Take-over Threat and Innovation

The effect of Antitakeover Provisions on Innovative Behavior and Quality

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Abstract

This research investigated whether the presence of Anti-takeover Provisions ('ATPs') has a influence on a company's quality of its innovation output, as measured by patent citations. An extensive database of U.S. companies in both a post-merger wave and a pre-merger wave period (2001-2006) from CapitalIQ and ISS is used. The relevance of this research lies in the need to understand the design of incentives for fostering innovative behavior, which drive societal progress and economic development. Moreover, the existing literature does not provide a clear distinction between measures enforced by law and self-initiated ones, making it essential for this study to clarify this differentiation. In the first hypothesis, I examined whether the adoption of ATPs is associated with variations in R&D spending, aiming to shed light on whether companies, when protected from hostile takeovers, exhibit more or less aggressive investment strategies in innovation. My research found that ATPs were not significantly related with R&D expenses. This suggests that the extent of protection from takeovers does not significantly influence a company's approach to investing in innovation. The second hypothesis examined whether the perceived threat of takeovers fosters value-enhancing innovations, as indicated by patent citations, which showed that ATPs did not have a statistically significant relationship with patent citations. The third hypothesis aimed to test whether ATPs moderate the relationship between R&D investments and patent citations. The most comprehensive model showed that ATPs did not exhibit a significant moderating effect on this relationship. This suggests that the degree of protection from takeovers does not dampen the impact of R&D investments on the quality of innovations. These findings were consistent even when employing the Hirschmann-Herfindahl-Index as instrumental variable, through multiple transforming methodologies. The fourth hypothesis delved into the possibility of a non-monotonic relationship between ATPs and patent citations, particularly within companies with an High R&D strategy. This research did not identify such a non-monotonic relationship, aligning with the results of previous hypotheses.

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1. Introduction

Understanding the dynamics of modern management and its relationship with innovation is complex, involving an array of economic theories. Particularly, theories related to corporate governance and take-over threats are mainly discussed within this topic, introducing both opportunities and challenges for innovation. A considerable body of literature exists, with two main opposing perspectives: one suggesting that take-over threats increase innovation, while the other argues the contrary.

In the realm of innovation within firms, especially in the context of principal-agent relationships, the concept of Moral Hazard is deeply influential. Moral Hazard could arise when a manager, motivated by career-related worries, focuses mainly on short-return rather than investing in valuable long-term innovations. (Hermalin and Weisbach, 1991) This strategic approach could mostly manifest through shirking behavior, including empire building, entrenchment, and value-destructive mergers (Malmendier & Tate, 2008). Therefore, the looming threat of a takeover serves as a deterrent for Moral Hazard, guiding management to focus on the most innovative and valuable projects to preserve good performance (Shleifer and Vishny, 1989). This dynamic not only diminishes the probability of the manager facing job loss, but also discourages conduct that could potentially undermine the company's value. It thereby cultivates a context in which innovation can thrive.

Conversely, while the threat of a hostile takeover can stimulate innovation, it also generates an environment of uncertainty that may discourage innovation. Given the heightened power dynamics favoring shareholders, managers might adopt a defensive stance leading to a decrease in innovation (Zingales, 1998). In addition, the natural risk and uncertainty tied to putting money into new ideas might make managers think twice about starting such projects, because successor managers or acquirors could benefit from the long-term achievements of the predecessor's investments. Aghion and Tirole (1994) highlight this "free-ride" situation often resulting from hostile takeovers, where the new ownership benefits from the innovative groundwork laid by the existing management, gaining from their work without bearing the innovation risks and costs. This scenario is consistent with The Incomplete Contract Theory, which states the inherent impossibility of a comprehensive, all-encompassing contract (Hart and Moore, 1988). Thus, innovation exists within a complex matrix of factors that can both promote and hinder it.

The effect of takeover threats on innovation is also influenced by Asymmetric Information, where one party holds more or superior information than the other. In such situations, shareholders might undervalue long-term innovation (Myers and Majluf, 1984), resulting in less investment in innovation. This perspective could pose significant hurdles to organizations aiming to improve their innovative capabilities. The challenge here is to reduce this information asymmetry, paving the way for better communication and more informed decision-making. Nonetheless, this uncertain environment may deter managers from making necessary investments in innovative projects, further amplifying the challenges of fostering an innovative culture. Furthermore, a substantial body of literature also suggests that takeover threats could suppress innovation due to the diminished authority of incumbent managers and the tendency of shareholders to undervalue long-term innovation (Stein, 1988). These considerations lead to a complex and somewhat conflicting interplay between the economic theories of Moral Hazard, Asymmetric Information, Incomplete Contract Theory, and the issue of Takeover Threats.

While considerable research supports various viewpoints, my research takes a distinct path by examining the impact of self-imposed takeover barriers by companies, measured using the Bebchuk Cohen Ferell Index (BCF) (Bebchuck et al., 2009). Unlike existing literature, my focus shifts to internally driven solutions rather than externally imposed legislation, in the context of innovation success. This research aims to contribute to the academic dialogue by investigating these internal strategies and their influence on the value generated through innovations. Atanassov (2013) and Masulis et al. (2007) both investigate the impact of corporate governance mechanisms on firm behavior and performance, yet from different angles.

Atanassov's findings suggest a significant decline in the number of patents and citations per patent for firms in states that pass anti-takeover laws, indicating a negative effect on innovation. However, it remains unclear whether these observed effects are tied directly to the forced introduction of these laws, or the laws' inherent implications. As addition, Masulis revealed that firms with more self-implemented anti-takeover provisions experience significantly lower stock returns post-acquisition announcement, suggesting these provisions can enable detrimental managerial behavior. In this case it remains unclear whether this has some link with innovation tendency rather than overall management performance.

In my research, I examine whether self-implemented anti-takeover provisions (ATPs) have a different effect than state-enacted anti-takeover laws as Atanassov researched. The rationale behind this distinction is that shareholders may intentionally implement ATPs to protect the management in engaging in risky and uncertain investments. Crucial to note, is that I use BCF as definition of self-induced ATPs, since ATPs are not by definition provisions induced by corporate policy. Furthermore, while Masulis' work focuses on Cumulative Abnormal Returns (CARs), providing a general view of managerial performance, I am specifically interested in the success of investments in innovation. I aim to expand our understanding of how corporate governance mechanisms impact firms' innovative success, adding a new dimension to the existing literature.

My research will take several structured steps to answer my research questions. For this research, I will use an extensive dataset consisting of 78.332 observations, sourced from S&P's Compustat and Capital IQ, ISS Legacy Data on Corporate Governance, the National Bureau of Economic Research (NBER), and the Center for Research in Security Prices ('CRSP'). The study will cover a period when M&A activity was relatively low, so there was little economy-wide mispricing to assure exogeneity. The choice of this time period is guided by the findings by Betton et al. (2008), that implicate that 2001 till 2008 was a period of post-wave downturn in merger activity.

First, I will check if BCF is related to R&D expenditure, as a measure of innovation input, through an Ordinary Least Squares (OLS) regression extended with controls and exogeneity interventions. Then I will measure if BCF is related to Citations, as a measure of innovation output. I will account for Year-Fixed Effects, Industry Fixed Effects, and Firm Fixed Effects, isolating the effect of the variable of interest from any overall endogenous influences from the year and industry. Furthermore, I will also introduce the Herfindahl-Hirschman-Index as instrumental variable, to instrument BCF, to reach a greater salience in exogeneity. Then, I aim to determine whether the BCF index has a moderating effect of the effect R&D has on the quality of innovations, measured by the number of patent citations. This should indicate whether the level of takeover protection functions as moderator in the efficacy of R&D. Parallel to this step, At last, I will run a quantile regression of a dummy variable indicating being a High R&D expending company on Citations, to check for any non-monotonic relations.

The remainder of this research will be structured as follow. Section 2 will discuss all relevant literature and academic stances, structured per each hypothesis. Section 3 discusses the data and methodology, by looking into the sample, the models and exogeneity. Section 4 discusses the findings and discussion, structured per each hypothesis. In this section, the effect of our variables of interests, its robustness and its discussion and implications will get covered. Then in Section 5, the conclusion of the findings will get discussed with a general and holistic approach. At last in Section 6, the research implications and limitations will get discussed, in which I cover the pitfalls and avenues for further research.

2. Literature review and hypothesis development

2.1 Innovation input: background and theory

The incentives of management form a complex topic that influences various innovation decisions. As mentioned in the introduction, the literature mainly offers a central perspective on why takeover threat would influence management behavior, namely Principal-Agency Theory. In the Theoretical Framework of this research, we take a structured approach to understand the influence of takeover threats on management behavior. This framework is divided into four sections, each focusing on a specific hypothesis. In each section, we delve into the relevant academic theories, debates, and nuances associated with the specific hypothesis, to shed light on all perspectives. Building on that theoretical foundation, we then lead up to the formulation of each hypothesis at the end of the sections. In each section, we also briefly cover the interplay between all the hypotheses and the central theories.

The importance of takeover threats for companies' innovation behavior can be understood from different theoretical perspectives. Each of these theories provides valuable insights into the possible mechanisms that can play a role in this dynamic. According to Principal-Agency Theory (Jensen & Meckling, 1976), takeover threats can act as disciplining mechanisms that stimulate managers to increase the value of the company to prevent a takeover. This can urge them to focus on short-term results and cost-saving measures to increase cash flow, such as limiting investments in R&D (Jensen, 1986). However, this type of behavior can be counterproductive in the long run, as it can lead to a decrease in the company's innovation potential. An example of the manifestation of this phenomenon, is when Microsoft tried to take over Yahoo. Due to this unforeseen threat for hostile takeover, Yahoo had to quickly find instruments to become more valuable to shareholders. This might have made Yahoo focus more on short-term goals and immediate financial outcomes. As a result, they could have spent less time on long-term projects or research. Even though Microsoft's takeover did not occur, simply the threat of it led to detrimental changes within Yahoo, that affected their innovative behavior (Coffin, 2008).

Contrary to the Principal-Agency Theory, the Resource-Based View (Barney, 1991) states that companies can improve their competitive position by investing in unique and difficult-to-imitate resources, including innovation strategy. From this perspective, a takeover threat can motivate managers to invest in innovation to increase the long-term value of the company and prevent a takeover. An instrument to achieve this goal, is to maintain a superior position in R&D. Building on the Resource-Based View, it is emphasized that not all resources are equal. Some resources, such as patents and highly educated employees, can specifically contribute to a company's innovative capability (Teece, 1986). In the face of a takeover threat, managers may choose to protect and strengthen these "innovation-critical" resources. For instance, a company may invest in recruiting and training highly educated employees or initiate new R&D projects to expand its patent portfolio.

Similar to the Resource-Based view, is the Dynamic Capabilities View (Teece, Pisano, & Shuen, 1997) in which companies also proactively can respond to takeover threats by adapting their organizational routines and R&D regimes to foster the development and implementation of innovations. This can help them respond quickly to changing market conditions and new technologies, thus maintaining a lead on potential acquirers (Zahra, Sapienza, & Davidsson, 2006). This strategy can help reduce the attractiveness of the company for potential acquirers while simultaneously increasing the long-term value of the company (Somaya, 2003). However, a study by Czarnitzki and Kraft (2009) shows that this strategy carries risks, as innovation projects are often uncertain, and the outcomes are difficult to predict. This phenomenon relates to the well-known ideas around Game Theory in Corporate Finance. Game Theory (Dixit & Nalebuff, 2008) in this context, provides a framework for understanding the strategic interactions between a target company and potential acquirers. In this framework, innovation can be seen as a strategic move that can help influence the power balance between the target company and potential acquirers. For instance, by investing in a disruptive technology, the target company can strengthen its market position and discourage potential acquirers (Fudenberg & Tirole, 1985).

In the sum of these perspectives and theories, the complexity of the relationship between takeover threats and R&D investments is confirmed. Despite the challenges that takeover threats bring, they also offer opportunities for companies to reconsider and strengthen their innovation strategies and practices. Grasping this dynamic remains an important area for future research and can contribute to the development of more effective strategies for managing takeover threats and stimulating innovation.

Institutional Theory (DiMaggio & Powell, 1983) further proposes that the behavior of organizations is partly determined by institutional factors, such as regulation, norms, and cultural expectations. For instance, a strong norm for R&D expenditure in a certain industry or country can prompt managers to invest in innovation, even in the face of takeover threats. In this regard, a study by Filatotchev and Wright (2011) suggests that the impact of takeover threats on R&D can also be moderated by the corporate governance structure of the company. Moreover, the central paper by Atanassov (2013) suggests that the effect of takeover threats on innovation can vary depending on the type of takeover. Friendly takeovers, in which the existing management is likely to be retained, may be less disruptive to the company's innovation efforts than hostile takeovers.

Then, the Transaction Cost Economics perspective (Williamson, 1981) can help understand the trade-offs that managers must make between the costs of R&D and the potential benefits of preventing a takeover. From this perspective, a higher degree of takeover threat could lead to a greater willingness on the part of managers to invest in innovation, despite the high costs and risks associated with it. This somewhat is in line with the earlier mentioned literature. From the perspective of the Behavioural Theory of the Firm (Cyert & March, 1963), takeover threats can also influence decision-making processes within a company. This theory builds further on the previous covered idea of the short-term orientation of managers and the idea of shirking behavior. Again, managers may, for example, decide to become more conservative in their innovation decisions, focusing on incremental innovation instead of radical innovation, which can help increase short-term operational efficiency at the cost of the company's long-term growth and competitive position (Levinthal & March, 1993).

According to Cai et al. (2018) on the other hand, managers facing takeover threats are more likely to engage in risk-reducing strategies, such as reducing R&D expenditures and focusing on incremental innovations rather than radical breakthroughs. Their study suggests that the fear of losing control over the firm drives risk-averse behavior among managers, resulting in a decrease in innovative activities. Takeover threats can also impact the allocation of resources towards innovation within organizations. Managers may redirect resources away from innovation projects to enhance short-term financial performance and deter potential acquirers. In the following section, this topic will be covered more elaborately, however it is important to keep in mind that this resource diversion could limit the investment in research and development (R&D), leading to a decline in innovative activities. In addition, an empirical study by Agyei-Mensah and Gounopoulos (2019) found that firms facing higher takeover threats tend to decrease their R&D intensity, indicating a reduction in resource allocation towards innovation. The study suggests that the potential loss of control due to takeover threats motivates managers to prioritize defensive measures over long-term innovative investments. However, innovation can also be employed as a defensive strategy by target firms facing takeover threats. By actively pursuing innovative initiatives, firms may enhance their value proposition, making themselves less attractive to potential acquirers. This defensive use of innovation aims to increase the costs and risks associated with a potential takeover.

Lastly, as one might expect, corporate governance mechanisms play a crucial role in moderating the relationship between takeover threats and innovation. Effective governance mechanisms can influence managerial behavior and shape the firm's strategic direction towards innovation. An empirical study by Liu et al. (2021) examined the moderating effect of board independence on the relationship between takeover threats and innovation. They found that the presence of independent directors on the board strengthens the positive relationship between takeover threats and innovation. Independent directors can act as a counterbalance to managerial risk aversion, encouraging innovative activities and long-term value creation.

Given these theoretical perspectives, the relationship between takeover threats and R&D expenditure can be shaped by multiple factors, including the firm's strategic orientation, its resource capabilities, and the behaviors of its managers. From an Agency Theory perspective, a high number of ATPs might lead to less managerial assertiveness and reduce the motivation to invest in innovation. Conversely, from a Resource-Based or Dynamic Capabilities View, a high number of ATPs might give the firm board the security and stability to invest in long-term innovation. When we consider the established theories and the discussed literature, the Agency Theory is more prevalent. The number of ATPs a firm has can show how protected it is from takeovers. Many ATPs might mean the company feels secure from external threats, meaning that with many ATPs, managers might be less eager to invest heavily in innovation, meaning their R&D expenditure will decrease. This leads to the following hypothesis:

H_1: The number of ATPs is negatively related to the R&D expenditure.

2.2 Innovation output: background and theory

In this section, we will elaborate on the briefly mentioned relevant stances around how Principal-Agency concerns influence innovation output. On the one hand, takeover threats can spur management to better innovation performance. As Jensen and Ruback (1983) illustrate, the threat of a potential takeover mainly stimulates managers to focus on value-enhancing projects and avoid value-destroying actions. This increased focus on shareholders' interests urges managers towards value creation, although it can also lead to a defensive culture in which management focuses on surviving the takeover threat rather than promoting innovation and growth (Walsh and Ellwood, 1991). On the other hand, takeover threats can urge management towards short-term thinking, in which managers focus more on short-term results at the expense of long-term investments and innovation (Amihud & Lev, 1981). Harford (1999) underwrites this idea by showing that managers under the influence of strong takeover threats can be cautious with investments in long-term projects, including product R&D as well as process R&D. As already mentioned, takeover threats can also lead to defensive behavior in the form of value-lowering mergers and acquisitions to safeguard personal interests (Stein, 1988). The motives behind this behavior, relate to topics as entrenchment and empire building. However, they could be aware that a failed takeover can undermine their position and make it easier for potential acquirers to gain control of the company.

Moreover, the research of Cremers and Nair (2005) shows that managers under strong takeover threats can receive higher rewards, designed to stimulate them to increase the value of the company and resist takeover attempts. This increased compensation can lead to riskier behavior by managers, such as taking more aggressive strategic innovation decisions. Again, the psychological aspect of takeover threats is emphasized in both scenarios, whereby pressure on managers can affect their decision-making and performance, either causing them to exhibit riskier behavior or focus on risk-averse short-term decisions to protect their personal interests (Brockner et al., 1986, and Tosi et al., 2000). Moreover, these principal-agent problems inherently give rise to agent costs, which are often overlooked in the literature within this context. Namely, takeover threats can increase agency costs, as managers spend more time and resources protecting their position, instead of focusing on creating value for shareholders (Fama and Jensen, 1983). This can be considered as a form of the mentioned shirking behavior, which probably leads to suboptimal corporate performance and can also disrupt the corporate governance system, reducing the effectiveness of management oversight (Shleifer and Summers, 1988). A classic example of this behavior is the infamous 2001 AOL Time Warner merger. The merger, one of the largest in history, ended up decreasing value for shareholders. Some experts believe that the top executives pushed for the merger to boost their own reputation and power, even though it wasn't the best decision for the company's investors. In conclusion, within realm of the principal-agent perspective, many stances and perspectives can be taken.

Besides concerns that relate to the shareholders, takeover threats can also influence the management's position within the firm, and therefore can have another kind of impact on innovation choices. This other reasoning behind innovation behavior, relates to path-dependency concerns. Takeover threats can reduce management's willingness to pursue radical transformations in corporate operations because of inertia. This can lead to a more conservative corporate strategy focused on maintaining the status quo rather than pursuing disruptive innovations or market-disrupting strategies (Hitt et al., 1998). On the other hand, takeover threats can create opportunities for management to tackle inefficiencies to maximize the profitability of the company (Giroud & Mueller, 2010). Although this can lead to greater operational efficiency, it may possibly come at the expense of crucial investments in areas such as research and development or staff development. Furthermore, the corporate governance structure of the company plays a crucial role in determining management's response to takeover threats. When management's power in the boardroom is high, there may be a tendency to place personal interests above those of the shareholders, resulting in defensive tactics to protect the company against a potential takeover (Bebchuk et al., 2002). At the same time, there are ethical considerations connected to management behavior under takeover threats. Managers may be inclined to act opportunistically and misuse corporate resources for personal gain in the face of a takeover threat (Denis et al., 1997). The way managers respond to takeover threats can also affect the reputation of the company and the perception of the company by external stakeholders.

How all the mentioned factors play out in practice can vary greatly and depends on many factors, including the specific nature of the takeover threat, the individual characteristics of the board, and the context of the industry and the company. A wide range of academic research has shown that takeover threats can significantly impact the behavior of managers, with consequences that can turn out positively or negatively, depending on the context and specific circumstances. It is essential to understand this dynamic in order to assess the impact of takeover threats on the innovation behavior of management and to formulate effective policy in the area of corporate governance and innovation. Considering the dynamics of takeover threats and managerial behavior, the focus is naturally drawn towards how these factors might influence strategic firm decisions such as in which form investments to R&D are done, meaning that a fundamental aspect of innovation is the role of R&D. What is most prevalent in the discussed literature, like in the findings presented by Cohen and Levin (1989), is that companies with higher R&D expenditures tend to exhibit increased innovative outputs. This observation, paired with the notion that dedicated research efforts can lead to new findings, underlines the importance of R&D as a potential driver for innovation. Considering this positive connection between R&D and innovation we arrive at the following hypothesis:

H_2: R&D expenditure is positively related to the quality of the innovations.

2.3 ATLs vs ATPs: similarities and discrepancies

Antitakeover Provisions (ATPs) and Antitakeover Laws (ATLs) constitute fundamental components of contemporary corporate governance. Each of these mechanisms performs a crucial role in protecting companies from hostile takeovers. Yet, their nature and applications vary slightly, with ATPs embodied within a company's statutes or corporate policies and ATLs implemented through legislative measures at regional or national level. This distinction forms the backbone of their differences, a subject addressed in the critical studies by Atanassov and Giroud. ATPs represent defensive strategies incorporated into a company's policies or statutes. They employ various tactics such as poison pills, golden parachutes, and supermajority requirements. The aim of these provisions is to create a protective barrier that makes it difficult for potential acquirers to gain control over a company for strategy purposes (Comment & Schwert, 1995). As a result of this protective buffer, management can divert their focus towards long-term objectives and strategies, including innovations that carry inherent risks but can potentially lead to significant rewards. On the other end of the spectrum are ATLs, which constitute regulatory measures implemented at regional or national levels to restrict or discourage hostile takeovers. These laws could necessitate the approval of a majority of independent shareholders for a takeover or make it challenging for acquiring firms to obtain voting rights (Karpoff & Malatesta, 1989). However, these laws can be a double-edged sword. While they offer some degree of protection to the management, they also impose greater accountability on them, potentially limiting their strategic flexibility. This does not account in cases of ATPs, since the shareholders know that a specific kind of investment regime is part of the company's strategy. Hence, in a tightly regulated environment brought about by ATLs, managers might become more cautious, thus preventing them from undertaking large-scale, risky innovation efforts which might not align with the short-term shareholder interests (Bhagat & Bolton, 2008).

While both ATPs and ATLs aim to protect companies from hostile takeovers, their influences on managerial behaviors, particularly innovation behaviors, can be notably different. In industries where innovation is the driving force of competitive advantage, how ATPs and ATLs are interpreted and implemented can have significant implications on managers' innovation behavior (Atanassov, 2013). Past research offers deeper insights into these nuanced effects of ATPs on managerial innovation. Chen and Hsu (2009) propose that the implementation of ATPs opposed to ATLs provides managers with a heightened sense of confidence and autonomy, enabling them to prioritize long-term goals, such as innovation. The rationale behind this is that when managers feel secure from immediate threats of takeovers due to company policy, they become more inclined to invest in R&D projects that carry high risk but promise substantial rewards in the long run. However, this stance is nuanced by research conducted by Masulis et al. (2007), which indicates a potential decrease in a company's innovation efforts following the implementation of ATPs. Their study suggests that a secure environment, free from the threats of a takeover, may lower the motivation levels of managers to remain competitive and innovative, just in line with the theory described in previous sections. As a result, the sense of satisfaction created by ATPs could lead to reduced investment in innovation.

In conclusion, in the development of hypothesis 2, I coined the assumption that R&D input leads to better innovation output in terms of citations. The literature discusses that ATPs and ATLs are designed to shield companies from hostile takeovers, they can have vastly different effects on managerial behavior and innovation. These measures offer a protective buffer for management, the implementation and subsequent effects of these measures are subject to dichotomy. As Atanassov and Giroud concluded, that number of citations decrease after the implementation of ATLs, we are going to test whether this same effect will be observed when looking at ATPs as opposed to measures forced by legislation. The presence of ATPs, as coined multiple times, is expected to have a disciplining effect on managers to invest R&D in high-value projects. This leads to the idea that every dollar invested in R&D should be higher efficiency, given a certain degree of protection of hostile takeovers.

Meaning, R&D is expected to have a smaller positive effect on Citations when a company is protected better from hostile takeovers. Formally, this leads to the following hypotheses:

H_{3a}: The influence R&D has on Citations is moderated by the number of ATPs.

H_{3b}: The number of ATPs has a negative effect on Citations.

2.4 High R&D: non-monotonic relationship of ATP and innovation

The relationship between ATPs and the value creation or destruction in firms, particularly high R&D-spending ones, is complex and ambiguous. While the researchers mentioned in previous sections argue for a linear relationship, some studies on the field of innovations suggest a potential non-monotonic relationship between these variables. Building on the already covered theory of managerial entrenchment (Shleifer & Vishny, 1989), ATPs may provide managers with a buffer against external market pressures, thereby allowing for riskier, but potentially more innovative R&D projects. In the presence of a high number of ATPs, managers could leverage the greater strategic flexibility and security to pursue aggressive R&D strategies. This could lead to "high upside gain" creating significant value for the firm if these projects succeed (Aghion, Van Reenen, & Zingales, 2013). On the other hand, there is also the possibility of "high downside bad luck," as ATPs may face the mentioned moral hazard concerns (Coad et al., 2016). The protection provided by ATPs may lead to "managerial complacency", excessive risk-taking, or even value-destroying activities, a phenomenon often referred to as the "dark side" of ATPs (Bebchuk, Cohen, & Ferrell, 2009). The subsequent risk could potentially lead to substantial value destruction in firms that heavily invest in R&D but fail to generate successful innovations. For instance, BlackBerry is illustrative of this duality. In its earlier days around 2009, protected leadership and a high R&D strategy led BlackBerry to innovate in an aggressive manner, resulting in the highly successful BlackBerry smartphone. Yet, this same protection combined with a cut on R&D activities later seemed to foster lagging behind on innovation, leading to the downfall of the company mainly due to managerial entrenchment. This implicates that apart from the presence of ATPs, a high R&D strategy might also be of tremendous importance.

Again, the mentioned research also suggests that a high number of ATPs might not necessarily lead to more value destruction than a small number of ATPs. ATPs might not always lead to managerial entrenchment or excess risk-taking. Instead, they could also provide a necessary shield against short-term market pressures, thereby allowing firms to undertake long-term, uncertain but potentially high-value R&D projects (Bebchuk & Cohen, 2005). In the context of high R&D-spending companies, ATPs might serve as crucial mechanisms to protect knowledge and technologies from hostile acquisition (Comment & Schwert, 1995). This indicates that the relationship between ATPs and firm value in high R&D-spending companies could exhibit a non-monotonic relationship and the relationship between ATPs and value destruction may not be linear. This leads to the formulation of the following hypotheses.

H_4: A non-monotonic relationship of the presence of ATPs will be observed, when observing solely High R&D companies

3. Data and Methodology

3.1 Empirical context

In constructing the methodological foundation of this research, I place my study within a specific empirical context - firms in the United States that have been using ATPs during the years 2001 to 2006. The early 2000s, particularly 2001 to 2006, were a period characterized by significant macroeconomic changes, which basically was a decline following a merger wave. In this economic downturn, companies in the United States might engage in various strategies, including the adoption of ATPs, to protect their interests. The economic environment of this period is likely to minimize relative economy-wide mispricing, providing a clear view of the influence of ATPs on R&D. Focusing on this timeframe offers a more current understanding of the dynamics between ATPs and firm innovation in the wake of economic downturns. Furthermore, concentrating on the United States' context provides the research with a stable institutional environment characterized by reliable legal, regulatory, and cultural aspects (La Porta et al., 1998). This consistent background facilitates more accurate and comparable results across the examined firms. This research, through its findings, aims to contribute to this discourse and shed light on the interaction of ATPs, R&D expenditure and innovation quality in a complex and shifting economic landscape (Comment & Schwert, 1995).

The methodology and execution of the study went through several steps to ensure the validity and robustness of the findings. The testing of the Ordinary Least Squares (OLS) assumptions lays the foundation of each model. Parallel to the regular regression, we also execute research on the efficacy of an instrument through a Two-Staged Least Squares, and the presence of a non-monotonic relationship through a quantile OLS.

This paper goes through several steps. First, it tests whether the presence of ATPs influences R&D expenditure. In this case, R&D serves as the dependent variable and ATPs as the independent variable. Next, the focus shifts and the number of citations per patent becomes the dependent variable. In this second part, both R&D expenditure and ATPs act as independent variables. It's important to note that R&D expenditure gets different roles throughout this study, first being influenced by ATPs and subsequently influencing the quality of innovation.

3.2 Sample: panel data retrieval, cleaning and preparation

The study uses an array of data retrieved from three renowned databases: ISS Governance Legacy, Standard & Poor's Compustat/Capital IQ through Wharton Research Data Services (WRDS), and the National Bureau of Economic Research (NBER) Patent Data Project. ISS Governance Legacy provided comprehensive data on Anti-Takeover Provisions (ATPs), offering detailed dummy variables on whether a firm had a specific ATPs in place. This information is served to represent the firms' defensive mechanisms against potential takeovers, contributing to creating the study's primary independent variable regarding the ATPs. In the following section, I will elaborate on the construction of this variable.

Then, firm-specific accounting data were sourced from Compustat/Capital IQ via WRDS. These data covered an extensive range of financial fundamentals, providing data on the firms' financial positions and performance. The data from Compustat/Capital IQ were mainly used as control variables in the study, ensuring a more accurate analysis by accounting for various firm-specific factors that could potentially influence the exogeneity of the variables of interest. Lastly, the study utilized the NBER Patent Data Project for data regarding the number of citations each patent received. These citation counts served as a rough measure of the quality and impact of a firm's innovation, forming the study's main dependent variable of interest. By merging these distinct data by using the identifier of the Committee on Uniform Security Identification Procedures (Cusip) as identifier from the three databases, the study was able to construct a dataset that facilitated the research of the interplay between ATPs, R&D expenditure, and the quality of innovation.

3.3 Dependent variable measures

The study utilizes the absolute number of patent citations as a metric for innovation, drawing on the understanding that each citation represents degree of a patent's value and relevance. To quantify this, a panel data structure was adopted. Each firm, identified by a unique Cusip-code, was traced annually for the number of citations their patents received. This created a time-series perspective of each firm's innovative output, linking it with other key variables of the study like ATPs and R&D expenditure. The cross-sectional and temporal variations captured in this panel data provided a perspective on the innovation dynamics within firms over time, establishing an analysis of how the introduction of factors like ATPs and R&D expenditure interplay with the impact of innovation.

3.4 Independent variable measures

Having established the assumptions of the OLS model, the study proceeded to research the relationship between the number of ATPs and R&D expenditure. This investigation aimed to shed light on whether an increase in the threat of takeovers led to an increase in R&D spending. Regression analyses were conducted with the inclusion of control variables followed by the addition of year, industry and firm fixed effects to account for any unobserved heterogeneity. After a possible relationship between ATPs and R&D has been observed, the study examines the effect of R&D expenditure on patent citations, while taking ATPs as a moderating variable. This means that the relationship between R&D investment and the quality of innovation, reflected by patent citations, is evaluated in the moderating context of ATPs. In doing so, the analysis checks whether ATPs change the strength or direction of the effect of R&D on innovation.

Research & Development (R&D)
The R&D figures we use are the expenditures reported in the annual financial statements. To provide a more accurate relative picture, these R&D expenditures are scaled by Total Net Assets. This approach allows us to assess the intensity of a firm's investment in R&D in relation to its overall resource base, offering a more meaningful measure than absolute R&D expenditure figures would.

ATPs: BCF-index
In this research I utilize an index that includes the ATPS, to provide a clear insight of ATP levels. This methodology is a straightforward yet effective way of representing the complexity of ATPs in an easily understandable format. Given the absence of enough data on the Gompers, Ishii, Metrick-Index (GIM-index), the most detailed index which includes 24 ATPs, we're using the BCF Index instead. This method is shown just as effective by a 2007 study by Masulis. The BCF-index includes the following six ATPs: a 'poison pill' plan, a 'classified board', a 'golden parachute' deal, a supermajority rule, and limits to what shareholders can do by law and the company's own rules. The index simply contains a sum of the ATPs, with a minimum of 0 and maximum of 6. This implies that the presence of three ATPs, will result in a value of 3 of BCF. This approach provides an efficient way to measure ATPs aside of the scarce data on the GIM Index. A 'poison pill' plan is a strategy used to discourage hostile takeovers by making the company's stock less attractive. A 'classified board' places directors into different classes serving overlapping terms, making a full board takeover more difficult. A 'golden parachute' deal is a substantial financial compensation that executives are guaranteed in the event of a company takeover. A supermajority rule requires a high percentage of shareholders to approve significant changes, offering additional protection. Lastly, limits set by law and company rules define what shareholders can and cannot do, providing a structured environment for corporate decision-making.

3.5 Instrumental variable measure

Herfindahl-Hirschman Index (HHI)

The measurement of the Herfindahl-Hirschman Index (HHI), an instrument in the study, was performed in an elaborate manner using the revenue data of firms and their respective Standard Industrial Classification (SIC) codes. HHI is a widely accepted measure of market concentration, computed by squaring the market share of each firm in each market, and then summing up these squared market shares. For this study, we decided to use the firms' revenue figures to compute their respective market shares. Each firm's revenue was divided by the total revenue of its industry, classified by the SIC code, for each specific year.[1] This allowed us to obtain a yearly market share for each firm, accounting for any annual changes in the firms' market positions. To arrive at the HHI, these annual market shares were squared and then summed up within each industry, resulting in a yearly HHI for each industry, denoting the concentration of competition for that particular year.

In order to establish further robustness within our results, we conduct the research with multiple transformations. Apart from ensuring the normality of the instrument, we can also compare the performance of the instrument across transformations. In this research, I compare four types of transformations, with the logarithm of HHI as the main central transformation. Then I conduct a Box-Cox transformation. With this transformation, the variable gets transformed using the optimal theta (θ) of HHI, representing the power parameter that best normalizes the distribution of a variable.[2] Thirdly, the HHI is transformed using the cube root. Lastly, the HHI is transformed using the square root. By doing this, we can assess the performance of the instrument in a more diligent manner.

3.6 Control variables measure

The control variables mainly capture characteristics unique to each firm that could potentially influence the dependent variables but are not the primary focus of this study. They help to control for the inherent heterogeneity among firms, which, if unaccounted for, could bias the estimation results. The second set represents several fixed effects, which were incorporated into the model to account for unobserved factors that are constant over time but could vary across firms or industries. These fixed effects could represent time-invariant factors such as corporate culture, managerial skills, or industry characteristics that are not explicitly measured by the available variables in the dataset. These fixed effects will be measured in a context of year, industry and firm. The use of fixed effects can help to control for omitted variable bias, as it accounts for the time-invariant unobserved individual heterogeneity. However, it's important to note that while fixed effects can control for time-invariant unobserved heterogeneity, they cannot control for unobserved factors that change over time. Therefore, the interpretation of the results should take this limitation into consideration.

Firm Size

The size of a firm often has significant implications for its innovative capacity. Larger firms generally have access to more substantial resources, including human capital and finances, which they can leverage to drive innovation. At the same time, larger firms may also be more bureaucratic with slower decision-making processes, which could hamper innovation. Therefore, by controlling for Firm Size, this study can distinguish the effect of the firm's scale on its innovation output from the impact of hostile takeovers. Controlling for Firm Size allows this study to disentangle the influence of company scale on innovation output from the impact of hostile takeovers, as larger firms possess greater resources for innovation while potentially facing slower decision-making processes (O'Donell et al., 2001). At last to establish normality, the Firm Size will be transformed by using the logarithm of it. This will be further specified in the model building section.

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[1] $\mathbf{HHI} = \sum_{i_1}^{i_n} \left(\frac{\mathbf{Revenue_i}}{\mathbf{Revenue_{total}}}\right)^2$

[2] **The optimal θ is found at -0.115. The HHI then got transformed through:** $\mathrm{Bc(HHI)} = \frac{(\mathrm{HHI}^{\theta} - 1)}{\theta}$

Capital Expenditure (CapEx)
CapEx is a key indicator of a company's investment in its future growth and development. Higher levels of CapEx can signal a firm's commitment to improving and expanding its operations, which could indirectly spur innovation. However, elevated CapEx might also imply a focus on tangible asset acquisition rather than intangible innovative efforts. Including CapEx as a control variable allows the model to account for these investment dynamics when examining the relationship between hostile takeovers and innovation. Again to establish normality, CapEx will be transformed by using the logarithm of it. This will be further specified in the model building section.

Sales
Sales performance can reflect a firm's market success and could be associated with its innovative prowess. High sales might be the result of successful innovative products, and increased revenue from sales can provide more resources for further innovation. Therefore, Sales is an important control variable as it helps account for the effects of a firm's commercial success on its innovation capacity. Again to establish normality, Sales will be transformed by using the logarithm of it. This will be further specified in the model building section.

Leverage
The degree of leverage a firm has - that is, the extent to which it relies on debt financing - could significantly influence its propensity to innovate. High levels of leverage could create financial stress, constraining a firm's ability to allocate resources to innovative activities. At the same time, leverage could stimulate innovation if the borrowed capital is used to finance R&D activities. By controlling for Leverage, the analysis can distinguish these financial dynamics from the impacts of hostile takeovers. High leverage might limit a firm's financial flexibility, constraining its innovation efforts, while low leverage could provide more resources for innovation. Thus, by incorporating Leverage as a control variable, this study can separate the potential influence of debt on innovation outcomes from the effects of hostile takeovers (Cassar, 2004). Again to establish normality, the Leverage will be transformed by using the logarithm of it. This will be further specified in the model building section.

Year fixed effects
Year fixed effects are included to control for any global shocks or trends that could impact all firms in our sample within a given year. These effects are based on the calendar year. This method helps to control for year-specific events or trends, like changes in economic conditions, legislation or global events, which might affect the firms' performance.

Industry fixed effects
Industry fixed effects, categorized by the Standard Industrial Classification (SIC) codes, are used to capture any unobserved industry characteristics that may impact the firms within that industry. By controlling for these effects, I account for any industry-wide shocks that might affect all firms in a specific industry but not firms in other industries.

By integrating these control variables and fixed effects, this study aims to provide a nuanced understanding of the impact of hostile takeovers on innovation. Each variable accounts for a different aspect of a firm's operational, financial, and strategic profile, thereby helping to isolate the specific effect of hostile takeovers on a firm's innovative output.

3.7 Descriptive Statistics

In examining data from two distinct periods, Panel A (2001-2006) and Panel B (1996-2001), we can identify nuanced shifts in market behavior. Observing R&D spending, Panel A has an average spend of 0.28 with a standard deviation of 6.02, indicating more entities invested as time progressed, although with greater variability. The average spends of 0.28 might be considered substantial in certain industries but negligible in others like pharmaceuticals or technology where R&D costs are typically high. (OECD, 2023)

In comparison, Panel B's average is slightly conservative at 0.17, with a reduced standard deviation of 2.03, suggesting that entities were either more uniform or cautious in their investments during this period. BCF values offer stability across the two timelines, with averages of 1.37 in Panel A and 1.33 in Panel B, both showcasing a moderate spread around these averages. Noteworthy is that BCF is in both panels rather low, indicating that the implementation of a high number of ATPs is quite uncommon. The HHI, an indicator of market concentration, presents quite usual insights. Panel A's average HHI stands at 460.92 with some outliers reaching 6037, suggesting a moderately concentrated market on average. A figure of 460.92 might mirror industries like the airline sector, which tends to have a higher concentration. In contrast, Panel B's average of 380.52, though lower, with some extreme but realistic values up to 10,000. This points to the occasional presence of some monopolistic markets.

When it comes to the size of entities in terms of thousands of employees, Panel A's average size of 7.61, supported by a standard deviation of 35.95, indicates larger entities this Panel. Panel B's entities, with an average size of 6.42, are relatively smaller.

CapEx reveal a trend of increased spending in Panel A with an average of 144.57, compared to Panel B's 115.08. The presence of negative values in both datasets hints at similar accounting practices or business activities that require adjustments in expenditures. Sales in Panel A outpace those in Panel B, averaging 1997.07 and 1308.85, respectively. The higher variation in Panel A's sales, demonstrated by its standard deviation, implies diverse revenue streams among entities.

Panel A's average leverage of 1979.19 surpasses Panel B's 1070.52. High values, especially the staggering 961732 in Panel A, suggest that certain entities might be adopting aggressive financial strategies, which could be characteristic of industries where high leverage is normative, such as real estate. Despite Panel B being from an older timeframe, its average citation count of 161.38 exceeds Panel A's 129.17, hinting at possibly more influential entities in the earlier period.

Table 1: Descriptive statistics across the Panels
This table provides detailed statistics on various firm attributes, including Year, Research and Development (RD), BCF, Herfindahl-Hirschman Index (HHI), Size, Capital Expenditure (CapEx), Sales, Leverage, and Citations. Panel A captures data from 2001 to 2006 with 70,741 observations, while Panel B encompasses the years 1996 to 2001 with 78,332 observations. Each metric is described with its mean, standard deviation, minimum, and maximum values.

	Mean	Sd	Min	max
Panel A				
Year	2003.46	1.71	2001	2006
RD	0.28	6.02	0	648
BCF	1.37	0.98	0	6
HHI	460.92	1382.01	4	6037
Size	7.61	35.95	0	2545
CapEx	144.57	868.14	-994	40595
Sales	1997.07	9752.85	-204	345977
Leverage	1979.19	21411.38	0	961732
Citations	129.17	557.17	0	11738
Observations	70741			
Panel B				
	Mean	Sd	Min	max
Year	1998.47	1.69	1996	2001
RD	0.17	2.03	0	270
BCF	1.33	0.97	0	6
HHI	380.52	1197.12	4	10000
Size	6.42	28.66	0	1383
CapEx	115.08	745.07	-994	33143
Sales	1308.85	6303.81	-204	218529
Leverage	1070.52	10981.22	-166	763467
Citations	161.38	599.23	0	9305
Observations	78332			

3.8 Building the Models

To ensure the validity of the regression analyses and the quality of the conclusions drawn from it, several key assumptions need to be verified: Hausman, linearity, homoscedasticity, absence of multicollinearity, and normality. A violation of these assumptions can bias the results or undermine the statistical power of the analysis.

Fixed Effects versus Random Effects

In the realm of panel data analysis, determining the appropriate model – whether Fixed Effects (FE) or Random Effects (RE) – is of great importance. The Hausman test serves as a diagnostic tool in this decision-making process, comparing the estimators from both models. If there is no systematic difference in these coefficients, the Random Effects model is favored. Conversely, if a discrepancy arises, the Fixed Effects model is preferred.

In panel data analysis, Fixed Effects (FE) models capture changes within entities over time, eliminating entity-specific patterns. This reduces the concern of autocorrelation. However, addressing issues like heteroscedasticity or endogeneity is essential. We use robust standard errors and the Hausman test to strengthen our analysis.

Choosing between Fixed Effects (FE) and Random Effects (RE) models in panel data analysis depends on your data's nature. FE models consider unobserved, constant traits specific to each unit that can affect the outcome. These unobserved traits are believed to be linked with the predictors. FE models focus on changes within each unit over time. Conversely, RE models treat these unobserved traits as random and unlinked to the predictors. RE models use both changes within and differences between units. The critical difference between the models is their assumptions about these unobserved traits. The Hausman test guides the choice between FE and RE models. It checks if the unique errors are unrelated to the predictors, a necessary assumption for the RE model. If this is not the case, the FE model is more suitable. Otherwise, the RE model can be used. Both models were tested in this research to confirm the consistency of the results.

Referring to Tabel 3, the p-values from the Hausman test for each hypothesis offer critical insights: For H1, with a p-value of 0.000, there's evidence of a significant difference between the FE and RE estimators. This prompts the recommendation to adopt the Fixed Effects model for H1, ensuring that the analysis remains free from potential biases inherent in the RE model. Similarly, H2 presents a p-value of 0.0038, again below the conventional 0.05 threshold, reinforcing the preference for the Fixed Effects model. This underscores the presence of individual-specific effects that are correlated with the predictors. Contrastingly, H3, bearing a p-value of 0.089, doesn't suggest a significant divergence between the FE and RE models. This predicts usefulness of the Random Effects model, leveraging its efficiency, with little concern about biases. Taken together, these findings underscore the nuanced nature of model selection in panel data regression. While the Fixed Effects model appears to be more fitting for H1 and H2, H3 benefits from the application of the Random Effects approach. This distinction ensures that the selected model aligns closely with the underlying data structure, bolstering the robustness and credibility of the ensuing results.

Linearity

The essence of regression analysis lies in representing the relationships between variables, since the relationship between predictor and response variables is not always linear. This non-linearity can be nuanced and may involve curved patterns which are essential to capture for a precise representation. In the model provided below, polynomial terms are incorporated to address such potential non-linearity. Incorporating these squared terms, is an attempt to check whether there is a linear or curved relationship between Citations and BCF. While denotes the intercept, the coefficients and represent the linear, quadratic, and cubic terms of BCF, respectively. Their significance will provide insight into how Citations and BCF interact. Additionally, the model includes the control variables to assure. The error term captures unobserved effects. Once the model is implemented, the significance of these polynomial terms becomes central. If they prove significant, it indicates a non-linear relationship between 'Citations' and 'BCF', suggesting that the polynomial regression is more appropriate than a linear model. Ultimately, the choice to include polynomial terms ensures a comprehensive understanding of the data, offering robust insights that are grounded in the observed data patterns. When running this regression, we observe that our second (**β_2**) and third (**β_3**) estimator respectively get p-values of **0.12** and **0.11**, whilst our first estimator (**β_1**) is significant with a p-value of **0.09**. [3] A possible quadratic and cubic relation is absent, indicating that the linearity assumption is not violated.

Multicollinearity

To rule out multicollinearity, the correlation matrix was examined. Multicollinearity occurs when independent variables in a regression model are correlated. Correlation matrices provide a simple but subjective way to identify if such a relationship exists between the variables.

Using Cohen's h (Cohen, 1988) as thresholds, we check whether multicollinearity exists within our datasets. Cohen's thresholds imply the following; 0.2 as small correlation, 0.5 as medium, and 0.8 as large. When observing our variables of interest, R&D, Citations and BCF, we only observe correlations smaller than 0.2 in both Panels. This implies that multicollinearity is probably not existent. We only observe medium and high correlations within the control variables, which could be explained with intuition. As more sizable firms typically have higher CapEx and greater sales, we are not concerned with unexplained correlations that could infer with the reliability of the results.

[3] **$\text{Citations} = \alpha + \beta_1 BCF + \beta_2 BCF^2 + \beta_3 BCF^3 + \gamma_{t-1} + \delta_{j-1} + \varepsilon_{it}$**

Table 2: Correlation Matrices across the Panels
This table displays the Pearson correlation coefficients between various financial and operational variables for two distinct periods. Panel A represents the correlations for the period 2001-2006, while Panel B covers the years 1996-2001. A coefficient of 1.00 along the diagonal signifies a perfect correlation of a variable with itself.

			Panel A				
	Citations b	RD b	BCF b	Size b	CapEx b	Sales b	Leverage b
Citations	1.00						
RD	0.01	1.00					
BCF	-0.16	-0.08	1.00				
Size	0.49	-0.01	-0.03	1.00			
CapEx	0.54	-0.01	-0.05	0.50	1.00		
Sales	0.53	-0.01	-0.09	0.72	0.71	1.00	
Leverage	0.22	-0.01	-0.08	0.28	0.35	0.45	1.00
			Panel B				
	Citations B	RD b	BCF b	Size b	CapEx b	Sales b	Leverage b
Citations	1.00						
RD	0.04	1.00					
BCF	-0.17	-0.03	1.00				
Size	0.49	-0.01	-0.08	1.00			
CapEx	0.36	-0.01	-0.08	0.48	1.00		
Sales	0.42	-0.01	-0.11	0.65	0.75	1.00	
Leverage	0.12	-0.00	-0.07	0.21	0.28	0.41	1.00

Normality

To ensure the validity of the regression analysis, it's essential to satisfy the assumption of normality. This implies that the residuals of the model should be normally distributed. In the pursuit of achieving this normality, I initially applied a 95% winsorization to the data to manage extreme values. Following this, I log-transformed all the independent variables. Log transformations are a standard method to address skewness and bring variables closer to a normal distribution. To further assess and validate the normal distribution of these transformed variables, I employed the Shapiro-Wilk test, widely recognized for its power in detecting deviations from normality.

As per the findings outlined in Table 3, the p-values for H1, H2, and H3 are 0.09028, 0.065, and 0.089 respectively. For H1, with a p-value of 0.09028, the data's distribution does provide sufficient evidence to assume normality. Thus, the underlying data for H1 can be treated as normally distributed. The distribution of data underpinning H2, having a p-value of 0.065, shows again consistency with normality. Lastly, for H3, the recorded p-value of 0.089 again shows consistency with normality. In sum, the Shapiro-Wilk test outcomes for all hypotheses, as presented in Table 3, confirm that the Normality assumption is not violated.

Table 3: P-values from Model Robustness Tests for Hypotheses 1 to 3 testing the most extensive model
This table presents the p-values resulting from the application of the Shapiro-Wilk, Hausman, and Wald tests for each of the three main research hypotheses. This table only considers Panel A. The Shapiro-Wilk test assesses the normality of data distributions, the Hausman test evaluates the consistency of estimator preferences between fixed and random effects, and the Wald test determines the joint significance of coefficients. P-values close to 0.000 suggest a high statistical significance, indicating the rejection of the null hypothesis for the respective test.

	Shapiro Wilk	**Hausman**	**Wald**
H_1	0.09028	0.000	0.000
H_2	0.065	0.0038	0.000
H_3	0.089	0.089	0.000

Homoscedasticity

Next, the assumption of homoscedasticity suggests that the variance of the errors is constant across all levels of the independent variables. To examine this, the White test was employed, which is a statistical test that establishes whether the variance of the errors in a regression model is constant. In addition, scatter plots were used to provide a visual inspection of the data, helping to identify outliers and patterns that might suggest heteroscedasticity. The results from the Wald test, as presented in Tabel 3, shows p-values of 0.000 for H1, H2, and H3. This signifies the importance of our chosen variables in predicting the outcome. Such significance, however, might also hint at heteroscedasticity in the data. Heteroscedasticity means that the variability of the errors differs across levels of the independent variables. If present, it can inflate the standard error of the coefficients, leading to unreliable and inconsistent estimations.

To combat this potential issue, I've opted to use robust standard errors in all models. Robust standard errors adjust for heteroscedasticity, making them a fitting choice for ensuring that the statistical inferences drawn from the models remain trustworthy and consistent. Therefore, while the variables are impactful, measures have been taken to ensure that potential heteroscedasticity doesn't compromise the integrity of the models.

Exogeneity

Several strategies have been implemented in my research to enhance exogeneity and reduce the likelihood of endogeneity. By incorporating commonly used control variables, I have aimed to isolate the effect of the independent variable on the dependent variable, thus mitigating the impact of potential confounding factors. Furthermore, I have applied the method of lagging these control variables by one time period. This idea, prevalent in panel data regressions, is instrumental in tackling endogeneity issues such as reverse causality and simultaneity bias, where the dependent variable could potentially impact the independent variable. The underlying assumption is that past values cannot be influenced by future or current error terms, therefore further establishing the exogeneity in the model.

Additionally, I have introduced fixed effects for year, industry, and firm in the model. As explained earlier, it controls for unobserved, time-invariant characteristics unique to each firm that could potentially bias the estimates. Secondly, it also accounts for common shocks experienced by firms within the same industry or in the same year, which could cause fluctuations in the dependent variable unrelated to the primary independent variable. By using these fixed effects, I am able to control for these factors, thus ensuring a more accurate measure of the causal effect of the primary independent variable.

In this context, the Herfindahl-Hirschman Index (HHI) emerges as a relevant IV. The HHI is a well-established measure of market concentration and competition within industries. It is calculated as the sum of squared market shares of firms within an industry, with a range from 0 (perfect competition) to 1 (monopoly). The HHI is theoretically unrelated to the adoption of ATPs by firms, making it a potentially exogenous instrument for studying the effects of ATPs. Consequently, the HHI is a suitable candidate for addressing endogeneity in the context of ATPs and firm outcomes.

The choice of HHI as an instrumental variable aligns with broader academic discourse. Building upon the work of Rhoades (1993), the HHI, as an indicator of market concentration, suggests that an increase in HHI (indicating heightened market concentration) results in a reduction in the number of competitors. Stigler (1964) further theorizes that in highly concentrated markets, where competition is scarce, dominant firms may perceive little need to fortify themselves with defensive measures against potential hostile takeovers. The rationale is straightforward: with fewer competitors possessing the means or motivation to execute such takeovers, the incentive to implement ATPs diminishes. Williamson (1975) echoes this perspective, implying that in such markets, firms may be less inclined to adopt ATPs. This hypothesis underscores the instrumental relevance of HHI when studying anti-takeover provisions. When looking at literature we see that Alexander and Cunningham (2004) for instance use the HHI as instrumental variable for market diversity. We could roughly state that market diversity relates to competitiveness. Diverse markets face less collusion and less spill-over, indicating a more aggressive climate of competition.

This reduction in competitors is theorized to make hostile takeovers more challenging for firms (Stigler, 1964). In a highly concentrated market, dominant firms may perceive it as less necessary to adopt defensive measures against potential hostile takeovers, given the scarcity of competitors with the requisite resources or motivations to execute such takeovers (Williamson, 1975). The HHI should be theoretically related to the adoption of ATPs. While ATPs are designed to thwart hostile takeovers, the decision to implement them should not be directly related to market concentration. Empirical evidence supports this assumption, as studies have shown that ATP adoption is primarily driven by managerial entrenchment motivations (Bebchuk, Cohen, & Ferrell, 2009). Consequently, one could infer that firms in such markets might exhibit fewer anti-takeover provisions, highlighting the significance of HHI as an instrumental variable for anti-takeover provisions. Furthermore, for the HHI to qualify as a valid instrumental variable, it must be exogenous to the outcome variable, in this case, Citations. Schumpeter (1942) argues that market structure, specifically concentration, can influence innovation. Larger firms in concentrated markets, owing to their economies of scale and scope, might possess an advantage in innovation over their smaller counterparts.

Conversely, Schumpeter also debates that apart from this ''Schumpeterian innovation", there also might be this "escape competition" or ''quite life" effect. These theorize that high competition could help innovation, because of this idea that survival in the market would not be possible otherwise.

The dichotomy and contradictions around this theory, will be the foundation of the idea that HHI is unrelated to ATPs. The HHI should be exogenous to the error term in the equation modeling the impact of ATPs on firm outcomes. This condition ensures that the HHI is not correlated with unobservable factors that might bias the estimates. Within the sample data, empirical tests have demonstrated the exogeneity of the HHI. Specifically, it was found that HHI has an insignificant effect on patent citations, indicating that HHI does not influence the quality of innovations. However, a significant effect of HHI on ATPs was observed in the model with the most controls, reinforcing the HHI's role as a valid instrument.

In conclusion, the HHI serves as a suitable exogenous instrumental variable for studying the impact of ATPs on various firm outcomes. Its relevance, exogeneity, and empirical validity within the sample data establish it as a robust tool for addressing the endogeneity problem associated with ATPs. Consequently, employing the HHI as an instrument in the 2SLS estimation method enables researchers to obtain unbiased estimates of the causal effect of ATPs on corporate behavior and outcomes.

Then, to ensure robustness of the results, a temporal adjustment is made. Specifically, it allows the examination of whether the findings hold both in periods characterized by high merger activity and potential mispricing (2001-2006) and in periods with relatively lower levels of these activities (1996-2001). This robustness check therefore tests the stability of the results across different market conditions and periods, contributing to the generalizability of the findings.

Overall, these measures represent an attempt to establish a more robust causal link by eliminating endogeneity, thereby refining the precision and reliability of the model's estimates.

4. Findings & Discussion

4.1 Hypothesis 1

After the Models are built and showed robustness, I run the first OLS regression. Included in the most elaborate model are the independent variables R&D, BCF, Xit – a lagged vector for all control variables –, γt – lagged time-fixed effects –, δj – lagged industry-fixed effects –, and the error term εit. The independent variables are measured for each company i, proxied as Cusip, and for each calendar year t.

To test the relation between BCF and R&D, we run the regression as displayed in the equation below. The coefficient β1 measures the effect of the **BCF** variable on **Citations**, while β_2 represents the effect of $\mathbf{X_{it}}$. The coefficient α represents the intercept of the regression equation.

$$\mathbf{R\&D = \alpha + \beta_1 BCF + \beta_2 X_{it-1} + \gamma_{t-1} + \delta_{j-1} + \varepsilon_{it}}$$

Controls

In examining the relationship between BCF on R&D four distinct models were analyzed. The four models and the regression results are displayed in Table 4. These models each differ in the degree of controlling, starting with the first controls in the second model. The controls mostly showed somehow a negative effect, including a highly significant negative effect of company size, with a coefficient of -0.23. Furthermore, CapEx was highly significantly positively linked to an increase in R&D, with a positive coefficient of 0.06, significant at 1%. On the other hand, Sales showed a negative effect on R&D, with a coefficient of -0.12 significant at 5% level. These effects, including their significance, remained rather the same in the fourth model, when also controlling for Industry, Year and Firm Fixed Effects. Contrasting in the third model, Industry Fixed effects were integrated along with the Year fixed effects. The inclusion of the Industry Fixed effects led to establishment of significance to our control variables. As could be seen in this model, the effect of leverage seemed to evolve in this model, showing a slight negative trend significant at the 10% level when removing the Industry Fixed effects. The fourth model largely mirrored the third but displayed shifts in the significance levels of various predictors.

Variable of interest

The first model revealed a slight negative but insignificant effect with a coefficient of -0.04. This indicates that an increase in one BCF – indicating an additional provision – leads to a decrease of 0.04 of the logarithmized ratio of R&D to Total Net Assets. This effect is nonetheless insignificant, hinting that an increase in BCF does not necessarily indicate an effect on R&D. When adding all controls to the model, we can roughly tell that no changes occur to the effect that BCF has on R&D expenditure. The effect gets even smaller with a coefficient of -0.01. The same conclusion stands in the best controlled model.

Robustness

When looking at Panel B, we observe a negative effect of BCF with a coefficient of -0.11, significant at the 5% level. This suggests that an increase in the BCF index might result in a decrease in R&D. When controlling with the control variables, we see that Size showed a negative association with R&D with a coefficient of -0.14, significant at the 5% level. In contrast, CapEx exhibited a positive relation with a coefficient of 0.10, significant at the 1% level. Increased Sales reduced R&D, as shown from the coefficient of -0.24, significant at the 1% level. Leverage also had a negative effect on R&D with a coefficient of -0.07, significant at the 1% level.

In model (3), Industry Fixed Effects were incorporated along with the Year Fixed Effects. The Year Fixed Effects displayed a mild negative trend with a coefficient of -0.03, significant at the 5% level. The significant effect of BCF got diminished after controlling, which indicates results consistent with Panel A. The reasons for this stark shift aren't immediately clear based on the data provided. Model 3 showcased an improvement in explaining variance, with an R^2 of 0.12 and an adjusted R^2 of 0.11. As with the previous interpretation, this analysis underscores the intricate nature of predicting R&D activities, even though some predictors offer valuable insights.

Table 4: Regression of First Hypothesis measuring the effect of BCF on R&D
Table depicting regression results on Log(RD) against various firm-level determinants for two distinct time periods. Panel A represents the results for the years 2001-2006, and Panel B for the years 1996-2001. The variable of interest is BCF, with control variables including, Log(Size) t-1, Log(CapEx) t-1, Log(Sales) t-1, and Log(Leverage) t-1. Specifications differ in the inclusion of industry and year fixed effects. Coefficient estimates are presented with standard errors in parentheses. Significance levels are denoted as follows: *** Sfor 1%, ** for 5%, and * for 10%.

Panel A

	(1) Log(RD)	(2) Log(RD)	(3) Log(RD)	(4) Log(RD)
BCF	-0.04	-0.01	0.02	-0.01
	(0.03)	(0.03)	(0.04)	(0.03)
$Log(Size)_{t-1}$		-0.23^{***}	0.04	-0.23^{***}
		(0.07)	(0.10)	(0.07)
$Log(CapEx)_{t-1}$		0.06^{***}	0.02	0.09^{***}
		(0.02)	(0.03)	(0.02)
$Log(Sales)_{t-1}$		-0.12^{**}	0.00	-0.13^{**}
		(0.05)	(0.07)	(0.06)
$Log(Leverage)_{t-1}$		-0.02	-0.02^{*}	-0.02
		(0.01)	(0.01)	(0.01)
INDUSTRY FIXED	NO	NO	NO	YES
YEAR FIXED	NO	NO	YES	YES
Constant	-3.12^{***}	-2.29^{***}	17.17	-15.81
	(0.06)	(0.32)	(15.97)	(14.67)
Observations	1996	1621	1590	1590
R^2			0.01	
Adjusted R^2			0.01	

Panel B

	(1) Log(RD)	(2) Log(RD)	(3) Log(RD)	(4) Log(RD)
BCF	-0.11^{**}	-0.08^{**}	-0.02	-0.06
	(0.05)	(0.04)	(0.06)	(0.04)
$Log(Size)_{t-1}$		-0.07	-0.03	-0.14^{**}
		(0.07)	(0.14)	(0.07)
$Log(CapEx)_{t-1}$		0.10^{***}	0.03	0.11^{***}
		(0.03)	(0.05)	(0.03)
$Log(Sales)_{t-1}$		-0.24^{***}	-0.18^{**}	-0.17^{***}
		(0.06)	(0.09)	(0.06)
$Log(Leverage)_{t-1}$		-0.07^{***}	-0.04^{*}	-0.06^{***}
		(0.01)	(0.02)	(0.02)
INDUSTRY FIXED	NO	NO	NO	YES
YEAR FIXED	NO	NO	YES	YES
Constant	-3.20^{***}	-1.60^{***}	67.92^{***}	52.32^{**}
	(0.07)	(0.31)	(25.34)	(22.38)
Observations	1147	988	975	975
R^2	0.01		0.12	
Adjusted R^2	0.01		0.11	

Discussion

At first, we can conclude that hypothesis 1 stating that an increase of BCF would lead to a decrease in R&D, is rejected. When looking at our results, we mainly take the idea in mind that ATPs might deter potential acquirers, particularly those that seek short-term financial gains at the expense of long-term R&D projects (Shleifer and Vishny, 1990). My results indicate a very small insignificant negative effect. Since this effect is both small and insignificant, we roughly could say that an effect of BCF on R&D could be nonexistent.

Considering the discussed literature, we know that there are some contradictions in the known literature. When looking at The Principal-Agent Theory (Jensen & Meckling, 1976), an increase in ATPs might lead to a reduced managerial drive to innovate. On the other hand, the Resource-Based View, suggested that a rise in ATPs might create a stable environment beneficial to long-term investment, including R&D. Our results could be the manifestation of the dichotomy on this behavior. This could confirm this possible idea that the relationship between ATPs and R&D might be contingent on other firm-specific factors like the firm's existing innovative capacity, importance of product differentiation, or structural corporate governance policy.

4.2 Hypothesis 2

Then, we run the second OLS to test the second hypothesis. Included in the most elaborate model are the independent variables R&D, BCF, Xit – a lagged vector for all control variables –, γt – lagged time-fixed effects –, δj – lagged industry-fixed effects –, and the error term εit. The independent variables are measured for each company i, proxied as Cusip, and for each calendar year t.

To test the effect of **R&D** on **Citations**, we run the regression as displayed in the equation below. In this regression equation, the dependent variable **Citations** is modeled as a linear function of several independent variables. In this regression equation, the dependent variable **Citations** is regressed on the independent variable **R&D** and **BCF**, and the same set of control variables. Note that in this regression, **BCF** is used as control variable. The coefficient β_1 represents the effect of **R&D** on **Citations**, while β_2 captures the effect of **BCF**. The coefficient α represents the intercept of the regression equation.

$$\mathbf{Citations} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{log(R\&D)} + \boldsymbol{\beta_2}\mathbf{BCF} + \boldsymbol{\beta}\mathbf{X_{it-1}} + \boldsymbol{\gamma_{t-1}} + \boldsymbol{\delta_{j-1}} + \boldsymbol{\varepsilon_{it}}$$

Controls

In examining the relationship between BCF and R&D on Citations, again four distinct models were analyzed. These models each differ in the degree of controlling.

The control variables highlighted the following: Size in the first two models seemed to have a significant positive effect, however this effect diminished when controlling for several fixed effects. The influence of CapEx was observed significant in model (2) with a coefficient of 0.20. The Sales variable presented varied outcomes, nonetheless three out of four models showed a significant effect of Sales. Models (1) and (2) shows that Sales seemed to be a negative related to Citations, as shown by coefficients of -0.42 and -0.69. In contrast, model (3) illustrated that firms with more sales received more citations indicated by a positive but insignificant coefficient of 0.64. Leverage displayed a consistent relation with Citations across all models, with its impact most evident in model (1) which had a coefficient of 0.09. The Year Fixed Effects, captured in models (3) and (4), conveyed a yearly decrease in Citations received, showcased by coefficients of -0.28 and -0.22. Model (3) possessed an R^2 value of 0.29, implying it accounted for around 29% of the variance in Citations received.

Variables of interest

Within the models ran to test this hypothesis, the findings of the effect of BCF on Citations remained rather stable. Across all models, an insignificant effect is observed. The coefficients stayed around null, with a coefficient of -0.05 of the effect of BCF on Citations in the most controlled model. This indicates an increase of BCF, in terms of an additional provision, leads to decrease of 0.05 of logarithmized Citations. Although this effect was insignificant, it became more negative when controlling more elaborately. Since we see a significant effect of R&D on Citations, we could expect based on hypothesis 1 that the effect of BCF on Citations would be small and insignificant. This means that across all models we do not observe an effect of BCF on Citations.

Robustness

Transitioning to the time period of Panel B, a similar effect of BCF on Citations was observed in all models, indicating results consistent with Panel A. The R&D variable in the initial two models showed that increased R&D activities correlated with a rise in Citations received. Specifically, an increase in R&D corresponded to an increment of 0.35 to 0.53 units in Citations received. The second model indicated this with a coefficient for R&D at 0.53, significant at the 1% level. The influence of CapEx came to light again, particularly in the third model. Here, an increase in CapEx corresponded with a 0.35-unit increase in Citations received.

Sales, in the second model, intimated that firms with a surge in sales generally had more Citations received, as reflected by a coefficient of 0.20. Leverage, examined in the third model, revealed that companies with higher leverage tended to have more Citations received, with a coefficient of 0.13, significant at 10%.

Table 5: Regression of Second Hypothesis measuring the effect of R&D on Citations
Table depicting regression results on Log(Citations) against various firm-level determinants for two distinct time periods. Panel A represents the results for the years 2001-2006, and Panel B for the years 1996-2001. The variable of interest is BCF, with control variables including, Log(RD) t-1, Log(Size) t-1, Log(CapEx) t-1, Log(Sales) t-1, and Log(Leverage) t-1. Specifications differ in the inclusion of industry and year fixed effects. Coefficient estimates are presented with standard errors in parentheses. Significance levels are denoted as follows: *** Sfor 1%, ** for 5%, and * for 10%.

Panel A				
	(1) Log(Citations)	(2) Log(Citations)	(3) Log(Citations)	(4) Log(Citations)
BCF		0.00	-0.03	-0.05
		(0.10)	(0.19)	(0.09)
Log(RD) $_{t-1}$	0.46***		0.05	0.56***
	(0.06)		(0.20)	(0.08)
Log(Size) $_{t-1}$	0.77***	0.79***	-0.85*	-0.16
	(0.14)	(0.19)	(0.45)	(0.22)
Log(CapEx) $_{t-1}$	0.03	0.20*	-0.07	0.08
	(0.06)	(0.11)	(0.16)	(0.13)
Log(Sales) $_{t-1}$	-0.42***	-0.69***	0.31	0.64***
	(0.12)	(0.21)	(0.46)	(0.25)
Log(Leverage) $_{t-1}$	0.09***	0.05	-0.01	0.03
	(0.03)	(0.06)	(0.07)	(0.06)
INDUSTRY FIXED	NO	NO	NO	YES
YEAR FIXED	NO	NO	YES	YES
Constant	6.08***	5.75***	447.00***	554.51***
	(0.64)	(1.08)	(83.43)	(54.96)
Observations	1352	622	540	540
R^2			0.29	
Adjusted R^2			0.28	

Panel B				
	(1) Log(Citations)	(2) Log(Citations)	(3) Log(Citations)	(4) Log(Citations)
BCF		-0.10	-0.12	-0.08
		(0.08)	(0.23)	(0.08)
Log(RD) $_{t-1}$	0.35***		-0.02	0.53***
	(0.05)		(0.24)	(0.07)
Log(Size) $_{t-1}$	0.13	0.04	-0.31	0.09
	(0.09)	(0.16)	(0.46)	(0.19)
Log(CapEx) $_{t-1}$	0.12**	0.16	-0.04	0.35***
	(0.05)	(0.12)	(0.23)	(0.12)
Log(Sales) $_{t-1}$	0.20**	0.35*	0.14	0.07
	(0.08)	(0.18)	(0.45)	(0.18)
Log(Leverage) $_{t-1}$	0.04	-0.01	0.08	0.13*
	(0.03)	(0.07)	(0.10)	(0.07)
INDUSTRY FIXED	NO	NO	NO	YES
YEAR FIXED	NO	NO	YES	YES
Constant	2.70***	0.56	125.14	101.46
	(0.45)	(0.87)	(96.56)	(83.83)
Observations	1739	492	407	407
R^2			0.02	
Adjusted R^2			0.01	

Discussion

At first, we can conclude that hypothesis 2 stating that an increase in R&D will lead to higher quality of innovation is not rejected. By researching specifically the effect of BCF on Citations, we keep two discussed ideas in mind. On the one hand, we keep in mind that the presence of takeover threats, which ATPs seek to mitigate, can push management to focus on value-enhancing projects, boosting innovative efforts (Jensen and Ruback, 1983). On the other hand, a defensive stance, like excessive use of ATPs, might lead management into a value-destroying or risk-averse path, inhibiting genuine innovative undertakings (Walsh and Ellwood, 1991). Again, our results display no result, which could be the manifestation of the dichotomy of the theoretical stances. Additionally, this also may mirror that management's defensive stance, heightened by the ATPs, may have disrupted their focus on value-enhancing innovation, leading to fewer ground-breaking innovations.

Furthermore, ATPs, by deterring the threat of takeovers, might give management a sense of security, but not always in a positive light. This sense of security can push management into short-term thinking, sacrificing long-term innovative behavior. BCF's stable but insignificant effect on Citations might be reflective of this balance - where the security provided by ATPs doesn't necessarily translate to increased innovative outputs or breakthroughs that earn citations. Then, excessive reliance on ATPs can create this culture where management's primary aim becomes self-preservation and defense against external threats (Stein, 1988). While this might secure their position, it can detract from genuine pursuits of value creation and groundbreaking innovation. The growing negative trend of BCF's impact on Citations, when more variables are controlled, might indicate this very phenomenon - as companies employ more ATPs, their primary focus shifts from innovation to defense. At last, under intense takeover threats, managers might be incentivized to make riskier decisions to enhance firm value (Cremers and Nair, 2005). However, excessive ATPs could dilute this threat, making managers less inclined to pursue radical innovations. BCF's consistent but insignificant influence on Citations can be indicative of a diminished risk appetite in innovation, due to the cushion provided by ATPs.

4.3a Hypothesis 3a: OLS

Then, I run the third analysis to test the third hypothesis, in two separate ways, starting with an OLS with a moderating interaction. Included in the most extended model are the independent variables R&D, BCF, Xit – a lagged vector for all control variables –, γt – lagged time-fixed effects –, δj – lagged industry-fixed effects –, and the error term εit. The independent variables are measured for each company i, proxied as Cusip, and for each calendar year t.

To test the effect of **BCF** on **Citations**, accounting for the degree of engaging in **R&D**, we basically run two parallel analyses. In this part I directly test the influence of **BCF**, accounting for **R&D**, on **Citations**. Similar to previous equations, this regression equation includes **R&D**, **BCF**, and the vector for the control variables as well as the fixed effects. In this model, **BCF** will function as moderating for the effects **R&D** has on **Citations**. The coefficient β1 represents the effect of **R&D** on **Citations**, while the two β2 coefficients capture the effect of **BCF**. β_3 will cover the moderating effect **BCF** has on **R&D** success. To apply the moderating effect, this regression equation introduces an interaction term between **R&D** and **BCF**. The coefficient α represents the intercept of the regression equation, and the same control variables will be used. The model that we will run is displayed in the Equation below.

$$\mathbf{Citations} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{log(R\&D)} + \boldsymbol{\beta_2}\mathbf{BCF} + \boldsymbol{\beta_3}\mathbf{log(R\&D * BCF)} + \boldsymbol{\beta_4}\mathbf{X_{it}} + \boldsymbol{\gamma_{t-1}} + \boldsymbol{\delta_{j-1}} + \boldsymbol{\varepsilon_{it}}$$

Variables of interest

At first, the results of the regression are displayed in Table 7. In the initial model, the interaction effect between R&D and BCF exhibits a positive coefficient, significant at the 0.01 level, suggesting that an increase in this interaction effect relates with a proportional increase in Citations, holding other factors constant. In the second model, the coefficient for this interaction turns negative and is significant with a coefficient of -2.20, indicating that BCF has a moderating negative effect of 2.20 on the effect additional R&D has on logarithmized Citations. This indicates that an additional provision (implied by an increase of BCF with one), decreases the effectiveness of additional R&D on getting Citations. However, this relationship becomes non-significant in the third and fourth models with a coefficient of 0.73, when controlling the most extended. This leads to the conclusion that we do not observe evidence for the moderating effect of BCF.

When considering Panel B, we can roughly say that the results are rather similar as in Panel A. The interaction between RD and BCF switches from significant in model 1 and 3, to insignificant in model 2 and 4. In all models the observed effect is positive, however in the most extended model the effect is insignificant. This implicates that BCF does not exhibit a moderating effect on R&D, which is consistent with the findings in Panel A.

In this regression model, an interaction term between Log(RD) and BCF is used to examine the potential conditional effect of LogRD on the dependent variable at various levels of BCF. For interpreting the interaction terms, the marginal effect of both variables are computed.[4] These results are displayed in Table 6. Analyzing the marginal effects across different BCF levels reveals the interaction between Log(R&D) and BCF. Specifically, while a unit increase in Log(R&D) results in a 1.821 increase in Citations when BCF=0, this effect grows to 2.844 when BCF=1, indicating a difference of 1.023. This difference illustrates how the influence of Log(R&D) on Citations amplifies as BCF increases from 0 to 1.

[4] **Using Stata-command: margins, dydx(Log(R&D) at(c.BCF =(1 2 3 4 5 6))**

Table 6: Marginal effect of separate BCF levels on the slope of Log(R&D)
The table displays the marginal effects of Log(R&D) on the outcome variable for distinct levels of BCF. Accompanying each marginal effect is the Delta-method standard error, giving an indication of the reliability of these estimates. As we observe various BCF levels, there's a variation in the marginal effects, which implies that the influence of Log(R&D) is influenced by the value of BCF. These coefficients can be understood as the change in the outcome variable for a unit increase in Log(R&D), keeping other variables constant, for each specified level of BCF.

	Margin dydx (Log(R&D))	Delta-method std. err.
Log(R&D)*BCF		
BCF=0	1.821	0.892
BCF=1	2.844	0.782
BCF=2	2.960	0.987
BCF=3	2.919	0.874
BCF=4	1.697	0.983
BCF=5	1.280	0.733
BCF=6	2.495	0.713

Controls

In examining the relationship between R&D on Citations with the moderating effect of BCF, again four distinct models were analyzed. These models each differ in the degree of controlling.
Across all models, we see that effect and significance of the control variables change. R&D, introduced in the next set of models, displays a positive relationship with Citations in one model, reaching statistical significance at a given level, but this relationship is not significant in later models. Size maintains significant in all models, however the effect goes from positive to negative when controlling for fixed effects. CapEx and Sales both exhibit a negative but insignificant effect in the most extended model. At last Leverage displays a significant and positive effect in the fourth model.

Table 7: Regression of Third Hypothesis measuring the combined effect of R&D and BCF on Citations

Table depicting regression results on Log(Citations) against various firm-level determinants for two distinct time periods. Panel A represents the results for the years 2001-2006, and Panel B for the years 1996-2001. The variable of interest is Log(RD*BCF), with control variables including, Log(RD)t-1, BCF, Log(Size) t-1, Log(CapEx) t-1, Log(Sales) t-1, and Log(Leverage) t-1. Specifications differ in the inclusion of industry and year fixed effects. Coefficient estimates are presented with standard errors in parentheses. Significance levels are denoted as follows: *** Sfor 1%, ** for 5%, and * for 10%.

Panel A				
	(1) Log(Citations)	(2) Log(Citations)	(3) Log(Citations)	(4) Log(Citations)
Log(RD)*BCF	0.37***	-2.20**	-1.55	0.73
	(0.09)	(1.07)	(1.11)	(1.12)
Log(RD)		2.12*	1.56	-0.13
		(1.10)	(1.13)	(1.13)
BCF		1.58**	0.81	-0.44
		(0.62)	(0.59)	(0.67)
Log(Size) $_{t-1}$			-1.18***	0.71***
			(0.44)	(0.25)
Log(CapEx) $_{t-1}$			-0.06	-0.02
			(0.17)	(0.15)
Log(Sales) $_{t-1}$			0.35	-0.34
			(0.51)	(0.27)
Log(Leverage) $_{t-1}$			0.04	0.13*
			(0.06)	(0.07)
INDUSTRY FIXED	NO	NO	NO	YES
YEAR FIXED	NO	NO	YES	YES
Constant	4.71***	1.76*	396.65***	7.02***
	(0.32)	(1.03)	(89.15)	(1.76)
Observations	476	476	432	432
R^2		0.01	0.30	
Adjusted R^2		0.00	0.28	

Panel B				
	(1) Log(Citations)	(2) Log(Citations)	(3) Log(Citations)	(4) Log(Citations)
Log(RD)*BCF	0.20**	1.85	1.95*	0.72
	(0.09)	(1.23)	(1.18)	(0.78)
Log(RD)		-1.64	-1.80	-0.26
		(1.29)	(1.24)	(0.79)
BCF		-1.10	-1.17	-0.60
		(0.80)	(0.74)	(0.44)
Log(Size) $_{t-1}$			-0.72	0.16
			(0.51)	(0.21)
Log(CapEx) $_{t-1}$			-0.02	0.35***
			(0.22)	(0.13)
Log(Sales) $_{t-1}$			0.51	0.03
			(0.48)	(0.19)
Log(Leverage) $_{t-1}$			0.07	0.10
			(0.10)	(0.08)
INDUSTRY FIXED	NO	NO	NO	YES
YEAR FIXED	NO	NO	YES	YES
Constant	4.80***	6.04***	200.49**	3.42**
	(0.27)	(1.25)	(89.69)	(1.44)
Observations	353	353	327	327
R^2		0.01	0.06	
Adjusted R^2		0.00	0.04	

Discussion

At first, we can state that hypothesis 3 stating that BCF has a moderating effect on the effect R&D has on innovation, is not rejected. To look further into it, we mainly shed light on the interaction effect between R&D and BCF. The idea behind this model was to check whether a moderating effect of BCF exists on the effect R&D has on Innovativeness. Furthermore, we also investigate empirical findings that could give insights into differences between ATPs and ATLs. On one hand, as per Comment & Schwert (1995), ATPs like BCF protect companies and potentially encourage long-term innovation. On the other hand, as Bhagat & Bolton (2008) posited, such protection might stifle innovation by preventing management from undertaking risky projects.

As discussed, the fundamental difference between ATPs and ATLs, is that the latter is forced by government as the first is implemented from firm policy. To reason around the difference, we have to take the idea in mind that resonates with Masulis et al. (2007) who suggested that a secured ATP environment might demotivate managers from continuous innovative pursuits. As per Chen and Hsu (2009), the implementation of ATPs provides managers with greater confidence, pushing them towards long-term, innovation-oriented strategies.

4.3b Hypothesis 3b: 2SLS

Then, parallel to the first analysis, we also try to conduct the research through the instrumental variable. This part of the study will employ a Two-Stage Least Squares (2SLS) regression analysis. In the first stage, we will regress the **BCF** on the **HHI**. This first stage equation will be as displayed in Equation 1.

$$\textbf{(1)}\ \mathbf{BCF = \alpha + \beta_1 log(HHI) + \beta_2 X_{it-1} + \gamma_{t-1} + \delta_{j-1} + \varepsilon_{it}}$$

From Equation 1, we can derive a predicted value of **BCF**, so the second stage involves regressing the predicted values of **BCF** from the first stage regression on **Citations**. The reason we use the predicted BCF – displayed as $\mathbf{P_{BCF}}$ – instead of actual BCF is to eliminate the endogeneity that might be present due to possible omitted variable bias or simultaneous causality. By using $\mathbf{P_{BCF}}$, which is purely a function of the instrumental variable and not correlated with the error term, we get consistent and unbiased estimates of our parameters. The control variables and fixed effects in this stage will be the same as those in the first stage. The coefficients resulting from this regression will give us insights into how **BCF** impacts the quality of **Citations**. The second regression that we will run, is the displayed in Equation 3.

$$\textbf{(2)}\ \mathbf{Citations = \alpha + \beta_1 P_{BCF} + \beta_2 X_{it-1} + \gamma_{t-1} + \delta_{j-1} + \varepsilon_{it}}$$

Then, apart from a self-conducted two staged regression, I also run the direct regression to apply different levels of controlling.[5] Noteworthy in here, is that the results are expected to deviate from the self-conducted regression because of a higher level of efficiency of the estimators. Nonetheless, we execute both analyses, since the first analysis will give us an idea of the relationship between HHI and BCF, and the second analysis will give us an overall idea of the efficacy of the instrument.

Instrument: result

When looking at Table 8, we observe the results when I run the two stages with a separate regression, to see what the intermediate effect is (ergo, the effect of HHI on BCF within the sample). The first stage is centered on predicting the BCF, while the second stage used the predicted BCF to estimate Citations. The outcome from the initial stage (pertaining to BCF) is utilized as an instrumental variable, with its fitted values employed in the subsequent stage to predict Citations. Consistent with previous hypotheses, we see that the instrumented fitted BCF does not show any relationship with Citations.

When looking at the controlling variables in the first stage, R&D indicates a negative association, achieving significance at 10%. Sales presents a negative relationship with BCF, with significance. Leverage suggests a positive association with BCF, marked at significance at 10%. In the initial stage, HHI demonstrates a positive and statistically significant relationship with BCF with a coefficient of 0.06. Transitioning to the second stage focusing on Citations, R&D surfaces as a significant control highly significant with 1%. CapEx also shows a positive relationship, significant at another level. Industry Fixed Effects display various influences on Citations. In both stages we control for both Year as Industry Fixed Effects.

When evaluating the instrument, we have to consider the low significance and R^2, indicating that the instrument might be weak. Apart from that this could indicate that the HHI might not reflect the presence of a threat of hostile takeover, it could also be a sign of a bias within the sample. For instance, in an industry, it might traditionally be customary to include ATPs in their policies or charters, while at the same time, competition is low, purely due to reasons related to path-dependency. This kind of overrepresentations in het sample could lead to the observed weak relationship.

[5] **Stata command: ivregress 2sls logcreceived (bcf = sqrt_hhi) logrd logsize logcapx logsales logleverage i.SicCat year, robust**

Table 8: Two Staged Regression, with instrumented BCF on Citations
Table depicting Two Staged Regression results with a regression of Log(HHI) on BCF in the first stage, and the predicted BCF on Citations in the second stage. Panel A represents the results for the years 2001-2006, and Panel B for the years 1996-2001. The variable of Fitted_BCF, with control variables including, Log(RD), BCF, Log(Size) t-1, Log(CapEx) t-1, Log(Sales) t-1, and Log(Leverage) t-1. Specifications differ in the inclusion of industry and year fixed effects. Coefficient estimates are presented with standard errors in parentheses. Significance levels are denoted as follows: *** for 1%, ** for 5%, and * for 10%.

	(First Stage) BCF	(Second Stage) Citations
Log(HHI)	0.06*	
	(0.03)	
Log(RD)	-0.05**	115.97***
	(0.02)	(25.23)
Log(Size) $_{t-1}$	0.06	27.32
	(0.04)	(26.21)
Log(CapEx) $_{t-1}$	-0.02	35.04**
	(0.03)	(15.01)
Log(Sales) $_{t-1}$	-0.11***	60.39
	(0.04)	(47.89)
Log(Leverage) $_{t-1}$	0.02*	-0.25
	(0.01)	(8.31)
Fitted_BCF		85.40
		(22.84)
INDUSTRY FIXED	YES	YES
YEAR FIXED	YES	YES
Constant	1.65***	81,114.02***
	(0.26)	(1253.39)
Observations	1621	1962
R^2	0.02	0.25
Adjusted R^2	0.01	0.24

Then, we observe the results displayed in Table 9, when I run the direct regression. When looking at the variable of interest **BCF,** we observe that the effect starts at -17.48 when not controlling, and ends at 19.64 when controlling the most extensive. The fact that the coefficient switches from negative to positive, leads to the suggestion that BCF does not have a effect on Citations. This is furthermore confirmed by the high standard errors, and therefore by the absence of significance.

Table 9: Two Staged Regression with instrumented BCF on Citations, controlled in different levels
Table depicting Two Staged Regression results of instrumented BCF on Log(Citations). The variable of BCF is instrumented, regressed along with control variables including, Log(RD), BCF, Log(Size) t-1, Log(CapEx) t-1, Log(Sales) t-1, and Log(Leverage) t-1. In this regression, the instrumental variable HHI is Log transformed. Specifications differ in the inclusion of industry and year fixed effects. Coefficient estimates are presented with standard errors in parentheses. Significance levels are denoted as follows: *** for 1%, ** for 5%, and * for 10%.

	(1) Log(Citations)	(2) Log(Citations)	(3) Log(Citations)	(4) Log(Citations)
BCF	-17.48	-19.15	17.81	19.64
	(23.11)	(64.22)	(67.71)	(46.07)
Log(RD)		-0.73	2.35	2.52
		(4.78)	(6.27)	(8.96)
Log(Size) $_{t-1}$		2.40	-1.28	-1.28
		(7.17)	(6.58)	(7.27)
Log(CapEx) $_{t-1}$		1.13	-0.74	-0.86
		(3.03)	(4.06)	(5.82)
Log(Sales) $_{t-1}$		-4.78	4.23	4.46
		(16.35)	(16.22)	(20.59)
Log(Leverage) $_{t-1}$		0.14	-0.19	-0.19
		(0.80)	(0.99)	(1.10)
INDUSTRY FIXED	NO	NO	YES	YES
YEAR FIXED	NO	NO	NO	YES
Constant	27.20	53.65	-34.29	-420.09
	(31.18)	(168.32)	(148.67)	(4834.21)
Observations	1543	1440	1440	1440

Instrument: performance

Then, since we concluded the instrumental variable does not perform optimally, we try to determine biases by comparing the results from the Two-Stage regression to the results of an OLS. When looking at Table 10, we observe that the BCF coefficient is approximately 19.64 in the 2SLS compared to 1.08 in the OLS, implying that we observe a substantially higher coefficient of BCF in the 2SLS, compared to the OLS. Apart from that, the standard error of the instrumented BCF in the 2SLS is slightly larger with 46.07 (2.3 times the coefficient) compared to the standard error in the OLS of 2.05 (1.9 times the coefficient).

On the one hand, the strong discrepancy between the OLS and 2SLS coefficients for BCF could suggest potential endogeneity in the OLS model, which 2SLS might be correcting for. However, the large standard error of the instrumented BCF in the 2SLS model indicates that the chosen instrument might be weak, leading to less precise estimates. The standard error in the 2SLS model being more than five times the coefficient's size further underscores this imprecision. This implies that it is necessary to closely evaluate the instrument's validity when deploying it in another sample.

Table 10: Two Staged Regression with instrumented BCF on Citations compared to Ordinary Least Squared
Table depicting Two Staged Regression results with a regression of Log(HHI) on BCF in the first stage, and the predicted BCF on Citations in the second stage. The OLS entails a regression a direct regression of BCF on Citations. The variable of Fitted_BCF, with control variables including, Log(RD), BCF, Log(Size) t-1, Log(CapEx) t-1, Log(Sales) t-1, and Log(Leverage) t-1. Specifications differ in the inclusion of industry and year fixed effects. Coefficient estimates are presented with standard errors in parentheses. Significance levels are denoted as follows: *** for 1%, ** for 5%, and * for 10%.

	Two Staged Least Squares	**Ordinary Least Squares**
	Log(Citations)	Log(Citations)
BCF	19.64	1.08
	(46.07)	(2.05)
Log(HHI)	2.52	0.06*
	(8.96)	(0.03)
Log(RD)	-1.28	-0.05**
	(7.27)	(0.02)
$Log(Size)_{t-1}$	-0.86	0.06
	(5.82)	(0.04)
$Log(CapEx)_{t-1}$	4.46	-0.02
	(20.59)	(0.03)
$Log(Sales)_{t-1}$	-0.19	-0.11***
	(1.10)	(0.04)
$Log(Leverage)_{t-1}$	0.00	0.02*
	(.)	(0.01)
INDUSTRY FIXED	YES	YES
YEAR FIXED	YES	YES
Constant	19.64	1.65***
	(96.07)	(0.26)
Observations	1621	1508
R^2	0.25	0.46
Adjusted R^2	0.2	0.45

Then, to ensure some certainty in the results, I employ several other transformation methods. When examining Table 11, we can conclude that the coefficients are quite similar to one another, with minimal variation: the smallest effect is 13.84 from the square root HHI, and the largest is 22.72 from the Box-Cox transformation. Based on the transformations, we can assert that all transformations perform relatively weakly, with standard errors ranging from almost twice as much to nearly 6 times the coefficient. Considering the smallest standard error, a logarithmic transformation of HHI appears to perform the best, which is why it is primarily used as an instrument in this research.

Table 11: 2SLS regressions conducted with different transformations
Table depicting Two Staged Regression results with a (direct) regression of Log(HHI) on BCF in the first stage, and the predicted BCF on Citations in the second stage. BCF represents the instrumented variable, with control variables including, Log(RD), BCF, Log(Size) t-1, Log(CapEx) t-1, Log(Sales) t-1, and Log(Leverage) t-1. The transformations respectively by column are: the logarithm, the square root, the cube root, and the Box-Cox transformation. Specifications differ in the inclusion of industry and year fixed effects. Coefficient estimates are presented with standard errors in parentheses. Significance levels are denoted as follows: *** for 1%, ** for 5%, and * for 10%.

	Logarithm (HHI)	**Square Rt. (HHI)**	**Cube Rt. (HHI)**	**Box-Cox (HHI)**
	Log(Citations)	Log(Citations)	Log(Citations)	Log(Citations)
BCF	19.64	13.84	15.02	22.72
	(46.07)	(48.95)	(56.95)	(128.38)
Log(RD)	2.52	1.98	2.09	2.81
	(8.96)	(4.55)	(5.30)	(11.99)
Log(Size) $_{t-1}$	-1.28	-0.88	-0.96	-1.50
	(7.27)	(3.90)	(4.48)	(9.57)
Log(CapEx) $_{t-1}$	-0.86	-0.50	-0.57	-1.05
	(5.82)	(2.97)	(3.45)	(7.79)
Log(Sales) $_{t-1}$	4.46	3.22	3.47	5.12
	(20.59)	(10.54)	(12.25)	(27.49)
Log(Leverage) $_{t-1}$	-0.19	-0.13	-0.14	-0.22
	(1.10)	(0.65)	(0.73)	(1.40)
INDUSTRY FIXED	YES	YES	YES	YES
YEAR FIXED	YES	YES	YES	YES
Constant	-420.09	-133.84	-191.83	-572.51
	(4834.21)	(2506.41)	(2902.68)	(6428.79)
Observations	1440	1440	1440	1440

Discussion

The positive relationship between HHI and BCF might suggest that companies in concentrated markets employ more ATPs, possibly to defend against the takeover threats amplified in such markets. This mirrors Karpoff & Malatesta (1989)'s commentary on how ATPs and ATLs might be contextual to market dynamics. In light of Atanassov (2013) and Giroud (2010)'s findings on the decline in Citations post ATL implementation, your regression results regarding BCF's fluctuating impact on Citations provide an intricate comparison. While ATLs have a documented effect on reducing innovation (as measured by Citations), ATPs like BCF might have a more nuanced and complex relationship with innovation, evidenced by the shifting coefficients across models.

4.4 Hypothesis 4

At last, we run the fourth OLS to test the Last hypothesis. Included in the most elaborate model are the independent variables R&D, BCF, Xit – a lagged vector for all control variables –, γt – lagged time-fixed effects –, δj – lagged industry-fixed effects –, and the error term εit. The independent variables are measured for each company i, proxied as Cusip, and for each calendar year t.

In our final model, we are performing a quantile regression where the dependent variable, $\mathbf{Q_{Citations}}$, is split into quantiles. The **HighRD** variable denotes firms that belong to the top 20% in terms of R&D expenditure. This model allows us to test the non-monotonic relationship between our variables of interest, incorporating firm, year, and industry fixed effects to control. The regression we will run for this part is as displayed in below.

$$\mathbf{Q_{Citations} = \alpha + \beta_1 BCF + \beta_2 HighRD + \beta_3 BCF * HighRD + \beta_2 X_{it-1} + \gamma_{t-1} + \delta_{j-1} + \varepsilon_{it}}$$

Variables of Interest

When first looking at HighRD, we see a highly significant positive effect on all quantiles. When introducing BCF, we see a negative but insignificant effect across all quantiles. When looking at the interaction effect we see a relatively large negative effect, which is only significant with 10% in the third quantile.

In our regression model, we introduced an interaction term between HighRD and BCF to examine the potential conditional effect of HighRD on the dependent variable at various levels of BCF. For interpreting the interaction terms, the marginal effect of both variables are computed.[6] These results are displayed in Table B in the Appendix. Analyzing the marginal effects across different BCF levels reveals the interaction between Log(R&D) and BCF. Specifically, while a unit increase in HighRD to 1 results in a 3.821 increase in Citations when BCF=0, this effect grows to 2.844 when BCF=1, indicating a difference of 1.023. This difference illustrates how the influence of HighRD being 1 on Citations amplifies as BCF increases from 0 to 1.

[6] **Using Stata-command: margins, at(c.HighR&D = (1 2)) at(c.BCF =(1 2 3 4 5 6))**

Table 12: Marginal effect of separate BCF levels on dummy variable HighRD

The table presents the marginal effects of Log(R&D) on the dependent variable for various combinations of HighR&D and BCF. For each combination, the Delta-method standard error is also provided, allowing us to estimate the precision of the marginal effect estimates. As we move across different levels of BCF, there appears to be variation in the marginal effects, suggesting that the impact of Log(R&D) is contingent upon the levels of both HighR&D and BCF. The coefficients should be interpreted as the change in the dependent variable for a one-unit increase in Log(R&D), holding other factors constant, for each specific combination of HighR&D and BCF.

	Margin: dydx(Log(R&D))	Delta- method std. err.
HighR&D*BCF		
0 1	3.821	0.454
0 2	3.844	0.487
0 3	3.960	0.454
0 4	3.941	0.416
0 5	3.741	0.412
0 6	3.840	0.412
1 1	3.724	0.448
1 2	3.683	0.448
1 3	3.982	0.485
1 4	3.179	0.212
1 5	2.879	0.131
1 6	1.697	0.493

Controls

When testing for a non-monotonic relationship, we conduct a quantile regression, to check whether BCF has a moderating effect on being a HighRD company within different categories Citations. When running the quantile regression, I use the most extended models in terms of controlling.

In Panel A, across three quantiles an insignificant negative effect of Size on all quantiles is observed, except for the highest quantile this negative effect becomes significant with 10%. CapEx exhibits a positive and highly significant effect across all quantiles. The effect of Sales on all quantiles is insignificant. At last, the effect of Leverage varies across models, with significant negative effect in the second and third quantile, and a significant effect in the first and last quantile.

Discussion

Apart from a possible non-monotonic relationship, my results displayed no significant effect at all when looking specifically at the interaction effect. Being a HighRD company has a positive effect on citations, as could be expected from intuition. This implicates that I did not find any evidence that the idea coined by Aghion et al (2013) holds, stating that BCF could function as defending mechanism while being a HighRD company. This also leads to the conclusion, as formulated by Comment & Schwert (1995) and Coad et al. (2016), there is no differing moderating effect of BCF across quantiles when being a HighRD company.

Table 13: Quantile Regression of Fourth Hypothesis measuring the effect of HighRD*BCF on Citations by quantile
Table depicting quantile regression results with a regression an interaction of HighRD and BCF on the quantiles. Panel A represents the results for the years 2001-2006, and Panel B for the years 1996-2001. The variable of interest is the interaction of HighRD and BCF, with HighRD being a dummy variable taking the value 1 if a company belongs the top 20% of RD. The regression included control variables including, HighRD, BCF, Log(Size) t-1, Log(CapEx) t-1, Log(Sales) t-1, and Log(Leverage) t-1. Specifications differ in the inclusion of industry and year fixed effects. Coefficient estimates are presented with standard errors in parentheses. Significance levels are denoted as follows: *** for 1%, ** for 5%, and * for 10%.

Panel A

	(1) 25%	(2) 50%	(3) 75%	(4) 100%
BCF	-0.10	-0.05	-0.09	-0.12
	(0.13)	(0.09)	(0.09)	(0.11)
HighRD	6.24**	5.80***	5.75***	4.34*
	(3.07)	(2.15)	(2.10)	(2.48)
HighRD*BCF	-4.14	-3.79	-3.90*	-3.39
	(3.40)	(2.38)	(2.32)	(2.75)
Log(Size) $_{t-1}$	-0.02	-0.03	-0.06	-0.41*
	(0.26)	(0.18)	(0.18)	(0.21)
Log(CapEx) $_{t-1}$	0.50***	0.67***	0.74***	0.78***
	(0.18)	(0.12)	(0.12)	(0.14)
Log(Sales) $_{t-1}$	0.19	0.16	0.27	0.34
	(0.32)	(0.22)	(0.22)	(0.26)
Log(Leverage) $_{t-1}$	-0.02	-0.15**	-0.19***	-0.06
	(0.10)	(0.07)	(0.07)	(0.08)
INDUSTRY FIXED	NO	NO	NO	YES
YEAR FIXED	NO	NO	YES	YES
Constant	681.48***	661.03***	652.88***	547.04***
	(154.89)	(108.31)	(105.77)	(125.07)
Observations	618	618	618	618
R^2				
Adjusted R^2				

Panel B

	(1) 25%	(2) 50%	(3) 75%	(4) 100%
BCF	-0.08	-0.09	-0.12	-0.19**
	(0.11)	(0.08)	(0.10)	(0.10)
HighRD	2.86*	4.03***	3.10**	2.62*
	(1.64)	(1.25)	(1.54)	(1.48)
HighRD*BCF	-0.55	-1.63	-1.39	-1.57
	(1.31)	(0.99)	(1.22)	(1.18)
Log(Size) $_{t-1}$	0.04	-0.07	0.07	0.02
	(0.21)	(0.16)	(0.19)	(0.18)
Log(CapEx) $_{t-1}$	0.34**	0.41***	0.41***	0.53***
	(0.16)	(0.12)	(0.15)	(0.15)
Log(Sales) $_{t-1}$	0.17	0.24	0.19	0.15
	(0.27)	(0.21)	(0.26)	(0.25)
Log(Leverage) $_{t-1}$	0.05	0.09	-0.03	0.01
	(0.09)	(0.07)	(0.08)	(0.08)
INDUSTRY FIXED	NO	NO	NO	YES
YEAR FIXED	NO	NO	YES	YES
Constant	145.76	167.29	197.52	177.23
	(203.59)	(154.76)	(190.30)	(183.53)
Observations	488	488	488	488
R^2				
Adjusted R^2				

5. Conclusion

The academic literature provides varied interpretations regarding frameworks of academic literature on corporate behavior, often presenting varying views on prominent theories such as the Principal-Agent Theory, Resource-Based View, and Dynamic Capabilities. In the midst of this stylized academic landscape, the work of Atanassov, Giroud, and Mueller suggests that when the threat of a hostile takeover ceases, it may result in a downturn in innovative performance, in terms of patent citations. Building on their findings, the current study embarked on a nuanced exploration. Instead of solely looking at government interventions, it examined the outcomes when firms took matters into their own hands, implementing Anti-takeover Provisions themselves. I test whether the number of ATPs has an effect on the number of citations.

With the first hypothesis, I first checked whether the presence of ATPs is related to R&D expenses, to test whether protection from takeover leads to a more or less aggressive investing strategy. I found that ATPs are not related to R&D, implying that the degree to which companies are protected from takeovers does not lead to different investing behavior. The results are robust across both time windows.

With the second hypothesis, I tested whether the threat of takeovers leads to more value-enhancing innovations, in terms of citations. In line with the results from the first hypothesis, I found that ATPs are not related to patent citations, implying that the degree to which companies are protected from takeovers does not lead to a higher quality of innovations.

With the third hypothesis, I tested whether ATPs have a moderating effect on R&D in relation to citations. I found that in the most elaborate model, ATPs do not display a moderating effect of R&D on citations, implying that the degree to which companies are protected from takeovers does not exhibit a dampening effect on the amount of R&D concerning the quality of the innovations. When conducting the same research with an instrumental variable, it displayed the same results. Again, this is in line with the findings in previous hypotheses.

With the fourth hypothesis, I tested if ATPs had a non-monotonic relationship to citations when being a High R&D company. In this research, no non-monotonic relationship was found. This confirms the findings of previous hypotheses.

6. Limitations and Implications

A major constraint in the study is related to endogeneity concerns. Identifying and incorporating all relevant control variables into a model is a common challenge in such investigations. My attempt to mitigate this, by using an Instrumental Variable, faced its own complications. The instrument HHI, did not maintain a perfect linear relationship with the variable it aimed to instrument, given the significance of 10%. Future research could benefit from exploring alternative instruments or to find a theoretical context in which the HHI as instrument might hold better. Apart from the relationship of the instrument to the instrumented variable, there also were some issues with the computation of HHI. The HHI was employed as a proxy for market concentration. However, its computation, which is based on revenue data, might not be flawless. If a firm's revenue does not precisely mirror its market power, then our derived HHI might not actually display the market concentration. This calls for alternative approaches or supplementary measures to assess market power more accurately.

Then, citations were used as a proxy for innovativeness, which presents another limitation. The data on citations might imply inconsistencies, making it less reliable as a measure. Moreover, the very assumption that a higher number of citations translates to greater innovativeness is disputable. While citations provide a quantitative metric, their qualitative implications for innovativeness might require more nuanced interpretations or complementary measures.

The findings of this research provide new perspectives into the understanding of the disciplining effect of anti-takeover provisions (ATPs). There's a noteworthy discrepancy with the existing literature. The current body of research has drawn certain conclusions about the impact and functioning of ATPs, but the results of this study present different viewpoints. This might lead to the idea that not specifically ATPs might have a disciplining effect on innovative behavior, but the context in which the ATPs are implemented. The results suggest that the voluntary introduction of ATPs might play a significant role in their overall effectiveness. This suggests the need to delve into the dynamics and motivations behind a company's decision to adopt ATPs voluntarily. In conclusion, the research adds depth to the discussion on ATPs and raises questions about how they are adopted and their subsequent effects on company behavior. The difference between voluntary and mandated ATPs is a notable aspect, suggesting further discussions and policy considerations.

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Appendix

Figure A: Average marginal effects with 95% Confidence interval by variable within Hypothesis 3a
A marginal effects plot table visually describes how the line represents the change in effect or the linear variation. The y-axis illustrates the magnitude of change, while the x-axis displays the changes themselves. This table provides insights into the marginal effects, along with their corresponding 95% confidence intervals, offering a comprehensive understanding of how variables influence the outcome.

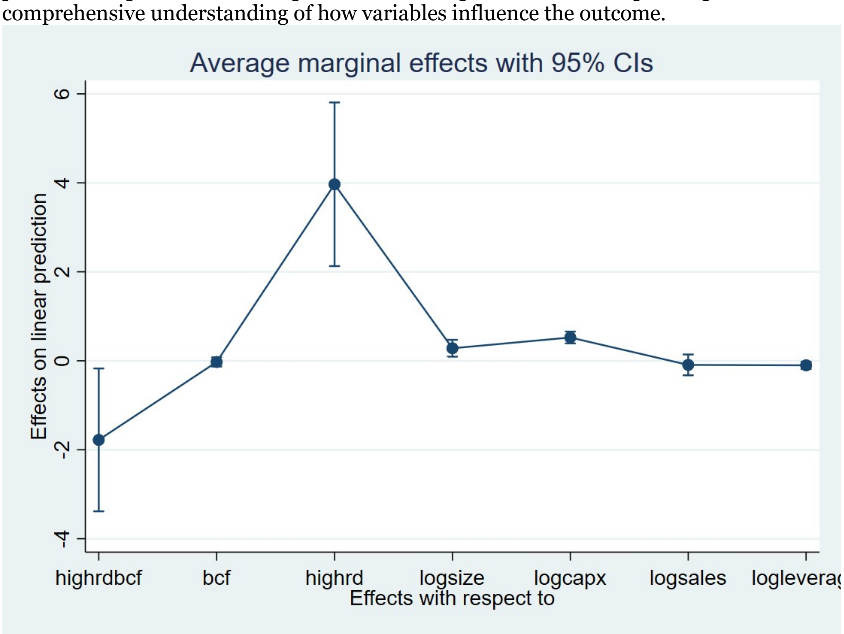

Table A: Two Staged Regression with instrumented BCF on Citations, controlled in different levels
Table depicting Two Staged Regression results of instrumented BCF on Log(Citations). The variable of BCF is instrumented, regressed along with control variables including, Log(RD), BCF, Log(Size) t-1, Log(CapEx) t-1, Log(Sales) t-1, and Log(Leverage) t-1. In this regression, the instrumental variable HHI is Box-Cox transformed. Specifications differ in the inclusion of industry and year fixed effects. Coefficient estimates are presented with standard errors in parentheses. Significance levels are denoted as follows: *** for 1%, ** for 5%, and * for 10%.

	(1)	(2)	(3)	(4)
	Log(Citations)	Log(Citations)	Log(Citations)	Log(Citations)
BCF	-15.98	-17.64	19.88	22.72
	(18.92)	(54.04)	(84.07)	(128.38)
Log(RD)		-0.62	2.54	2.81
		(4.03)	(7.79)	(11.99)
Log(Size) $_{t-1}$		2.23	-1.46	-1.50
		(6.06)	(8.07)	(9.57)
Log(CapEx) $_{t-1}$		1.07	-0.87	-1.05
		(2.61)	(5.03)	(7.79)
Log(Sales) $_{t-1}$		-4.40	4.72	5.12
		(13.79)	(20.12)	(27.49)
Log(Leverage) $_{t-1}$		0.13	-0.21	-0.22
		(0.72)	(1.19)	(1.40)
INDUSTRY FIXED	NO	NO	NO	YES
YEAR FIXED	NO	NO	YES	YES
Constant	25.17	49.71	-38.81	-572.51
	(25.53)	(141.73)	(184.39)	(6428.79)
Observations	689	543	540	540

Table B: Two Staged Regression with instrumented BCF on Citations, controlled in different levels
Table depicting Two Staged Regression results of instrumented BCF on Log(Citations). The variable of BCF is instrumented, regressed along with control variables including, Log(RD), BCF, Log(Size) t-1, Log(CapEx) t-1, Log(Sales) t-1, and Log(Leverage) t-1. In this regression, the instrumental variable HHI is cube root transformed. Specifications differ in the inclusion of industry and year fixed effects. Coefficient estimates are presented with standard errors in parentheses. Significance levels are denoted as follows: *** for 1%, ** for 5%, and * for 10%.

	(1) Log(Citations)	(2) Log(Citations)	(3) Log(Citations)	(4) Log(Citations)
BCF	-24.64	-24.53	14.41	15.02
	(49.08)	(108.99)	(45.13)	(56.95)
Log(RD)		-1.13	2.03	2.09
		(8.09)	(4.17)	(5.30)
Log(Size) $_{t-1}$		2.99	-0.97	-0.96
		(12.08)	(4.50)	(4.48)
Log(CapEx) $_{t-1}$		1.34	-0.53	-0.57
		(4.87)	(2.72)	(3.45)
Log(Sales) $_{t-1}$		-6.12	3.41	3.47
		(27.58)	(10.84)	(12.25)
Log(Leverage) $_{t-1}$		0.17	-0.15	-0.14
		(1.12)	(0.72)	(0.73)
INDUSTRY FIXED	NO	NO	NO	YES
YEAR FIXED	NO	NO	YES	YES
Constant	36.85	67.71	-26.86	-191.83
	(66.18)	(285.29)	(99.39)	(2902.68)
Observations	689	543	540	540

Table C: Two Staged Regression with instrumented BCF on Citations, controlled in different levels
Table depicting Two Staged Regression results of instrumented BCF on Log(Citations). The variable of BCF is instrumented, regressed along with control variables including, Log(RD), BCF, Log(Size) t-1, Log(CapEx) t-1, Log(Sales) t-1, and Log(Leverage) t-1. In this regression, the instrumental variable HHI is square root transformed. Specifications differ in the inclusion of industry and year fixed effects. Coefficient estimates are presented with standard errors in parentheses. Significance levels are denoted as follows: *** for 1%, ** for 5%, and * for 10%.

	(1) Log(Citations)	(2) Log(Citations)	(3) Log(Citations)	(4) Log(Citations)
BCF	-31.31	-27.90	13.47	13.84
	(82.13)	(144.15)	(40.04)	(48.95)
Log(RD)		-1.37	1.95	1.98
		(10.69)	(3.70)	(4.55)
Log(Size) $_{t-1}$		3.37	-0.89	-0.88
		(15.94)	(4.03)	(3.90)
Log(CapEx) $_{t-1}$		1.47	-0.47	-0.50
		(6.30)	(2.42)	(2.97)
Log(Sales) $_{t-1}$		-6.97	3.19	3.22
		(36.40)	(9.63)	(10.54)
Log(Leverage) $_{t-1}$		0.19	-0.13	-0.13
		(1.36)	(0.66)	(0.65)
INDUSTRY FIXED	NO	NO	NO	YES
YEAR FIXED	NO	NO	YES	YES
Constant	45.84	76.52	-24.82	-133.84
	(110.75)	(377.19)	(88.28)	(2506.41)
Observations	689	543	540	540