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Innovative disruption and the choice between market and bank debt capital

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A B S T R A C T

Innovative disruption stemming from the acceleration in technology-related innovations in the past two decades raises the question of how a firm's choice between market and bank debt capital is affected. By applying logistic and fixed effect (FE) regression models to panel data of U.S. firms, observed during the period from 2006 to 2022, this study reveals that disruption risk leads to incumbent firms, ceteris paribus, relying more on bank debt financing. While it is not clear from these findings if credit risk is the only channel through which disruption affects debt choice, disruption risk is shown to increase credit risk. This research also finds that innovative disruption leads to proportionately more bank debt financing for more opaque firms, ceteris paribus. There is no evidence of firm-level innovation moderating the relation between disruption and debt choice.

K e y w o r d s

Innovative disruption, debt choice, credit risk, logit model

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1. Introduction

This research examines how innovative disruption[1]–when new or less established firms in an industry gain a competitive advantage through innovation (Becker and Ivashina, 2023)–affects the debt financing choice of a firm. Corporates raising debt capital can either ask a bank for a loan or tap the credit market directly. This research defines the debt financing decisions of a firm as the choice between market debt (i.e., bond issuance) and bank debt (i.e., bank loans). Consistent with the notion that firms facing a potential increase in competition favor more stable sources of funding, I find that an increase in the risk of disruption is associated with an increase in the likelihood of firms opting for bank, rather than market, debt capital.

The motivation for this thesis stems from significant growth in technology-related innovations and the wide adoption of technology in society in the past two decades. This acceleration in disruption can in part be explained by the technology revolution (Greenwood and Jovanovic, 1999) and globalization (Melitz, 2003), and this raises the question of how the debt financing decisions of a corporate are affected. An understanding of this relation between disruption and debt choice can help firms manage their financing costs and make informed decisions about their optimal capital structure, particularly in industries facing disruption risk where financing needs may be different. Lenders can use these findings to understand that disruption risk alters risk profiles and financing choices of incumbents. This can help investors and banks manage their exposure to different financing sources and foster more informed credit lending decisions. To examine the relation between innovative disruption and firms' debt choice, this research applies logistic and FE regression models to panel data, consisting of U.S. firms observed during the period from 2006 to 2022.

Prior literature shows that incumbent firms facing disruption risk exhibit elevated levels of distress, which is reflected in the bond market through higher yields (Becker and Ivashina, 2023). Firms are shown to prefer financing that both lowers their cost of capital and maintains financial flexibility (Myers and Majluf, 1984), and riskier firms are more likely to rely on loans as banks are better able to support distressed firms and may be more willing to provide capital when the market will not (Cantillo and Wright, 2000). In line with this literature and to the best of my knowledge, this is the first study to find that disruption risk leads to incumbent firms, ceteris paribus, relying more on bank debt financing. Given that there is no previous literature that explores this relationship, this is the central contribution of this thesis. In addressing this

[1] This thesis uses the term "disruption" to reflect the entry of new or less established firms in an industry. During this process, disruptive firms capture significant market share at the expense of incumbents (Bower and Christensen, 1995). Incumbents reflect successful firms in an industry that use established business models and technology (Becker and Ivashina, 2023).

central research question–does disruption risk affect a firm's choice between market and bank debt capital–I implement a multivariate logistic regression of debt choice on empirical proxies for disruption and firm-level controls. Innovative disruption is proxied by venture capital (VC) flow and initial public offering (IPO) share. All else being equal, whatever the probability is of a firm choosing a loan compared to issuing a bond, this probability increases by 73% for a one percentage point increase in IPO Share, and it increases by 34% for a one percent increase in in the natural logarithm of VC Flow. Not only are these findings statistically significant, but this effect is economically relevant given that the average unconditional probability of a firm choosing a loan relative to a bond in my sample is 39%. Regulators may consider imposing additional capital requirements for banks heavily exposed to high-disruption industries, to ensure banks are better equipped to manage heightened risk.

The theorized effect of disruption risk on capital structure decisions is expected to operate via a credit risk channel: disruption increases credit risk, and more risky firms are more likely to opt for bank financing. To test for this specific channel, I investigate the relation between disruption and credit risk and whether controlling for the latter weakens the relation between disruption and the choice between loans and bonds. The evidence is mixed: consistent with Becker and Ivashina (2023), I find an increase in disruption to be associated with a higher level of credit risk. At the same time, controlling for credit risk does not appear to significantly change the relation between disruption and the likelihood of firms opting for bank credit.

A further secondary research question–does firm opacity[2] moderate the relation between disruption risk and debt choice–is a further contribution of this thesis as it helps provide a more comprehensive understanding of the relation between disruption and debt choice. As new firms enter an industry, markets may be more keen to analyze incumbent firms as they exhibit heightened risk. Because opaque firms are harder to assess, the market may be less willing to extend credit (Lemmon and Zender, 2010). Banks' critical function as a monitor and their information processing advantage (Hooks, 2003), suggests that they may be more willing than the market to finance informationally opaque firms even in the face of added uncertainty and risk. The findings in this research corroborate this notion. By rerunning the logistic regression used to examine the central research question and including firm opacity (proxied by Amihud's (2002) illiquidity measure) as a control and as an interaction term with my disruption proxies, this study shows that disruption risk, ceteris paribus, leads to proportionately more bank debt financing for more opaque firms. Because disruption has a

[2] In corporate finance "firm opacity" reflects the level of asymmetric information that exists between the managers and investors of a firm (Dahiya et al., 2017).

larger effect on more opaque firms, to facilitate firms' ongoing access to market debt regulators may consider imposing stricter reporting requirements for opaque firms prone to disruption risk. Sustained access to the bond market for these firms amidst disruption can enhance financial stability, as it alleviates the risk of the banking sector becoming heavily exposed to firms that exhibit elevated levels of risk.

A final contribution of this study addresses if firm-level innovation moderates the relation between disruption risk and debt choice. This research question aims to contribute to this existing literature by providing a deeper understanding of the relation between disruption and firms' debt financing decisions. I rerun the logistic regression that I use to examine the central research question and include innovation (proxied by R&D expenditure at the firm level) as a control and as an interaction term with my disruption proxies. Literature that follows in section 2.4. of this study suggests that firm-level innovation may have a complementary opposite hypothesis, with disruption risk leading to proportionately more (or less) bank debt financing for more innovative firms. However, I find no statistical evidence of firm-level innovation moderating the relation.

The remainder of this thesis is organized as follows. Section 2 provides an overview of the theoretical framework and an extensive report on the current literature. Based on prior findings and research gaps, the hypotheses that this study analyzes are presented. Section 3 provides an overview of the data and Section 4 presents the methodology. The empirical results are presented and discussed in Section 5. Section 6 concludes with final remarks.

2. Literature Review and Theoretical Framework

The Modigliani and Miller proposition on capital structure is a cornerstone of corporate finance theory that has stimulated great discourse surrounding a firm's optimal capital structure. In a perfect and efficient market, Modigliani and Miller (1958) posit that the capital structure of a company is irrelevant because firm value is not affected by a firm's financing decisions. This has led to a large body of research that has generated insight into the importance of a firm's financing decisions in the presence of market frictions.

While much of this literature focuses on the choice between equity and debt (see, e.g., Marsh (1982) and Hovakimian et al. (2001)), the focus of this thesis is to investigate a related but less extensively researched topic, namely a firm's market and bank debt financing decisions. Many published papers focus on traditional theories such as asymmetric information (see, e.g., Bolton and Freixas (2000)) and firm-level characteristics to explain the choice between market and bank debt. For example, Becker and Benmelech (2021) show that bond issuers tend to be less risky companies that are of higher credit quality compared to riskier firms that rely more on bank loans. Between 2009 and 2019, 87% of all companies that issued bonds in the U.S. were of high investment grade. Faulkender and Petersen (2006) show that companies with more tangible assets–firms with a high level of property plant and equipment relative to total assets– exhibit lower costs of financial distress and are more likely to raise public debt. In line with these findings, Becker and Ivashina (2014) proxy asset tangibility for a firm's collateral value and find a positive association between asset tangibility and bond issuance. Firms with more leverage are more likely to have access to the bond market (Faulkender and Petersen, 2006), and Lemmon and Zender (2010) and Becker and Ivashina (2014) both show that all else being equal, firms with higher levels of leverage are more likely to issue bonds. Furthermore, firms with a high return on assets (ROA) are likely to have high credit ratings and hence are better able to access cheaper credit in the bond market. Chemmanur and Fulghieri (1994) find a positive relation between ROA and bond issuance and show that less profitable firms tend to raise bank debt capital. Becker and Ivashina (2014) also find a positive relation between bond issuance and ROA, albeit their findings lack statistical significance.

In light of prior literature concerning a firm's debt financing decision, there appears to be no research that relates how innovative disruption in an industry affects the choice between market and bank debt capital, which is the central contribution of this thesis. To examine this study's central research question, this research builds on the work by Becker and Ivashina (2014) and Becker and Ivashina (2023). Becker and Ivashina (2014) analyze the choice firms make between bank credit and market debt to quantify fluctuations in bank-loan supply. They focus on U.S. firms and classify the substitution from bank debt to market debt as evidence of a change in the supply of bank credit. Conditional on new debt issuance by a firm, they interpret the substitution of loans with bonds as a contraction in bank-credit supply. They find strong evidence of firms' switching from loans to bonds during periods of tight lending standards, tight monetary policy, weak bank performance and depressed aggregate lending.

Becker and Ivashina (2023) examine innovative disruption as a central mechanism behind understanding corporate defaults. In this paper, they define innovative disruption as the phenomenon in which new or less established firms in an industry gain a commercial or technological innovation advantage. They focus on U.S. firms and find that disruption risk in industries negatively affects incumbent firms. Specifically, industries facing disruption risk exhibit higher default rates, higher exits by conglomerates, and firms in these industries that issue bonds face higher yields. This paper uses VC investments, IPO-based measures and patents as the main proxies for disruption.

2.1 Disruption risk and debt choice

I hypothesize that disruption risk leads to incumbent firms relying on bank debt financing more. In line with Becker and Ivashina (2023), I use VC flows and IPO announcements to proxy for disruption risk in an industry.

The pecking order theory provides a framework for understanding a firm's financing decisions. The theory implies that firms create a preference ranking over financing sources. Firms first use internal funds, followed by debt, and finally equity. This theory posits that companies have a preference for financing based on the notion that firms want to lower their cost of capital and maintain financial flexibility (Myers and Majluf, 1984). Given that market debt and bank debt provide varying levels of flexibility and costs, this theory can help to explain the choice a firm makes between these two sources of debt financing.

Bolton and Freixas (2000) show that bank loans are a more expensive form of financing than bonds because of intermediation costs. In line with the pecking order theory, they show that in equilibrium only riskier firms choose bank loans over bonds and safer firms prefer to tap the credit market directly. The authors' reasoning is that banks can provide more flexible financing and are better able to help firms during periods of financial distress than market lenders. Therefore, ceteris paribus, firms facing distress that require greater flexibility are more likely to rely on bank debt capital. Alternatively, it is more cost-effective for firms facing less financial distress to avoid the intermediation cost of banks and tap the credit market instead.

Building on the work by Bolton and Freixas (2000), Lemmon and Zender (2004) provide a "modified" pecking order to understand financing behavior, by showing that financial distress costs are an important factor for financing decisions. Similarly, Cantillo and Wright (2000) show that banks are better able to reorganize and support financially distressed firms but provide a more expensive form of funding than bondholders.

Becker and Ivashina (2023) find that incumbent firms experiencing disruption risk are at risk of losing market power and seeing a deterioration in earnings and performance. High-disruption industries are categorized by the success of new firms and distress of incumbent firms and they find a positive relation between credit risk and industries experiencing disruption risk. This suggests that incumbent firms facing disruption risk are likely to experience increased risk and financial distress. Therefore, these firms are likely to rely more on bank debt capital, as banks are better able to support distressed firms and are better able to offer more flexible financing, as suggested by Bolton and Freixas (2000), Lemmon and Zender (2004), and Cantillo and Wright (2000).

Furthermore, empirical evidence shows that firms in high-disruption industries typically find it harder to access market debt and are faced with higher yields on bonds as they are perceived riskier (Becker and Ivashina, 2023). This may entice incumbents in an industry to keep a good relationship with banks who are still willing to provide them capital when the market will not.

Diamond (1984) argues that the information production task delegated to financial intermediaries suggests that banks have more knowledge about industry-specific information than the market. Banks have access to market trends, regulatory requirements, and technological advancements. Banks can harness this information to assess the risks stemming from innovation and can help corporates navigate these changing market conditions.

Banks may also have long-standing relationships with corporates facing disruption risk. Relationship lending enables banks to generate more insight into firms' operations, creditworthiness, and financial performance and hence, are in a better position to make informed credit lending decisions (Diamond, 1984). This indicates that in industries facing disruption risk, banks may be more willing than the market to provide capital to incumbents experiencing financial distress.

2.2 Disruption risk, credit risk and debt choice

Following on from the central research question, I examine if credit risk is the primary channel in which innovative disruption affects debt choice. I hypothesize that disruption risk leads to more bank financing because credit risk is higher.

Becker and Ivashina (2023) find that disruption risk increases credit risk of incumbent firms. Bolton and Freixas (2000) show that in equilibrium, only riskier firms choose bank loans over bonds. Therefore, if an industry faces disruption risk, incumbents are more likely to rely on bank financing as they experience higher levels of credit risk, ceteris paribus. Findings from Cantillo and Wright (2000) and Lemmon and Zender (2004) support this reasoning, as they show that riskier firms facing financial distress are likely to rely more on bank debt capital than market debt.

2.3 Firm opacity, disruption risk and debt choice

A secondary research question of this thesis is to explore how the level of firm opacity moderates the relation between an industry facing disruption risk and the choice between market and bank debt capital. Many published papers have investigated how firm opacity (see, e.g., Ojah and Pillay (2009) and Lin et al. (2013)), influences a firm's financing choice, but it is not known how this variable moderates the relation. I hypothesize that disruption risk leads to proportionately more bank debt financing for more opaque firms.

The idea behind firm opacity is that the outsiders of a firm (i.e., the investors) do not have access to the same level of information as the insiders (i.e., the managers) concerning the inner workings of the firm. There exists asymmetric information and hence investors are unable to make fully informed decisions. This difference in information between insiders and outsiders creates costs concerning adverse selection and moral hazard. The pecking order theory made popular by Myers and Majluf (1984), suggests that the costs that arise from information asymmetry between insiders and outsiders create a preference ranking over a firm's choice of financing. This theory posits that firms work their way up the pecking order by choosing financing that enables them to minimize costs.

Firms that tap the credit market directly generally have sufficient levels of informational transparency. Informational transparency enables firms to access arms-lengths debt and enjoy access to cheaper credit (Lemmon and Zender, 2010). In line with the pecking order theory, these firms are more likely to use market debt than bank debt as it is a relatively less expensive source of financing. Alternatively, firms that are opaque generally exhibit higher levels of asymmetric information. These firms find it more difficult to access credit markets and are faced with higher yields. Financial intermediaries such as banks can help bridge this information gap and reduce costs arising from asymmetric information. Therefore, these firms are likely to demand less market debt and rely more on bank debt via loans (Lemmon and Zender, 2010).

Disruptive innovation in an industry creates uncertainty and risk surrounding the future prospects of a firm (Becker and Ivashina, 2023) and hence, incumbent firms have increased uncertainty and risk. When an industry faces disruption risk, the market may be even more keen to analyze the firms in this industry so that they can assess their financial performance to determine their future prospects before extending them credit. Opaque firms make it harder for the market to assess their information. Because these firms are harder to evaluate than transparent firms, investors may perceive these corporates as riskier. The added uncertainty and risk in industries experiencing disruption risk, and the inability of market investors to assess opaque firms, means that the market may be even less willing to extend credit and may demand higher yields. This suggests that opaque firms are likely to turn to bank debt capital as they may find it harder to access market debt.

Furthermore, even in industries facing disruption risk, banks are more equipped to assess the creditworthiness of opaque firms because they can better overcome information asymmetries than the market (Boot, 2000). Some banks may have long-standing relationships with firms that have a high degree of information symmetry. Therefore, despite these firms being opaque to the market, a close relationship means that the bank may have more insight into the firm's operations, credit worthiness and financial performance, which helps inform credit lending decisions (Diamond, 1984). This means that even if the market is unwilling to extend credit to opaque firms in the face of added uncertainty and risk, banks may still be willing to provide finance.

Building on these findings, Hooks (2003) shows that firms that are more difficult to observe may choose higher levels of bank debt than market debt. This paper argues that monitoring and screening roles play a central role in lending decisions, which are particularly important for more opaque firms. The ongoing relationship between a firm and a lender such as a bank, allows the bank to generate informational advantages and ultimately lower monitoring costs in lending to the firm (Hooks, 2003). Similarly, Berger et al. (2001) suggest that the production of relationship information between a bank and a borrower can be costly and that the costs are likely passed on to the borrower. However, this paper argues that informationally opaque firms may be more willing to absorb these costs to secure access to external financing and enjoy the flexibility that bank loans offer.

2.4 Firm-level innovation, disruption risk and debt choice

The final research question of this thesis is to explore how innovation at the firm level moderates the relation between an industry facing disruption risk and the choice between market and bank debt capital. Many published papers have investigated how firm-level innovation intensity influences a firm's financing choice (see, e.g., Casson et al. (2008) and Magri (2009)), but it is not known how this variable moderates the relation. I hypothesize that disruption risk leads to proportionately less bank debt financing for more innovative firms. As a complementary, opposite hypothesis, I hypothesize that disruption risk leads to proportionately more bank debt financing for more innovative firms.

Eisdorfer and Hsu (2011) show that as technology advances and there is innovation in an industry, firms need to operate in a highly competitive environment. Firms that can utilize this technology and take advantage of these opportunities may be able to become market leaders. Alternatively, firms that fail to innovate and lose in the technological race may be outperformed by their peers and face a higher risk of bankruptcy (Eisdorfer and Hsu, 2011).

Similarly, Hsu et al. (2015) find that more innovative firms, measured through the number and quality of patents, are associated with a lower default probability. They find a negative relation between innovation measures and perceived default risk. This paper argues that firms that have a higher level of innovation intensity are more competitive. Investors consider these firms to have a higher survival likelihood, which is reflected in credit markets with these firms securing lower yields on issued bonds.

This suggests that if an industry faces disruption risk, more innovative firms are more likely to adapt to changes in the industry and remain competitive due to their innovative and technological capabilities. These firms are likely to face less distress and less risk than firms that are less able to adapt and evolve to changing market dynamics. In line with findings from Bolton and Freixas (2000), more innovative firms are more likely to continue to tap cheaper credit in the market and use proportionately less bank debt as they are perceived to be less risky, ceteris paribus. Alternatively, less innovative firms are likely to be perceived riskier and hence are more likely to use more expensive bank loans, ceteris paribus. Bank debt offers greater flexibility than market debt which firms generally prefer if they experience financial distress (Bolton and Freixas (2000) and Cantillo and Wright (2000)).

Firm-level innovation could also possibly have the opposite effect, with more innovative firms relying more on bank debt capital. Market financing of innovative projects faces many obstacles that may make it harder for innovative firms to raise market debt. Moral hazard and asymmetric information are key problems that pose challenges for firms to secure external financing for innovative projects. Guiso (1998) argue that asymmetric information is more sensitive with more innovative firms. Innovative firms are less understood by outside investors since past experiences provide little insight into assessing the prospects of truly new innovative projects. The firm has more knowledge about the prospects of innovative projects and the likelihood of its success. This raises issues concerning moral hazard and makes it harder for outside investors to distinguish between good and bad projects (Guiso, 1998).

In line with this literature, Arrow (1972) argues that moral hazard problems create challenges for innovative firms making it harder to secure access to external financing for innovative projects. High-tech firms have less incentive to communicate information regarding their innovative projects, since it may reveal sensitive information to their competitors (Bhattacharya and Ritter, 1983). This implies that innovative firms may be harder to assess by external investors, and thus find it more difficult to secure access to external credit markets.
Given that banks are better able to overcome information asymmetries and can reduce the costs arising from asymmetric information, these firms are likely to demand less market debt and rely more on bank loans (Lemmon and Zender, 2010).

Banks can bridge the information gap, are better equipped than the market to assess the prospects of innovative projects and can generate insight into the future performance of the firm (Diamond, 1984). All else being equal, innovative firms are typically associated with a lower default probability, face less financial distress (Eisdorfer and Hsu, 2011), and are more likely to remain competitive as technology advances (Hsu et al., 2015). This suggests that in an industry facing disruption risk, banks are more able to assess how firm-level innovation can protect a firm, and thus are more willing to offer lower interest rates than the market. This supports the notion, that in an industry facing innovative disruption, more innovative firms are likely to rely on proportionately more bank debt capital than market debt.

Summary of hypotheses to be tested:

Central hypothesis:

Hypothesis 1. Disruption risk leads to incumbent firms relying more on bank debt financing.

Secondary hypotheses:

Hypothesis 2. Disruption risk leads to more bank financing because credit risk is higher.

Hypothesis 3. Disruption risk leads to proportionately more bank debt financing for more opaque firms.

Hypothesis 4.a Disruption risk leads to proportionately less bank debt financing for more innovative firms.

Hypothesis 4.b Disruption risk leads to proportionately more bank debt financing for more innovative firms.

3. Data

3.1 Sample

This study employs multiple data sets including Compustat, Mergent FISD[3], FactSet and data made available by Becker and Ivashina (2023).[4] The sample is built using Compustat and includes annual firm-level panel data of U.S. firms. Annual data is used in this research because key explanatory variables regarding IPO and VC data are only available on an annual basis. Standard Industry Classification (SIC)[5] codes for each firm in the Compustat sample are also retrieved because industry classifications are used to underpin the entry of new firms as a group (disruptors) and incumbent firms.

[3] Compustat and Mergent FISD databases are retrieved via Wharton Research Data Services (WRDS).

[4] This data can be found in the supporting information in the online version of Becker and Ivashina (2023); https://onlinelibrary.wiley.com/doi/10.1111/jofi.13187.

[5] SIC codes are a standardized system of codes used to classify firms based on their primary activities and are used in this research to classify the sector in which each firm in the sample belongs to.

The maximum time period provided by FactSet for firm-level loan data is 2006 to 2022, and therefore, firm-level data between 2006 and 2022 is retrieved from Compustat. This results in 6,090 firm-year observations. To ensure the sample is limited to non-financial firms, companies with SIC codes from 6000 to 6900 are removed and I further exclude firms with non-classified SIC codes. An important consideration regarding SIC codes is that this industry classification system can be problematic for large established companies that operate in more than one industry. This may lead to this research associating firms with erroneous levels of disruption activity (Becker and Ivashina, 2023). Fama-French 30-industry classifications[6] provide more representative industry classifications (Chen et al., 2016) and therefore it is the preferred industry classification for the purpose of this research. The remaining SIC codes in the firm Compustat sample are mapped to Fama-French 30-industry classifications using risk-based industry classifications from Kenneth French's website.

Observations for which the necessary firm-level variables are missing–described in section 3.4–are removed and because this research analyses the choice firms make between bonds and loans, years where firms do not issue either type of debt are excluded. Years, where firms issue both types of debt are also excluded because this often reflects corporate transactions such as takeovers (Becker and Ivashina, 2014). The exclusion of simultaneous debt issuance helps focus the results on real economic activity and general corporate financing, which is the focus of this thesis. The final number of firm-year observations in the sample is 3,326 for 231 firms. I henceforth refer to this subset of the data as the dataset used in this research. Table 1 and Table 2 present the distribution of this dataset by sector and year, respectively.

[6] Fama-French 30-industry classifications are a risk-based industry classification that divides the market into 30 industry sectors. This framework maps firms to one of these industries based on primary business activities. This classification system can be found on Kenneth French's website.

Table 1

This table presents the distribution of the observations in this dataset in each sector.

Fama-French 30-Industry Classification	Number of observations	Proportion (%)
Aircraft, ships, and railroad equipment	46	1.4
Apparel	10	0.3
Automobiles and Trucks	77	2.3
Beer & Liquor	35	1.1
Business Equipment	477	14.3
Business Supplies and Shipping Containers	76	2.3
Chemicals	124	3.7
Communication	67	2.0
Construction and Construction Materials	158	4.8
Consumer Goods	66	2.0
Electrical Equipment	46	1.4
Everything Else	131	3.9
Fabricated Products and Machinery	179	5.4
Food Products	121	3.6
Healthcare, Medical Equipment, Pharmaceutical Products	266	8.0
Personal and Business Services	283	8.5
Petroleum and Natural Gas	138	4.2
Precious Metals, Non-Metallic, and Industrial Metal Mining	12	0.4
Printing and Publishing	37	1.1
Recreation	51	1.5
Restaurants, Hotels, Motels	57	1.7
Retail	134	4.0
Steel Works Etc	67	2.0
Textiles	29	0.9
Transportation	120	3.6
Utilities	357	10.7
Wholesale	161	4.8
Total	3326	100

Table 2

This table presents the distribution of the observations in this dataset in each year.

Year	Number of observations	Proportion (%)
2006	286	8.6
2007	266	8.0
2008	251	7.5
2009	241	7.2
2010	231	6.9
2011	221	6.6
2012	209	6.3
2013	197	5.9
2014	186	5.6
2015	180	5.4
2016	174	5.2
2017	165	5.0
2018	158	4.8
2019	154	4.6
2020	151	4.5
2021	145	4.4
2022	111	3.3
Total	3326	100

3.2. Dependent variable

In this analysis, the main dependent variable, *Debt Choice*, is a binary indicator reflecting the choice a firm makes between bonds and loans. U.S. Firm-level data on loan issuance between 2006 and 2022 is retrieved from FactSet and bond data between 2006 and 2022 is retrieved from Mergent FISD. Multiple loan issues or bond issues for a given year and firm are counted as one. To identify which firms in my Compustat sample issue a bond in a given year, I match each bond to the issuing firm based on its CUSIP identifier and company name. Loans retrieved from FactSet are matched to firms in the Compustat sample based on each firm's ticker identifier.

In creating the dependent variable, I first create indicator variables for loan and bond issuance. *D_loan* is an indicator variable equal to 1 if firm *i* receives a loan in year *y* and 0 otherwise. *D_bond* is an indicator variable equal to 1 if firm *i* issues a bond in year y and 0 otherwise. *D_loan* and *D_bond* are used to create my dependent indicator variable, *Debt Choice,* which takes value 1 if *D_loan* is equal to 1, and value 0 if *D_bond* is equal to 1. The variable *Debt Choice* is set to missing whenever *D_bond* is equal to *D_loan*. The analyses thus focus on the mutually exclusive choice between the two alternative sources of financing while conditioning on the firm being willing and able to raise debt capital in a given year. Regarding the distribution of *Debt Choice,* the mean is 0.389 (see Table 3), which implies that the average unconditional probability of a firm choosing a loan relative to a bond in my sample is 39%.

3.3. Disruption

The main independent variables are empirical proxies for disruption at the industry level, which includes VC capital flow and IPO share. Multiple proxies for disruption are used in this research to provide a more reliable representation of the effect of disruption on debt choice. Using multiple proxies also reduces measurement error because no single proxy is a perfect measurement of disruption. If both IPO share and VC Capital flow consistently show the same effect on debt choice, this can strengthen the evidence of disruption on debt choice and add to the robustness of my findings. Given data availability constraints, this thesis uses VC capital flow and IPO share variables that are made available by Becker and Ivashina (2023)[7]. VC investments in an industry allow me to focus on the fastest-growing start-ups to proxy for early-stage disruption in an industry. IPOs enable me to widen the scope of disruption as they reflect both successful firms' exit from VC financing and capture the arrival of companies in an industry that do not pursue VC investments.

The VC capital flow sample period is from 1967 to 2022. Becker and Ivashina (2023), use the dollar amount invested in each industry and year in the U.S. and uses Fama-French 30-industry classifications. VC capital flow is aggregated over a five-year rolling period and the natural logarithm of this variable is taken. I use this variable and name it *VC Flow* and match it to debt choice in the following year. The reasoning is that *VC Flow* over the period [t-4, *t*], predicts debt choice in *t*+1. *VC Flow* is matched to firms in the Compustat sample based on each firm's ticker identifier.

IPO share data is from 1960 to 2022. Becker and Ivashina (2023) define their IPO variable as the number of IPOs as a fraction of the total number of public firms in a given industry. IPO share is computed over a five-year rolling period, with IPO share in the period [t-4, *t*], predicting debt choice in *t*+1. In creating this variable, Becker and Ivashina (2023) exclude reverse leveraged buyouts (LBOs), which are exits from buyout transactions that are identified using the Pitchbook database. This papers reasoning for excluding reverse LBOs is

[7] Becker and Ivashina (2023) use VentureXpert and Burgiss to construct their VC-based disruption measures and Pitchbook to construct their IPO measure of disruption. This data can be found in their supporting information in the online version of this paper; https://onlinelibrary.wiley.com/doi/10.1111/jofi.13187.

because postbuyout firms are not reflective of disruption at a significant enough level. I use their IPO variable and name it *IPO Share*. *IPO Share* is matched to firms in the Compustat sample based on each firm's ticker identifier.

Concerning the distribution of my disruption proxies (see Table 3), the average number of IPOs as a fraction of the total number of firms in a given industry is 0.129 (i.e., 12.9%). The maximum and minimum IPO share is 0.339 and 0 respectively. For the natural logarithm of VC flow, the average is 8.603 million U.S. dollars and the maximum and minimum are 11.540 and 1.728 million U.S. dollars, respectively. The industries in my sample that exhibit the highest levels of disruption include Business Equipment, Chemicals, Healthcare, Medical Equipment, Pharmaceuticals, Transportation, and Utilities. During 2006 and 2022, 60% of all IPOs and 58% of the total VC Flow in my sample occurred in these industries.

3.4. Firm-level variables

In addition to the main explanatory variables, this thesis makes use of firm-level characteristics to address the secondary research questions, and firm-level control variables to help isolate the effect of the key explanatory variables on *Debt Choice.* All firm-level variables are lagged one year in this study because the value of these variables in year *t-1* informs *Debt Choice* in time *t.*

As a proxy for credit risk, I use firm-level time-varying probability of default estimates provided by the National University of Singapore's Credit Research Initiative (NUS-CRI).[8] NUS-CRI provides forward-looking measures of credit risk that use default histories, financial performance, industry characteristics and macroeconomic conditions to estimate the probability of default for a particular firm. Probability of default estimates provided by NUS-CRI are widely used in academic research as a measure of credit risk (see, e.g., Kanno (2020)). One-year horizon estimates are collected between 2006 and 2022, which I assign to the variable *PD*. Probability of default estimates for individual companies are matched to firms in my sample based on company ticker. The average *PD* is 0.5%, with the maximum and minimum *PD* being 76.5% and 0% respectively (see Table 3).

As a proxy for firm opacity, this thesis follows the work of Dahiya et al. (2017) who tests the effectiveness of nine widely used empirical measures for firm opacity. Of the different measures evaluated in this paper, Amihud's (2002) illiquidity measure and the number of analysts following a firm are the two measures shown to be the most consistent measures for

[8] The NUS-CRI database covers over 80,000 exchange-listed global firms and provides firm-level probability of default estimates with sample horizons from 1 month to 5 years. See: https://nuscri.org/

firm opacity. Given data constraints concerning the number of analysts following a firm, this research uses Amihud's (2002) illiquidity measure to proxy for firm opacity.

Amihud's illiquidity measure is calculated by taking the ratio between the absolute value of a stocks daily return and the daily trading volume. Higher resulting values reflect a higher level of illiquidity (Dahiya et al., 2017). This metric relates opaque firms to higher values and transparent firms to lower values and it is widely adopted in academic literature to measure firm opacity. The intuition behind this measure as a proxy for firm opacity, is that investors are more exposed to a risk of uninformed trading for opaque stocks because it is harder to obtain reliable information about the firm. Therefore, the shares of opaque firms will be less liquid and more expensive to trade, which is reflected through a higher value of this measure (Dahiya et al., 2017).

I compute Amihud's (2002) illiquidity measure and assign it to the variable *Amihud ratio.* FactSet is used to retrieve U.S. firm-level daily returns and daily trade volumes between 2006 and 2022. I take the ratio between the absolute daily return and daily dollar volume. The ratio is measured for each trading day and for each firm. The average over a year is taken of these daily ratios; see Eq. 1.

$$Amihud\ ratio_i = \left(\frac{1}{D_i}\right) \sum_{t=1}^{D_i} \frac{|r_{i,t}|}{VOL_{i,t}} \tag{1}$$

D_i is the number of observations for stock i during the quarter and $VOL_{i,t}$ is the dollar trade volume of stock i on day t. *Amihud ratio* is matched to firms in the Compustat sample based on each firm's ticker identifier.

To answer *hypothesis 3,* I am interested in analyzing how firm opacity moderates the relation between an industry facing disruption risk and the choice between market and bank debt capital. To address this hypothesis, I create an indicator variable for my illiquidity measure and assign it to the variable *Amihud*, which I interact with my disruption variables. To create *Amihud*, I compute the median of my *Amihud* variable in each year in my final sample. For each individual firm-year observation, I assign value 1 to the indicator if the value of *Amihud ratio* for that observation is greater than or equal to the median, and value 0 if it is less than the median. Value 1 reflects firms that have a high level of opacity, and value 0 reflects firms that have a low level of opacity. The average of *Amihud is* 0.451 (see Table 3), meaning that there are slightly fewer firms with a high level of opacity in my sample, relative to firms with a low level of opacity.

To proxy for firm-level innovation, I collect annual firm-level R&D spend for U.S. companies between 2006 and 2022. In previous literature (see, e.g., Pakes (1985) and Bastin and Hübner (2006)), patents are considered the most effective proxy for firm-level innovation output and have several advantages for assessing technological competitiveness than other innovation proxies (Hsu et al., 2015). Moreover, given the delays involved in patent filing, patent results are unlikely to reflect macroeconomic factors (Becker and Ivashina, 2023). However, given data availability constraints and the difficulties in matching firm-level patent data to my sample, this research uses R&D spend to proxy for firm-level innovation, which is another widely adopted proxy in previous literature for firm-level technological innovation (see, e.g., Guo et al. (2018); Griliches, (1984); and Casson et al. (2008)).

R&D expenditure is retrieved from FactSet and reflects annual R&D expenditure in millions of U.S. dollars that is disclosed on the income statement of public U.S. companies. The distribution of this variable is highly skewed and has extreme outliers. I windsorize the variables using 1 and 99 percentiles to address extreme values and take the natural logarithm of this variable to address the asymmetric distribution and assign it to the variable *R&D expenditure.* The resulting transformed variable is more reflective of a normal distribution.

To answer *hypothesis 4,* I am interested in analyzing how firm-level innovation moderates the relation between an industry facing disruption risk and the choice between market and bank debt capital. To address this hypothesis, I create an indicator variable for my firm-level innovation measure and assign it to the variable *R&D,* which I interact with my disruption variables. To construct *R&D*, I follow the same procedure used to create *Amihud*. Value 1 reflects firms that have a high level of innovation intensity, and value 0 reflects firms that have a low level of innovation intensity. The average of *R&D is* 0.632 (see Table 3), meaning that there are slightly more firms with a high level of innovation in my sample, relative to firms with a low level of innovation.

In this research, Compustat is used to build time-varying annual firm-level variables to control for firm-level effects. In line with prior literature, the control variables used in this study are *Tangibility*, *Leverage*, and *ROA*. Similarly to Faulkender and Petersen (2006), *Tangibility* is defined as the ratio of the firm's property plant and equipment to total assets. In line with Becker and Ivashina (2014), *Leverage* is the sum of long-term debt and debt in current liabilities divided by total assets, and *ROA* is the ratio of EBITDA to total sales. These control variables are assigned to *X,* a vector of explanatory variables. Regarding the distribution of these controls, the average level of *Tangibility*, *Leverage* and *ROA* in the dataset, is 38.8%, 33.8%, and 18.9%, respectively. Summary statistics of all variables used in this research are presented in Table 3.

Table 3

This table presents descriptive statistics for all variables used in my final firm-year sample. *Debt Choice* is an indicator variable that takes value 1 if a loan is received and value 0 if a bond is issued. *IPO Share* is the number of IPOs as a fraction of the total number of public firms in a given industry, computed over a five-year rolling period and excludes reverse LBOs. *VC Flow* is the natural logarithm of the U.S. dollar amount invested in each industry in millions, computed over a five-year rolling period. Both *IPO Share* and *VC Flow* are matched to debt choice in the following year. *PD* is firm-level time-varying annual probability of default estimates expressed as a percentage, lagged one year. *Amihud ratio* is the ratio of firm-level absolute daily returns and daily dollar volume. The ratio is measured for each trading day and for each firm and the average over a year is taken of these daily ratios. *Amihud* is an indicator variable (lagged one year) that is equal to 1 when *Amihud ratio* for observation firm *i* and year *y*, is greater than or equal to the median *Amihud ratio* value in year *y*, and value 0 otherwise. *R&D expenditure* is the natural logarithm of annual R&D expenditure expressed in millions of U.S. dollars and winsorized using 1 and 99 percentiles. *R&D* is an indicator variable (lagged one year) that is equal to 1 when *R&D expenditure* for observation firm *i*, and year *y*, is greater than or equal to the median *R&D expenditure* value in year *y*, and value 0 otherwise. *Tangibility* is the ratio of property, plant, and equipment to total assets, lagged one year. Leverage is the ratio of long-term debt and debt in current liabilities to total assets, lagged one year. ROA is the ratio of EBITDA to total sales, lagged one year.

Variable	N	Mean	Median	Std. Dev.	Maximum	Minimum
Debt Choice	3,781	0.389	0	0.238	1	0
IPO Share	3,781	0.129	0.116	0.059	0.339	0.000
VC Flow	3,781	8.603	8.824	1.433	11.540	1.728
PD	3,326	0.527	0.029	2.106	76.513	0.000
Amihud ratio	3,781	0.230	0.150	0.561	0.998	0.008
Amihud	3,781	0.451	0	0.498	1	0
R&D expenditure	3,781	5.642	5.384	1.679	9.995	1.224
R&D	3,781	0.632	1	0.443	1	0
Tangibility	3,543	0.388	0.297	0.271	0.914	0.004
Leverage	3,543	0.338	0.310	0.174	0.985	0.001
ROA	3,543	0.189	0.214	0.209	0.753	0.057

4. Methodology

This research uses multivariate logit models to analyze disruption risk and debt choice. Logit regressions are generally preferred for this type of research (see, e.g., Denis and Mihov, (2003) and Ojah and Pillay (2009)) because the dependent variable is a binary variable (i.e., the choice between bonds and loans), and the model ensures that the estimated probabilities are bounded between zero and one. Firm fixed effects are also included in the regression to control for potential confounding factors. Including firm fixed effects help isolate the effect of disruption on debt choice, as it controls for unobserved time-invariant factors specific to each firm in the sample. Before running each regression that follows in Section 4, I test for multicollinearity using the Variance Inflation Factor (VIF) test. The VIF test reveals that there are no issues concerning multicollinearity.

To derive my logit model, I define an underlying latent dependent variable y^*, which we do not observe and assume it relates in a linear way to the independent variables x. We observe only if this variable takes on a value larger than 0 or not. In the latter case, the observed dependent variable (*y*) takes on a value 1, which I formalize in Eq. 2.

$$y^* = \beta_0 + x\beta + e$$
$$y = \begin{cases} 0 & if \;\; y^* \leq 0 \\ 1 & if \;\; y^* > 0 \end{cases} \tag{2}$$

For the probability of y = 1, and to ensure that the probabilities are bounded between 0 and 1, I apply a nonlinear logistic function. To answer this study's central research question and test *hypothesis 1*, I implement multivariate logistic regressions of the choice between bonds and loans on empirical proxies for disruption and firm-level controls. The probability of a firm choosing a bank loan over a bond is modeled using the logit function and it is estimated using maximum likelihood estimation (MLE); see Eq. 3.

$$\text{Prob}\,(\textit{Debt Choice}_{i(s)t}) = \beta_0 + \beta_1 \textit{Disruption}_{st} + X_{i(s)t} + \alpha_i \tag{3}$$

Debt Choice is the dependent variable, which is an indicator variable that takes the value 1 when a bank loan is received by firm *i*, at time *t* and in sector *s*. The variable takes value 0 when a bond is issued. This regression models the log-odds of the dependent variable taking value 1 (i.e., the natural logarithm of the probability of a firm choosing a bank loan over a bond) given the level of *Disruption* in sector *s* and at time *t*, and given the level of firm-level control variables ($X_{i(s)t}$) and firm-fixed effects (α_i).

In this research design, the choice a firm makes between bonds and loans does not require perfect substitutability. Previous academic literature offers several reasons why bonds and loans are fairly close substitutes for firms that are able to tap the credit market. Loans and bonds share similar characteristics concerning bankruptcy, corporate tax treatment, covenants protection, and contractual features including collateralization. Both types of debt are also comparable in terms of repayment characteristics and maturities (Becker and Ivashina, 2014). Additionally, Kashyap et al. (1994), Johnson (1997), and Faulkender and Petersen (2006) provide evidence that bonds and loans offer close substitutability in debt financing for firms with credit ratings.

Depending on the model specification, *Disruption* is equal to *VC Flow* or *IPO Share*. The relation between *Disruption* and *Debt Choice* is measured by observing the variation in each disruption measure across industries and within a particular industry over time. In line with *hypothesis 1* and the literature review, I expect the coefficients on both disruption measures to be positively related to the probability of receiving a bank loan relative to issuing a bond. In line with the literature review, I expect the coefficient on all three control variables, *X*, to be negatively related to the probability of receiving a bank loan relative to issuing a bond.

To test *hypothesis 2*, I run two separate regressions. First, I run a FE regression with credit risk as the dependent variable and my measures for disruption as the explanatory variables. This enables me to test if disruption increases credit risk. Given that I have panel data, and my interest is in within effects – how a change over time in disruption affects credit risk – a FE model is the appropriate model; see Eq. 4.

$$PD_{i(s)t} = \beta_0 + \beta_1 Disruption_{st} + \alpha_i + u_{ist} \tag{4}$$

PD proxies for credit risk, for firm *i*, at time *t*, and in sector *s*. *Disruption* is equal to *VC Flow*, or *IPO Share* depending on the model specification. The firm fixed effects (α_i) capture unobservable time-invariant factors that affect the credit risk of firms in my sample. u_{ist} is the idiosyncratic error term with expected value zero and constant variance. I expect the coefficient on both disruption measures to be positively related to credit risk, for firm *i*, at time *t*, and in sector *s*. If *Disruption* increases credit risk as I hypothesize, I rerun equation E.q.3. and add my proxy for credit risk as a control variable. This enables me to test if credit risk is the channel through which disruption affects debt choice; see E.q. 5.

$$\text{Prob}\,(Debt\ Choice_{i(s)t}) = \beta_0 + \beta_1 Disruption_{st} + \beta_2 PD_{i(s)t} + X_{i(s)t} + \alpha_i \tag{5}$$

After controlling for credit risk, if credit risk is indeed the only channel in which disruption risk results in more loans than bonds, the effect of *Disruption* on *Debt Choice* will be insignificant. However, if the coefficient on *Disruption* indicates a significant effect on *Debt Choice*, this implies that there is another channel (in addition to credit risk) in which disruption risk affects a firm's debt financing decision.

To test *hypothesis 3*, I implement the same multivariate logistic regression in Eq.5. and add my proxy for firm opacity as both a control and interaction term; see Eq. 6.

$$\begin{aligned}\text{Prob}\,(Debt\ Choice_{i(s)t}) = {} & \beta_0 + \beta_1 Disruption_{st} + \beta_2 PD_{i(s)t} + \beta_3 Amihud_{i(s)t} \\ & + \beta_4 Disruption_{st} * Amihud_{i(s)t} + X_{i(s)t} + \alpha_i\end{aligned} \tag{6}$$

Amihud proxies for firm opacity and the interaction term between *Disruption* and *Amihud* is added to analyze how the effect of disruption as a predictor of *Debt Choice* differs depending on the level of firm opacity. In line with *hypothesis 3* and the literature review, I expect the coefficient on the interaction term to be positively related to the probability of receiving a bank loan relative to issuing a bond, regardless of the model specification for disruption.

To test *hypothesis 4*, I implement the same multivariate logistic regression in Eq.5. and add my proxy for firm-level innovation as both a control and interaction term; see Eq. 7.

$$\text{Prob}\ (\mathit{Debt\ Choice}_{i(s)t}) = \beta_0 + \beta_1 \mathit{Disruption}_{st} + \beta_2 \mathit{PD}_{i(s)t} + \beta_3 \mathit{R\&D}_{i(s)t} + \beta_4 \mathit{Disruption} {*} \mathit{R\&D}_{i(s)t} + X_{i(s)t} + \alpha_i \tag{7}$$

The interaction term between *Disruption* and *R&D* is added to examine how the effect of *Disruption* as a predictor of *Debt Choice* differs depending on firm-level innovation. In line with *hypothesis 4.a*, *hypothesis 4.b*, and the literature review, I expect the coefficient on the interaction term to be either negatively or positively related to the probability of receiving a bank loan relative to issuing a bond.

For the post-regression analysis, I test for heteroskedasticity using the Breusch-Pagan procedure and autocorrelation using the Breusch-Godfrey procedure in the regression models specified in equations 3 to 7. I reject the null hypothesis and find evidence of heteroskedasticity in each of the specified models and apply robust standard errors to correct for this. No evidence of autocorrelation is found.

5. Results & Discussion

In this section, I present and discuss the empirical results of this study. To address each research question, I proxy *Disruption* with *IPO share* and *VC Flow* in Model 1 and Model 2 respectively. For each model, the coefficients and the odds ratios based on these estimates are reported. Odds ratios are interpretable as percentage changes in probabilities. Section 5.1 focuses on the central hypothesis, addressing disruption risk and the choice between bonds and loans. Section 5.2 addresses if credit risk is the primary channel in which disruption risk affects debt choice. I then address how firm opacity and firm-level innovation moderate the relation between disruption risk and debt choice, in sections 5.3 and 5.4, respectively. Finally, I reflect on the implications of these findings for practitioners in section 5.5, and I address the limitations of this research in section 5.6.

5.1 Disruption risk and debt choice

Table 3 and Table 4 address the central hypothesis of this research and present the results for logistic regressions of disruption risk on debt choice, with Table 4 including firm-level control variables.

Considering the results in Table 3, all else being equal, whatever the probability is of a firm choosing a loan compared to issuing a bond, this probability increases by 73.1% for a one percentage point increase in *Disruption* in Model 1 (*IPO Share*), and it increases by 33.8% for a one percent increase in in the natural logarithm of *Disruption* in Model 2 (*VC Flow*). These findings are statistically significant at the 10% and 1% confidence levels respectively. With the inclusion of additional control variables in Table 4, all else being equal, whatever the probability is of a firm choosing a loan compared to issuing a bond, this probability increases by 76.6% for a one percentage point increase in *Disruption* in Model 1, and it increases by 21.5% for a one percent increase in the natural logarithm of *Disruption* in Model 2. These findings are statistically significant at the 10% and 5% confidence levels respectively. In addition to the findings in Tables 3 and 4 being statistically significant, the effect of *Disruption* on *Debt Choice* is economically relevant, given that the average unconditional probability of a firm choosing a loan relative to a bond in my sample is 39%. While the odds ratios reported in Model 1 are of similar magnitude in Tables 3 and 4, the odds ratio reported by Model 2 is materially lower (12.3%) in Table 4 relative to Table 3. This suggests that by including additional control variables, some of the variance that was attributed to *Disruption* alone in Table 3 is captured by the control variables, which leads to a reduction in the effect of *Disruption* on *Debt Choice*. Albeit, the fact that both proxies for *Disruption* have a similar effect exemplifies the robustness of the nexus between the success of new firm entrance and incumbent firms' debt financing decisions.

The firm-level control variables in Table 4 are all negatively associated with loan issuance as predicted. This suggests that whatever the probability is of a firm choosing a loan, higher values of these variables lead to a decrease in the probability of a firm choosing a loan compared to issuing a bond. These findings are consistent with prior literature. Faulkender and Petersen (2006) show that companies with more tangible assets are more likely to raise public debt. Becker and Ivashina (2014) find that firms with higher levels of leverage are more likely to issue bonds. Chemmanur and Fulghieri (1994) show that less profitable firms tend to raise more bank debt capital. *Leverage* and *ROA* are significant at the 10% and 1% confidence levels, respectively, while *Tangibility* is statistically insignificant.

The empirical results reported in Tables 3 and 4 suggest that as predicted, disruption risk leads to incumbent firms relying more on bank debt financing, ceteris paribus. Incumbent firms facing disruption risk face higher levels of distress as they are at risk of losing market power and seeing a deterioration in earnings and performance (Becker and Ivashina, 2023). The findings in Tables 3 and 4 are consistent with Bolton and Freixas (2000), Lemmon and Zender (2004), and Cantillo and Wright (2000), who suggest that firms facing increased risk and financial distress are likely to rely more on loans because banks are better able to support distressed firms and can offer more flexible financing.

Table 3

Disruption risk and debt choice. This table presents coefficient estimates and odds ratios for logistic regression models of disruption risk on debt choice. The dependent variable is *Debt Choice*. Depending on the model specification for *Disruption*, the independent variable is either *IPO Share* (Model 1) or *VC Flow* (Model 2). For the variable *VC Flow*, the natural logarithm of this variable has been taken. All of the variables are as defined in Table 3. Standard errors robust to heteroskedasticity are reported in parentheses and firm FE are used. There are 3,781 observations in both models. *, **, add *** indicate statistical significance at the 10%, 5% and 1% confidence levels respectively.

	Model 1	Model 1	Model 2	Model 2
	Coefficient	Odds Ratio	Coefficient	Odds Ratio
IPO Share	0.549	1.731		
	(0.336)*	(0.582)*		
VC Flow			0.291	1.338
			(0.090)***	(0.120)***
Firm Fixed Effects	Yes	Yes	Yes	Yes
No. Observations	3,781		3,781	
Pseudo R^2	0.0113		0.0361	

Table 4

Disruption risk and debt choice. This table presents coefficient estimates and odds ratios for logistic regression models of disruption risk on debt choice with additional control variables. The dependent variable is *Debt Choice.* Depending on the model specification for *Disruption*, the independent variable is either *IPO Share* (Model 1) or *VC Flow* (Model 2). *Tangibility*, *Leverage*, and *ROA* are lagged 1 year. For *VC Flow*, the natural logarithm of this variable has been taken. All of the variables are as defined in Table 3. Standard errors robust to heteroskedasticity are reported in parentheses and firm FE are used. There are 3,543 observations in both models. *, **, add *** indicate statistical significance at the 10%, 5% and 1% confidence levels respectively.

	Model 1	Model 1	Model 2	Model 2
	Coefficient	Odds Ratio	Coefficient	Odds Ratio
IPO Share	0.569	1.766		
	(0.381)*	(0.673)*		
VC Flow			0.195	1.215
			(0.096)**	(0.116)**
Tangibility	-0.424	0.654	-0.435	0.647
	(0.691)	(0.452)	(0.365)	(0.236)
Leverage	-2.219	0.109	-2.333	0.097
	(1.246)*	(0.135)*	(1.278)*	(0.124)*
ROA	-0.601	0.548	-0.557	0.573
	(0.233)***	(0.128)***	(1.946)***	(0.112)***
Firm Fixed Effects	Yes	Yes	Yes	Yes
No. Observations	3,543		3,543	
Pseudo R^2	0.081		0.084	

5.2 Credit risk, Disruption risk and debt choice

In this section, I address *hypothesis 2*. I first test if *Disruption* increases credit risk by running a FE regression of disruption risk on credit risk. The results are reported in Table 5.

A one percentage point increase in *Disruption* in Model 1 is associated with an increase in the expected annual default probability of 0.16%, ceteris paribus. A one percent increase in the natural logarithm of *Disruption* in Model 2 is associated with an increase in the expected annual default probability of 0.005%, ceteris paribus. These findings are statistically significant at the 10% and 1% confidence levels, respectively. The empirical results thus suggest that as predicted, disruption risk increases credit risk for incumbent firms, ceteris paribus. These findings are consistent with Becker and Ivashina (2023), who also find that disruption risk increases credit risk of incumbent firms.

Table 5

Disruption risk and credit risk. This table presents the coefficient estimates for FE regression models of disruption risk on credit risk. The dependent variable is *PD.* Depending on the model specification for *Disruption*, the independent variable is *IPO Share* (Model 1) or *VC Flow* (Model 2). For the variable *VC Flow*, the natural logarithm of this variable has been taken. The variables are as defined in Table 2. Standard errors robust to heteroskedasticity are reported in parentheses and firm FE are used. There are 3,326 observations in both models. *, **, add *** indicate statistical significance at the 10%, 5% and 1% confidence levels respectively.

	Model 1	Model 2
	Coefficient	Coefficient
IPO Share	0.158	
	(0.084)*	
VC Flow		0.494
		(0.516)***
Firm Fixed Effects	Yes	Yes
No. Observations	3,326	3,326
R^2	0.463	0.679

After confirming that disruption risk increases credit risk as hypothesized, I control for credit risk to analyze if credit risk is indeed the only channel in which *Disruption* results in more loans than bonds. Table 6 presents the findings for logistic regressions of disruption risk on *Debt Choice*, with *PD* added as an additional control variable.

After controlling for credit risk, the coefficients on *Disruption* in both models are of similar magnitude and significance to those reported in Table 4. This suggests that *Disruption* has a similar effect even when controlling for credit risk, and hence it appears that credit risk is not the only channel through which *Disruption* affects a firm's debt financing choice. Further research could build on this study, by testing additional risk channels through which innovative disruption affects a firm's debt financing choice. Another possible explanation for these findings is that perhaps firm-level time-varying probability of default estimates is not a perfect proxy for credit risk. It is plausible that credit risk serves as the sole conduit through which *Disruption* affects *Debt Choice*; however, this model may not entirely account for credit risk. Further research could build on this study by testing additional proxies for credit risk to test if credit risk is indeed the only channel through which disruption risk affects *Debt Choice*. The firm-level control variables in Table 6 are all negatively associated with loan issuance, and the coefficients are of similar magnitude and significance, as reported in Table 4.

Table 6

Disruption, credit risk, and debt choice. This table presents coefficient estimates and odds ratios for logistic regression models of *Disruption* on *Debt Choice* with *PD* (lagged 1-year) added as a control variable. The dependent variable is *Debt Choice.* Depending on the model specification for disruption, the independent variable is either *IPO Share* (Model 1) or *VC Flow* (Model 2). *Tangibility*, *Leverage*, and *ROA* are lagged 1 year. For *VC Flow*, the natural logarithm of this variable has been taken. All of the variables are as defined in Table 2. Standard errors robust to heteroskedasticity are reported in parentheses and firm FE are used. There are 3,326 observations in both models. *, **, add *** indicate statistical significance at the 10%, 5% and 1% confidence levels respectively.

	Model 1	Model 1	Model 2	Model 2
	Coefficient	Odds Ratio	Coefficient	Odds Ratio
IPO Share	0.537	1.710		
	(0.395)	(0.676)		
VC Flow			0.167	1.182
			(0.130)	(0.153)
PD	0.567	1.763	0.564	1.758
	(0.382)	(0.161)	(0.371)	(0.191)
Tangibility	-0.622	0.537	-0.679	0.507
	(0.706)	(0.379)	(0.737)	(0.374)
Leverage	-2.115	0.121	-2.235	0.107
	(1.268)*	(0.153)*	(1.328)*	(0.142)*
ROA	-0.577	0.562	-0.523	0.593
	(0.236)**	(0.132)**	(0.235)**	(0.139)**
Firm Fixed Effects	Yes	Yes	Yes	Yes
No. Observations	3,326		3,326	
Pseudo R^2	0.091		0.094	

5.3 Moderating effect of firm opacity on disruption risk and debt choice

In this section, I address *hypothesis 3* by investigating how firm opacity moderates the relation between *Disruption* and *Debt Choice*, as reported in Table 7.

Considering the results in Table 7, given the firm has a high level of opacity (i.e., *Amihud* takes value 1) whatever the probability is of a firm choosing a loan, this probability increases by 82.6%[9] if *Disruption* increases by one percentage point in Model 1, and it increases by 52.0%[10] for a one percent increase in the natural logarithm of *Disruption* in Model 2. Alternatively, given the firm has a low level of opacity (i.e., *Amihud* takes value 0) whatever the probability is of a firm choosing a loan, this probability increases by 61.1% if *Disruption* increases by one percentage point in Model 1, and it increases by 30.8% for a one

[9] 82.6% is calculated as such: exp (0.125+0.477) = 1.826

[10] 52.0% is calculated as such: exp (0.150+0.269) = 1.520

percent increase in the natural logarithm of *Disruption* in Model 2. The probability of a firm choosing a loan compared to issuing a bond for high-opaque firms relative to low-opaque firms is approximately 13.4% and 16.1% higher in Models 1 and 2, respectively. These findings are statistically significant at the 5% and 10% confidence levels, respectively.

These findings suggest that firm opacity moderates the relation between *Disruption* and *Debt Choice.* As predicted, disruption risk leads to proportionately more bank debt financing for more opaque firms. Boot (200) and Diamond (1984) support these findings who suggest that banks may still be willing to finance informationally opaque firms even in the face of added uncertainty and risk because banks can better overcome information asymmetries than the market. These findings also correspond with Lemmon and Zender (2010) and Myers and Majluf (1984) who suggest that more opaque firms are more likely to rely on bank debt financing because financial intermediaries can reduce costs arising from asymmetric information.

Regarding *Amihud* as a control variable, whatever the probability is of a firm choosing a loan, this probability is higher by 24.6%-93.5% for high-opaque firms relative to low-opaque firms. These findings suggest more opaque firms are more likely to rely on bank debt capital, consistent with literature from Lemmon and Zender (2010) and Myers and Majluf (1984). *Leverage, ROA, and Tangibility* are all negatively associated with loan issuance, consistent with findings in Tables 4 and 6. *PD* is positively associated with loan issuance, consistent with findings from Bolton and Freixas (2000) who show that riskier firms choose bank loans over bonds, ceteris paribus.

Table 7

The moderating role of firm opacity on *Disruption* and *Debt Choice*. This table presents coefficient estimates and odds ratios for logistic regression models of disruption risk on *Debt Choice* with *Amihud* (lagged 1-year) added as a firm-level control variable and as an interaction term with *Disruption*. The dependent variable is *Debt Choice.* Depending on the model specification for *Disruption*, the independent variable is either *IPO Share* (Model 1) or *VC Flow* (Model 2). *Tangibility*, *Leverage*, and *ROA* are lagged 1-year. For *VC Flow*, the natural logarithm of this variable has been taken. All of the variables are as defined in Table 2. Standard errors robust to heteroskedasticity are reported in parentheses and firm FE are used. There are 3,326 observations in both models. *, **, add *** indicate statistical significance at the 10%, 5% and 1% confidence levels, respectively.

	Model 1	Model 1	Model 2	Model 2
	Coefficient	Odds Ratio	Coefficient	Odds Ratio
IPO Share x Amihud	0.125	1.134		
	(0.061)**	(0.069)**		
VC Flow x Amihud			0.150	1.161
			(0.093)*	(0.108)*
Amihud	0.660	1.935	0.221	1.246
	(0.487)	(0.943)	(0.792)	(0.987)
IPO Share	0.477	1.611		
	(0.412)	(0.663)		
VC Flow			0.269	1.308
			(0.190)	(0.248)
PD	0.531	1.701	0.545	1.725
	(0.474)	(0.619)	(0.445)	(0.767)
Tangibility	-0.790	0.454	-0.262	0.769
	(0.867)	(0.393)	(0.843)	(0.649)
Leverage	-2.648	0.071	-2.326	0.097
	(1.380)*	(0.098)*	(1.411)*	(0.137)*
ROA	-0.460	0.631	-0.566	0.568
	(0.260)*	(0.164)*	(0.273)**	(0.155)**
Firm Fixed Effects	Yes	Yes	Yes	Yes
No. Observations	3,326		3,326	
Pseudo R^2	0.173		0.184	

5.4 Moderating effect of firm-level innovation on disruption risk and debt choice

In this section, I address *hypothesis 4* by investigating how firm-level innovation moderates the relation between disruption risk and debt choice. These findings are reported in Table 8.

Considering the results in Table 8 and Model 1, all else being equal, given the firm has a high level of innovation (i.e., *R&D* takes value 1) whatever the probability is of a firm choosing a loan, this probability increases by 98%[11] if *Disruption* increases by one percentage

[11] 98% is calculated as such: exp (0.216+0.468) = 1.981

point. Alternatively, given the firm has a low level of innovation (i.e., *R&D* takes value 0) whatever the probability is of a firm choosing a loan, this probability increases by 59.7% if disruption increases by one percentage point, ceterus paribus. The difference in the probabilities of a firm choosing a loan compared to issuing a bond for more innovative firms relative to less innovative firms is approximately 24.2% higher. Despite these findings not being statistically significant, they are consistent with *hypothesis 4.b*, and support the notion that disruption risk leads to proportionately more bank debt financing for more innovative firms. Innovative firms face less financial distress and are more likely to remain competitive as technology advances (Hsu et al., 2015). Given that banks are better able to assess the prospects of innovative projects and a firm's future performance (Diamond, 1984), banks are more able to assess how firm-level innovation can protect a firm and thus are more willing to offer lower interest rates than the market.

In relation to Model 2, the odds ratio of 1 for the interaction term suggests that there appears to be no moderating role of firm-level innovation. This result is also not statistically significant at any level of significance. Regarding *R&D* as a control variable in both models, *R&D* appears to not influence a firm's debt financing choice (results are statistically insignificant).

A possible reason for the conflicting findings across Models 1 and 2, and the statistically insignificant results is the limitation concerning R&D expenditure as a proxy for firm-level innovation. In previous literature (see, e.g., Pakes (1985) and Bastin and Hübner (2006)), patents are considered the most effective proxy for firm-level innovation output. Patents also have several advantages for assessing technological competitiveness over other innovation proxies such as R&D (Hsu et al., 2015). Perhaps a more robust proxy for firm-level innovation can generate better insight into how innovation moderates the relation between disruption risk and debt choice. Further research could build on this study by assessing how patents as a proxy for firm-level innovation moderate this relation.

In relation to the remaining control variables, these variables have a similar association with loan issuance, as reported in Tables 4, 6, and 7, with *Leverage* and *ROA* both being statistically significant.

Table 8

The moderating role of firm-level innovation on *Disruption* and *Debt Choice*. This table presents coefficient estimates and odds ratios for logistic regression models of disruption risk on *Debt Choice* with *R&D* (lagged 1-year) added as a firm-level control variable and as an interaction term with *Disruption*. The dependent variable is *Debt Choice*. Depending on the model specification for *Disruption*, the independent variable is either *IPO Share* (Model 1) or *VC Flow* (Model 2). *Tangibility, Leverage,* and *ROA* are lagged 1 year. For *VC Flow*, the natural logarithm of this variable has been taken. All of the variables are as defined in Table 2. Standard errors robust to heteroskedasticity are reported in parentheses and firm FE are used. There are 3,326 observations in both models. *, **, add *** indicate statistical significance at the 10%, 5% and 1% confidence levels, respectively.

	Model 1	Model 1	Model 2	Model 2
	Coefficient	Odds Ratio	Coefficient	Odds Ratio
IPO Share x R&D	0.216	1.242		
	(0.203)	(0.253)		
VC Flow x R&D			0.000	1.000
			(0.000)	(0.000)
R&D	0.000	1.000	-0.001	0.999
	(0.000)	(000)	(0.001)	0.001
IPO Share	0.468	1.597		
	(0.507)	(0.809)		
VC Flow			0.104	1.110
			(0.101)	(0.112)
PD	0.502	1.652	0.556	1.744
	(0.426)	(0.703)	(0.392)	(0.684)
Tangibility	-0.398	0.672	-0.672	0.511
	(0.427)	(0.287)	(0.787)	(0.402)
Leverage	-2.136	0.118	-2.445	0.087
	(1.146)*	(0.135)*	(1.332)*	(0.116)*
ROA	-0.576	0.562	-0.546	0.579
	(0.157)***	(0.088)***	(0.250)**	(0.144)**
Firm Fixed Effects	Yes	Yes	Yes	Yes
No. Observations	3,326		3,326	
Pseudo R^2	0.0971		0.099	

5.5 Implications of Findings

This research provides a real-world perspective that has important societal relevance. The pattern of failure across incumbent firms is a consistent symptom of disruptive innovation (Bower and Christensen, 1995). Such phenomenon alters the landscape for incumbents and produces a myriad of risks and challenges. The findings in this thesis provide much-needed insight into how innovative disruption affects a firm's debt financing choice, which can help corporates navigate these challenges. Firms can use these findings to manage their financing costs and make informed decisions about their optimal capital structure, particularly in industries facing disruption risk where financing needs may be different.

While it is unclear from these findings if credit risk is the primary channel through which disruption affects debt choice, these findings show that disruption increases credit risk and disruption leads to incumbent firms relying more on bank debt capital, ceteris paribus. Lenders can use these findings to understand that disruption risk alters risk profiles and financing choices of incumbents. This can help investors and banks manage their exposure to different financing sources and foster more informed credit lending decisions.

The nexus between innovative disruption and debt choice can also inform policy decisions related to financial regulation to enhance financial stability. Given that disruption is shown to increase credit risk and that disruption results in firms relying on proportionately more bank debt capital, regulators may consider imposing additional capital requirements for banks heavily exposed to high-disruption industries to ensure banks are better equipped to manage this increased risk.

Disruption risk is also shown to have a larger effect on more opaque firms. In industries experiencing disruption, more opaque firms rely proportionately more on bank debt financing than less opaque firms, ceteris paribus. A possible explanation for this is that banks are better able to overcome information asymmetries and are still willing to provide capital when the market will not. Financial regulators can leverage this information and emphasize the importance of disclosure requirements, especially for firms operating in high-disruption industries. Stricter reporting requirements for high-opaque firms can help the market better assess firms experiencing disruption, and thus lessen the effect of disruption on a firm's debt choice. This will alleviate financing constraints for these firms and potentially enable them to continue to tap the credit market as outside investors will be able to assess these firms. If these firms are able to continue to access market debt in the face of disruption, this may negate banks being overexposed to firms that exhibit increased risk and promote financial stability.

5.6 Limitations

Like any study, there are limitations in this research that should be considered when reflecting on the findings.

First, this study makes use of data from multiple databases. In creating my dependent variable, *Debt Choice*, matching bond data from Mergent to my firm sample in Compustat is not perfect. I matched bonds issued by firms in Mergent by Cusip identifier. Because the Cusip identifier between Mergent and Compustat are not perfectly aligned, many firms are excluded from the sample when matched solely by Cusip. I also matched on company name between the two databases to include additional firms that are not matched solely by Cusip. Because company name and Cusip can change over time, many firms are unable to be matched and thus are excluded from my sample. Consequently, the presence of non-matched companies can potentially introduce selection bias into my analysis, as the excluded companies may not exhibit a random pattern.

While Fama-French 30-industry classifications were used in this study to overcome the limitations concerning SIC codes, a caveat with the industry-based approach is that assigning firms to industries is not without limitations. Boundaries within industries are not always clearly defined, firms may operate in multiple industries at once, and industry classifications for a firm may change over time. Because it is not clear how to address this limitation for the purpose of this study, I leave it for future research.

Another limitation of my study is the use of R&D expenditure as a proxy for firm-level innovation. This limitation is discussed in section 5.4. and it offers a possible explanation for the inconsistent findings and statistically insignificant results concerning the moderating role of firm-level innovation on the relation between disruption risk and debt choice. Future research can build on this study by assessing how additional proxies (e.g., firm-level patents) moderate this relation.

Another important consideration is the use of probability of default estimates as a proxy for credit risk. It is unclear from my findings in section 5.2 whether credit risk is the primary channel through which disruption affects debt choice. Because firm-level time-varying probability of default estimates is not a perfect proxy for credit risk, this model may not entirely account for credit risk, and therefore, it is plausible that credit risk serves as the only channel through which disruption affects debt choice. Future research could build on this study by testing additional proxies for credit risk to better understand if credit risk is the primary conduit through which disruption affects debt choice.

6. Conclusion

A comprehensive literature review has revealed that the relation between innovative disruption and a firm's debt financing decision was an unknown domain. Examining a period from 2006 to 2022 and utilizing logistic and fixed effects regressions to panel data of U.S. firms, the purpose of this thesis was to examine how innovative disruption impacts a firm's choice between market and bank debt capital.

Several contributions have been made to the current literature. In an industry experiencing innovative disruption there is new firm entrance and incumbent firms are perceived riskier (Becker and Ivashina, 2023). Riskier incumbents turn to banks that are better able to support distressed firms that are still willing to provide capital when the market will not (Bolton and Freixas (2000) and Lemmon and Zender (2004)). This research supports this notion, and to the best of my knowledge, this is the first study to find that disruption risk leads to incumbent firms, ceteris paribus, relying more on bank debt financing. The fact that both proxies for *Disruption* (*IPO Share* and *VC Flow*) in this research give consistent findings exemplifies the robustness of the nexus between new firm entrance and incumbent firms' debt financing decisions. By excluding reverse LBOs from *IPO Share*, postbuyout firms that are not reflective of disruption at a significant enough level are excluded. This allows me to focus the analysis on truly disruptive events, thereby adding to the validity of my findings. Fama-French 30-industry classifications, as opposed to SIC codes, were also used in this study to reduce the misclassification issues that arise with large established companies that may operate in more than one sector. By utilizing Fama-French 30-industry classifications, this research more accurately associates firms with the appropriate level of disruption, thereby enhancing the validity of the findings in this research.While it is not clear from these findings if credit risk is the only channel through which disruption affects debt choice, all else being equal, disruption risk is shown to increase credit risk.

As new firms enter an industry, markets may be more keen to analyze incumbent firms as they exhibit heightened risk. Because opaque firms are harder to assess, the market may be less willing to extend credit (Lemmon and Zender, 2010). Banks' critical function as a monitor and their information processing advantage (Hooks, 2003), suggests that they may be more willing than the market to finance informationally opaque firms even in the face of added uncertainty and risk. This research supports this notion and finds that disruption has a larger effect on more opaque firms. All else being equal, innovative disruption leads to proportionately more bank debt financing for more opaque firms. Capturing the moderating role of firm opacity is a secondary contribution of this thesis as it helps to provide a more in-depth understanding of the relation between disruption risk and debt choice.

A possible reason for the conflicting findings and insignificant results concerning firm-level innovation as a moderating role on disruption and debt choice, is the use of R&D expenditure as a proxy for firm-level innovation. Perhaps a more robust proxy for firm-level innovation, such as patents, is needed to investigate the moderating role of firm-level innovation. Given data availability constraints and the difficulties in matching firm-level patent data to my sample, I leave it for future research to assess additional proxies.

These findings have important implications as they provide much-needed insight into how innovative disruption affects a firm's debt financing choice. Regulators may consider imposing additional capital requirements for banks heavily exposed to high-disruption industries to ensure banks are better equipped to manage this increased risk. Because disruption has a larger effect on more opaque firms, regulators may also consider imposing stricter reporting requirements for more opaque firms prone to disruption risk to facilitate firms' ongoing access to market debt. Sustained access to the bond market for these firms amidst disruption can enhance financial stability as it alleviates the risk of the banking sector becoming heavily exposed to firms that exhibit elevated levels of risk.

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