otherwise. *PostBiosimilarAct* is a dummy variable that takes a value of 1 for the year 2010, and zero otherwise, where 2010 is the year following the passage by the U.S. Senate of the Biologics Price Competition and Innovation Act (BPCIA) on December 24, 2009. We exclude from the estimation sample firms operating in industries with SIC codes 2800 - 2899 (*Chemical & Related Products*), because their activities are close to the pharmaceutical industry and therefore could be indirectly affected by the Act. Results in columns (1) and (2) are based respectively on the estimations that include market leverage and book leverage as one of the control variables. Standard errors reported in parentheses are based on heteroskedastic consistent errors adjusted for clustering across observations of a given firm (Petersen, 2009).

	(1)	(2)
$Pharmaceutical \times PostBiosimilarAct$	0.201***	0.197***
	(0.047)	(0.047)
$Pharmacautical$	0.017	0.026
	(0.022)	(0.021)
$PostBiosimilarAct$	-0.097***	-0.085***
	(0.025)	(0.025)
Q	0.016***	0.025***
	(0.005)	(0.005)
$MarketLeverage$	-0.233***	
	(0.043)	
$BookLeverage$		-0.106***
		(0.034)
$LogSize$	0.067***	0.067***
	(0.005)	(0.005)
$Tangibility$	-0.073*	-0.087**
	(0.037)	(0.037)
$DebtRating$	0.088***	0.088***
	(0.016)	(0.016)
$Profitability$	-0.280***	-0.264***
	(0.038)	(0.038)
$EarningsVolatility$	-0.067	-0.063
	(0.079)	(0.078)
Obs.	11,317	11,659
Adj.-R^2	0.163	0.157

Note: ***, ** and * indicate statistical significance at the 1%, 5%, and 10% (two-tail) test levels, respectively.

Table 8 - Change in Unsecured Debt for Pharmaceutical Firms Following the Passage of the Biologics Price Competition and Innovation Act (BPCIA): Controlling for Pharmaceutical-Specific Trends

This table reports OLS estimation results from unsecured debt regressions (Eq. (2) in the text), adding $Pharmaceutical \times Trend$ as a control variable. All firm level data are from the COMPUSTAT industrial database. The sample includes firms with SIC codes 2000 - 2999 over the period 1981-2010. Refer to Table 1 for detailed variable definitions. *Pharmaceutical* is a dummy variable that takes a value of 1 for firms operating in the industry with SIC code 2834, and zero otherwise. $PostBiosimilarAct$ is a dummy variable that takes a value of 1 for the year 2010, and zero otherwise, where 2010 is the year following the passage by the U.S. Senate of the Biologics Price Competition and Innovation Act (BPCIA) on December 24, 2009. We exclude from the estimation sample firms operating in industries with SIC codes 2800 - 2899 (*Chemical & Related Products*), because their activities are close to the pharmaceutical industry and therefore could be indirectly affected by the Act. Results in columns (1) and (2) are based respectively on the estimations that include market leverage and book leverage as one of the control variables. Standard errors reported in parentheses are based on heteroskedastic consistent errors adjusted for clustering across observations of a given firm (Petersen, 2009).

	(1)	(2)
$Pharmaceutical \times PostBiosimilarAct$	0.183***	0.180***
	(0.048)	(0.048)
$Pharmacautical$	-0.037	-0.026
	(0.032)	(0.032)
$PostBiosimilarAct$	-0.097***	-0.085***
	(0.025)	(0.025)
$Pharmaceutical \times Trend$	0.005**	0.004**
	(0.002)	(0.002)
Q	0.015***	0.025***
	(0.005)	(0.005)
$MarketLeverage$	-0.237***	
	(0.043)	
$BookLeverage$		-0.112***
		(0.034)
$LogSize$	0.067***	0.066***
	(0.005)	(0.005)
$Tangibility$	-0.070*	-0.084**
	(0.037)	(0.037)
$DebtRating$	0.087***	0.087***
	(0.016)	(0.016)
$Profitability$	-0.284***	-0.269***
	(0.038)	(0.038)
$EarningsVolatility$	-0.050	-0.046
	(0.079)	(0.078)
Obs.	11,317	11,659
Adj.-R^2	0.164	0.158

Note: ***, ** and * indicate statistical significance at the 1%, 5%, and 10% (two-tail) test levels, respectively.

Table 9 - Capital Structure Adjustment for Pharmaceutical Firms Following the Passage of the Biologics Price Competition and Innovation Act (BPCIA)

This table reports average $UnsecuredDebt$, $BookLeverage$ (as defined in Table 1), and issuance/repurchase activities of debt and equity for pharmaceutical firms in the period around the passage by the U.S. Senate of the Biologics Price Competition and Innovation Act (BPCIA) on December 24, 2009. Pharmaceutical firms are those operating in the industry with SIC code 2834. $Long-TermDebtIssuance$ is the ratio of long-term debt issuance ($dltis$) to book assets (at). $Long-TermDebtReduction$ is the ratio of long-term debt reduction ($dltr$) to book assets. $Unsecured-DebtIssuance$ ($Reduction$) is the ratio of unsecured-debt issuances (reductions) to book assets. $Secured-DebtIssuance$ ($Reduction$) is the ratio of secured-debt issuances (reductions) to book assets. To obtain the secured and unsecured debt issuance/reduction figures, we combine information on secured debt from COMPUSTAT (dm) with information hand-collected directly from annual reports. $Short-TermDebtChange$ is the ratio of short-term debt change ($dlcch$) to book assets. $EquityIssuance$ is the ratio of equity issuance ($sstk$) to book assets. $EquityReduction$ is the ratio of stock repurchases ($prstkc$) and changes in retained earnings (re) to book assets.

	2009		2010
$UnsecuredDebt$	0.722		0.784
$BookLeverage$	0.252		0.236
$Long-Term\ Debt\ Issuance$			0.057
$Unsecured-Debt\ Issuance$		0.031	
$Secured-Debt\ Issuance$		0.026	
$Long-Term\ Debt\ Reduction$			0.042
$Unsecured-Debt\ Reduction$		0.013	
$Secured-Debt\ Reduction$		0.029	
$Short-Term\ Debt\ Change\ (Reduction)$			0.001
$Equity\ Issuance$			0.039
$Equity\ Reduction$			0.009

Table 10 - The Relation between Leverage, Unsecured Debt and Q

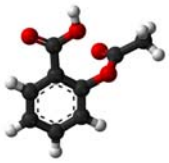
This table reports OLS and IV-GMM estimation results from leverage regressions (Eq. (3) in the text). In the IV-GMM estimations, all variables are in first-difference. Estimations also include year dummies. All firm level data are from the COMPUSTAT industrial database. The sample includes all non-financial firms over the period 1981-2010. Refer to Table 1 for detailed variable definitions. Standard errors reported in parentheses are based on heteroskedastic consistent errors adjusted for clustering across observations of a given firm (Petersen, 2009).

	OLS		IV-GMM	
	Market Leverage	Book Leverage	Market Leverage	Book Leverage
$UnsecuredDebt \times Q$	0.020***	0.020***	0.041***	0.038***
	(0.001)	(0.002)	(0.010)	(0.015)
$UnsecuredDebt$	-0.076***	-0.074***	-0.105***	-0.081**
	(0.005)	(0.006)	(0.021)	(0.033)
Q	-0.052***	-0.027***	-0.092***	-0.057***
	(0.001)	(0.002)	(0.009)	(0.011)
$LogSize$	-0.001	-0.003**	-0.003	-0.018**
	(0.001)	(0.001)	(0.006)	(0.009)
$Tangibility$	0.156***	0.199***	0.180***	0.250***
	(0.006)	(0.008)	(0.012)	(0.020)
$DebtRating$	0.077***	0.120**	0.076***	0.140***
	(0.004)	(0.005)	(0.009)	(0.016)
$Profitability$	-0.063***	-0.118***	-0.249***	-0.318***
	(0.005)	(0.009)	(0.061)	(0.077)
$EarningsVolatility$	-0.106***	-0.040**	-0.165	-0.226
	(0.011)	(0.016)	(0.058)	(0.072)
$InvestmentTaxCredit$	-0.030***	-0.035***	-0.056***	-0.226***
	(0.011)	(0.016)	(0.058)	(0.072)
$LossCarryForwards$	0.039***	0.054***	0.058*	0.009
	(0.002)	(0.003)	(0.031)	(0.042)
$AbnormalEarnings$	0.049***	0.073***	-0.522***	-0.931***
	(0.004)	(0.005)	(0.163)	(0.364)
Obs.	85,774	88,567	78,149	80,790
Adj.-R^2	0.240	0.130	0.238	0.134
Hansen's J (p-value)			0.450	0.382
F-test (p-value) (Excluded Instruments)			<0.001	<0.001

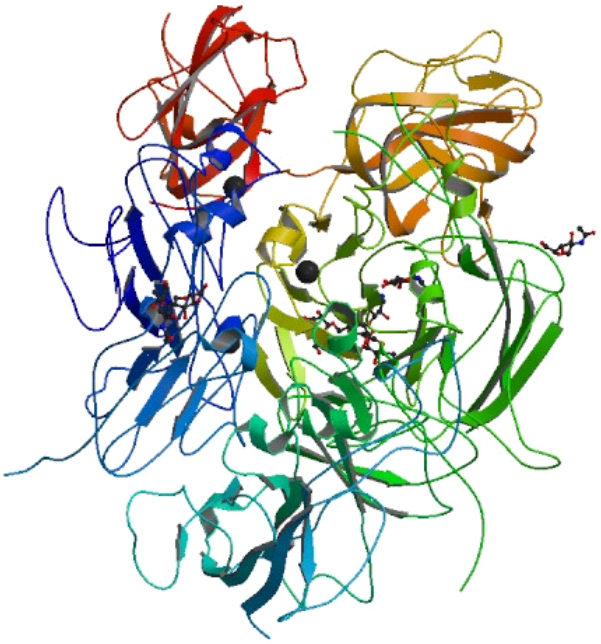
Note: ***, ** and * indicate statistical significance at the 1%, 5%, and 10% (two-tail) test levels, respectively.

Figure 1 - The Molecular Structure of Pharmaceutical and Biological Drugs: Aspirin and Factor VIII

This figure shows a microscope-style image of the molecular structure of the aspirin - a pharmaceutical drug - and Factor VIII (FVIII), a blood-clotting protein used in the biological segment for the treatment of Hemophilia A (a coagulation disorder). The aspirin is a low molecular weight (MW) drug, with only 0.2 kda's (units of molecular mass). The FVIII is a high MW drug, with about 330 kda's and 2330 Amino Acids (AA).



Aspirin
MW: 0.2 kDa



FVIII
~2330 AA,
MW: ~330 kDa

Source: Protein Data Bank