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Financing Stagnating Firms:

Technological Obsolescence as Asymmetric Information in Market Timing

by
Alessandro Luigi Tiberio

HEC Montréal

Supervised by
Jakub Hajda

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Finance

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Résumé

Le but de ma thèse est de déterminer si l'obsolescence technologique est une forme d'information asymétrique que les entreprises peuvent utiliser lorsqu'elles déterminent leurs moyens de financement corporatif. L'obsolescence technologique est définie comme le changement annuel de la pertinence académique des brevets cités par une entreprise mais n'appartenant pas à cette entreprise. J'utilise une période d'échantillonnage de 41 ans, de 1976 à 2016, afin d'éviter tout problème de troncature à gauche ou à droite. Toutes les variables de contrôle utilisées sont les plus courantes et les plus pertinentes pour la structure du capital. Je constate que l'obsolescence technologique est fortement corrélée avec l'endettement, pendant les deux premières années où une entreprise entre dans un état d'obsolescence. Le laps de temps court et la forte corrélation impliquent que l'obsolescence technologique est une forme précieuse d'information asymétrique qui a une période d'utilité limitée avant que cette information asymétrique ne devienne publique.

Mots-clés: Obsolescence Technologique, Information Asymétrique, Timing du Marché, Couverture Analyste, Lois Anti-OPA, Finance d'Entreprise.

Abstract

The purpose of my thesis is to determine if technological obsolescence is a form of asymmetric information that firms can use when determining their means of corporate financing. Technological obsolescence is defined as the year-over-year change in academic relevance of patents cited by a firm but not belonging to a firm. I use a sample period over 41 years, from 1976-2016, to avoid any left or right truncation issues. All control variables used are the most common and relevant variables for capital structure. I find that technological obsolescence is strongly correlated with leverage, for the first two years when a firm enters a state of obsolescence. The short time frame and strong correlation implys that technological obsolescence is a valuable form of asymmetric information that has a limited, usable time frame before this asymmetric information becomes public.

Keywords: Technological Obsolescence, Asymmetric Information, Market Timing, Analyst Coverage, Antitakeover Laws, Corporate Finance.

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1. Introduction

Explanations for firms choosing between debt, equity, and internal funds to finance their activities have been subject to a debate that has raged on since Modigliani and Miller (1958) first attempted to present an explanation for such opaque decision-making practices. Contestation and alternative explanations came by the way of Myers and Majluf (1984) and Baker and Wurgler (2002), introducing asymmetric information and market timing as additional contributing factors. Primarily, relative valuations are considered as a form of asymmetric information, which can be explanatory of corporate financing decisions. Conversely, when also considering how innovation can have a drastic effect on valuations[1], the variables which influence valuations, rather than the valuations themselves, cannot not be disregarded as a form of asymmetric information in their own right. Moreover, the reduced response of capital markets to a firm's failure to innovate (Ma 2021), partially as a consequence of analyst bias (Doukas, Kim and Pantzalis, 2005), is a factor which can further help in explaining the causal effects asymmetric information can have on corporate financing decisions.

As such, a firm's failure to innovate, or its technological obsolescence[2], is a form of asymmetric information that firms may leverage when choosing their means of financing. Additionally, if firms are considering their level of technological obsolescence when deciding their optimal means of financing, they are most likely engaging in market timing, rather than looking to achieve an optimal target debt-equity ratio. Does that then mean asymmetric information,

[1] For more information on the sudden reaction of equity valuations to innovation, see: Pakes (1985), Austin (1993), Hall, Jaffe, and Trajtenberg (2005), and Nicholas (2008).

[2] Technological Obsolescence is the metric used to define the academic relevance of a firm's *technological base*. A *technological base* is the accumulation of all patents cited by firm f, but not belonging to firm f, up to year $t - \omega$. These concepts are further defined within Section 4.1 and the appendix.

stemming from technological obsolescence, influences a firms corporate financing decisions? As a result, do firms with higher states of technological obsolescence have higher leverage? Does oversight or firm size affect the ability for firms to leverage their level technological obsolescence? Finally, does state policy contribute to the ability of a firm utilizing their level of technological obsolescence when determining their optimal means of financing?

My thesis adds to the existing literature by detailing the relationship between technological obsolescence and corporate financing. I build primarily on the research of Baker and Wurgler (2002) and Elliot, Kant, and Warr (2008), employing technological obsolescence, rather than the market-to-book ratio, as an explanatory variable for financing choices. Previous studies focused on mispricing, represented by the ratio between book value and market value, as a proxy of asymmetric information. If firms know they are mispriced, they will attempt to time the market accordingly. I distinguish my thesis from these studies by utilizing technological obsolescence as an alternative metric to proxy asymmetric information. Furthermore, I test how certain biases and environments can affect the viability and relevance of technological obsolescence. Ma (2021) notes that while much attention has been paid to innovation, seldom is there any interest in technological obsolescence, both from researchers and analysts alike. My thesis helps to understand the role technological obsolescence can play when firms are determining their optimal means of financing.

Primarily, when building on the model of Baker and Wurgler (2002), I find that technological obsolescence can be explanatory of leverage up for up to 2 years. Patent data is the benchmark for measuring the value or importance of innovation; but said data has a right truncation issue where there is a 2-year delay between patent filing and granting (Lerner and Seru 2017). This right truncation issue is most likely what creates an asymmetric advantage. Firms understand their relative level of technological obsolescence before the general public, as this information is unavailable to outsider and as such, will base their finance decisions on their prospective value of innovation.

I also determine what portion of the market-to-book ratio can be explained by technological obsolescence. As previously noted, the market-to-book ratio is the traditional explanatory variable used to determine the presence of asymmetric information in financing decisions and represents firms attempting to time the market based on their relative market valuation. I find that a substantial portion of the market-to-book's explanatory power can be attributed to technological obsolescence, indicating that previously models may have suffered from an omitted variable bias. While relative market valuations are one contributing factor to market timing, they are not the only factor which firms may take into consideration.

Furthermore, I build on the notion of asymmetric information and market timing by determining if firm size or analyst coverage can influence a firm's ability to utilize their asymmetric advantage. I find that both of these variables have a substantial impact on a firm's ability to time the market. Additionally, smaller firms experienced the greatest impact from analyst coverage. Small firms, while having the greatest amount of asymmetric information, also require a smaller amount of analyst oversight to ensure transparency, when compared to larger firms.

The final contribution I make is establishing if state policy can affect this form of asymmetric information. I focus on antitakeover legislation, as previous literature provides evidence to support the notion that the passing of this type of legislation encourages manager entrenchment. In fact, I establish that firms in states with antitakeover laws are at greater liberty to finance according to their level of technological obsolescence, after such laws were enacted.

Moreover, I conduct some robustness tests to further support the strength of my results. Primarily, I use an alternative definition for the market-to-book ratio. This is to determine that the previous results were not a consequence of the way the market-to-book ratio is defined. Second, I use multiple antitakeover legislation laws. The original model focuses on one specific law. I extend the model to include the 3 main laws, to see if the same results still hold. The final results from these alternative models provide the same conclusions as the one presented in the paper, indicating that the models are strong, and the relationships are valid.

The remainder of my thesis is structured as follows: Section 2 provides a literature review on capital structure theories, asymmetric information, patent data, innovation, and technological obsolescence. Section 3 contains the three main testable hypotheses, the first relating to market timing, the second incorporating oversight and stakeholders, and the third determining causality. Section 4 is the data description along with the relevant descriptive statistic tables. Section 5 presents the models used to test each respective hypothesis from Section 3. Section 6 presents and interprets the baseline results. Section 7 details the impact of oversight on the asymmetric advantage stemming from technological obsolescence. Section 8 determines causality and addresses any remaining endogeneity issues. Section 9 further confirms the strength of the models used by presenting and interpreting the results from various robustness checks. Section 10 concludes my paper.

2. Literature Review

Market conditions are a major contributing factor to the capital structure of firms. In the context of a perfectly efficient market, Modigliani and Miller (1958) provide evidence to suggest that the need for capital structure is irrelevant as the value of a firm would solely be comprised of its cashflows and risk. Debt or equity would be perfectly interchangeable and does not affect the value of the overall firm. The introduction of various market imperfections, such as taxes, bankruptcy costs and agency costs, create an environment where firms attempt to achieve an optimal debt-equity ratio, in order to maximize their value whilst capitalizing on tax benefits (Modigliani and Miller 1958).

2.1 Corporate Finance and Capital Structure Theories

The static trade-off theory argues that firms prefer debt financing over equity financing, so long as the tax benefits of debt remain balanced with its destress costs (Modigliani and Miller 1958). A higher tax shield for non-debt deductibles, such as depreciation and investment tax credits, reduces the debt load required to achieve an optimal leverage ratio, indicating that debt is only beneficial, so long as the trade-off tax benefit comes in the form of debt deductibles (DeAngelo and Masulis 1980). According to Modigliani and Miller (1958), firms set an optimal debt ratio, which they attempt to achieve under the guise of symmetric information; but if this were an accurate representation of the fundamental motivations behind a firm's corporate financing decisions, then capital structure would experience a much greater amendment, than what is currently observed (Miller 1977).

The absence of asymmetric information in the static-trade off model is inefficient as insiders tend to have more information than traders, as to the motivations behind a company's actions. Myers and Majluf (1984) introduce the concept of asymmetric information having an impact on corporate financing through the pecking order theory. Traders are aware that managers have unique and valuable information, so any attempt at financing is considered a signal to external investors as to the perceived value and strength of a firm. As a result, "asymmetric information leads firms to avoid external equity financing", creating an environment where managers prefer to utilize internal financing primarily (Elliot, Kant and Warr 2008). Additionally, debt is preferred to equity as a dilution of shares acts as a negative signal to external investors, signaling a potential lack of internal funding or access to debt financing (Myers and Majluf 1984). Moreover, an inability of outsiders to accurately assess a firm's true value is compensated through the demand of a financing premium, priced in by the market, as compensation for the uncertainty and risk undertaken by external investors.

Under the pecking order theory, internal financing is utilized to finance projects and business activities in the same regard as debt or equity; however, for firms to obtain internal financing, they must first be profitable. While profitable firms typically have lower leverage, it is not a consequence of utilizing internal funds as a means to finance projects, thus requiring less debt financing, but rather internal funds are exploited as a resource to pay down existing debt (Titman and Wessels 1998). Likewise, equity issuance is not a strong indicator of asymmetric information because firms issue equity so often that a new issuance tends to have a minimal impact on the firm valuation (Fama and French 2002).

2.2 Asymmetric Information

For equity issuance to be a strong indicator of asymmetric information, it would have to be based in the irrationality of external investors after the issuance (Elliot, Kant and Warr 2008). While the lack of response contradicts the pecking order theory's claims that asymmetric information is observed within equity issuances, it does not dismiss the concept that asymmetric information plays a role in management's corporate financing decisions.

For two-thirds of CFOs, Graham, and Harvey (2001) reported that "the amount by which [their] stock is undervalued or overvalued was an important or very import consideration" in deciding when and how to raise capital. When market values exceed book values, managers are more inclined to finance through equity, regardless of their optimal debt-equity ratio (Baker and Wrugler 2002). Although asymmetric information may not dissuade managers from issuing equity because of the external investors' perception, managers do utilize asymmetric information to engage in market timing. Instead of firms engaging in financing decisions in an attempt to reach an optimal capital structure, Baker and Wurgler (2002) provide evidence to suggest that the capital structures of firms are just the "cumulative effect of past attempts to time the market" (Frank and Goyal 2009). Optimal ratios are never realized because they are invariably changing with each financing decisions and the choice between debt or equity is simply mitigated by which alternative provides the firm with the most capital as well as how much internal capital a firm possesses in a given period. As a result, profitable firms tend to always be under-levered as they prefer to issue equity instead of debt and use internal capital to retire existing debt (Hovakimian, Opler, and Titman 2001).

2.3 Patent Data and Innovation

The role equity financing plays in funding innovation has been widely studied (Hall & Lerner 2010; Brown, Martinsson & Petersen 2013), creating a consensus where efficient markets are a driving force in funding promising innovative projects (King & Levine 1993a, b; Levine 1997; Brown, Fazzari & Petersen 2009; Hsu, Tian & Xu 2014; Comin & Nanda 2019). Furthermore, the impact that successful innovation has on the equity market has demonstrated that markets react quickly to disruptive technologies, pricing in the anticipated growth opportunities expeditiously (Pakes, 1985; Austin, 1993; Hall, Jaffe, and Trajtenberg, 2005; Nicholas, 2008).

Traditionally, studies which measured innovation utilized a citation-weighted patent count (Trajtenberg 1990) or exploited "the volume of patenting and … patent citations" (Kerr and Nanda 2015) as an indicator for innovative importance. The idea that patent data could be leveraged as a means to determine the importance or value of a firm's innovation has been theorized since Kuznets (1962), with the idea of patent citation indicating the academic importance of an innovative technology being initially proposed by Garfield (1966).

An abundance of research pertaining to the relationship between innovation and banking deregulation, firm cash holdings and state-antitakeover protection has emerged since Kuzents (1962) and Garfield (1966); however, less focus has been placed on the obsolescence observed within patent data (Lerner and Seru 2017, Ma 2021). Song Ma's (2021) technological obsolescence metric focuses not on the growth aspect of innovation, but rather the destructive nature that is a consequence of disruptive technologies.

2.4 Technological Obsolescence

Technological obsolescence builds on Schumpeter's (1934) idea of "creative destruction", quantifying exactly how innovation disrupts the relevance of existing knowledge contained within each respective firm. Contrary to the immediate impact innovation has on firm valuations, an increase in technological obsolescence disseminates much more slowly, often being ignored by analysts in forecasting models (Ma 2021). Additionally, the right truncation issue associated with patent data may create a problem of information asymmetry, where outside investors are unable to accurately determine the current level of firm obsolescence (Lerner and Seru 2017; Ma 2021). This could create an environment where firms are able to choose financing options, based on their current state of obsolescence, without external investor being immediately privy to how obsolete they may be. Firms could time the market, utilizing their level of technological obsolescence as a means of asymmetric information to more accurately determine their fair market value.

3. Testable Hypotheses

The following section develops testable hypotheses, based on past literature, and details how they are linked to the market timing theory. Hypothesis 1 presents the baseline regression model. Hypothesis 2 describes the impact oversight, in the form of analyst coverage and firm size, has on asymmetric information, specifically obsolescence's explanatory power of leverage. Hypothesis 3 builds on the impact of oversight on asymmetric information further and addresses endogeneity concerns, determining how the passing of antitakeover laws can foster obsolescence's predictability of leverage.

3.1 Hypothesis 1: Market Timing

While the market-to-book ratio alone has very little predictive power for stock returns (Lee, Myers and Swaminathan 2002), Baker and Wurgler (2002), provide evidence to suggest that the market-to-book ratio is predictive of capital structure. Prior literature has also expanded on this relationship, illustrating how high market equity valuations relative to low book valuations have been found to coincide with equity issuances.[3] Elliot, Kant and Warr (2008) further establish that the market-to-book ratio has a significant deterministic impact on leverage, indicating that corporate financing decisions are primarily based on equity valuations rather than target debt ratios. When choosing optimal financing, market timing is the primary goal of firms, since they

[3] The following research papers have all detailed this relationship between high market-to-book ratios and equity issuances: Taggart (1977), Marsh (1982), Asquith and Mullins (1986), Korajczyk, Lucas, and McDonald (1991), Jung, Kim, and Stulz (1996), and Hovakimian, Opler, and Titman (2001).

are prone to issue equity when stock prices rise (Masulis and Korwar 1986, Asquith and Mullins 1986).

The challenge surrounding market-to-book's predictive power is related to its interpretation. The market-to-book ratio is a broad metric which represents at least three attributes, growth opportunities, asymmetric information, and the irrational equity mispricing of external investors (Elliot, Kant, and Warr 2008). Consequently, understanding what portion of market-to-book's predictive power can be attributed to each of these three individual factors is rather challenging.

The intrinsic valuation model by Elliot, Kant and Warr (2008) decomposes the market-to-book ratio into two sperate parts, value-to-price, which represents mispricing, and book-to-value, which corresponds to growth opportunities. Additionally, they use a valuation model to account for asymmetric information as value-to-price does not differentiate between asymmetric information and irrationality. While they concur that stock mispricing does have a deterministic impact on corporate financing decisions, the model proposed by Elliot, Kant, and Warr (2008) may not entirely control for asymmetric information when considering that analysts do not adequately account for technological obsolescence in their forecasting models (Ma 2021).

Analyst forecasts have a propensity to underestimate the impact of technological obsolescence, creating a biased estimate where "the under-reaction favors the obsolete firms" (Ma 2021). Hence, a valuation model based on analyst earnings forecasts would not entirely account for asymmetric information, as analysts do not accurately price the value of obsolescence. The impact asymmetric information has on mispricing may not be entirely accounted for in the model proposed by Elliot, Kant and Warr (2008), due to biased analyst coverage, leading to greater asymmetric information in obsolete firms. Furthermore, due to a right truncation problem associated with patent data, technological obsolescence is a form of asymmetric information not readily available to outside investors in the short term (Hall, Jaffe, and Trajtenberg, 2001).

The presence of asymmetric information allows firms to make informed financing decisions at the expense of external investors. Typically, firms tend to prefer equity over debt when financing growth opportunities, but as firms enter deeper states of obsolescence, their options for growth become scarce or nonexistent (Hovakimian, Opler, and Titman 2001). As a result, I expect that obsolescent firms will prefer to use more debt financing, thus increasing their leverage ratios, in a bid to time the market rather than to reach a target debt ratio.

Hypothesis 1**:** Firms in heightened states of technological obsolescence will have higher leverage as managers who attempt to time the market will prefer debt financing over equity financing to capitalize on their asymmetric information advantage.

3.2 Hypothesis 2: Analyst Coverage and Firm Size

As previously mentioned, the decision for a firm to issue equity over debt tends to coincide with a rise in stock prices (Masulis and Korwar 1986, Asquith and Mullins, 1986). According to past literature, analyst coverage has a major influence on stock prices, valuations, investments, and financing decisions[4]. According to Marcus and Wallace (1991), analysts play a substantial role in how the market perceives firms, with markets tending to immediately react to new information presented by analysts (Womack, 1996).

[4] These are a few significant sources which discuss the relationship between analysts and their influence on firms: Brennan and Subrahmanyam, 1995; Hong, Lom, and Stein, 2000; Das, Guo, and Shang, 2006; Yu, 2008; Ellul and Panayides, 2018.

While analysts are perceived as being a source of meaningful information, they also carry with them two major biases. Primarily, analyst coverage itself can be interpreted as a proxy for market sentiment by investors (Chang, Dasgupta, and Hilary, 2006). Firms with higher coverage are deemed important by the market, whilst those with lower analyst coverage tend to be disregarded by investors. Secondly, the incentive structure for analysts drives their focus to firms which are economically aligned with investment banks (Doukas, Kim and Pantzalis, 2005).[5] Essentially, analysts tend to cover firms which investment banks have a vested interest in.

This all culminates to a market where over-coverage and under-coverage can lead to over- or under-valuation (Doukas, Kim and Pantzalis, 2005).[6] Furthermore, analyst coverage acts as a mechanism of oversight. In addition to being under-valued, firms with low analyst coverage also have a higher amount of information asymmetry (Chang, Dasgupta, and Hilary, 2006). According to Chang, Dasgupta, and Hilary (2006), the negative correlation being analyst coverage and information asymmetry can most likely be attributed to a reduction in information asymmetry from said analyst coverage or a bias of analysts to prefer covering transparent firms with readily accessible information.

Regardless of the cause, "market timing [theory] suggests the effect of factors that mitigate information asymmetry (such as greater analyst coverage) should be greatest for smaller firms" (Chang, Dasgupta, and Hilary, 2006). Additionally, echoing the findings of Doukas, Kim and Pantzalis (2005), "firms with weak analyst coverage are more likely to be plagued by information asymmetries and engage in non-value maximizing corporate activities". Therefore, building on the

[5] See also Lin and McNichols, 1998; Michaely and Womack, 1999.
[6] One of the main causes of stock mispricing is due to investor judgement bias. See Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subramanyam, 1998; and Hirshleifer and Teoh, 2003.

findings of past literature, I expect that smaller firms who lack oversight are less likely to finance themselves based on a target debt-equity ratio. As these types of firms enter deeper states of technological obsolescence, they are more likely to try and time the market based on their state of technological obsolescence; but, as it is more likely that they will be undervalued by the market, they will prefer to finance their operations through debt.

***Hypothesis 2*:** Smaller firms with low analyst coverage are more likely to account for their level of technological obsolescence when choosing their means of financing; thus, preferring debt over equity in deeper states of obsolescence, as they lack the oversight and stakeholder influence to dissuade their market timing efforts.

3.3 Hypothesis 3: Antitakeover Policy

As presented in *Hypothesis 2*, there are many deterrents which can inhibit a firm from utilizing asymmetric information. Firm characteristics, market capitalization and government policy can all act as hindrances or catalysts for a firm attempting to capitalize on their asymmetric information[7]. In this regard, changes in state policy can have a major effect on both how a firm chooses to innovate and how they choose to finance their operations.

Antitakeover laws are one of the major policies which affects financing, innovation, oversight, and asymmetric information. While it is widely agreed upon that they do have an effect on all of these corporate financing issues, the scope of this effect is still a topic of contestation.[8] Chemmanur and Tian (2018) argue that antitakeover laws are most valuable in instances with high

[7] For more information on influences on asymmetric information for firms, see: Baker and Wurgler (2002); Doukas, Kim and Pantzalis (2005); Chang, Dasgupta, and Hilary (2006); Elliot, Kant and Warr (2008).
[8] For contrasting views on the impact of takeover threat, moral hazard, and antitakeover laws, see: Jensen and Ruback, 1983; Jensen 1988; Shleifer and Vishny 1997; Bertrand and Mullainathan 2003; Atanassov, 2013; Seru, 2014; Chemmanur and Tian 2018.

information asymmetry and high short-term competitive pressure. Over the long-term, however, antitakeover laws shift power from shareholders to managers, thus decreasing oversight and increasing manager entrenchment (Bertrand and Mullainathan, 2003), fostering an ideal environment for under-supervised managers to capitalize on their asymmetric advantage.

Antitakeover laws create an agency problem, wherein managers who are no longer facing the threat of takeover, "engage in … value-destroying activates" (Atanassov 2013). The threat of takeover acts as a twofold benefit for shareholders. Primarily, its forces managers to adapt to technological changes, making them more forward thinking and motivated to innovate (Jensen and Ruback 1983; Jensen 1988). Moreover, the threat of takeover acts as a disciplinary measure, forcing managers to make "value-enhancing decisions" (Shleifer and Vishny 1997).

As illustrated by Atanassov (2013), antitakeover laws create an environment where the lack of oversight allows managers the ability to put their own careers ahead of the needs of the firm. The choice of financing is at the discretion of the under supervised managers who choose to invest in lower risk projects, thus lowering their firm's value over time. As a result, firms in states which enacted antitakeover laws will innovate less, choosing safer and less profitable innovative investment opportunities (Atanassov, 2013). Moreover, they will have the ability to base their choice of financing on their current firm value and level of technological obsolescence, as antitakeover laws allow for poor financial decisions, without reaping the consequence of hostile takeover.

Of the various antitakeover laws enacted throughout the 1980-90s, one of the most restrictive laws were the Business Combination Laws (Atanassov, 2013).[9] When compared to alternative antitakeover laws and states who did not enact any such laws, the enactment of Business Combination Laws created a larger increase in manager entrenchment, in addition to an increase in both employee and CEO pay (Bertrand and Mullainathan, 2001; 2003). Antitakeover laws not only stifle innovation, they also foster an environment where the agency problem from the lack of oversight allows managers to operate freely and attempt to time the market, under the guise that they no longer face a threat of takeover. As a result, I expect antitakeover laws to foster an environment where managers are more likely to base their financing decisions on asymmetric information, due to their lack of oversight and absence of takeover threat, further contributing to financing decisions being based on technological obsolescence in states with such laws.

Hypothesis 3**:** Managers in states that enacted antitakeover laws are more likely to have changes in leverage based on the changes in their technological obsolescence, as they lack the threat of takeover to hinder their market timing efforts, thus allowing them to engage in value-destroying activities instead of value maximizing corporate financing decisions.

4. Data Description

The following section discusses the various datasets used as well as filters applied and relevant summary statistics.

[9] Refer to the paper by Atanassov (2013) for a detailed description of what factors contributed to Business Combination Laws being the most strict of antitakeover laws.

4.1 Patent Data

The primary database I used for this research paper is the United States Patent and Trademark Office (USPTO)[10], which contains over eight million granted patents from 1976-2022 as well as over one-hundred and twenty million citations. A small portion of this database contains patents which were submitted with incorrect filing dates; however, the amount is not significant enough to affect the empirical findings. This is apparent as all granting years are accurately recorded and produce similar descriptive statistics. Notwithstanding, for the purposes of my thesis, filing years are preferential to granting years as they are more representative when attempting to capture the real timing of change in a patent's significance.

Linking patents with proprietary firms can also prove rather challenging. Conventionally, a fuzzy matching technique, resembling Ma (2020) and Bernstein, McQuade, and Townsend (2021), was used to link patents to companies, as USPTO tends to be inconsistent with assignee names.[11] NBER also provides a dataset which links firms to patents; however, they do not account for mergers and acquisitions, creating an issue of double counting, exclusion and inaccurate estimations (Hall, Jaffe, and Trajtenberg 2001; Lerner and Seru 2017). Furthermore, the NBER dataset ends at the year 2006. When accounting for the right truncation problem, this bridging dataset is only relevant for studies with an analysis window ending around turn of the millennium (Lerner and Seru 2017).

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[10] Patent data is provided by USPTO and available at https://patentsview.org/download/data-download-tables

[11] A major company like IBM has hundreds of variations in assignee names for their proprietary patents (Lerner and Seru 2017)

To account for these issues, my study utilizes the KPSS bridging dataset, updated to 2022, which employs machine learning to manually match patents with companies (Kogan, Papanikolaou, Seru, and Stoffman 2017).[12] A bridging file is used to convert PERMNO to GVKEY for the KPSS sample, so that it can later be merged with Compustat firm-year observations. The observation window for the main analysis of the bridged file is then reduced to a thirty-year period, ranging from 1986-2016. Patent data has a widely recognized left and right truncation problem.[13] The left truncation problem stems from the inaccuracy or incompleteness of information for patents granted before 1976 and the right truncation problem is a consequence of patents only being entered into the database after they are already granted (Lerner and Seru 2017; 2021). There is an average delay of two years from when a patent is filed to when a patent is granted (Hall, Jaffe, and Trajtenberg 2001). As both the KPSS and the USPTO datasets extend into 2022, an observation window ending in 2016 is sufficient to account for the right truncation problem.

A method of backward and forward citations is used to determine the significance of each patent, year over year. Backward citations of patent p can be considered as the Technological Base of said patent. These are all the pre-existing patents which were necessary and integral in the creation of patent *p*. As noted by Ma (2021), each patent *p* makes an average of "fifteen backward citations". The mean number of patents for a firm's *technological base* is 2268 patents, with a median of 222 patents. Forward citations are all the patents which cite patent p. As previously noted, citations of patent p are only entered into the database after the citing patent has been

[12] KPSS's updated bridging datasets are available through their repository at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data
[13] See Lerner and Seru (2017) for a list of papers which address these truncation issues, in addition to methods to correct for these issues.

granted. Moreover, the use of patent citations instead of patent values is permissible as patents which are scientifically impactful, meaning they have many forward citations, are usually economically lucrative as well (Kogan, Papanikolaou, Seru, and Stoffman 2017).[14]

Finally, $Obsolescence_{f,t}^{\omega}$ itself is constructed under the specifications of Ma (2021). The technological obsolescence metric is defined as follows:

$$Obsolescence_{f,t}^{\omega} = -\left[\ln\left(Cit_{\,t} \left(TechnologyBase_{f,t-\omega}\right)\right) - \ln\left(Cit_{t-\omega} \left(TechnologyBase_{f,t-\omega}\right)\right)\right]$$

Detailed construction of the $Obsolescence_{f,t}^{\omega}$ metric can be found in Ma (2021). To keep the observations relatively constant between the different Omegas, the firm-year observations of $\omega = 5$ are used as a baseline. The obsolescence variables are then winsorized by year at the 1% and 99% level.

4.2 Corporate Financing and Firm Characteristics Data

I also use the Compustat database to acquire annual accounting and financial data on publicly traded US firms between 1976-2020. This dataset contains accounting information for publicly traded firms both post- and pre-IPO. Before any filtering, there are a total of 505,552 firm-year observations with 40,630 unique GVKEYs. Firms with minimum book values under $10 million are omitted from the sample. Financial firms with an SIC between 6000 – 6999 are dropped from this dataset as well.

[14] Both Harhoff, Narin, Scherer, and Vopel (1999) and Hall, Jaffe, and Trajtenberg (2005) find strong correlation between number of citations and patent value.

The Compustat variables are then merged with the previously constructed firm-year obsolescence observations by GVKEY and year. This merger ensures that only the firm-year obsolescence observations of active operating years are entered into this study. There were 5 separate lags used to construct the obsolescence metric, $\omega = 1, 2, 3, 5$ & 10; but the main analysis of this paper will focus on $\omega = 1$, unless otherwise stated. The variables are then winsorized at the 1% and 99% level. The resulting data is used to calculate book leverage, market-to-book, tangibility, profitability, and firm size as defined by Fama and French (2002).[15] Firm-year observations with market-to-book ratios above 10 are also excluded from the sample. Any outlier infinite observations resulting from calculating these key variables are considered as a missing observation. The subsequent dataset is limited to the observation window consisting of the time period between 1986-2016 and contained 2 334 unique GVKEYs.

4.3 I/B/E/S Historical Summary Data

Data on the number of analysts following publicly traded firms is obtained from the I/B/E/S Summary Statistics dataset for Summary History. This dataset summarizes the number of cumulative analysts reporting on a firm over a 12-month period. To annualize the monthly observations, the maximum number of analysts is taken for each year. As the I/B/E/S database uses a CUSIP identifier, the I/B/E/S dataset is then merged onto a GVKEY bridging file to only keep firm-year observations that are contained within the Compustat database. This dataset is also filtered between the years 1986 – 2016. All firms with missing analyst information are assumed to

[15] Formulas and variables used to calculate book leverage, market-to-book, tangibility, profitability, and firm size are contained within the appendix.

have no analyst coverage, so these Nan values are filled with 0. The median number of analysts following a firm for all firm-year observations is 5.

The median number of analysts per year is taken as a benchmark to determine if a firm had high or low analyst coverage. Per year median analyst coverage is used because analyst coverage is not time invariant. Analyst coverage has increased, on average, for my sample spanning over 3 decades. Firm-year observations are then categorized as having high or low analyst coverage based on the median analyst coverage for a given year.[16] This dataset is then merged onto all ω obsolescence datasets, and only firm-year observations present within my obsolescence samples are kept. These datasets are then separated into their respective high and low categorizations.

4.5 Summary Statistics

The final ω = 1 sample is comprised of 36,412 firm-year observations, contained within the observation window of 1986 – 2016 as described in Table 1. Of these 36,412 observations, this sample contains a total of 2,340 unique firms. As omega increases, the relative means and standard deviations increase as well. In this sample, ω = 1 has a mean and standard deviation of 6.794 and 36.229; whereas the mean and standard deviation of ω = 5 is 22.084 and 56.788, respectively. This could be a consequence of how firm age influences obsolescence. With an ω = 5, the firms in the sample have at least 5 years of observable operating data. In these 5 years, there are firms which will be at the forefront of innovation while others will become obsolete. Under a smaller lag, ω = 1, the change of relevance in a firm's technological base will be much less drastic. The impact of new disruptive technology takes a minimum of 6 quarters, with full adoption taking an average of

[16] Firm-year observations less than or equal to the median year observation are low. Firm-year observations with a larger number of analysts than the median are considered high.

4 – 6 years (Baron and Schmidt 2014); therefore, the impact of innovation on obsolescence is more drastic over larger lags.

The resulting summary statistics for the key variables and ratios are presented in Table 2.[17] Before removing firm-year observations with missing data, market-to-book has 33,708 observations with an average ratio of 1.877 per year and a standard deviation of 1.281. Within this sample, the average firm has a higher market value of equity than book value in any given year. Profitability has a high standard deviation compared to its mean, 7.327 and 20.991 respectively, indicating that a substantial portion of firms in this sample are unprofitable in any given year. All summary statistics are comparable to those of Frank and Goyal (2009), except for Book Leverage. I used Baker and Wurgler's (2002) definition of Book Leverage for the purposes of my study; accordingly, my summary statistics for Book Leverage are essentially identical to theirs. All variables used to calculate these key variables and ratios in Table 2 were winsorized at the 1% and 99% levels every year.[18]

The summary statistics for the sample splitting are contained within Table 3. The sample is split on analyst coverage (Low & High) and firm size (Small, Medium, & Large). Around 77% of firms within the sample are covered at some point in time by at least 1 analyst. It is also apparent that smaller firms receive less coverage than medium/large firms. Only 45% of small firms within my sample receive any coverage, with the median number of small firms receiving no analyst coverage whatsoever. In contrast, 72% of large firm-year observations have at least 1 analyst

[17] These summary statistics are calculated with respect to $\omega = 1$, but all summary statistics over all omegas are relatively similar.
[18] Additional notable trends are presented in Figures A1 and A2 in the appendix. Figure A1 shows the various trends associated with median obsolescence over the sample period. Figure A2 shows the median values for control variables over the sample period. Most notably from Figure A2, firm size and tangibility seem to follow opposite trends.

Table 1. Summary Statistics of Technological Obsolescence

Table 1. Firm-Year Level Summary Statistics of Technological Obsolescence

	Count	Mean	Std	10%	25%	50%	75%	90%
Obsolescence, Horizon ω = 1 (%)	36,412	6.794	36.229	-32.850	-10.740	6.290	23.566	47.183
Obsolescence, Horizon ω = 2 (%)	36,417	9.396	40.916	-37.021	-12.346	9.280	30.551	56.182
Obsolescence, Horizon ω = 3 (%)	36,399	12.399	45.281	-40.547	-12.669	12.407	36.843	65.577
Obsolescence, Horizon ω = 5 (%)	36,446	22.084	56.788	-42.744	-9.698	20.371	51.083	89.097
Obsolescence, Horizon ω = 10 (%)	23,435	44.160	74.449	-40.673	0.000	40.547	84.877	136.820

Table. 1. This table summarises the obsolescence metric calculated as per Ma's (2021) definition, referencing equation (1) above. The measures of ω reported are ω = 1, 2, 3, 5 & 10. The observations of ω = 5 are used as the base firm-year for all other ω used. Variables are merged with Compustat data from 1986-2016 to only keep relevant dates of operation. Obsolescence is winsorized at the 1% and 99% levels every year.

Table 2. Summary Statistics of Capital Structure and Financing Decisions

Table 2. Firm-Year Level Summary Statistics of Explanatory Variables

	Count	Mean	Std	10%	25%	50%	75%	90%
Market-to-Book	33,708	1.877	1.281	0.885	1.088	1.457	2.183	3.379
Tangibility (%)	36,404	24.272	19.345	4.319	9.541	19.309	33.962	52.503
Profitability (%)	36,280	7.327	20.991	-11.174	5.124	11.464	16.852	22.697
Size (%)	36,100	6.064	2.296	3.247	4.506	6.082	7.603	9.011
Book Leverage (%)	33,004	42.053	20.898	14.871	25.063	41.414	56.555	70.274

Table 2. This table summarises the calculated variables used in the regression model at the firm-year level for *hypothesis 1*. The variables are merged with the obsolescence data to only keep relevant firm-year observations from 1986-2016. Market-to-book is Compustat item 6 (Assets Total) minus Book Equity plus Market Equity all divided by Assets Total. Tangibility is Compustat item 8 (Plant, Property & Equipment) divided by Compustat item 6 (Assets Total). Profitability is Compustat item 13 (EBITDA) divided by Compustat item 6 (Assets Total). Firm size is the natural logarithm of Compustat item 12 (Sale). Book Leverage is Book Debt divided by Compustat item 6 (Assets Total). The observations of $\omega = 5$ are used as the base firm-year for all other ω used. All Compustat variables are winsorized at the 1% and 99% levels every year. Any infinite observations are considered as missing.

following, with a median of 9 analysts covering said large firms.[19] This is to be expected as larger firms have more stakeholders and as such, will have a higher analyst following than small firms. Surprisingly, large, and medium size firms have a similar amount of coverage.

Table 3. Summary Statistics for Analyst Coverage

Table 3. Firm-Year Level Summary Statistics of Analyst Coverage

	Overall	*Low*	*High*	*Small*	*Medium*	*Large*
Count	36,412	21,433	14,979	12,138	12,137	12,137
Median	3	0	11	0	5	9
Mean	6.08	0.98	13,38	1.51	5.64	11.09
Standard Deviation	8.12	1.50	8.17	2.47	5.62	10.69
Percentage of Firms Being Covered	77.21%	38.78 %	100%	44.99 %	75.33 %	71.57 %

Table 3. This table summarises the number of analysts following a firm in a given year between 1986-2016. The table also summarises the variation in summaries between each respective sample split. *Percentage of Firms Being Covered* is the percentage number of firms in the sample which had at least 1 analyst following for any given year.

5. Empirical Tests

The following section details the empirical models used test each hypothesis. The baseline regression model is explained, followed by the isolation model. Then, the various sample splits employed are described. The natural experiment, consisting of a variation in a difference-in-difference model, as well as the variables unique to this model, are outlined in the final section.

[19] Refer to Table A5 in the appendix for a detail of median analyst coverage per firm, per year, segmented by firm size.

5.1 Hypothesis 1: Debt Issuance Regression Models

These regression models are constructed to determine if the technological obsolescence of a firm impacts its book leverage. The first regression model builds on the baseline models of both Baker and Wurgler (2002) and Elliot, Kant and Warr (2008). Both of these models use a variation of the market-to-book ratio as the explanatory variable with various similar firm characteristics as controls. The dependent variable in this regression model is the change in book leverage with the key independent variable being $Obsolescence^{\omega}_{f,t}$. The baseline regression model is as follows:

$$\left(\frac{D}{A}\right)_{f,t} - \left(\frac{D}{A}\right)_{f,t-1} = \alpha_1 + \beta_1\ Obsolescence^{\omega}_{f,t} + \gamma_1\left(\frac{M}{B}\right)_{f,t-1} + \gamma_2\left(\frac{PPE}{A}\right)_{f,t-1}$$

$$+\gamma_3\left(\frac{\text{EBITDA}}{A}\right)_{f,t-1} + \gamma_4 \log{(S)}_{f,t-1} + \gamma_5\left(\frac{D}{A}\right)_{f,t-1} + \gamma_6 u_t + \gamma_7 v_f + \varepsilon_{f,t}$$

$(D/A)_{f,\,t}$ - $(D/A)_{f,\,t\text{-}1}$ is the change in book leverage with respect to firm f and time t. The controls used are market-to-book $(M/B)_{f,\,t\text{-}1}$, profitability $(PPE/A)_{f,\,t\text{-}1}$, tangibility $(EBITDA/A)_{f,\,t\text{-}1}$, the natural logarithm of size $log(S)_{f,\,t\text{-}1}$, and book leverage $(D/A)_{f,\,t\text{-}1}$. These controls are all firm characteristics which are lagged by 1 year and implemented as per the specifications of Baker and Wurgler (2002) and Elliot, Kant and Warr (2008). $Obsolescence^{\omega}_{f,t}$ is already lagged by its ω value, hence why it is not noted as $t - 1$, as is the case with the other variables. Both firm fixed effects v_f and time fixed effects u_t are included in this regression model as well.

Additionally, the following regression model is constructed to further explore what amount of market-to-book's explanatory power can be predicted by technological obsolescence. Elliot, Kant and Warr (2008) concede that market-to-book is predictive of capital structure; however, the interpretation of why market-to-book is predictive is less apparent. As previously stated, Elliot, Kant and Warr (2008) attempt to refine the explanation behind the predictive nature of market-to-book by deconstructing the ratio into two separate parts, book-to-value, and value-to-market. In similar fashion to an instrumental variable (IV) approach, the following regression model attempts to conduct a method akin to the one by Elliot, Kant and Warr (2008) to assess what portion of market-to-book is predicted by $Obsolescence^{\omega}_{f,t}$. For this model, market-to-book is broken down into the portion which is predicted by technological obsolescence and the portion which is not. The equation to calculate market-to-book's residual observations is as follows:

$$e^{\omega}_{f,t} = \left(\frac{M}{B}\right)_{f,t-1} - \left(\frac{\widehat{M}}{B}\right)^{\omega}_{f,t},$$

where:

$\left(\frac{M}{B}\right)_{f,t-1}$ = Lagged Market-to-Book Ratio

$\left(\frac{\widehat{M}}{B}\right)^{\omega}_{f,t}$, = Predicted Market-to-Book Ratio

$e^{\omega}_{f,t}$ = Residuals

The residual $\hat{e}_{f,t}$ is the difference between the calculated market-to-book ratio $(M/B)_{f,\,t-1}$, and the portion of market-to-book which is predicted by $Obsolescence^{\omega}_{f,t}$ $(\widehat{M}/B)_{f,\,t-1}$. The resulting predicted and residual market-to-book variables, $(\widehat{M}/B)_{f,\,t-1}$ and $\hat{e}_{f,t}$, are calculated with the above equation and are used as a deconstruction of market-to-book in the following regression model:

$$\left(\frac{D}{A}\right)_{f,t} = \alpha_1 + \beta_1\left(\frac{\widehat{M}}{B}\right)^{\omega}_{f,t} + \beta_2 e^{\omega}_{f,t} + \gamma_1\left(\frac{PPE}{A}\right)_{f,t-1} + \gamma_2\left(\frac{\text{EBITDA}}{A}\right)_{f,t-1}$$

$$+\gamma_3 \log\,(S)_{f,t-1} + \gamma_5 u_t + \gamma_6 v_f + \varepsilon_{f,t}$$

As with the baseline regression model, profitability $(PPE/A)_{f,\,t\text{-}1}$, tangibility $(EBITDA/A)_{f,\,t\text{-}1}$ and the natural logarithm of size $log(S)_{f,\,t\text{-}1}$ are used as controls. Both firm fixed effects v_f and time fixed effects u_t are included. In contrast to the baseline regression model, this model uses book leverage $(D/A)_{f,\,t\text{-}1}$ as the dependent variable. Additionally, predicted and residual market-to-book, $(\widehat{M}/B)_{f,\,t\text{-}1}$ and $\hat{e}_{f,t}$, are not lagged within the regression model as they were previously lagged in their initial calculation. This model used to quantify the determinants of leverage is similar to models used by both Baker and Wurgler (2002) and Elliot, Kant and Warr (2008).

5.2 Hypothesis 2: Analyst Coverage and Size Models

The previous models were to determine if an asymmetric information advantage, stemming from technological obsolescence, exists and if firms use this asymmetric advantage when choosing their means of financing. These regression models are to further understand if oversight and stakeholder influence discourage firms from utilizing their asymmetric advantage. The sample is split primarily on analyst coverage and later on size.

In line with Hypothesis 2, firms with higher analyst coverage should have a lower propensity to capitalize on asymmetric information when compared to firms with lower or no analyst coverage, as firms with higher coverage will be under a greater amount of scrutiny. Additionally, the size of firms are correlated with their number of stakeholders; therefore, larger firms should also be less likely to use their asymmetric information when compared to smaller firms.

The primary regression model is utilized as a basis for variation. All variables and fixed effects are employed in the same manner as the previous models, but regressions are split based on the number of analysts following a firm. Firms are split by mean analyst coverage in a given year, where firms with an analyst following less than or equal to the median in a given year are considered low and those with a greater than median following are high.[20]

The base sample is then split on size relative to my sample. Small, medium, and large firms are determined by the value of total assets, split into 3 equal quantiles. The firm size regression model is as follows:

$$\left(\frac{D}{A}\right)_{f,t} - \left(\frac{D}{A}\right)_{f,t-1} = \alpha_1 + \beta_1\ Obsolescence^{\omega}_{f,t} + \gamma_1 \text{Analyst}_{f,t} + \gamma_2 \left(\frac{M}{B}\right)_{f,t-1} + \gamma_3 \left(\frac{PPE}{A}\right)_{f,t-1}$$

$$+\gamma_4 \left(\frac{\text{EBITDA}}{A}\right)_{f,t-1} + \gamma_5 \log{(S)}_{f,t-1} + \gamma_6 \left(\frac{D}{A}\right)_{f,t-1} + \gamma_7 u_t + \gamma_8 v_f + \varepsilon_{f,t}$$

Firm-year analyst coverage ($\text{Analyst}_{f,t}$) is included in this model as an additional control variable. All other control variables are the same as the base line regression model. Time and firm fixed effects, v_f and u_t respectively, are included as well.

The final model further splits size into high and low analyst coverage based on the respective median analyst coverage in a given year for a given sample split by size. Small firms with a median analyst following equal or lower than the median-year are considered as low, whereas those with an analyst following greater than the median-year are considered high.

5.3 Hypothesis 3: Antitakeover Laws

I use a natural experiment to compare the impact of antitakeover laws before and after they were enacted, as well as between states which chose to enact them and those that didn’t, as a means to determine the causal effect of technological obsolescence. States that enacted antitakeover laws

[20] Table A4 summarizes the median amount of analyst coverage in each year for each sample split.

receive a 1 for the date after the laws were enacted.[21] All other observations, dates before the antitakeover laws were enacted and states without any antitakeover laws, received a value of zero.

The 3 most common antitakeover laws enacted during the 1980s-90s in the United States were the Business Combination Laws, the Fair Price Laws, and the Control Share Acquisition Laws, with the Business Combination Laws being the most restrictive of the three. The Business Combination Laws impose a 3-to-5-year prohibition on certain types of business altering transactions, to restrict large shareholders from obtaining control of the business without the approval of the board of directors (Atanassov, 2013).

I use a difference-in-difference test[22], building of off the previously employed models in my paper, as specified below:

$$\left(\frac{D}{A}\right)_{f,t} - \left(\frac{D}{A}\right)_{f,t-1} = \alpha_1 + \beta_1 \boldsymbol{BC}_{f,t} + \beta_2 \boldsymbol{BC}_{f,t} * \ Obsolescence^{\omega}_{f,t} + \gamma_1 \left(\frac{M}{B}\right)_{f,t-1} + \gamma_2 \left(\frac{PPE}{A}\right)_{f,t-1}$$

$$+\gamma_3 \left(\frac{\text{EBITDA}}{A}\right)_{f,t-1} + \gamma_4 \log\left(S\right)_{f,t-1} + \gamma_5 \left(\frac{D}{A}\right)_{f,t-1} + \gamma_6 u_t + \ \gamma_7 v_f + \varepsilon_{f,t}$$

All control, explanatory and dependent variables are described in previous models. The addition of the Antitakeover law difference-in-difference ($\boldsymbol{BC}_{f,\, t}$)[23] holds a value of 1 for states after the Business Combination Laws were enacted and 0 for all other observations. $\boldsymbol{BC}_{f,\, t}$ is also replaced by $\boldsymbol{FA}_{f,\, t}$ (First Antitakeover Laws), which takes a value of 1 for the states after the dates where either of the 3 main antitakeover laws and 0 otherwise.

[21] Refer to Table A5 in the appendix for the dates in which states enacted each antitakeover law.
[22] For a more in-depth description of difference-in-difference tests and their validity in econometric modeling, refer to Bertrand, Duflo, and Mullainathan (2004).
[23] This variable can take the shape of $\boldsymbol{FP}_{f,\, t}$ (Fair Price Laws) and $\boldsymbol{CSA}_{f,\, t}$ (Control Share Acquisition Laws) in further models.

The main variable of concern in this regression model is the interaction between $\boldsymbol{BC}_{f,\,t}$ and $Obsolescence^{\omega}_{f,t}$. I want to see if the introduction of antitakeover laws, specifically the Business Combination Laws, have an impact on the choice of firms to utilize their asymmetric information, specifically their level of technological obsolescence, when choosing their means of financing. This type of natural experiment is valuable in determining if the relationship between financing choice and technological obsolescence is causal.

6. Leverage and Obsolescence: Main Results

This section first discusses the baseline regression model and interprets obsolescence's impact on book leverage. Obsolescence's contribution to the explanatory power of market-to-book is further expanded upon and specified in the following section. Endogeneity concerns, particularly attributed to patent data, are then addressed.

6.1 Baseline Regression

Table 4 summarizes the resulting coefficient estimates from the baseline regression model. Consistent with Hypothesis 1, Table 4 indicates that firms act upon their asymmetric information and change their book leverage with respect to their level of technological obsolescence, in an attempt to time the market. Therefore, $Obsolescence^{\omega}_{f,t}$ has a strong explanatory power for the change in book leverage of firms.

When time and firm fixed effects are included, $Obsolescence^{\omega}_{f,t}$ has a coefficient estimate of 0.4247, significant at the 5% level. This coefficient indicates that a 1-unit change in $Obsolescence^{\omega}_{f,t}$, on year prior, is associated with a 42.27% change in book leverage. Additionally, when firm fixed effects are omitted, $Obsolescence^{\omega}_{f,t}$ has a coefficient estimate of

0.4477, significant at the 1% level. This indicates that between firms, irrespective of time, a 1-unit change in $Obsolescence^{\omega}_{f,t}$ can be associate with a 44.77% increase in the change in book leverage.

Table 4. Determinants of Change in Leverage

$$\left(\frac{D}{A}\right)_{f,t} - \left(\frac{D}{A}\right)_{f,t-1} = \alpha_1 + \beta_1\ Obsolescence^{\omega}_{f,t} + \gamma_1 \left(\frac{M}{B}\right)_{f,t-1} + \gamma_2 \left(\frac{PPE}{A}\right)_{f,t-1} + \gamma_3 \left(\frac{\text{EBITDA}}{A}\right)_{f,t-1}$$

$$+\gamma_4 \log{(S)}_{f,t-1} + \gamma_5 \left(\frac{D}{A}\right)_{f,t-1} + \gamma_6 u_t + \gamma_7 v_f + \varepsilon_{f,t}$$

Table 4. Change in Book Leverage (Δ(D/A)) %

	(1)	(2)	(3)	(4)
	Δ Book Leverage			
Obsolescence	0.4247**	0.3653**	0.3686**	0.4477***
	(0.1684)	(0.1736)	(0.1538)	(0.1587)
Lag Market-to-Book	-0.8723***	-0.5918***	-0.7074***	-0.5439***
	(0.0936)	(0.0645)	(0.0905)	(0.0634)
Lag Tangibility	0.0334***	0.0051***	0.0262***	0.0092***
	(0.0100)	(0.0031)	(0.0096)	(0.0030)
Lag Profitability	-0.0827***	-0.0717***	-0.0877***	-0.065***
	(0.0115)	(0.0072)	(0.0110)	(0.0070)
Lag Size	0.5677***	0.5894***	0.9066***	0.5393***
	(0.1639)	(0.0384)	(0.1200)	(0.0355)
Lag Book Leverage	-0.3654***	-0.1373***	-0.3631***	-0.1341***
	(0.0078)	(0.0039)	(0.0077)	(0.0039)
Firm FE	Yes		Yes	
Time FE	Yes	Yes		
Observations	28,742	28,742	28,742	28,742
R^2	0.1791	0.0686	0.1754	0.0658

Table 4. This table summarizes the regression results for Hypothesis 1. Obsolescence is the ω change in a firm's technological base. Change in Book Leverage is the difference between Book Leverage at time t and $t-1$. All other variable definitions are presented in Table 2. All control variables are measured at time $t-1$. Standard errors are clustered and reported in parenthesis. Significance levels of coefficient estimates are denoted by *, ** & *** representing the 10%, 5% and 1% confidence levels.

According to these results, firms are deciding their optimal means of corporate financing 1 year into the future, based on their current level of technological obsolescence and not their target-debt equity ratio because managers appear to be making financing decisions based on past levels of obsolescence. The more obsolescent a firm becomes, the more they will prefer debt over equity as their growth opportunities will continue to dwindle (Hovakimian, Opler, and Titman 2001). There are some endogeneity concerns, such as selection bias and reverse causality, which will be later addressed in Section 7 and by the natural experiment in Section 8. Nevertheless, these resulting estimates indicate that the explanatory power of $Obsolescence_{f,t}^{\omega}$ is robust and reliable since it is both significant with and without fixed effects included and all signs of the coefficient estimates remain constant.

Additional resulting estimates from the OLS regression model are summarized in Table 5. Each row presents the coefficient estimate for the different omegas, their p-values, and their respective standard errors below. Similar to $\omega = 1$, $Obsolescence_{f,t}^{\omega}$ with $\omega = 2$ has a coefficient estimate of .3724 with a p-value of .0163. While this result is also significant at the 5% level, its p-value increased and coefficient estimate decreased relative to $\omega = 1$, indicating a slight decrease in the amount of influence $Obsolescence_{f,t}^{\omega}$ has on a firm's change in book leverage.

It is worth noting that as the ω increases, the predictive power of obsolescence decreases. A significant decrease in the predictive power of $Obsolescence_{f,t}^{\omega}$ is apparent at $\omega = 3$ & 5. The coefficient estimates and p-value of $\omega = 3$ are .0958 and .4981, while the coefficient estimates and p-value of $\omega = 5$ are -.0044 and .9719 respectively. The larger the ω, the less meaningful $Obsolescence_{f,t}^{\omega}$ becomes at predicting a change in book leverage. Additionally, the significance of $Obsolescence_{f,t}^{\omega}$ drops dramatically after $\omega = 2$.

Table 5. Horizons for the Determinants of Change in Leverage

Table 5. Change in Book Leverage (Δ(D/A)) %

Omega	Obsolescence			R^2
	N	*b*	*p-value*	
Horizon ω = 1 (%)	28,742	0.4247**	0.0117	0.1791
		(0.1684)		
Horizon ω = 2 (%)	28,746	0.3724**	0.0163	0.1789
		(0.1550)		
Horizon ω = 3 (%)	28,729	0.0958	0.4981	0.1790
		(0.1414)		
Horizon ω = 5 (%)	28,762	-0.0044	0.9719	0.1797
		(0.1255)		
Horizon ω = 10 (%)	18,465	0.2324*	0.0775	0.177
		(0.1316)		

Table 5. This table summarizes additional regression results for Hypothesis 1. Obsolescence is the ω change in a firm's technological base. All variable definitions are presented in Table 2. All control variables are measured at time $t-1$. Time and firm fixed effects are utilized in every model with standard errors clustered and reported in parenthesis. Significance levels of coefficient estimates are denoted by *, ** & *** representing the 10%, 5% and 1% confidence levels.

These results can be most likely attributed to the previously mentioned limitations ascribed to patent data. The right truncation problem creates a lag of 2 years between patent filing and granting. As patents are only made public after granting, firms hold unique and valuable information not available to the market. Therefore, firms who wish to act on their asymmetric advantage, do so primarily within that 2-year window. Once patents are granted, outsiders can more accurately value a firm, thus reducing or eliminating a firm's asymmetric advantage. As was depicted in Table 5, following this 2-year window, the predictive power of $Obsolescence_{f,t}^{\omega}$ decreases dramatically as new patent data and subsequently the relative *technological obsolescence* of a firm are made available to the market. Consistent with Hypothesis 1, firms act upon this asymmetric information and change their book leverage with respect to their level of technological obsolescence. The causality between obsolescence and leverage is established when the change in obsolescence over the previous year or two, represented by $\omega = 1$ & 2 respectively, is associated with a change in the current year's leverage. These results echo those of Baker and Wurgler (2002), who illustrated how a mispricing from one year prior is also associated with a change in leverage. Therefore, these results imply that firms are not always basing their financing choices on optimal debt-equity ratios, but rather internal factors, such as obsolescence, and external factors, such as market conditions, in a bid to time the market.

6.2 Isolating the Effect of Obsolescence

Both Baker and Wurgler (2002) as well as Elliot, Kant and Warr (2008) demonstrate that the past market-to-book ratio is associated with current book leverage, implying that firms attempt to time the market when choosing how to finance their operations. Additionally, these authors attempt to explain what are the individual factors which contribute to market-to-book's explanatory power. As presented in section 6.1 of my thesis, technological obsolescence is an additional factor which can determine how a firm will choose to finance themselves. This following section will further expand on how technological obsolescence influences corporate financing decisions by isolating what portion of market-to-book's explanatory power can be attributed to technological obsolescence.

Table 6 summarizes the estimation results from the OLS regression used to calculate the residual and predicted portions of market-to-book with respect to $Obsolescence_{f,t}^{\omega}$. As I am only concerned with the portion of market-to-book which is predicted by technological obsolescence, no fixed effects were used in this model. The coefficient estimates of $Obsolescence^{\omega}_{f,t}$ are presented in Table 6.

Table 6. Determinants of Market-to-Books Predictive Power

$$\left(\frac{M}{B}\right)_{f,t} = \alpha_1 + \beta\ Obsolescence^{\omega}_{f,t} + \varepsilon_{f,t}$$

Table 6. Market-to-Book $(M/T)_{t-1}$

Omega	Count	Intercept	Obsolescence	R^2
Horizon ω = 1 (%)	30,493	1.884***	-0.1319***	0.001
		(0.007)	(0.021)	
Horizon ω = 2 (%)	30,495	1.8946***	-0.206***	0.004
		(0.008)	(0.018)	
Horizon ω = 3 (%)	30,478	1.9004***	-0.2035***	0.005
		(0.008)	(0.017)	
Horizon ω = 5 (%)	30,517	1.9056***	-0.1591***	0.004
		(0.008)	(0.014)	
Horizon ω = 10 (%)	19,413	1.8376***	-0.1459***	0.008
		(0.01)	(0.012)	

Table 6. This table summarizes the regression results required to calculate the predicted and residual market-to-book observations. Obsolescence is the ω change in a firm's technological base. Variable definitions are presented in Table 2. Significance levels of coefficient estimates are denoted by *, ** & *** representing the 10%, 5% and 1% confidence levels.

The coefficient estimates of market-to-book and $Obsolescence^{\omega}_{f,t}$ for $\omega = 1$ are 1.884 and -0.1319 respectively. Obsolescence is negatively correlated with market-to-book, so as obsolescence increases, the market value of a firm with respect to its book value decreases. Additionally, both of these coefficient estimates are statistically significant at the 1% level. Congruently, all other ω have similar coefficient estimates and all are also significant at the 1% level. These predicted and residual values of market-to-book are then used in my main regression model to determine what portion of market-to-book is predicted by $Obsolescence^{\omega}_{f,t}$.

The estimation results from my OLS regression model, which incorporates the portion of market-to-book predicted by technological obsolescence, are summarized within Table 7. The coefficient estimates for model (1) indicate that a substantial portion of market-to-book's predictive power can be attributed to technological obsolescence. The coefficient estimate for the portion of market-to-book predicted by technological obsolescence is -4.2959; whereas the residual is equal to -0.8065, both significant at the 1% level. These results indicate that technological obsolescence and market-to-book are directly related to one another. Additionally, a substantial portion of market-to-book's predictive power can be attributed to technological obsolescence. That being said, technological obsolescence does not entirely account for market-to-book's explanatory power since the residual market-to-book's coefficient estimates are still significant. Congruent with the findings of Elliot, Kant and Warr (2008), the residual market-to-book's explanatory power can most likely be attributed to irrationality and growth opportunities.

The additional regressions, model (2), (3) and (4) in Table 7, indicate that the portion of market-to-book predicted by technological obsolescence is relatively robust and reliable. In all 4 regressions, the sign of the predicted coefficient estimate remains negative and except for model (2), all predicted estimates remain significant. While model (2) suggests there might be some time-specific trends between firms which reduces the explanatory power of the predicted coefficient, this trend does not hold true when controlling for firm fixed effects.[24]

[24] Table A3 in the Appendix further illustrates the relationship between Book Leverage and the different ω values of obsolescence.

Table 7. Determinants of Leverage

$$\left(\frac{D}{A}\right)_{f,t} = \alpha_1 + \beta_1\left(\frac{\widehat{M}}{B}\right)_{f,t-1} + \beta_2\hat{e}_{f,t-1} + \gamma_1\left(\frac{PPE}{A}\right)_{f,t-1} + \gamma_2\left(\frac{\text{EBITDA}}{A}\right)_{f,t-1} + \gamma_3\log{(S)}_{f,t-1} + \gamma_5 u_t + \gamma_6 v_f + \varepsilon_{f,t}$$

Table 7. Book Leverage

	(1)	(2)	(3)	(4)
		Book Leverage		
Predicted	-4.2959***	-1.9699	-3.3743**	-6.0686***
	(1.6549)	(2.5208)	(1.5135)	(2.3189)
Residual	-0.8065***	-2.0724***	-0.6533***	-2.1445***
	(0.1073)	(0.0971)	(0.1035)	(0.0950)
Lag Tangibility	0.0976***	0.0886***	0.0989***	0.1222***
	(0.0133)	(0.0063)	(0.0127)	(0.0061)
Lag Profitability	-0.2293***	-0.2788***	-0.2348***	-0.2422***
	(0.0126)	(0.0092)	(0.0121)	(0.0088)
Lag Size	2.3177***	4.1871***	2.7316***	3.8464***
	(0.1930)	(0.0585)	(0.1501)	(0.0559)
Firm FE	Yes		Yes	
Time FE	Yes	Yes		
Observations	28,742	28,742	28,742	28,742
R^2	0.046	0.2111	0.052	0.2025

Table 7. This table summarizes the regression results for Hypothesis 1. Obsolescence is the ω change in a firm's technological base. Change in Book Leverage is the difference between Book Leverage at time t and $t-1$. All other variable definitions are presented in Table 2. All control variables are measured at time $t-1$. Standard errors are clustered and reported in parenthesis. Significance levels of coefficient estimates are denoted by *, ** & *** representing the 10%, 5% and 1% confidence levels.

It is worth noting that since the residual market-to-book remains significant in this model, it also has predictive power, further confirming that the portion of market-to-book not explained by technological obsolescence is partially explanatory of book leverage as well. Additionally, technological obsolescence plays a significant role in how firms choose to finance themselves. The lower the market-to-book ratio, the more pronounced the impact of obsolescence. Contrary to Elliot, Kant and Warr (2008), a large portion of market-to-book's predictive power can be attributed to $Obsolescence_{f,t}^{\omega}$. As firms choose their future financing based on their current market-to-book ratio, they are also timing the market by choosing their financing based on their current state of technological obsolescence. Firms that have low market-to-book ratios and high technological obsolescence today are more likely to have higher leverage in the future.

6.3 Endogeneity and Patent Data

The use of patent data within research presents a myriad of unique issues. As noted by Lerner and Seru (2017), there exists endogeneity problems inherent with patent data, beyond the left and right truncation issues. Primarily, patent citations are exponentially increasing over time as firms patent more now than they have in the past (Lerner and Seru 2017). This effect is ever present when observing patenting and patent citations decade over decade. One solution is to implement time fixed effects to account for this issue. While this might be adequate to account for the variation attributed to time within the control variables, it does not completely account for the endogeneity in research using a traditional patent citation method.

The $Obsolescence_{f,t}^{\omega}$ metric itself accounts for this time issue in the way it is constructed. Instead of using raw patent citations numbers, the log change in a firm's technological base over a specific lag window, ω, controls for the natural variation in patenting and patent citation over time. Patent citations are normalized, so that 90% of all observation of ω = 1, 2, 3, & 5 are contained within [-1,1]. Patent citations are not taken as a raw number, but rather a relative ratio, which nullifies the exponential increase in patenting and patent citations over the observation window.

For the additional variation between firms, firm fixed effects are utilized in the above regressions. My thesis aims to provide a better understanding of the within-firm impact technological obsolescence has on corporate financing decisions rather than the between firm. As there are natural variations between firms, firm fixed effects aids in controlling for these endogeneity issues.

7. Oversight and Market Timing

In this section, I first discuss the regression results of my baseline model, segmented by analyst coverage, to understand how technological obsolescence can influence corporate financing decisions with respect to analyst coverage. I then analyze if firm size can negate the effect of asymmetric information stemming from technological obsolescence through subsample analysis.

7.1 Analyst Coverage

Table 8 summarizes the results of the regression model which splits my sample between high and low analyst coverage based on median-year analyst coverage. Consistent with Hypothesis 2, the coefficient estimates from Table 8 illustrates how the amount of analyst coverage a firm receives impacts whether their level of technological obsolescence will be correlated with their financing decisions. The less coverage a firm receives, the more likely they are to time the market based on their level of technological obsolescence.

The coefficient estimate for the $Obsolescence^{\omega}_{f,t}$ of firms with low analyst coverage is .4785, significant at the 5% level; whereas the same coefficient estimate for firms with high analyst coverage is insignificant. As established in Section 6, technological obsolescence is a form of asymmetric information which firms can leverage when choosing their means of corporate financing. Echoing the results of past literature[25], analyst coverage can negate the benefits firms obtain from asymmetric information. Firms with more oversight are either more transparent or more scrutinized than those who lack analyst coverage; therefore, they are not at liberty to time the market and must attempt to finance themselves in a means more consistent with the interest of stakeholders, such as achieving a target debt-equity ratio.

Table 8. Debt-Equity Choice and Analyst Coverage

Table 8. Change in Book Leverage (Δ(D/A)) %

	Δ Book Leverage	
	Low	*High*
Obsolescence	0.4785**	0.4172
	(0.2162)	(0.2677)
Lag Market-to-Book	-1.1184***	-0.6185***
	(0.1546)	(0.1079)
Lag Tangibility	0.0494***	0.0121
	(0.0147)	(0.0152)
Lag Profitability	-0.0870***	-0.0721***
	(0.0145)	(0.0168)
Lag Size	0.6766***	0.4953**
	(0.2438)	(0.2405)
Lag Book Leverage	-0.3953***	-0.3706***
	(0.0109)	(0.0123)
Observations	16,905	11,837
R^2	0.1906	0.1871

Table 8. This table summarizes the regression results for Hypothesis 2. Firms are split on analyst coverage, where *Low* <= median and *High* > median. Obsolescence is the ω change in a firm's technological base. Change in Book Leverage is the difference between Book Leverage at time t and $t-1$. All other variable definitions are presented in Table 2. All control variables are measured at time $t-1$. Time and firm fixed effects are utilized in every model with standard errors clustered and reported in parenthesis. Significance levels of coefficient estimates are denoted by *, ** & *** representing the 10%, 5% and 1% confidence levels.

[25] The most notable past literature being referenced is: Doukas, Kim, and Pantzalis, 2005; Chang, Dasgupta., and Gilles, 2006; He, and Tian, 2013; among others. These papers demonstrate how asymmetric information is negatively correlated with analyst coverage.

Additionally, the positive correlation between $Obsolescence_{f,t}^{\omega}$ and book leverage for firms with low analyst coverage is consistent with the findings of Chang, Dasupta, and Gilles (2006). Firms with less coverage are more likely to be undervalued as they suffer from a bias wherein investors conflate low analyst coverage with unattractive investment opportunities. While firms with low analyst coverage have the ability to time the market due to their lack oversight, they are more inclined to prefer debt over equity as their equity is likely undervalued as a consequence of their limited analyst coverage.

Conversely, there could be an endogeneity issue stemming from selection bias. As previously mentioned, one reasoning for firms having a limited analyst following could be attributed to a lack of transparency; therefore, it may not be oversight which limits asymmetric information, but rather the choice of each individual firm to be transparent. This endogeneity issue will be discussed further in the following section.

7.2 Firm Size and Market Timing

Table 9 summarizes the coefficient estimates for the regression models, split on size, with analyst coverage as an additional control. Surprisingly, these results seem to contradict Hypothesis 2. Small firms should have the greatest amount of asymmetric information, but it seems as though only medium firms capitalize on their level of technological obsolescence when choosing financing and controlling for analyst coverage.

Medium size firms have a coefficient estimate of obsolescence equal to .5835, significant at the 5% level and large firms have a coefficient estimate which is insignificant. This is to be expected, as when firms get larger, the number of stakeholders for firms increases as well. Large firms have a substantial number of stakeholders who act as overseers of the firm, further forcing large firms to choose optimal financing which is congruent with the demands of stakeholders.

Table 9. Debt-Equity Choice and Firm Size

$$\left(\frac{D}{A}\right)_{f,t} - \left(\frac{D}{A}\right)_{f,t-1} = \alpha_1 + \beta_1\ Obsolescence^{\omega}_{f,t} + \gamma_1 \text{Analyst}_{f,t} + \gamma_2 \left(\frac{M}{B}\right)_{f,t-1} + \gamma_3 \left(\frac{PPE}{A}\right)_{f,t-1}$$

$$+\gamma_4 \left(\frac{\text{EBITDA}}{A}\right)_{f,t-1} + \gamma_5 \log{(S)}_{f,t-1} + \gamma_6 \left(\frac{D}{A}\right)_{f,t-1} + \gamma_7 u_t + \gamma_8 v_f + \varepsilon_{f,t}$$

Table 9. Change in Book Leverage (Δ(D/A)) %

	Δ Book Leverage		
	Small	*Medium*	*Large*
Obsolescence	0.4247	0.5835**	0.0157
	(0.2984)	(0.2718)	(0.2719)
Analyst Coverage	-0.3003***	-0.1092***	-0.0326*
	(0.0993)	(0.0387)	(0.0176)
Lag Market-to-Book	-0.9360***	-0.4007***	-0.6986***
	(0.1736)	(0.1504)	(0.1572)
Lag Tangibility	0.0449**	0.0785***	0.0057
	(0.0220)	(0.0193)	(0.6832)
Lag Profitability	-0.1072***	-0.0682**	-0.0357*
	(0.0156)	(0.0299)	(0.0193)
Lag Size	1.0742***	0.1628	0.5482**
	(0.3420)	(0.3585)	(0.2756)
Lag Book Leverage	-0.4678***	-0.4109***	-0.3354***
	(0.0160)	(0.0144)	(0.0119)
Observations	9,241	9,802	9,699
R^2	0.2209	0.2096	0.1694

Table 8. This table summarizes the regression results for Hypothesis 2. Firms are split on firm size, determined as *Small*, *Medium*, or *Large* based on current value of Total Assets. Obsolescence is the ω change in a firm's technological base. Change in Book Leverage is the difference between Book Leverage at time t and t – 1. All other variable definitions are presented in Table 2. All control variables are measured at time t – 1. Time and firm fixed effects are utilized in every model with standard errors clustered and reported in parenthesis. Significance levels of coefficient estimates are denoted by *, ** & *** representing the 10%, 5% and 1% confidence levels.

Medium size firms, who lack the same number of stakeholders as large firms, are more at liberty to time the market, due to the reduction of oversight.[26]

Small firms have a coefficient estimate of technological obsolescence which is insignificant as well. As previously stated, this result appears to contradict Hypothesis 2; but, the findings of Chang, Dasupta, and Gilles (2006) indicate that while smaller firms are more likely to time the market, they are also subject to the greatest impact of information asymmetry mitigation when they receive oversight. To account for this, small firms are further split into high and low analyst coverage, based on median-year coverage, with the resulting coefficient estimates summarized in Table 10.

The coefficient estimate of technological obsolescence for low analyst coverage is 0.8252, significant at the 5% level, whereas the same estimate for high analyst coverage is insignificant. These results are consistent with Chang, Dasupta, and Gilles (2006), depicting how small firms with analyst coverage will experience the greatest adverse effects towards their use of asymmetric information, when compared to larger firms. Contrary to the initial statement of this section, the results of Tables 8, 9 and 10 are consistent with Hypothesis 2 as small firms with limited analyst coverage are more likely to finance themselves with debt in states of technological obsolescence. Small firms will use their $Obsolescence_{f,t}^{\omega}$ as a form asymmetric information, choosing to time the market if they lack oversight, rather than financing themselves based on target debt-equity ratios, tax benefit maximization or any other myriad of corporate financing optimization reasoning.

[26] Median-year analyst coverage is summarized in the appendix Table A5.

Table 10. Debt-Equity Choice and Analyst Coverage of Small Firms

Table 10. Change in Book Leverage (Δ(D/A)) %

	Δ Book Leverage	
	Low	*High*
Obsolescence	0.8252**	0.0082
	(0.4005)	(0.0171)
Lag Market-to-Book	-1.3075***	-0.5271**
	(0.2811)	(0.2159)
Lag Tangibility	0.0493	0.0149
	(0.0309)	(0.0390)
Lag Profitability	-0.0589***	-0.2098***
	(0.0200)	(0.0270)
Lag Size	1.1206**	1.2270*
	(0.4426)	(0.6422)
Lag Book Leverage	-0.4870***	-0.5142***
	(0.0216)	(0.0285)
Observations	5,131	4,110
R^2	0.2329	0.2502

Table 10. This table summarizes the regression results for Hypothesis 2. Firms deemed *Small* are further split based on analyst coverage for small firms, where *Low* <= median and *High* > median. Obsolescence is the ω change in a firm's technological base. Change in Book Leverage is the difference between Book Leverage at time t and t – 1. All other variable definitions are presented in Table 2. All control variables are measured at time t – 1. Time and firm fixed effects are utilized in every model with standard errors clustered and reported in parenthesis. Significance levels of coefficient estimates are denoted by *, ** & *** representing the 10%, 5% and 1% confidence levels.

The results from Table 8, 9 and 10 also address the endogeneity concern relating to selection bias. If the influence of asymmetric information stemming from technological obsolescence on corporate financing was solely based on analysts choosing to cover firms according to a firm's transparency, then firm size would not have an effect in the sample splits of Table 9 and 10. Referring to Table 3, the proportion of medium and large firms covered in the sample are 75.33% and 71.57%, respectively. Even though the medium and large samples have a comparable rate of firms being covered, larger firms are unlikely to engage in market timing when financing as they are more highly scrutinized by their larger number of stakeholders. Congruently, small firms which have the greatest amount of information asymmetry are unlikely to engage in market timing, unless they lack oversight, as their asymmetric advantage is subject to the greatest adverse effects from analyst coverage (Chang, Dasupta, and Gilles, 2006).

In summation, analyst coverage does act as a mechanism of controlling for market timing when asymmetric information is present. Furthermore, smaller firms with low analyst coverage do base their financing decisions on their level of technological obsolescence. Additionally, the under-coverage of a firm can lead to under-valuation of their equity, forcing small firms with low analyst coverage and high technological obsolescence to choose debt financing, in an attempt to time the market.

8. Natural Experiment: Antitakeover Laws

This section first discusses the results from the difference-in-difference model and interprets its interaction with obsolescence. Both the *Business Combination Laws* as well as *General Antitakeover Laws* are discussed in this section. Endogeneity concerns, particularly relating to reverse causality, are then addressed.

8.1 Antitakeover Legislation and Leverage

As stated in Hypothesis 3, managers in states that enacted *Business Combination Laws*, did engage in value destroying activities. Firms in states with *Business Combination Laws* innovate less and produce fewer valuable innovations (Atanassov 2013), thus contributing to their technological obsolescence. The removal of the threat of takeover creates an agency problem where managers are more likely to utilize asymmetric information and choose their method of financing based on their level of technological obsolescence, without fear that poor financing choices will lead to the unwanted takeover of their firm.

Table 11. Antitakeover Laws and Changes in Leverage

Table 11. Antitakeover Legislation and Leverage

	(1)	(2)	(3)
		Δ Book Leverage	
*BC*Obsolescence*	0.4494**	0.4623**	0.4104**
	(0.1877)	(0.1938)	(0.1743)
Business Combination	1.5647***	0.5513***	1.8148***
	(0.5900)	(0.1441)	(0.4081)
Lag Market-to-Book	-0.8708***	-0.5915***	-0.7146***
	(0.0936)	(0.0645)	(0.0906)
Lag Tangibility	0.0346***	0.0061**	0.0287***
	(0.0099)	(0.0031)	(0.0096)
Lag Profitability	-0.0827***	-0.0727***	-0.0872***
	(0.0115)	(0.0072)	(0.0110)
Lag Size	0.5776***	0.6097***	0.8726***
	(0.1634)	(0.0391)	(0.1205)
Lag Book Leverage	-0.3649***	-0.1379***	-0.3634***
	(0.0078)	(0.0039)	(0.0077)
Firm FE	Yes	No	Yes
Year FE	Yes	Yes	No
Observations	28,769	28,769	28,769
R-Squared	0.1791	0.0692	0.1757

Table 11. This table summarizes the difference-in-difference test results for Hypothesis 3. *Business Combination* is the indicator specifying when and where the *BC* laws were passed. Similarly, *First Antitakeover* is an indicator specifying when and where the first antitakeover laws were passed. Obsolescence is the ω change in a firm's technological base. Change in Book Leverage is the difference between Book Leverage at time t and t – 1. All other variable definitions are presented in Table 2. All control variables are measured at time t – 1. Standard errors are clustered and reported in parenthesis. Significance levels of coefficient estimates are denoted by *, ** & *** representing the 10%, 5% and 1% confidence levels.

Table 11 summarizes the results from 3 different regression models, all of which are incorporating a difference-in-difference test for the *Business Combination Laws*. As is present in Table 11, when controlling for various firm characteristics, firms in states that enacted *Business Combination Laws*, did experience an increase in their changes in book leverage. Additionally, firms did choose their financing based on their level of technological obsolescence, experiencing greater changes in leverage as their technological obsolescence increased, within firms that enacted such laws. These results are robust as they remain significant when controlling for only time or firm fixed effects as well, indicating that these trends are not firm or time specific.

The managers in these states are contributing to their own technological obsolescence, but the lack of oversight also allows them to further engage in value destroying activities, by preferring to finance through debt rather than equity, as their firms become more technologically obsolete. *Business Combination Laws* do contribute to a firm's technological obsolescence (Atanassov 2013), but the entrenchment of management is what further drives firms to utilize their asymmetric information without repercussion. The removal of the threat of takeover further contributes to this agency problem, as managers can confidently time the market and increase their leverage or destroy their firm value, without facing the repercussions of a hostile takeover.

8.2 Endogeneity Concerns (Reverse Causality)

As I mentioned in Section 6.1 for the baseline regression model, there is a concern relating to reverse causality, where leverage could influence technological obsolescence as well. To address this, I ran the difference-in-difference model over all ω values. Table 12 summarizes the coefficient estimates for both *Business Combination Laws* (BC Law) and *Obsolescence*.

Previous literature addresses the immediate decline in firm value following the passing of antitakeover laws[27]; however, this impact is short lived and dissipates rather quickly. The coefficient results of Table 12 observe the relationship between *Business Combination Laws* and leverage over a much longer period, in addition to the relationship between technological obsolescence and leverage over larger ω values.

Table 12. Business Combination Laws and Reverse Causality

Table 12. Antitakeover Legislation and Obsolescence

Omega	Count	BC Law	BC*Obsolescence	R^2
Horizon ω = 2 (%)	28,773	1.5395***	0.5113***	0.1790
		(0.5923)	(0.1722)	
Horizon ω = 3 (%)	28,756	1.6683***	0.0742	0.1789
		(0.5914)	(0.1565)	
Horizon ω = 5 (%)	28,787	1.5655***	0.0850	0.1796
		(0.5893)	(0.1361)	
Horizon ω = 10 (%)	18,486	1.3160*	0.2914**	0.1762
		(0.7867)	(0.1430)	

Table 12. This table summarizes the difference-in-difference test results for Hypothesis 3. BC Law is the indicator specifying when and where the law was passed. BC*Obsolescence is the ω change in a firm's technological base interacted with states which Business Combination Laws, after the laws were enacted. Change in Book Leverage is the difference between Book Leverage at time t and t – 1. All other variable definitions are presented in Table 2. All control variables are measured at time t – 1. Time and firm fixed effects are utilized in every model with standard errors clustered and reported in parenthesis. Significance levels of coefficient estimates are denoted by *, ** & *** representing the 10%, 5% and 1% confidence levels.

[27] For more information on the effects of antitakeover laws on firm value, see Karpoff and Malatesta (1989); Easterbrook and Fischel (1991).

When compared to the results presented in Table 5, the coefficient estimates for $Obsolescence^{\omega}_{f,t}$ are nearly identical, being significant at the 5% level for ω = 2 and insignificant for ω = 3 & 5. As addressed by Atanassov (2013), antitakeover laws do contribute to a decrease in innovation, patent citation and, as a consequence, overall firm value. Atanassov's (2013) findings are consistent with my coefficient estimates for BC Law, where firms in states with antitakeover laws experience greater changes in leverage than other firms.

While antitakeover laws do contribute to a firm's obsolescence and increase in leverage, the overall environment these laws foster, where they shift the power from shareholders to managers (Bertrand and Mullainathan 2003), allows managers to engage in market timing behaviour. According to past literature and the results from Table 12, it is unlikely that reverse causality is a present endogeneity concern. Firms are not obsolescent because they accumulate more leverage; rather they prefer to finance with leverage in states of obsolescence, when they lack oversight and have an asymmetric advantage they can utilize.

Antitakeover laws do have a significant and lasting effect on changes in leverage, but the two-year asymmetric advantage firms have when they enter a state of obsolescence is a unique indicator which is explanatory of changes in leverage for firms in states with antitakeover laws.

9. Robustness Tests and Additional Results

Additional robustness tests are conducted and detailed in the following section. The first robustness check is utilizing a varying definition of the market-to-book ratio. The second robustness check uses multiple antitakeover laws to see if the relationship can be replicated, if other types of antitakeover laws are considered as well.

9.1 Alternative Definitions of Market-to-Book

To ensure that my results are not a consequence of specific variable definitions which are intentionally correlated with one another, I employee an alternative definition for market-to-book. The market-to-book ratio was the explanatory variable used by past papers to illustrate the market timing theory.[28] Frank and Goyal's (2009) definition of the market-to-book ratio is applied in the robustness check of this baseline regression model.[29]

Table 13. Alternative Market-to-Book

Table 13. Change in Book Leverage (Δ(D/A)) %

Omega	Obsolescence			R^2
	Count	*b*	*P-Value*	
Horizon ω = 1 (%)	28,680	0.4204** (0.1691)	0.0129	0.1766
Horizon ω = 2 (%)	28,684	0.3788** (0.1555)	0.0149	0.1764
Horizon ω = 3 (%)	28,667	0.1024 (0.1419)	0.4705	0.1765
Horizon ω = 5 (%)	28,700	0.0091 (0.1259)	0.9426	0.1772
Horizon ω = 10 (%)	18,452	0.2326* (0.1319)	0.0779	0.1749

Table 13. This table summarizes additional regression results for the robustness checks. Obsolescence is the ω change in a firm's technological base. All variable definitions are presented in Table 2 except for the alternative definition of market-to-book. All control variables are measured at time $t - 1$. Time and firm fixed effects are utilized in every model with standard errors clustered and reported in parenthesis. Significance levels of coefficient estimates are denoted by *, ** & *** representing the 10%, 5% and 1% confidence levels.

[28] See Baker and Wurgler (2002) and Elliot, Kant and Warr (2008), among others.
[29] Frank and Goyal (2009) define Market-to-Book as Compustat Item 199 (Price Close) multiplied by Compustat Item 54 (Shares Outstanding), plus Compustat Item 34 (Short-Term Debt), Compustat Item 9 (Long Term Debt) and Compustat Item 10 (Preferred Liquidation Value), minus Compustat Item 35 (Deferred Taxes and Investment Tax Credits), all divided by Compustat Item 6 (Assets Total).

Table 13 summarizes the coefficient estimates of this robustness check. Time and firm fixed effects are used as they were in the baseline regression model from Section 6. When compared with the coefficient estimates in Table 5, these resulting estimates are nearly identical, indicating that technological obsolescence is a robust metric for determining corporate financing decisions.

The same pattern as was observed in Table 5 is present in this table as well. $Obsolescence_{f,t}^{\omega}$ is a predictive metric for corporate financing decisions, primarily for ω = 1 & 2. After the first two years, obsolescence's explanatory power drops off dramatically until ω = 10. As previously mentioned in section 6, this can most likely be attributed to the right truncation problem associated with patent data. When patent data is made public, a firm loses it asymmetric information advantage; thus, it can no longer time the market based on its level of technological obsolescence.

9.2 Alternative Antitakeover Laws

To further check the robustness of my natural experiment relating to antitakeover laws, I ran the difference-in-difference model with 3 separate antitakeover laws included. These laws consist of the *Business Combination Laws* which I previously used, the *Control Share Acquisition Laws* and the *Fair Price Laws*. I take the first instance any of these laws were enacted as the starting date for antitakeover laws. This gives a much broader inclusion for antitakeover laws, including additional states and earlier dates. Moreover, these additional laws were not as strict as the *Business Combination Laws*, so the inclusion of these laws could reduce the significance of my results if antitakeover laws themselves were not as strong a contributing factor as I had present in Section 8 of my paper.

Table 14. Alternative Antitakeover Legislation

Table 14. First Year Antitakeover Legislation

	(1)	(2)	(3)
	Δ Book Leverage		
*FA*Obsolescence*	0.4425**	0.4554**	0.3990**
	(0.1823)	(0.1886)	(0.1694)
First Antitakeover	1.2030*	0.4993***	1.7661***
	(0.6304)	(0.1511)	(0.4662)
Lag Market-to-Book	-0.8707***	-0.5914***	-0.7116***
	(0.0936)	(0.0645)	(0.0906)
Lag Tangibility	0.0344***	0.0057*	0.0281***
	(0.0099)	(0.0031)	(0.0096)
Lag Profitability	-0.0827***	-0.0729***	-0.0874***
	(0.0115)	(0.0072)	(0.0110)
Lag Size	0.5757***	0.6097***	0.8819***
	(0.1634)	(0.0392)	(0.1204)
Lag Book Leverage	-0.3648***	-0.1377***	-0.3631***
	(0.0078)	(0.0039)	(0.0077)
Firm FE	Yes	Yes	No
Year FE	Yes	No	Yes
Observations	28,769	28,769	28,769
R-Squared	0.1790	0.0690	0.1755

Table 14. This table summarizes the difference-in-difference test results for Hypothesis 3. *First Antitakeover* is the indicator specifying when and where any of the 3 major antitakeover laws were passed. *FA*Obsolescence* is the interaction between *First Antitakeover* and *Obsolescence* with obsolescence being the ω change in a firm's technological base. Change in Book Leverage is the difference between Book Leverage at time t and t – 1. All other variable definitions are presented in Table 2. All control variables are measured at time t – 1. Time and firm fixed effects are utilized in every model with standard errors clustered and reported in parenthesis. Significance levels of coefficient estimates are denoted by *, ** & *** representing the 10%, 5% and 1% confidence levels.

Table 14 summarizes the results from my difference-in-difference regression model which includes 3 separate antitakeover laws. I ran this model with time and firm fixed effects separately, as I did in Table 11, to further test the robustness of this model. As with Table 11, these results remain constant when controlling for time and firm fixed effects separately, indicating that the relationship between $Obsolescence^{\omega}_{f,t}$ in states that enacted antitakeover laws and leverage is not solely driven by time-invariant firm characteristics or by factors common to all firms across time.

Furthermore, these results are almost identical to those of Table 11 in Section 8, further indicating that the difference-in-difference model I used is robust and reliable. States which enacted antitakeover laws, did contribute to manager entrenchment, leading to more technological obsolescence and an ability to engage in market timing based on their asymmetric information.

10. Conclusion

In this thesis, I explore if firms utilize their level of technological obsolescence as a form of asymmetric information when determining their means of financing. Primarily, I determined that firms appear to time the market when choosing their means of financing based on their level of technological obsolescence, rather than attempting to achieve an optimal target debt-equity ratio. Furthermore, they prefer to finance with debt rather than equity in deeper states of obsolescence.

Certain conditions can encourage or inhibit firms from utilizing this form of asymmetric information. Primarily, oversight and the number of stakeholders can both act as deterrents for firms attempting to capitalize on their asymmetric advantage. The more oversight a firm has or the more stakeholders they have, the less likely managers are to be entrenched; thus, removing this agency problem where managers put their own interests ahead of the firm's.

Furthermore, policy changes can contribute to a firm's ability in capitalizing on their asymmetric information. Specifically, the introduction of antitakeover laws cultivated an environment which bred manager entrenchment. Managers, no longer fearful of takeover, are free to engage in value-destroying activities. Putting their own needs ahead of the firm's, contributes to their decision to time the market and prefer debt financing in states of obsolescence.

As a result, I found that firms do utilize their state of technological obsolescence as a type of asymmetric information when determining their preferred means of financing. Firms do engage in market timing if they lack oversight to negate this type of behaviour. Finally, this behaviour becomes more pronounced as managers become entrenched and the consequences of their value destroying choices are reduced.

Future researchers may be interested in considering how debt cycles could factor into this type of market timing as well. I found that obsolescence over a period of $\omega = 10$ is also significant within the models I used in my thesis. This may be caused by financing cycles, such as those explored by Geelen, Hajda, Morellec and Winegar (2022), where maturing debt must be replaced by new debt over these longer periods.

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Appendix.

Figure A1. Median Obsolescence

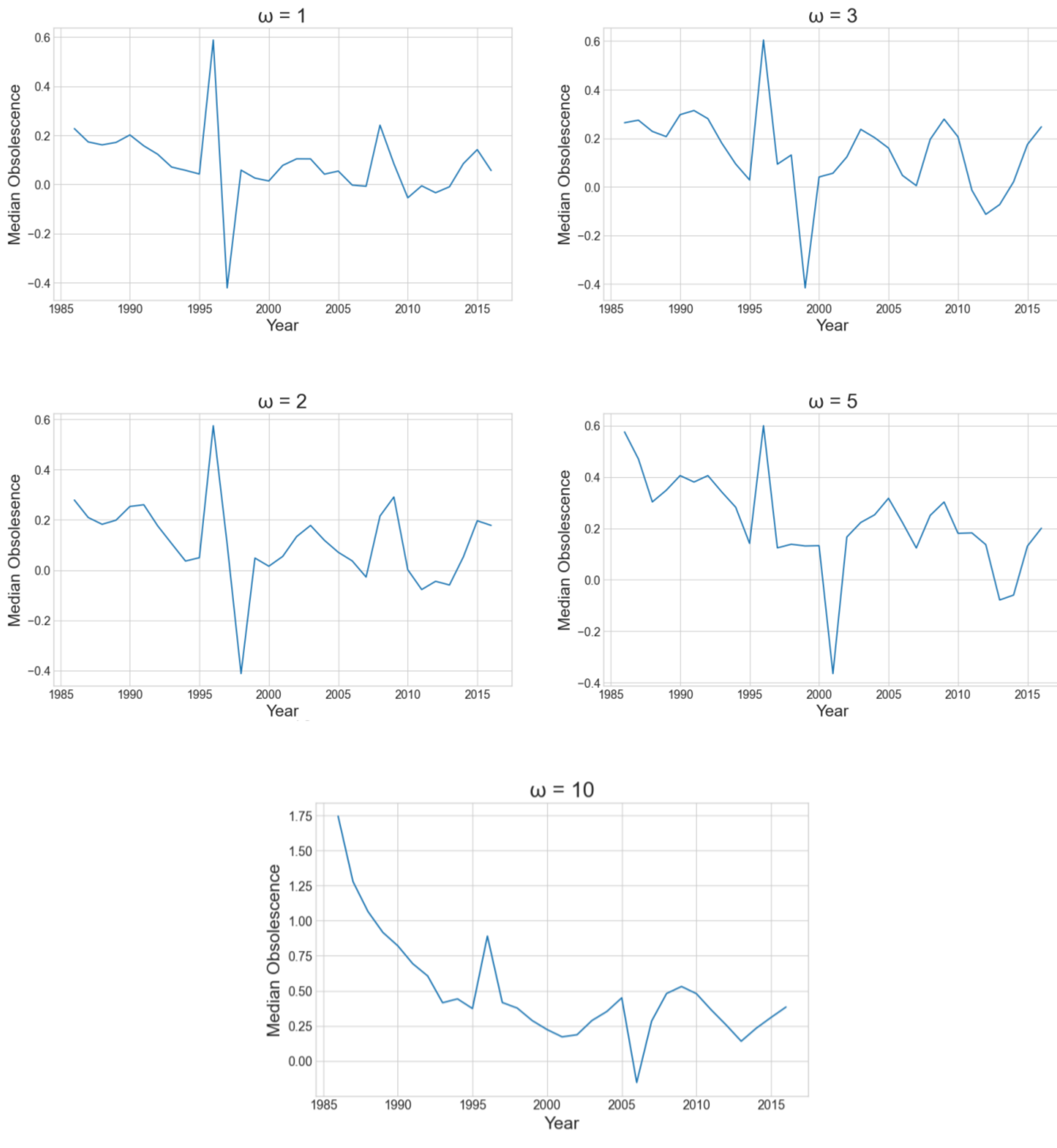

Figure A1. These figures plot the median obsolescence of sample firms over each year. Median is used to observe any potential trend the majority of firms experienced in a given year. Prior to plotting, all obsolescence observations are winsorized with respect to year at 1% and 99%

Figure A2. Median Firm Characteristics

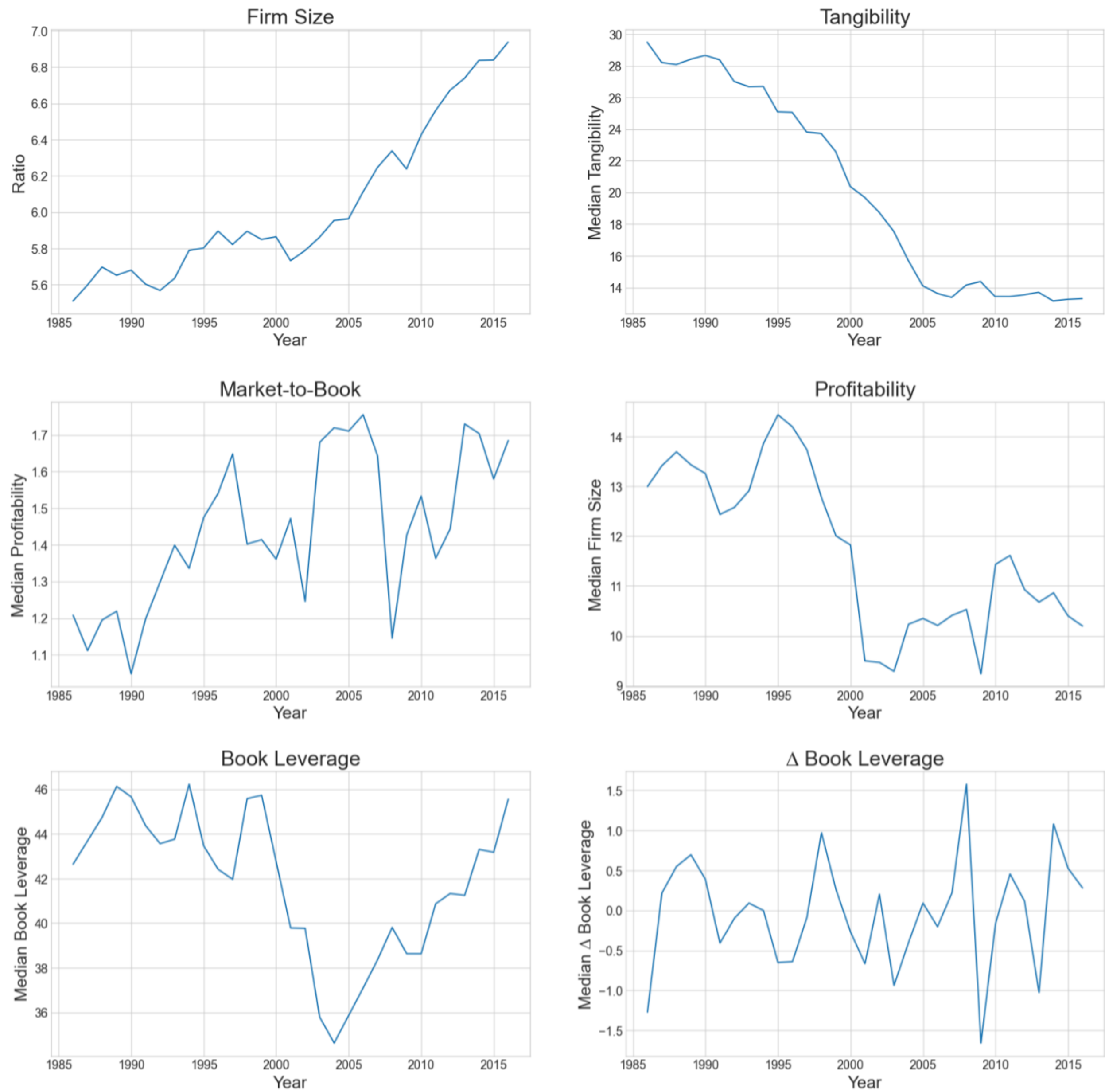

Figure A2. These figures plot the median value of firm characteristic variables per year. Media is used to observe any trend the majority of firms experienced in a given year. Prior to calculation and plotting, all Compustat variables are winsorized with respect to year at 1% and 99%.

Table A1. State Antitakeover Legislation

incorp	State	Year BC Passed	Year FP Passed	Year CSA Passed
AZ	Arizona	1987	1987	1987
CT	Connecticut	1989	1984	
DE	Delaware	1988		
GA	Georgia	1988	1985	
HI	Hawaii			1985
ID	Idaho	1988	1988	1988
IL	Illinois	1989	1984	
IN	Indiana	1986	1986	1986
KS	Kansas	1989	1989	1988
KY	Kentucky	1987	1989	
LA	Louisiana		1985	1987
ME	Maine	1988		
MD	Maryland	1989	1983	1988
MA	Massachusetts	1989		1987
MI	Michigan	1989	1985	1988
MN	Minnesota	1987		1984
MS	Mississippi		1985	1991
MO	Missouri	1986	1986	1984
NE	Nebraska	1988		1988
NV	Nevada	1991		1987
NJ	New Jersey	1986	1986	
NY	New York	1985	1985	
NC	North Carolina		1987	1987
OH	Ohio	1990	1990	
OK	Oklahoma	1991		1987
OR	Oregon			1987
PA	Pennsylvania	1989	1989	1989
RI	Rhode Island	1990		
SC	South Carolina	1988	1988	1988
SD	South Dakota	1990	1990	1990
TN	Tennessee	1988	1988	1988
UT	Utah			1987
VA	Virginia	1988	1985	1988
WA	Washington	1987	1990	
WI	Wisconsin	1987	1985	1991
WY	Wyoming	1989		1990

Table A2. Determinants of Annual Changes in Leverage

$$\left(\frac{D}{A}\right)_{f,t} - \left(\frac{D}{A}\right)_{f,t-1} = \alpha_1 + \beta_1\ Obsolescence^{\omega}_{f,t} + \gamma_1\left(\frac{M}{B}\right)_{f,t-1} + \gamma_2\left(\frac{PPE}{A}\right)_{f,t-1} + \gamma_3\left(\frac{\text{EBITDA}}{A}\right)_{f,t-1} + \gamma_4 \log(S)_{f,t-1} + \gamma_5\left(\frac{D}{A}\right)_{f,t-1}$$

$$+\gamma_6 u_t + \gamma_7 v_f + \varepsilon_{f,t}$$

Table A2. Change in Book Leverage (Δ(D/A)) %

Omega		Intercept		Obsolescence		Lag Market-to-Book		Lag Tangibility	
	Count	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*
Horizon ω = 1 (%)	28,742	13.898***	(13.299)	0.4247**	(2.5215)	-0.8723***	(-9.3213)	0.0334***	(3.3441)
		(0)		(0.0117)		(0)		(0.0008)	
Horizon ω = 2 (%)	28,746	13.7472***	(13.071)	0.3724**	(2.4024)	-0.8684***	(-9.2665)	0.0344***	(3.4396)
		(0)		0.0163		(0)		(0.0006)	
Horizon ω = 3 (%)	28,729	13.6234***	(12.8899)	0.0958	(0.6776)	-0.8575***	(-9.1136)	0.0349***	(3.4829)
		(0)		(0.4981)		(0)		(0.0005)	
Horizon ω = 5 (%)	28,762	13.9002***	(13.1322)	-0.0044	(-0.0352)	-0.8739***	(-9.2952)	0.0335***	(3.353)
		(0)		(0.9719)		(0)		(0.0008)	
Horizon ω = 10 (%)	18,465	15.0919***	(9.5509)	0.2324*	(1.7654)	-0.792***	(-5.7532)	0.0277**	(2.3174)
		(0)		(0.0775)		(0)		(0.0205)	

Table A2. *cont.* Change in Book Leverage (Δ(D/A)) %

Omega		Lag Profitability		Lag Size		Lag Book Leverage		*R-Squared*
	Count	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*	
Horizon ω = 1 (%)	28,742	-0.0827***	(-7.1855)	0.5677***	(3.4634)	0.3654***	(-46.842)	0.1791
		(0)		(0.0005)		(0)		
Horizon ω = 2 (%)	28,746	-0.0825***	(-7.1792)	0.5906***	(3.5984)	-0.366***	(-46.8091)	0.1789
		0		(0.0003)		(0)		
Horizon ω = 3 (%)	28,729	-0.0852***	(-7.367)	0.614***	(3.7305)	-0.3662***	(-46.8677)	0.179
		(0)		(0.0002)		(0)		
Horizon ω = 5 (%)	28,762	-0.083***	(-7.2142)	0.5886***	(3.5667)	-0.3675***	(-46.8918)	0.1797
		(0)		(0.0004)		(0)		
Horizon ω = 10 (%)	18,465	-0.0775***	(-4.6184)	0.355	(1.5032)	-0.3561***	(-36.176)	0.177
		(0)		(0.1328)		(0)		

Table A2. This table summarizes the regression results for Hypothesis 1. Obsolescence is the ω change in a firm's technological base. Market-to-book is Compustat Item 6 (Assets Total) minus Book Equity plus Market Equity all divided by Total Assets. Tangibility is Compustat item 8 (Plant, Property & Equipment) divided by Compustat item 6 (Assets Total). Profitability is Compustat item 13 (EBITDA) divided by Compustat item 6 (Assets Total). Firm size is the natural logarithm of Compustat item 12 (Sale). Book Leverage is Book Debt divided by Compustat item 6 (Assets Total). All control variables are measured at time $t - 1$. Observations where SICs are between 6000 – 6999, firm with less than 10 million in assets and firm-year observations where Market-to-Book are above 10 are omitted. Firm and time fixed effects are utilized. Significance levels of coefficient estimates are denoted by *, ** & *** representing the 10%, 5% and 1% confidence levels.

Table A3. Determinants of Leverage

$$\left(\frac{D}{A}\right)_{f,t} = \alpha_1 + \beta_1\left(\frac{\widehat{M}}{B}\right)_{f,t-1} + \beta_2\hat{e}_{f,t-1} + \gamma_1\left(\frac{PPE}{A}\right)_{f,t-1} + \gamma_2\left(\frac{\text{EBITDA}}{A}\right)_{f,t-1} + \gamma_3\log(S)_{f,t-1} + \gamma_5 u_t + \gamma_6 v_f + \varepsilon_{f,t}$$

Table A3. Book Leverage

Omega		Intercept		Predicted Market-to-Book		Residual Market-to-Book		Lag Tangibility	
	Count	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*	*b*	*t(b)*
Horizon ω = 1 (%)	28,742	35.8229***	(10.7274)	-4.2959***	(-2.5958)	-0.8065***	(-7.514)	0.0976***	(7.3504)
		(0)		(0.0094)		(0)		(0)	
Horizon ω = 2 (%)	28,746	34.5794***	(15.5297)	-3.6817***	(-3.7471)	-0.8038***	(-7.4981)	0.0982***	(7.3958)
		(0)		(0.0002)		(0)		(0)	
Horizon ω = 3 (%)	28,729	33.3096***	(15.7521)	-3.0418***	(-3.3463)	-0.7868***	(-7.3182)	0.0984***	(7.4067)
		(0)		(0.0008)		(0)		(0)	
Horizon ω = 5 (%)	28,762	31.8361***	(14.1488)	-2.2144**	(-2.221)	-0.8117***	(-7.5599)	0.0963***	(7.2342)
		(0)		(0.0264)		(0)		(0)	
Horizon ω = 10 (%)	18,465	41.2833***	(14.7558)	-4.4605***	(-3.801)	-0.6462***	(-4.2797)	0.0502***	(2.9575)
		(0)		(0.0001)		(0)		(0.0031)	

Table A3. *cont.* Book Leverage

Omega		Lag Profitability		Lag Size		*R-Squared*
	Count	*b*	*t(b)*	*b*	*t(b)*	
Horizon ω = 1 (%)	28,742	-0.2293***	(-18.1285)	2.3177***	(12.0081)	0.046
		(0)		(0)		
Horizon ω = 2 (%)	28,746	-0.2287***	(-18.1159)	2.329***	(12.0746)	0.0461
		(0)		(0)		
Horizon ω = 3 (%)	28,729	-0.2309***	(-18.2274)	2.3422***	(12.1437)	0.0465
		(0)		(0)		
Horizon ω = 5 (%)	28,762	-0.23***	(-18.1883)	2.3417***	(12.1041)	0.0462
		(0)		(0)		
Horizon ω = 10 (%)	18,465	-0.2322***	(-11.9891)	1.8134***	(6.5111)	0.0343
		(0)		(0)		

Table A3. This table summarizes the regression results for Hypothesis 1. Market-to-book is Compustat Item 6 (Assets Total) minus Book Equity plus Market Equity all divided by Total Assets. Market-to-Book is then divided into predicted and residual. Predicted Market-to-Book is the level of which Market-to-Book is predicted by obsolescence. Residual Market-to-book is the amount of Market-to-Book which is not explained by obsolescence. Tangibility is Compustat item 8 (Plant, Property & Equipment) divided by Compustat item 6 (Assets Total). Profitability is Compustat item 13 (EBITDA) divided by Compustat item 6 (Assets Total). Firm size is the natural logarithm of Compustat item 12 (Sale). Book Leverage is Book Debt divided by Compustat item 6 (Assets Total). All control variables are measured at time $t - 1$. Observations where SICs are between 6000 – 6999, firm with less than 10 million in assets and firm-year observations where Market-to-Book are above 10 are omitted. Firm and time fixed effects are utilized. Significance levels of coefficient estimates are denoted by *, ** & *** representing the 10%, 5% and 1% confidence levels.

Table A4. Horizons for the Determinants of Leverage

Table A4. Book Leverage

Omega	Predicted			*R-Squared*
	Count	*b*	*P-Value*	
Horizon ω = 1 (%)	28,742	-4.2959*** (1.6549)	0.0094	0.046
Horizon ω = 2 (%)	28,746	-3.6817*** (0.9825)	0.0002	0.0461
Horizon ω = 3 (%)	28,729	-3.0418*** (0.9090)	0.0008	0.0465
Horizon ω = 5 (%)	28,762	-2.2144** (0.9970)	0.0264	0.0462
Horizon ω = 10 (%)	18,465	-4.4605*** (1.1735)	0.0001	0.0343

Table A4. This table summarizes additional regression results for Hypothesis 1. Obsolescence is the ω change in a firm's technological base. All variable definitions are presented in Table 2. All control variables are measured at time $t-1$. Significance levels of coefficient estimates are denoted by *, ** & *** representing the 10%, 5% and 1% confidence levels.

Table A5. Median Firm-Year Analyst Coverage Observations

Date	Overall	Group 1 (Small)	Group 2 (Medium)	Group 3 (Large)
1986	2	1	6	2
1987	2	1	5.5	0
1988	1	0	5	6
1989	2	0	6	3.5
1990	1	0	6	3
1991	1	0	6	4
1992	1	0	6	4
1993	1	0	5	6
1994	1	0	4	7
1995	1	0	4	5
1996	2	0	4	8
1997	2	1	4	9
1998	2	0	4	9
1999	2	0	4	9
2000	2	0	4	8.5
2001	2	0	4	8
2002	2	0	3	7
2003	2	0	4	7
2004	2	0	4	7
2005	3	0	4	8
2006	3	0	5	8
2007	4	0	5	9
2008	4	0	5	9
2009	4	0	5	9
2010	4	0	5	10
2011	5	0	5	12
2012	5	0	5	13
2013	5	0	5	13
2014	5	0	5	13
2015	5	0	5	12
2016	6	0	5	12

Table A5. This table summarizes the median analyst coverage a firm receives per year. *Overall* is the median for the entire sample. *Group 1, 2 & 3* segments the observations into equal quantiles based on total assets in a given year.

Appendix. Key Variable Definitions

Variable	Definition
Technological Base	A *technological base* is the accumulation of all patents cited by firm *f*, but not belonging to firm *f*, up to year $t - \omega$. This is the collective knowledge a firm possesses and references to further their R&D.
Technological Obsolescence	*Technological obsolescence* is the metric used to define the academic relevance of a firm's *technological base*. It observes the change in number of citations, year over year, up to year $t - \omega$, for a firm's *technological base*. The equation is defined in the paper as equation (1).
Market-to-book	*Market-to-book* ratio compares a firm's market value of equity to its book value of equity. *Market-to-book* is calculated as Compustat Item 6 (Assets Total) minus *Book Equity* plus *Market Equity* all divided by Assets Total lagged at $t - 1$.
Tangibility	*Tangibility* ratio is used to measure the financial strength of a firm. *Tangibility* is calculated as Compustat item 8 (Plant, Property & Equipment) divided by Compustat item 6 (Assets Total) lagged at $t - 1$.
Profitability	*Profitability* ratio is the comparison of a firms profits to its assets. *Profitability* is calculated as Compustat item 13 (EBITDA) divided by Compustat item 6 (Assets Total) lagged at $t - 1$.
Size	*Size* is a measured used to reduce the large differences in size between firms to fall within a normal distribution. *Size* is calculated as the natural logarithm of Compustat item 12 (Sale) lagged at $t - 1$.
Book Leverage	*Book leverage* ratio is a firm's book value of debt compared to its book value of total assets. *Book leverage* is calculated as Book Debt divided by Compustat item 6 (Assets Total).
Change in Book Leverage	*Change in book leverage* is calculated as the difference in *book leverage* between year t and year $t - 1$.
Book Equity	*Book equity* calculates the theoretical amount of cash left in a firm if all assets were sold off and all liabilities were paid down. *Book equity* is calculated as the difference between Compustat item 6 (Assets Total) and the summation of Compustat item 18 (Total Liabilities) and Compustat item 35 (Deferred Taxes). The result is then added to Compustat item 35 (Deferred Taxes) and Compustat item 79 (Convertible debt). Any missing values of preferred stock are replaced by Compustat item 56 (Redemption Value of Preferred Stock).

Appendix. Key Variable Definitions

Variable	Definition
Market Equity	*Market Equity* (market capitalization) is the theoretical value of a company, based on the current market price and shares outstanding. *Market equity* is calculated and the product of Compustat item 25 (Common Shares Outstanding) and Compustat item 199 (Closing Fiscal Year Price)
Book Debt	*Book debt* is a firm's debt relative to its *book equity*. *Book debt* is calculated as Compustat item 6 (Assets Total) less *book equity*.
R&D	*R&D* stands for research and development. It is a cost associated with innovative businesses. Firm's undertake *R&D* costs in an attempt to bring innovative products to market and add value to their firm.
Instrumental Variable	*Instrumental variable* (IV) is a regression model used to address endogeneity in econometric models. An IV is utilized to deduce if the significance of an explanatory variable can be further explained by a third unrelated but correlated variable.
Analyst Coverage	Analyst coverage is determined as the amount of analyst following firm *f* in a given year *t*.
Alternative Market-to-Book	*Alternative Market-to-book* is variation of the market-to-book ratio as defined by Frank and Goyal (2009) calculated above and is used as means to test the robustness of my models. *Alternative market-to-book* is calculated as Compustat Item 199 (Price Close) multiplied by Compustat Item 54 (Shares Outstanding), plus Compustat Item 34 (Short-Term Debt), Compustat Item 9 (Long Term Debt) and Compustat Item 10 (Preferred Liquidation Value), minus Compustat Item 35 (Deferred Taxes and Investment Tax Credits), all divided by Compustat Item 6 (Assets Total).
Business Combination Laws	The *Business Combination Laws* metric is defined by a 1 or a 0. A value of 1 is given for all years preceding the passing of any *Business Combination Laws* in a state and a value of 0 is given for all other observations.
First Antitakeover Laws	The *First Antitakeover Laws* metric is defined by a 1 or a 0. It is the first iteration of any of the 3 main antitakeover laws, *Business Combination Laws, Fair Price Laws, and Control Share Acquisition Laws*. A value of 1 is given for all years preceding the passing of any of the *First Antitakeover Laws* in a state and a value of 0 is given for all other observations.