# Security issuance activities:
# Insights from crisis and peer influences

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# Abstract

This thesis is composed of three essays related to security issuance activities. Chapter 2 documents substantial increases in corporate security offerings during the COVID pandemic. While the increase in seasoned equity offerings (SEOs) can be attributed to shifts in macroeconomic conditions, the increases in convertible and straight bond offerings cannot be explained by standard security choice determinants or government interventions. COVID period SEO announcements are often contaminated with Research and Development (R&D)-related news, with the proceeds more likely to be hoarded as cash. Overall, COVID period SEOs align with market timing behavior, while COVID period convertibles and straight bonds cannot be reconciled with pre-pandemic rationales. We demonstrate that the COVID pandemic differs significantly from the Global Financial Crisis (GFC). There is no abnormal increase in convertible and straight bond offerings, nor is there evidence of an increase in the packaging of R&D news with SEO announcements during the GFC period.

Chapter 3 examines the influence of peers' Management Discussion and Analysis (MD&A) narratives on firms' seasoned equity issuance activities. Findings indicate that firms are more likely to issue seasoned equity when the tone of their peers becomes more positive. This peer influence is more pronounced for firms that face greater product market competition. Firms only respond to the changing MD&A tone of leader peers that are larger, have more market share, and are more tangible than them, but not vice versa. These findings indicate that this peer effect is based on learning motivations. In addition, a firm's equity financing decisions are more sensitive to current and new peers but not to firms that are no longer their peers. The relation between firms' equity issuance activities and the changing tone of peers' MD&A narratives is driven by the sentences that contain numerical content. Equity issuers are more likely to use proceeds for R&D investment, and they have a lower post-issuance return when peers increase their positive tone before the issuance.

Chapter 4 investigates the impact of shifts in the investor base on convertible bond announcement returns from April 1986 to June 2021. The convertible bond market witnessed two significant changes in its investor base: a shift from traditional long-only investors to convertible arbitrage hedge funds after 2000, followed by a reversion to traditional long-only investors after the GFC. The announcement effect of convertible bonds is more negative during periods dominated by convertible arbitrage hedge funds than those dominated by traditional long-only investors. This discrepancy diminishes when considering the impact of arbitrage-

induced short-selling. Additionally, convertible bonds announced during the dominance of convertible arbitrage hedge funds show a price reversal, supporting the idea that the negative announcement effect is driven by price pressures from short-selling activities by these hedge funds.

# Declaration

This thesis is an original work of my research and contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, or any use of generative artificial intelligence technologies, except where due reference is made in the text of the thesis.

Signature: ……………………

Print Name: …QING WANG….

Date: ……8 May 2024…….

# Thesis including published works declaration

I hereby declare that this thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, or any use of generative artificial intelligence technologies, except where due reference is made in the text of the thesis.

This thesis includes one submitted publication. The core theme of the thesis is security issuance activities during the COVID crisis. The ideas, development, and writing up of all the papers in the thesis were the principal responsibility of myself, the student, working within the Department of Banking and Finance under the supervision of Prof. Chris Veld, Dr. Joshua Shemesh, and Prof. Marie Dutordoir.

In the case of Chapter 2, my contribution to the work involved the following:

| **Thesis Chapter** | **Publication Title** | **Status** *(published, in press, accepted or returned for revision, submitted)* | **Nature and % of student contribution** | **Co-author name(s) Nature and % of Co-author's contribution*** | **Co-author(s), Monash student Y/N*** |
|---|---|---|---|---|---|
| *2* | *Security Offerings Following the COVID-19 Pandemic: Do Existing Corporate Finance Theories Still Hold?* | *returned for revision* | *85%*<br>*Original idea, data processing, methodology, and writing of the first draft* | 1. *Chris Veld* *Supervision and writing review & editing. 5%.*<br>2. *Joshua Shemesh* *Supervision and writing review & editing. 5%.*<br>3. *Marie Dutordoir* *Supervision and writing review & editing. 5%.* | *N* |

**If no co-authors, leave fields blank*

I have renumbered sections of submitted or published papers in order to generate a consistent presentation within the thesis.

**Student name:** Qing Wang

**Student signature:** **Date:** 8 May 2024

I hereby certify that the above declaration correctly reflects the nature and extent of the student's and co-authors' contributions to this work. In instances where I am not the responsible author I have consulted with the responsible author to agree on the respective contributions of the authors.

**Main Supervisor name:** Prof. Chris Veld

**Main Supervisor signature:** **Date:** 8 May 2024

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# Chapter 1. Introduction

Corporate financing decisions are crucial for firms throughout their lifecycle. One of the key objectives of corporate finance research is to identify the factors that influence firms' financing decisions. Previous literature primarily focuses on firm-specific characteristics to explain the motives behind firms' financing decisions. Studies have shown that firms seek external financing to adjust their capital structure, seize investment opportunities, time the market, increase precautionary cash reserves, meet short-term liquidity needs, and fund payouts. However, the impact of external factors on corporate financing decisions remains largely understudied. This thesis aims to broaden our understanding of corporate financing decisions by exploring three external factors: the COVID crisis, peers' characteristics, and the changes in the investor base of the securities market. Through empirical studies, this thesis investigates how these factors affect firms' willingness to access public securities markets for funding and the subsequent market reaction to security issuance activities. Specifically, this thesis focuses on seasoned equity offerings (SEO), convertible bond offerings (CBO), and straight bond offerings (SBO).

Chapter 2 investigates security issuance activities during the COVID crisis. Unlike previous crises originating inside the financial sector, the COVID pandemic originated as a public health crisis and immediately affected the real economy, initially unrelated to the availability of external finance. Moreover, many pandemic-related factors affecting corporate financing decisions happened simultaneously, such as uncertainty increases, demand and supply shock, and government interventions. The COVID pandemic provides an unfortunate but valuable opportunity to gain insights into corporate financing decisions using a truly exogenous shock. The complex and multidimensional nature of the COVID pandemic warrants research on how it has shaped corporate finance decisions and their outcomes. This Chapter builds and tests a comprehensive model using data from all U.S. industry firms between January 2010 and June 2021 to analyze changes in security issuance decisions during the pandemic relative to pre-pandemic periods. Security offering volumes have experienced sharp growth since March 2020, with univariate results indicating a threefold increase in monthly seasoned equity and convertible bond issue volumes and a twofold increase in monthly straight bond volumes relative to pre-pandemic volumes. While the increase in SEOs can be attributed to shifts in macroeconomic conditions, the increases in convertible and straight bond offerings cannot be explained by standard security choice determinants or government interventions. As an additional avenue to examine security offering motives, this Chapter compares the ex-post offering outcomes regarding stock price effects and uses of proceeds during the COVID period with pre-pandemic outcomes. COVID period SEO announcements are often contaminated with R&D-related news, with the proceeds more likely to be hoarded as cash. The findings indicate that COVID SEOs tend to be used for market timing reasons. On the other hand, while pre-pandemic security offering studies document evidence for convertible and straight bond offerings consistent with the main corporate finance theories, the increase in convertible and straight bond offerings during the COVID pandemic cannot be attributed to corporate demand, investor supply, or government intervention explanations. The findings suggest that firm-specific and macroeconomic empirical measures derived from traditional corporate finance theories cannot fully explain security issuance behavior during the COVID crisis.

Chapter 3 examines the impact of peers' Management Discussion and Analysis (MD&A) narratives on firms' seasoned equity issuance activities. Peer characteristics and actions play a central role in shaping a number of corporate policies, such as investment decisions. This Chapter focuses on firms' financing decisions. Peers' financial reports represent a prominent information source, particularly the MD&A section in the annual report. Firms will change their MD&A sections after changes in operations, capital resources, and other major activities. Accordingly, firms can use other firms' MD&A narratives to better understand industry-wide opportunities and challenges. This Chapter finds that firms are more likely to issue seasoned equity when the tone of their peers becomes more positive, and this peer influence remains after controlling for other corporate financing determinants. This peer influence on seasoned equity financing is more pronounced for firms that face greater product market competition. Firms only respond to the changing MD&A tone of leader peers who are larger, have more market share, and are more tangible than them, but not vice versa. In addition, a firm's equity financing decisions are more sensitive to current and new peers but not to firms that are no longer their peers. The relation between firms' equity issuance activities and the changing tone of peers' MD&A narratives is driven by the numerical sentences. Equity issuers are more likely to use proceeds for R&D investment, and they have a lower post-issuance return when peers increase their positive tone before the issuance. Overall, the findings enrich the literature on the information content of MD&A narratives and the role of peers in corporate financing decisions.

Chapter 4 examines the impact of shifts in the investor base on convertible bond announcement returns from April 1986 to June 2021. Convertible bonds are hybrid securities with both debt and equity attributes that not only offer investors coupon income but also give them an option to convert their bonds into stocks. Over time, the convertible bond market has served as an important funding source for firms. The convertible bond market witnessed two significant changes in its investor base: a shift from traditional long-only investors to convertible arbitrage hedge funds after 2000, followed by a reversion to traditional long-only investors after the GFC. The announcement effect of convertible bonds is more negative during periods dominated by convertible arbitrage hedge funds than those dominated by traditional long-only investors. This discrepancy diminishes when considering the impact of arbitrage-induced short-selling. Additionally, convertible bonds announced during the dominance of convertible arbitrage hedge funds show a price reversal, supporting the idea that the negative announcement effect is driven by price pressures from short-selling activities by these hedge funds. This Chapter highlights how the demand side of the market influences market reactions to convertible bond announcements.

Overall, this thesis contributes to the literature by documenting the significant influence of external factors on corporate financing decisions and their outcomes. Chapter 2 demonstrates that the COVID crisis has a material impact on security issuance activities and the ex-post offering outcomes in terms of stock price effects and uses of proceeds. Notably, it highlights abnormal increases in convertible and straight bond volumes that cannot be explained by firm characteristics and macroeconomic characteristics derived from traditional corporate finance theories. Chapter 3 identifies another determinant of corporate financing that is external to the firm's own characteristics, the changing tone of peers' management narratives. Chapter 4 examines the impact of the shift in the investor base, another external factor, on market reactions to security offerings, documenting that a more negative convertible bond announcement effect is attributed to the price pressure caused by short-selling activities from convertible arbitrage hedge funds.

# Chapter 2. Security Offerings Following the COVID-19 Pandemic: Do Existing Corporate Finance Theories Still Hold?

## 2.1 Introduction

It is widely acknowledged that the COVID pandemic represents a unique, unprecedented, and unexpected global shock. Reinhardt (2020) argues that the COVID pandemic diverges materially from past crises with respect to its cause, scope, and severity. Goldstein, Koijen, and Mueller (2021) exclaim: *"Is the COVID-19 crisis just "another" large-scale shock? We think not."* Miescu and Rossi (2021) state that it is problematic, both theoretically and empirically, to disentangle the many confounding factors happening contemporaneously during the COVID pandemic. Pandemic-related factors that may affect firms include increases in uncertainty, changes in consumer demand, supply chain disruptions, the introduction of social distancing and working from home, and government interventions aimed at improving credit access (Baker, Bloom, Davis, and Terry, 2020; Ramelli and Wagner, 2020). Baqaee and Farhi (2022) conclude that the COVID crisis represents a *"messy combination"* of disaggregated sectoral demand and supply shocks.

The complex and multidimensional nature of the COVID-19 pandemic, hereafter referred to as the COVID pandemic or the COVID crisis, warrants research on how it has shaped corporate finance decisions. This question is the focus of our paper. We are the first, to our knowledge, to build and test a comprehensive model of firms' choice between seasoned equity, convertibles, straight bonds, and bank loans, enabling us to verify shifts in COVID-period security offering decisions relative to pre-COVID decisions. As an additional avenue to examine security offering motives, we compare the offering outcomes in terms of stock price effects and uses of proceeds during the COVID period with pre-pandemic stock price effects and uses of proceeds. More particularly, we investigate four related research questions: Did the COVID pandemic affect firms' choice between different security types ($Q_1$)? Did the COVID pandemic affect the immediate ($Q_2$) and longer-term ($Q_3$) shareholder wealth effects of corporate security offerings? And, did the COVID pandemic affect firms' uses of security offering proceeds ($Q_4$)?

We consider these research questions through the lens of four major relevant theories on corporate finance: the trade-off theory (Kraus and Litzenberger, 1973), the pecking order theory (Myers, 1984), the market timing theory (Baker and Wurgler, 2002; Lee, 2021), and the precautionary demand for cash theory (Bates, Kahle, and Stulz, 2009). We also consider convertible bond rationales, which are built on these theories (Brennan and Kraus, 1987; Brennan and Schwartz, 1988; Stein, 1992). In addition to these corporate demand-driven theories, we derive predictions from the investor supply-driven flight to quality theory (Caballero and Krishnamurthy, 2008). The COVID crisis represents a cluster of severe and long-lived shocks, some of which yield opposite predictions regarding firms' security choices, even for a given corporate finance theory. Predictions for pandemic-induced shocks' net effect on stock price reactions and uses of proceeds of security offerings are equally ambiguous.[1] Therefore, the answers to $Q_1$ - $Q_4$ are essentially empirical matters.

Our sample includes the three main security types available to firms: seasoned equity offerings (SEOs), convertible bond offerings (CBOs), and straight bond offerings (SBOs). We obtain security offering data by publicly listed non-financial and non-utility U.S.-domiciled firms from Thomson Securities Data Company Platinum's New Issues database (hereafter: SDC). Our dataset also includes bank loans obtained from DealScan, because firms may trade off security offerings against bank debt. The sample period ranges from January 2010 to June 2021. Whilst COVID pandemic infection and mortality rates waxed and waned since the onset of the crisis in the U.S. in March 2020, it is fair to say that the COVID crisis lasted for the full duration of the interval between March 2020 and the end of our sample period (World Health Organization, 2022). We, therefore, label the entire interval from March 2020 until June 2021 the "COVID period" and the associated security offerings "COVID offerings," whilst designating the period before March 2020 the "pre-COVID period" and the associated security offerings "pre-COVID offerings."

[1] In Section 2.2, we derive testable predictions for each of the four research questions by mapping COVID-related shocks to relevant corporate demand and investor supply theories. Table 2.1 in Section 2.2 summarizes the relevant COVID-related shocks and associated predictions.

Our key empirical results are as follows. With regards to $Q_1$, we find a sharp growth in security offering volumes since March 2020, with univariate results indicating a threefold increase in monthly SEOs and CBOs issue volumes and a twofold increase in monthly straight bond volumes relative to pre-pandemic volumes. We next estimate a multinomial probit model analyzing the choice between the three security types, bank loans, and not raising external financing. The model includes firm and macroeconomic characteristics suggested by demand-driven corporate finance theories and used in previous security selection models (Lewis, Rogalski, and Seward, 1999; Erel, Julio, Kim, and Weisbach, 2012; Gomes and Phillips, 2012), industry controls, and a *COVIDPeriod* dummy equal to one for security offerings made since March 2020. The coefficients of the firm and macroeconomic characteristics inform us of the extent to which the existing theories can explain the security issuance activities, while the significance of the *COVIDPeriod* dummy captures gaps in security offerings not explained by the pre-pandemic rationales. Our security choice model results indicate that the *COVIDPeriod* dummy variable no longer has a significant positive impact on SEOs after controlling for shifts in macroeconomic conditions during the COVID crisis. By contrast, the *COVIDPeriod* dummy continues to have a significantly positive impact on CBOs, SBOs, and bank loans even after controlling for firm and macroeconomic characteristics derived from existing corporate finance theories.

We subsequently conduct additional tests to deepen our understanding of the impact of the COVID crisis on security issuance activities. We first re-estimate the security choice model with two separate dummies representing different phases of the COVID period. We distinguish between the first ten “feverish” months of the COVID period and the remaining months that witnessed some relaxation of social distancing measures and the advent of vaccines. We document a consistent abnormal increase in straight bond issuance throughout the two stages of the COVID period. In contrast, we only observe an abnormal increase in convertible bond issuance in the second stage of the COVID period. Inconsistent with the flight to quality theory, which predicts bond issuance increases predominantly for investment grade firms, the COVID-period increases in straight bond offerings hold both for investment grade and non-investment grade firms, while for convertibles, we in fact only observe abnormal COVID-period increases for non-investment grade issuers. We furthermore detect significant shifts in corporate security choice determinants in the COVID period. Proxy variables capturing a precautionary demand for cash have a weaker role in driving COVID SEOs than in driving pre-COVID SEOs. Finally, we document that applying pre-COVID security choice model coefficients leads to significant underestimations of COVID-period convertible and straight bond offerings. The rise in COVID-period security issuance activity does not crowd out bank loans, as our security choice model results suggest that the latter also increases.

With regards to $Q_2$, we find that COVID SEOs are associated with higher average announcement returns compared to pre-COVID SEOs. However, this difference vanishes after incorporating the fact that COVID SEO announcements are significantly more likely to be accompanied by confounding information. Most of the COVID-period contaminated announcements are distinctly positive in nature. Notably, 17.46% of COVID SEO announcements are accompanied by statements on research and development (R&D) progress, while only 5.18% of pre-COVID SEO announcements are accompanied by such news. Further tests indicate that the increased prevalence of R&D-related news during the COVID period is specific to healthcare industry issuers. A possible explanation for this pattern is that issuers are aware of investors' keen anticipation of favorable healthcare research developments during the COVID crisis and cater to this investor demand. For convertible bond offerings, we find more negative stock price reactions during the COVID period, with differences disappearing after controlling for shifts in issuer and macroeconomic characteristics during the crisis. We do not observe an increase in contaminating news for COVID-period convertible bond announcements. Straight bond announcement effects remain stable throughout the sample period.

Regarding $Q_3$, we detect more negative average longer-term stock returns following COVID SEOs in comparison with pre-COVID SEOs, further corroborating a market timing motive for COVID SEOs. In contrast, there are no significant differences in the average longer-term stock returns for COVID versus pre-COVID convertible and straight bonds. Also consistent with a market timing interpretation for COVID SEOs, our analysis of ex-post uses of proceeds ($Q_4$) indicates that COVID SEO proceeds are more likely to be stored as cash than pre-COVID SEO proceeds.

We validate our findings through a set of robustness and additional tests. First, we verify whether our finding of an abnormal increase in COVID (convertible) bond offerings could be driven by government interventions supporting corporate credit during the pandemic. The Federal Reserve's Primary Market Corporate Credit Facility (PMCCF) and Secondary Market Corporate Credit Facility (SMCCF) were in effect from March 2020 to December 2020. Inconsistent with government support driving the increase in (convertible) bond issuance, we find that firms continue to issue more convertible and straight bonds in the remaining part of the COVID period without support from corporate credit facilities, from January 2021 to June 2021.[2] It is also important to note that these credit facilities aim to buy primary market debt of up to four years in maturity and secondary market debt of up to five years in maturity. If the increase in COVID convertible and straight bond offerings was driven by these government interventions, we would expect that the maturities of COVID bond offerings tend to fall below these maximum numbers, which is not what we find. Moreover, as noted earlier, we find that non-investment grade firms, which are not eligible for PMCCF or SMCCF, still issue more convertible bonds and straight bonds during the COVID period. Overall, these results indicate that governmental credit facilities are not the primary driver of the observed increase in COVID convertible and straight bond offerings.

Second, we show that our baseline security choice results hold across firms that have different cash flow implications from the COVID crisis, including firms with a high versus low resilience to social distancing measures identified using the Koren and Peto (2020) measure. Third, we document that our security choice and event study findings are robust to the use of alternative model specifications, e.g., using different fixed effects structures. Fourth, we examine whether the COVID-period deviations in security offerings and SEO announcement returns documented in our baseline analyses resemble those observed during the Global Financial Crisis (GFC). We find that firms do not increase their straight bond and bank loan

[2] The PMCCF was instated in March 2020 to enable the Federal Reserve to buy new bond issues directly from corporations and to provide loans to corporations. Borrowers could defer interest and principal payments for at least the first six months. Under the subsequent SMCCF, the Federal Reserve could purchase existing corporate bonds as well as exchange-traded funds investing in investment grade corporate bonds (Milstein and Wessels, 2021). The Federal Reserve announced on June 2, 2021 that it would gradually wind down its $13.7 billion portfolio of corporate bonds (Federal Reserve, 2021). Both the PMCCF and the SMCCF ceased to exist in December 2020.

issuance activities during the GFC. In addition, we observe more negative rather than more favorable average SEO announcement effects during the GFC period, with no evidence of an increase in the packaging of confounding news with SEO announcements during the GFC period. These findings further highlight the unique characteristics of the COVID crisis.

Taken together, our empirical results indicate that the COVID crisis had a distinct and material impact on corporate financing decisions and their outcomes. Pre-pandemic studies suggest that SEOs are mostly driven by near-term cash needs, with market timing motives only playing an ancillary role (DeAngelo, DeAngelo, and Stulz, 2010; McLean, 2011; Huang and Ritter, 2021). Conversely, our combined evidence on the four research questions indicates COVID SEOs tend to be used for market timing reasons rather than for funding immediate cash requirements, with firms opportunistically packaging the offerings' announcements with confounding news. Moreover, while pre-pandemic security offering studies document evidence for convertible and straight bond offerings consistent with the main corporate finance theories (Lewis et al., 1999; Erel et al., 2012; Gomes and Phillips, 2012), we find that the firm-specific and macroeconomic empirical measures derived from existing corporate finance theories cannot fully explain convertible and straight bond offerings during the COVID crisis. Further tests indicate that government interventions cannot account for the observed abnormal increases in COVID bond issuance either.

Our paper adds to three streams of literature. First, our study contributes to empirical studies on corporate finance decisions during (financial) crises. Previous studies focus on the Great Recession (Giroud and Mueller, 2017), the Asian financial crisis (Almeida, Kim, and Kim, 2015), and the GFC (Campello, Graham, and Harvey, 2010; Beber and Pagano, 2013; Kahle and Stulz, 2013). These studies predominantly use crises as a laboratory to examine the effects of severe increases in financing or short-selling constraints. The COVID crisis differs from previous crises by originating as a health crisis and immediately affecting the real economy rather than as a financial crisis (Brunnermeier and Krishnamurthy, 2020; Fahlenbrach, Rageth, and Stulz, 2021) and by representing a cluster of diverse, long-lived shocks for corporations. It has been argued that "once in a lifetime" events like the COVID crisis will become much more common in the years to come due to the combined effects of an increased population, climate change, political instability, global integration, and urbanization

(Whiting, 2020; Hague, 2022). Despite its extreme and unprecedented nature, the COVID crisis is, therefore, likely to be more representative of future crises than are earlier crises such as the GFC.

Secondly, our paper contributes to studies on corporate disclosure around security offerings. Prior studies document strategic increases in earnings management and disclosure activity *prior to* SEO announcements (Lang and Lundholm, 2000; Cohen and Zarowin, 2010). Our evidence suggests that firms also time positive but unrelated announcements *contemporaneously* with the SEO announcement. This finding is consistent with documented "impression offsetting" activity in the context of Mergers and Acquisitions (M&A), where acquiring firms deliberately time the announcement of an M&A to occur with favorable news (Graffin, Haleblian, and Kiley, 2016).

Thirdly, we add to studies on the financial impact of the COVID crisis. A growing body of literature addresses the influence of the COVID pandemic on stock returns.[3] In comparison, the impact of pandemic-induced shocks on corporate financing decisions had received scant attention so far. Previous (working) papers in this substream of literature tend to focus on individual corporate financing decisions. Cejnek, Randl, and Zechner (2021) and Pettenuzzo, Sabbatucci, and Timmermann (2023) examine changes in corporate dividend policy during the pandemic. Acharya and Steffen (2020), Hasan, Politsidis, and Sharma (2021), and Li, Strahan, and Zhang (2020) document the pandemic's effect on bank loans. Darmouni and Siani (2022), Halling, Yu, and Zechner (2020), Becker and Benmelech (2021), and Almeida (2021) study bond issuance. Halling et al. (2020) also report univariate results on equity issuance during the pandemic. Baig and Chen (2022) show that the COVID crisis adversely impacts the IPO market. Pagano and Zechner (2022) document an increase in corporate cash ratios and a decrease in corporate leverage ratios in the years 2020 and 2021. Hotchkiss, Nini, and Smith (2021) analyze the impact of forecasted revenue and earnings shocks during the COVID crisis on net capital raised by firms. Our study contributes to this line of research by being the first to build a comprehensive security choice model, including all major external financing choices

[3] Examples of studies in this area include Albuquerque, Koskinen, Yang, and Zhang (2020), Alfaro, Chari, Greenland, and Schott (2020), Baker et al. (2020), Croce, Farroni, and Wolfskeil (2020), Pagano, Wagner, and Zechner (2023), Ramelli and Wagner (2020), Ding, Levine, Lin, and Xie (2021), and Fahlenbrach et al. (2021).

available to firms. Our empirical design is based on the premise that firms' incremental financing decisions likely result from a tradeoff against other external financing options, requiring simultaneous modeling of all choices in firms' external financing menu, as well as the option not to raise any financing. Moreover, to our knowledge, we are the first to compare COVID-period security offering stock price reactions and uses of proceeds with pre-COVID outcomes.

The remainder of the paper is structured as follows. Section 2.2 develops our testable predictions from relevant theory. Section 2.3 describes the data and methodology. Sections 2.4, 2.5, and 2.6 provide empirical results on the determinants, shareholder wealth effects, and uses of proceeds of COVID versus pre-COVID security offerings, respectively. Section 2.7 delivers a battery of robustness checks and additional tests. Section 2.8 concludes and provides the practical implications of our research.

## 2.2 The impact of the COVID pandemic on corporate security offerings

In this section, we consider our four research questions through the lens of major relevant corporate capital structure theories. Theories on corporate capital structure all start from the impact of equity versus debt on firms' risk or (expected) cash flows. To formulate testable predictions, we, therefore, need to map out the crisis' implications for corporate risk and expected cash flows. In terms of corporate risk, it is widely argued that the pandemic provoked a massive increase in uncertainty (Albuquerque et al., 2020; Baker et al., 2020; Ellul, Erel, and Rajan, 2020; Miescu and Rossi, 2021), with sources of ambiguity including the spread, severity and mortality rate of the disease, the duration of policy responses, the effectiveness of testing and vaccine strategies, and the disease's effects on human behavior and corporate productivity (Baker et al., 2020; Ramelli and Wagner, 2020). Consistent with this argument, empirical studies show a substantial growth in uncertainty measures during the COVID crisis (Altig, Barrero, Bloom, Davis, Meyer, and Parker, 2022; Coibion, Gorodnichenko, and Weber, 2020; Hanspal, Weber, and Wohlfart, 2021; Pagano and Zechner, 2022). In terms of (expected) cash flows, the picture is more complex in that the crisis caused declines in cash flows for some firms due to (among other elements) the effects of lockdowns on consumer behavior, whilst other firms benefitted from an increased demand for their goods or services (Pagano et al., 2023; Papanikolaou and Schmidt, 2022). When relating these crisis characteristics with the main corporate finance theories, we obtain the following predictions.

The trade-off theory on corporate finance rests on the premise that the financial distress and agency costs associated with taking on more debt can be traded off against the (tax) benefits of doing so, resulting in an optimal debt ratio firms try to adhere to (Kraus and Litzenberger, 1973; Frank and Goyal, 2009). Even in normal macroeconomic conditions, bankruptcy and other forms of financial distress can provoke substantial costs for firms (Andrade and Kaplan, 1998). The pandemic may have affected firms' financial distress costs, thereby shifting their optimal debt ratios. In theory, the direction of this effect is unclear, as it depends on the direction of the pandemic's impact on corporate cash flows. To the extent that the COVID crisis resulted in cash flow declines, firms' financial distress costs may have increased, resulting in a lower debt capacity and a higher likelihood for firms to choose equity-like over debt-like securities. To the extent that the COVID crisis created more demand for particular goods and services (e.g., for certain healthcare products and online delivery platforms), however, it may have increased firms' cash flows, thereby lowering their risk of financial distress and bankruptcy and increasing their capacity to issue more debt-like securities.[4] Moreover, Hanson, Stein, Sunderam, and Zwick (2020) make the interesting observation that, due to the unprecedented uncertainty associated with the pandemic, the relationship between a firm's potentially reduced pandemic cash flows and its long-run post-pandemic viability is likely to be much weaker than in a typical economic downturn. If market participants are aware of this weaker link and believe the pandemic cash flow declines are precipitous and short-lived, this will dampen the extent to which (apparent, current) financial distress risk is priced into corporate debt. The latter argument again implies that firms may issue more debt-like securities during the COVID crisis despite temporary decreases in their cash flows. Thus, the answer to $Q_1$ is an empirical matter. In practice, empirical studies find that financial distress costs have increased during the COVID crisis (Altman, 2020; Greenwood, Iveson, and Thesmar, 2020;

[4] We verify the differential effects of COVID on firms with positive versus negative cash flow effects of the pandemic in a robustness test in Section 7.

Wang, Yang, Iverson, and Kluender, 2020; Huang and Ye, 2021).[5] The tradeoff theory yields no testable implications for $Q_2$ to $Q_4$.

Signaling and pecking order theories, in turn, rest on an assumption of adverse selection problems resulting from information asymmetry between managers and investors, making equity-like security offerings less attractive relative to more debt-like offerings (Myers, 1984; Myers and Majluf, 1984; Choe, Masulis, and Nanda, 1993). Whilst the pandemic undisputedly provoked a marked increase in uncertainty, this does not necessarily imply that information asymmetry, i.e., the extent to which information is unequally distributed between firm insiders and outsiders, also increased. Theoretically, it may be possible that uncertainty levels increased in a similar way for both firm insiders and outsiders, thereby leaving the overall level of information asymmetry for a given firm unaltered. In practice, we believe it is more reasonable to assume that the COVID crisis affects external investors' ability to accurately evaluate the current state and future prospects of firms more strongly than it does for managers' ability. The reason is that the latter will have access to internal data and have direct oversight regarding the operational impacts of the pandemic on their firms. Supporting this argument, Gofran, Gregoriou, and Haar (2022) empirically document a significant increase in information asymmetry during the COVID pandemic, as captured by the adverse selection component of bid-ask spreads (Huang and Stoll, 1997). Assuming that information asymmetry is indeed higher during the COVID crisis, we predict that firms will have a higher propensity to issue debt-like over equity-like securities during the crisis ($Q_1$). We also obtain a prediction of more negative immediate stock price reactions to equity-like security offerings during the COVID period, relative to those in the pre-COVID period, due to the higher adverse selection costs caused by elevated information asymmetry ($Q_2$). We do not obtain predictions for $Q_3$ or $Q_4$.

The market timing theory predicts that firms resort to opportunistic exploitation of "windows of opportunity" during the COVID crisis to the extent that the firms' own valuation or macroeconomic conditions generate favorable circumstances for doing so (Graham and

[5] Greenwood et al. (2020) furthermore argue that the legal and financial systems, typically capable of managing firm restructuring during economic downturns, faced significant challenges due to the sheer volume of expected bankruptcies and the complexity introduced by the pandemic. These challenges included potential court congestion and a risk of excessive liquidation of small firms, which are less likely to successfully restructure and more likely to be forced into liquidation due to their financial vulnerability.

Harvey, 2001; Baker and Wurgler, 2002; Barry, Mann, Mihov, and Rodriguez, 2008). The theory yields no predictions as to what particular security type firms will choose during the COVID crisis ($Q_1$), as this choice depends on companies' pragmatic weighing of the relative timing benefits of raising equity-like versus debt-like securities. To the extent that investors are unaware of opportunistic issuer motives at the time of the offering's announcement, the market timing theory yields no predictions about immediate stock price reactions to offering announcements either ($Q_2$). However, it does predict a negative longer-term stock price reaction following the security offering's announcement, as investors gradually realize that the offering is inspired by the exploitation of issuer overvaluation. This prediction should hold more strongly for equity-like than for debt-like offerings, as the former securities are more sensitive to issuer overvaluation. Thus, to the extent that we have a higher prevalence of market-timed offerings during the COVID period, we should observe more negative longer-term stock price reactions during that period, particularly for equity-like offerings ($Q_3$). Finally, the market timing theory predicts a higher likelihood for security offering proceeds to be opportunistically hoarded as cash instead of being used for investment purposes because it presumes firms have no genuine need for the security offerings (Kim and Weisbach, 2008) ($Q_4$).

Theory on the precautionary demand for cash (hereafter "precautionary motive"), in turn, predicts a higher likelihood of issuing equity-like securities during the crisis ($Q_1$) since firms wish to increase their cash holdings as a buffer to deal with future adverse cash flow shocks (Keynes, 1936; McLean, 2011).[6] We expect precautionary security offerings to result in less negative stock price reactions to the extent that investors are aware of their issuers' motives. The underlying rationale is the following. Myers and Majluf's (1984) signaling model implies that firms with substantial financial slack have more negative stock price reactions to equity offering announcements because investors perceive high amounts of slack as a sign that the firm does not strictly need the additional funding, therefore inferring an overvaluation motive for the offering. Reversing this argument, a security offering by a firm with high values for

[6] Debt-like securities are less suitable for firms with strong precautionary motives, which typically exhibit characteristics such as high R&D spending, a high cash flow volatility, and strong financial constraints (McLean, 2011).

proxy variables capturing a precautionary motive should signal a lower likelihood of an overvaluation motive, yielding more favorable investor reactions ($Q_2$). The precautionary motive theory does not have implications regarding longer-term stock price reactions to security offerings ($Q_3$), but it does predict a higher likelihood of offering proceeds being stored as cash, as firms use the funding as "dry powder" for dealing with future cash flow shocks ($Q_4$) (McLean, 2011; Erel et al., 2012).

Whilst the above theories are framed around the dual choice between seasoned equity and straight bonds, firms can also opt for hybrid, convertible bond financing. The literature offers several rationales for CBOs.[7] Two of these theories are particularly relevant in the context of our paper, as they highlight convertible bond issuance motives that may be affected by the COVID crisis. The Brennan and Kraus (1987) and Brennan and Schwartz (1988) risk uncertainty rationale implies that convertibles are useful for firms with high uncertainty about firm risk, which would otherwise face the high costs of raising straight bond financing. The Stein (1992) backdoor equity rationale implies that convertibles are useful for firms with a high information asymmetry about firm value, which would otherwise face the high costs of raising seasoned equity. Together, these two theories predict that firms are more likely to substitute convertibles for straight bonds and equity, respectively, during the COVID period, to the extent that this period is marked by heightened adverse selection costs engendered by risk uncertainty and information asymmetry about firm value, respectively ($Q_1$). Heightened adverse selection costs would also imply more negative immediate stock price effects for COVID convertibles ($Q_2$). The theories have no testable implications regarding $Q_3$ and $Q_4$.

In addition to these corporate demand-driven theories, we consider the supply-driven flight to quality theory. This theory argues that investors will flock to safer assets during crisis times (Caballero and Krishnamurthy, 2008) due to Knightian uncertainty (Knight, 1921) or an increased investor risk aversion (Guiso, Sapienza, and Zingales, 2018). The stronger investor appetite for safer assets will make it relatively more attractive for companies to issue "safer" debt-like securities during crises. The flight to quality theory thus predicts a higher likelihood

[7] Dutordoir, Lewis, Seward, and Veld (2014) provide a comprehensive overview of convertible bond theories and their empirical tests.

of more debt-like securities during the COVID period ($Q_1$), particularly by investment grade issuers. Whilst the theory has no direct implications for $Q_2$ and $Q_3$, it also predicts that companies are more likely to store the security offering proceeds as cash, as they primarily make the offerings to cater to investor preferences and have no immediate need for the funding ($Q_4$) (Erel et al., 2012). Table 2.1 summarizes the predictions of the four theories for our research questions. We now bring these predictions to the data.

<< Please insert Table 2.1 here >>

## 2.3 Dataset and variables

In this section, we describe the construction of our dataset and provide a univariate analysis of pre-COVID and COVID security offerings and bank loans. This section also motivates the industry, firm, and macroeconomic characteristics included in the security choice model.

### 2.3.1 Sample construction

Our dataset includes security offerings and bank loans made by U.S.-domiciled, publicly listed firms. We exclude utilities (SIC codes 4900-4999) and financial firms (SIC codes 6000-6999) because these firms may face regulatory restrictions on their capital structure. Our sample period ranges from January 2010 until June 2021. In line with previous studies (Darmouni and Siani, 2022; Halling et al., 2020; Li et al., 2020), we use March 2020 as the start of the COVID period. We label the remaining period between January 2010 and February 2020 as the pre-COVID period.[8]

We retrieve samples of SEOs, CBOs, and SBOs from the SDC database. We subject the raw data to standard data screens (e.g., Duca, Dutordoir, Veld, and Verwijmeren, 2012; Kim and Purnanandam, 2014; Kim, 2016). More particularly, we remove offerings with missing issue proceeds (Dahiya, Klapper, Parthasarathy, and Singer, 2017). We also exclude privately placed non-Rule 144A security offerings due to the very low numbers of these offerings during the COVID period. Specifically, we register no privately placed non-Rule 144A SEOs or CBOs and only one privately placed non-Rule 144A SBOs during the COVID period. We do not

[8] The pre-COVID period does not contain any economic recessions. The recession most closely preceding the start of our sample period, according to the National Bureau of Economic Research’s definition, lasted from January 2008 to June 2009.

exclude Rule 144A offerings since these are highly similar to public offerings (Gomes and Phillips, 2012). We furthermore eliminate units, warrants, preferred stocks, exchangeable bonds, and mandatory convertible bonds from the security offering sample and delete purely secondary share offerings from the SEOs sample (Hovakimian and Hu, 2016). When security offerings have multiple tranches, we only include the main tranche to avoid double counting (Hanselaar, Stulz, and Van Dijk, 2019).

We retrieve deal-based bank loan data from the DealScan database. To match bank loan data with firm characteristics, we use the DealScan-Compustat link provided by Chava and Roberts (2008) and extend this link to June 2021 by using the CUSIP and company names provided by DealScan and the Center for Research in Security Prices (CRSP)-Compustat merged database (hereafter CCM). We manually verify the accuracy of the matched pairs.

Following Erel et al. (2012), we collapse firms' security offerings and bank loans at the monthly level. In the case of multiple security offerings and bank loans made by one firm in a given calendar month, we only include the security offering or bank loan with the highest proceeds (Ball, Hail, and Vasvari, 2018). To ensure that the sample firms are, in principle, able to raise external financing through bank loans or security offerings, we impose the requirement that firms make at least one security offering or initiate at least one bank loan during the sample period, in line with Erel et al. (2012). Finally, we match these firm-month observations with quarterly accounting data from the CCM database and stock price data from the CRSP database. We restrict the sample to firms listed on the New York Stock Exchange (NYSE), NYSE American, and NASDAQ with a CRSP share code of 10 or 11. After applying these criteria, we obtain a final sample consisting of 3,295 firm-months with SEOs made by 1,412 firms, 644 firm-months with CBOs made by 443 firms, 3,198 firm-months with SBOs made by 828 firms, 3,984 firm-months with bank loans made by 1,832 firms, and 264,358 "no issue" firm-months with no security offering or bank loan, totaling 275,479 firm-months from 3,077 firms.

### 2.3.2 Security offerings and bank loans in pre-COVID and COVID periods

Table 2.2 reports summary statistics of monthly SEOs, CBOs, SBOs, and bank loans during the pre-COVID period and the COVID period.

<<Please insert Table 2.2 here >>

Specifically, Table 2.2 reports the proportion of months in which firms choose to make a particular security offering or obtain a new bank loan (out of all firm-months) and the proportion of proceeds raised from each type of external financing. Compared with the pre-COVID period, we observe a significant increase in the monthly number of all security offerings in the COVID period, while the number of bank loans decreases. Average monthly seasoned equity and convertible bond issue volumes in the COVID period are approximately triple the size of average pre-COVID volumes, and average monthly COVID-period straight bond volumes are approximately twice the size of pre-COVID volumes. Figure 2.1 corroborates that all three types of security offerings reach record-high issuance proceeds during the COVID period.

<<Please insert Figure 2.1 here>>

Figure 2.1 also shows average *Leverage* and *Cash* ratios over the sample period, defined as outlined in the Appendix B1. Similar to Pagano and Zechner (2022), we document a sharp increase in *Leverage* in the years immediately preceding the crisis. We then observe a further smaller increase at the onset of the crisis, followed by a modest decrease further into the crisis. We emphasize that our focus in this paper is on firms' *incremental* security choices rather than on their overall debt ratios since we wish to disentangle the impact of the pandemic on different types of corporate debt (convertible bonds, straight bonds, and bank loans). Also, in line with the findings of Pagano and Zechner (2022), we find a substantial surge in *Cash* as of the start of the COVID crisis.

Table 2.3 presents the industry distribution of security offerings and bank loans during the pre-COVID and COVID periods, using the Fama and French (1997) 12-industry classification.

<<Please insert Table 2.3 here >>

We find that COVID-period industry distributions resemble pre-COVID distributions. Remarkably, approximately 60% of SEOs occur in the Healthcare industry, both in the pre-COVID and the COVID period. For convertible bonds, straight bonds, and loans, most issuance activity occurs in the Business Equipment and Software industry in both eras under consideration.

### 2.3.3 Firm and macroeconomic control variables

In our security choice analysis, we verify whether the increase in security offerings during the COVID crisis documented in the univariate results persists after controlling for relevant security choice determinants suggested by the main corporate finance theories. In general, these theories predict higher equity-related (debt-related) costs to result in a higher likelihood of issuing more debt-like (equity-like) securities. It is difficult to uniquely link a given firm or macroeconomic characteristic to a given corporate finance theory. To give just one example, the ratio of fixed to total assets can be used as an inverse proxy for firms' financial distress costs in the context of the trade-off theory, as well as acting as an inverse proxy for the level of information asymmetry about the firm's asset value in the context of the pecking order theory. For ease of exposition, we discuss the firm-specific and macroeconomic variables in the context of the corporate finance theories they are most often associated with in empirical studies.[9] To better capture the impact of the COVID crisis on firm characteristics such as profitability, we use quarterly rather than annual accounting data. We also include variables based on stock prices and macroeconomic conditions, measured at a higher frequency. We measure all variables as closely as possible but prior to the given month to avoid a simultaneity bias (Bayless and Chaplinsky, 1991).[10] The Appendix B1 provides detailed definitions and sources of all variables. All continuous variables are winsorized at the 1st and 99th percentiles to reduce potential problems caused by influential outliers.

To capture trade-off considerations in corporate financing decisions, we use *Tax* as a proxy for tax shields provided by interest payments, *Leverage* as a proxy for risk-shifting incentives and financial distress costs, and *InterestCoverage* and *Profitability* as proxies for firms' ability

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[9] We base the firm-specific and macroeconomic variables on empirical analyses in security choice and capital structure studies by MacKie-Mason (1990), Blume, Lim, and MacKinlay (1998), Lewis et al. (1999), Shyam-Sunder and Myers (1999), Korajczyk and Levy (2003), Welch (2004), Bates et al. (2009), Lee and Masulis (2009), DeAngelo et al. (2010), McLean (2011), Erel et al. (2012), Gomes and Phillips (2012) and Goyal and Wang (2013). For space reasons, we do not repeat these reference papers when motivating each of the individual control variables.

[10] Since we need to rely on ex ante information and accounting data are only available on a quarterly basis, the issuer accounting information may still be captured in the pre-COVID period for corporate financing decisions in the first months of the COVID period. Reassuringly, in robustness tests reported and discussed further in the paper, we obtain similar results when focusing on security offerings in the second half of the COVID crisis, for which issuer accounting data are exclusively captured during the COVID crisis. This indicates that our findings are not attributable to staleness in the accounting information used.

to pay off their debt obligations. *Tax*, *InterestCoverage*, and *Profitability* thus act as inverse debt-related cost proxies, whilst *Leverage*, in principle, acts as a direct debt-related cost proxy (Frank and Goyal, 2009), although we note that a low current *Leverage* could also capture higher barriers to raising debt financing and thus higher debt-related costs. Pecking order models predict higher equity-related adverse selection costs for firms with a higher financial slack and information asymmetry (Myers and Majluf, 1984). We include *Cash* as a proxy for financial slack. We use the following standard issuer characteristics to capture information asymmetry: firm size (*TotalAssets*), age (*Age*), the fixed to total assets ratio (*FixedAssets*), a dummy equal to one for firms with a long-term credit rating (*RatedFirm*), and idiosyncratic stock return volatility (*ResidualVolatility*). The first four measures act as inverse proxies for information asymmetry, while *ResidualVolatility* captures higher information asymmetry. To measure market timing determinants at the firm level, we include the firm’s pre-issue stock runup (*StockReturn*) and market to book value (*MarkettoBook*). In addition to overvaluation, these variables can capture growth opportunities. Under both interpretations, we would expect them to have a positive impact on firms’ likelihood of issuing more equity-like security types because higher growth opportunities enhance debt-related agency costs (Jung, Kim, and Stulz, 1996). As standard measures for precautionary motives, following Opler, Pinkowitz, Stulz, and Williamson (1999), Bates et al. (2009), and McLean (2011), we use industry cash flow volatility (*CashFlowVolatility*), R&D expenditure (*R&DExpenditure*), and dividend-paying status (*DividendPaying*).

Table 2.4 shows the average values of firm characteristics for each external financing option as well as for no-issue firm months for the pre-COVID- and COVID period subsamples.

<<Please insert Table 2.4 here>>

The pre-COVID averages and the differences in these averages across external financing type subsamples are highly consistent with descriptive statistics and patterns reported in other (pre-COVID) security choice studies (Lewis et al., 1999; Erel et al., 2012; Gomes and Phillips, 2012). More interesting for our research purpose is that Table 2.4 presents test statistics for differences in firm characteristics between the pre-COVID and COVID periods. We find that COVID-period issuers of straight bonds and bank loans have higher values on trade-off debt-related cost proxies than pre-COVID issuers. COVID-period seasoned equity issuers, in turn, have higher values on proxies for market timing (*StockReturn* and *MarkettoBook*) motives than pre-COVID issuers.

Apart from firm characteristics, we control for macroeconomic conditions capturing economy-wide equity- or debt-related financing costs. We employ two proxies to measure timing opportunities in the equity market: the S&P 500 return (*MarketReturn*) and the *CAPE* ratio, introduced by Campbell and Shiller (1988), to proxy for the U.S. stock market valuation. We use ten-year U.S. Treasury Bond rates (*TBYield*) to measure market timing opportunities in the bond market. Debt issuance may also be favorably influenced by lower default spreads (*DefaultSpread*) and term spreads (*TermSpread*) (Barry et al., 2008). We furthermore include stock market volatility (*MarketVolatility*) in our analysis. Higher stock market volatility could be associated with higher adverse selection costs resulting from information asymmetry about firm risk and firm value, resulting in higher costs of accessing external finance (Choe et al., 1993). We include *GDPGrowth* to capture growth opportunities at the macroeconomic level, expecting a stronger growth to increase firms' likelihood of tapping security markets and bank loans. Given the documented impact of convertible arbitrage funds on convertible bond issuance, we also control for changes in the arbitrage-related demand for convertible bonds by including convertible arbitrage hedge fund flows (*CAFundFlow*) (Choi, Getmansky, Henderson, and Tookes, 2010). To account for bank loan supply at the macroeconomic level, we include a bank lending tightness (*LoanSupplyTightness*) measure based on the Federal Reserve System's Senior Loan Officer Opinion Survey on Bank Lending Practices (Lown, Morgan, and Rohatgi, 2000). A higher value of *LoanSupplyTightness* indicates tighter lending criteria and a lower loan supply. Figure 2.2 plots these macroeconomic variables over the sample period.

<< Please insert Figure 2.2 here >>

We observe steep declines in proxies for equity market valuation (*MarketReturn* and *CAPE*) at the origin of the COVID crisis, followed by a sharp correction thereafter. By the end of the sample period, *MarketReturn* oscillates around pre-COVID levels, whilst *CAPE* is still increasing. *GDPGrowth* shows a similar pattern. The opposite pattern, that is, an initial sharp increase followed by a decrease, holds for *DefaultSpread*, *MarketVolatility*, and

*LoanSupplyTightness*. *TBYield* drops to historically low levels at the onset of the crisis and remains lower than in pre-COVID times during the entire COVID period.

In an unreported analysis of pairwise correlations between the explanatory variables, we find that the highest pairwise correlation (in absolute value) is between *Profitability* and *R&DExpenditure*, which is 0.68, is well-below the commonly accepted threshold of 0.80 for multicollinearity (Shrestha, 2020). The variance inflation factor (VIF) for the baseline security choice model is 2.79, again substantially below the VIF threshold of 10 (Thompson, Kim, Aloe, and Becker, 2017). Therefore, our results are unlikely to suffer from multicollinearity problems.

### 2.4 Does the COVID crisis affect corporate security choices?

To examine the impact of the COVID crisis on corporate security choices ($Q_1$), we estimate a model analyzing firms' choice between seasoned equity, convertibles, straight bonds, bank loans, or no external financing in a calendar month. Because the dependent variable is categorical without any clear ordering of the alternatives, a multinomial probit model is a suitable option (Gujarati and Porter, 2009).[11] We estimate the following specification:

$$\Pr(\text{External financing option}=j) = \frac{e^{\beta_j^{'}X}}{\sum_{k=0}^{4} e^{\beta_k^{'}X}} \tag{1}$$

where *j* equals 0 for no external financing, 1 for SEOs, 2 for CBOs, 3 for SBOs, and 4 for bank loans for a given firm-month (we do not include subscripts denoting firm-months in Equation (1) for clarity of exposition). $\beta_j$ is a vector of coefficients for option *j*, relative to the baseline of not raising any external financing, and *X* is a vector of explanatory variables. All security choice regressions use robust standard errors clustered by industry. Table 2.5 Panel A reports the multinomial probit results.

<< Please insert Table 2.5 here >>

[11] We conduct a Hausman and McFadden test (1984) and Small-Hsiao test (1985) to examine if the independence of irrelevant alternatives (IIA) assumption holds for the choice alternatives in our sample, which is a prerequisite for using a multinomial logit model. The IIA assumption requires that the log odds ratio for any two external financing choices is independent of the inclusion or exclusion of any other external financing choices. Hausman and Small-Hsiao test results indicate that the IIA assumption is violated in our sample, leading us to employ the multinomial probit model instead.

Column (1) only includes the *COVIDPeriod* dummy. In line with the univariate analysis, we find that firms are more likely to make SEOs, CBOs, and SBOs during the COVID crisis. The significant effect of the *COVIDPeriod* dummy could be caused by shifts in industry or firm characteristics during the pandemic. We, therefore, add firm-specific control variables outlined in the previous section to the model in Column (2). We do not report the coefficients on the industry fixed effects (FE) for brevity. We find that the C*OVIDPeriod* dummy variable is still significantly positive for all three security types. The negative coefficients on *TotalAssets* for SEOs and on *InterestCoverage* for SBOs go against our expectations for these proxies. Significant coefficients on the other firm characteristics are largely in line with predictions and are therefore not discussed in detail. Column (3), in turn, adds macroeconomic characteristics as control variables to the specification in Column (1). We find that the C*OVIDPeriod* dummy variable is no longer significant for the SEOs choice, suggesting that firms' higher propensity of issuing equity during the pandemic is attributable to macroeconomic conditions. Coefficients on the significant macroeconomic variables are mostly in line with predictions, except for the positive impact of *MarketVolatility* on the likelihood of an SEO. In addition, the *COVIDPeriod* dummy variable becomes significantly positive for bank loans. Column (4) includes both firm and macroeconomic characteristics as control variables. The *COVIDPeriod* dummy maintains its significant positive impact on convertible and straight bond offerings, suggesting that the increased convertible and straight bond offerings during the COVID period cannot be fully explained by firm-specific and macroeconomic empirical measures associated with existing corporate financing theories. In addition, the *COVIDPeriod* dummy is still significantly positive for bank loans. We henceforth refer to the model in Column (4) as our baseline security choice analysis.

We perform additional tests to enhance our understanding of the impact of the COVID crisis on security offerings. In Panel B, we re-estimate the security choice model with two separate dummies representing different phases of the COVID period. The first dummy (*COVIDPeriod1*) captures the start of the crisis until December 2020. These initial months are marked by lockdowns affecting corporate cash flows and a high level of uncertainty about the severity and treatment of the pandemic. The second dummy (*COVIDPeriod2*) captures the subsequent months, with the approval of vaccines, some reduction in social distancing measures, but also new variants of the pandemic and high uncertainty prevailing on many dimensions.[12] We find a consistent increase in straight bond and loan issuance across the two COVID subperiods, while we only document an increased convertible bond issuance during the latter subperiod.

The control variables capture corporate demand-driven security choice determinants rather than investor preferences. In Panel C, we gauge whether the increase in bond issuance during the COVID period could be explained by the investor supply-driven flight to quality theory rather than by corporate demand explanations. If a flight to quality explanation holds, the abnormal COVID-period increases in debt issues should predominantly pertain to "safer" investment grade firms (Erel et al., 2012). To test this prediction, we estimate the baseline security choice analysis for subsamples of investment grade and non-investment grade issuers, identified based on S&P long-term issuer credit ratings obtained from Compustat as of the month before the given month.[13] Panel C indicates that the increase in straight bonds and bank loans pertains to both types of issuers, whilst for convertibles, it actually only holds for non-investment grade issuers. A Wald test indicates that the coefficient on the *COVIDPeriod* dummy for non-investment grade straight bond issuers is significantly higher than that for investment grade bond issuers. This pattern is inconsistent with a flight to quality rationale.

Finally, we examine differences in security choice determinants in the pre-COVID versus COVID periods by estimating the baseline security choice analysis separately for pre-COVID months (Table 2.6, Column (1)) and COVID months (Table 2.6, Column (2)).

<<Please insert Table 2.6 here >>

For SEOs, we find that the precautionary motive proxies (*CashFlowVolatility*, *R&DExpenditure*, and *DividendPaying*) are all significant with the predicted signs during the pre-COVID period, but only *R&DExpenditure* remains significant during the COVID period. Conversely, we find a significantly positive impact of *MarketReturn* and *CAPE* during the

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[12] The Food and Drug Administration (FDA) first granted emergency use authorization to the Pfizer-BioNTech vaccine on December 10, 2020, and mass vaccinations commenced four days later (FDA, 2020).

[13] We code unrated issuers as non-investment grade, following Campello, Giambona, Graham, and Harvey (2012). We cannot include industry FE in the security choice analysis for the investment grade sample as the number of investment grade seasoned equity and convertible bond issuers is very small, preventing the multinomial probit analysis from converging when we include these dummy variables.

COVID period, whilst these two market timing proxies are not significant for pre-COVID SEOs. Overall, this pattern suggests a stronger prevalence of market timing motives and a weaker importance of precautionary motives for COVID SEOs relative to pre-COVID SEOs. Furthermore, we find a negative impact of *ResidualVolatility* on the likelihood of COVID convertibles, whilst it does not significantly influence pre-COVID convertible offerings. A lower volatility is consistent with lower information asymmetry and, therefore, lower adverse selection costs. This pattern thus suggests that COVID-period convertible issuance is unlikely to be explained by motives described in theories by Brennan and Kraus (1987), Brennan and Schwartz (1988), and Stein (1992). For straight bond offerings, we do not find material differences in determinants across the two periods.

Consistent with the approach in Custodio, Ferreira, and Laureano (2013), we subsequently verify the extent to which a pre-COVID security choice model can explain COVID offerings. We estimate predicted probabilities of external financing options by applying the coefficients from Column (1) of Table 2.6, Panel A, and multiplying these with the corresponding firm and macroeconomic characteristics of COVID firm-months. Table 2.6, Panel B reports the results of this analysis. The predicted probabilities of convertible bond offerings, straight bond offerings, and bank loans are significantly lower than their actual frequencies during the COVID period, further corroborating that pre-COVID security choice models cannot account for the increase in COVID convertible and straight bond offerings and bank loans. In contrast, there are no significant differences in predicted and actual probabilities of SEOs.

## 2.5 Does the COVID crisis affect stock price reactions to corporate security offerings?

In this section, we examine the impact of the COVID crisis on security offering announcement returns ($Q_2$) and longer-term stock returns following security offerings ($Q_3$).

### 2.5.1 The impact of the COVID crisis on security offering announcement returns

To examine $Q_2$, we first identify the announcement date for each security offering. Following the approach of previous studies, we use the issue date as the announcement date for Rule 144A private offerings and Rule 415 shelf offerings and the filing date as the announcement date for the non-144A and non-shelf offerings.[14] We exclude a small number of security offerings that do not have an identifiable announcement date. We do not incorporate bank loans in this analysis since they typically do not have a clearly identifiable announcement date (Maskara and Mullineaux, 2011). We then calculate the cumulative abnormal stock return (*CAR*) over the three trading days surrounding the announcement dates by employing the conventional event study methodology described by Brown and Warner (1985). We use the CRSP equally-weighted market index to proxy for the market return and estimate market model regressions over trading days −240 to −40 before the announcement date. We require a minimum of 30 daily returns in the estimation period. The final sample used for the analysis of security offering announcement returns consists of 3,237 SEOs, 508 CBOs, and 1,719 SBOs. Table 2.7 presents univariate results for security offering announcement returns.

<< Please insert Table 2.7 here >>

In line with previous studies (Heron and Lie, 2004; Duca et al., 2012), we find that pre-COVID SEOs have a significantly negative announcement return, with an average of −5.16% and a median of −4.58%. By contrast, COVID SEOs have a significantly positive average *CAR* of 2.50%. The median CAR for COVID SEOs, in turn, is negative (−5.36%) and not significantly different from the pre-COVID median. COVID convertible bonds are associated with a negative average announcement return of −5.85%, significantly lower than the pre-COVID average (−3.84%). Median announcement return tells a similar story. Straight bond announcement returns are statistically insignificant during the COVID and pre-COVID periods.

The large dispersion between average and median *CAR* values for COVID SEOs suggests the existence of some extremely high SEO announcement returns during the COVID period. To verify the reason for these outliers, we examine whether there are any major confounding announcements within the three trading days around the SEO announcement date. We perform the same analysis for convertible bond announcements, for which we also register significant

[14] Kim and Purnanandam (2014) argue that the firm's intention to issue a security is generally announced on the filing date. However, Rule 144A offerings have no filing date and are often announced and issued overnight, leading us to use the issue date instead. For shelf offerings, the filing date can fall several years before the actual offering date. The announcement of the shelf takedown and the actual shelf takedown typically occur very closely together, also leading us to use the issue date (Duca et al., 2012).

stock price reactions. We conduct a manual search in Factiva for each SEO and convertible bond announcement. We define major announcements as any firm-specific news that is potentially relevant to the firm's stock price, including news about corporate actions such as M&A and dividends, financial results, management team changes, R&D, and other important corporate operations. We report the results in Table 2.8.

<< Please insert Table 2.8 here >>

Panel A contains the results for the SEO announcements. Our search reveals that 42.84% of the COVID SEOs are combined with confounding news, a significantly higher percentage than the 20.57% recorded for pre-COVID SEOs. Upon closer inspection, we notice that the information released together with COVID SEOs is predominantly favorable in nature. To cite just one example, Aclaris Therapeutics Inc. (NASDAQ: ACRS) revealed positive mid-stage clinical trial results for its experimental rheumatoid arthritis therapy on January 19, 2021, and announced an SEO on the same day (George, 2021). We find a *CAR* of 209.58% for this SEO announcement. This example is illustrative for a part of our sample: 17.46% of companies that announce an SEO during the COVID period package the information with updates on R&D progress, compared with only 5.18% of pre-COVID SEO announcements. The difference between the two periods is significant at the 1% level. Apart from the category "Other," we do not find any further significant differences in contamination between the pre-COVID and COVID periods.

Given that more than half of SEOs are made by healthcare firms, we separately analyze the healthcare sector in Panel B. For SEO announced by healthcare industry firms during the COVID period, 27.54% of announcements incorporate contaminating news on R&D progress, in stark contrast to the pre-COVID period, where only 8.51% of announcements are contaminated by such information. One possible explanation for this pattern is that seasoned equity issuers recognize investors' heightened anticipation of favorable developments in healthcare research during the COVID crisis and respond by catering to this preference. In contrast, Panel C shows that seasoned equity issuers in other industries do not exhibit a significant increase in the dissemination of news regarding R&D progress around SEO announcements during the COVID period. In Panel D of Table 2.8, we report no significant increases in the prevalence of confounding news for convertible bond announcements, unlike for SEOs.

To further examine the drivers of differences in announcement returns between pre-COVID and COVID periods, we estimate Ordinary Least Squares (OLS) regressions of seasoned equity and convertible bond *CAR*. In line with previous event studies on security offering announcement effects that we cited earlier, we employ annual accounting data in the announcement returns analysis, to increase the likelihood that investors have these data available at the time of the offering announcement. A maximum three-month lag, as would be the case with quarterly accounting data, may be too short for that purpose (Hirshleifer, Hou, Teoh, and Zhang, 2004).

As control variables, we include the issuer and macroeconomic characteristics described in Section 2.3.3. By capturing a range of equity- and debt-related costs derived from corporate finance theories, these variables are also expected to influence the stock price reaction to an equity(-linked) security offering. Notably, we predict equity-related adverse selection and market timing proxies to have a negative influence on stock price reactions to SEOs. Debt-related cost proxies and precautionary motive proxies, in turn, should have a positive impact, as investors are less likely to perceive SEOs by firms with higher costs of obtaining debt and a higher need for capital as signs of overvaluation (Bayless and Chaplinsky, 1991). In addition, we include a set of issue characteristics obtained from SDC. While these characteristics are omitted from the security choice models to avoid a simultaneity bias (Bayless and Chaplinsky, 1991), we can still explore their role in explaining announcement returns. We include the offering's size (*IssueSize*), measured as the ratio of offering proceeds to total assets. A larger issue size may indicate firm overvaluation and hence induce higher adverse selection costs (Krasker, 1986). On the other hand, there are economies of scale in securities issuance costs, making a larger offering relatively cheaper (Lee, Lochhead, Ritter, and Zhao, 1996). Therefore, we have no clear expectations about the impact of *IssueSize* on announcement returns. We include a shelf dummy (*Shelf*) indicating whether the security offering is shelf-registered. Shelf offerings face higher adverse selection costs due to the lack of investment bank certification, leading us to expect a negative impact (Bhagat, Marr, and Thompson, 1985; Denis, 1991). Following Lee and Masulis (2009) and Dutordoir, Strong, and Sun (2018), we further include a *Secondary* dummy equal to one if an SEO includes shares sold by existing shareholders. Investors may perceive the sales of secondary equity as an overvaluation signal. Therefore, we expect a negative impact of *Secondary* on SEO announcement returns. Table 2.9 Panel A presents the regression results of SEO announcement returns. We present *t*-statistics calculated using robust standard errors clustered at the industry level in parentheses.

<<Please insert Table 2.9 here>>

Column (1) only includes the *COVIDPeriod* dummy. In line with the univariate analysis, we find that COVID-period announcement returns are significantly higher than those during the pre-COVID period. Column (2)-(4) cumulatively add issuer and industry characteristics, macroeconomic conditions, and issue characteristics. The coefficient of the *COVIDPeriod* dummy is still significantly positive after these additions. Findings for the control variables are largely in line with expectations, except for the positive impact of *Tax* and the negative impacts of *TBYield* and *DefaultSpread*. Having established that the positive coefficient on *COVIDPeriod* cannot be explained by standard control variables, we next examine the role of contaminating news. As shown in Column (5), the coefficient of the *COVIDPeriod* dummy is no longer significantly positive after we add a *ContaminatingNews* dummy variable equal to one for offerings for which we identified major confounding news in the trading days surrounding the announcement date. This result suggests that the significantly more favorable SEO announcement returns during the COVID crisis can be attributed to the fact that an increased proportion of SEO firms publish confounding news around the SEO announcement date. In Columns (6) and (7), we replicate the prior two columns with dummy variables capturing the first ten months (*COVIDPeriod1*) and the second stage (*COVIDPeriod2*) of the COVID crisis. We find that stock price reactions are more favorable in the first subperiod, but the significance of the dummy variable disappears again after controlling for contaminating news.

We next investigate the impact of the COVID crisis on stock price reactions to convertible bond announcements, with our results reported in Table 2.9, Panel B. As with our analysis of SEOs, the regression employs issuer characteristics and macroeconomic conditions as control variables. The only difference comes from the issue characteristics, where the convertible bond analysis includes the bond's credit rating (*CreditRating*), a dummy variable capturing Rule

144A offerings (*144A*), *IssueSize*, *Maturity*, and the conversion premium (*ConvPremium*) as additional control variables. After including firm characteristics and macroeconomic conditions, the coefficient on the *COVIDPeriod* dummy is no longer significant, suggesting that the documented univariate difference in announcement returns is attributable to shifts in these determinants during the crisis. Results do not change after we include a *ContaminatingNews* dummy, which itself does not affect the convertible bond announcement returns.

### 2.5.2 The impact of the COVID crisis on medium-term stock returns following security offerings

To examine $Q_3$, we calculate cumulative abnormal stock returns (*CAR*) measured over the window (2, 60) relative to the security offering announcement date, employing the market model event study methodology described by Brown and Warner (1985). To verify robustness, we also calculate buy and hold abnormal returns (*BHAR*) using the Fama and French (1993) three-factor model. Table 2.10 presents the results.

<<Please insert Table 2.10 here>>

Panel A shows that SEOs announced during the COVID period have a negative average post-announcement *CAR* of −15.79%, significantly lower than the pre-COVID average *CAR* of −4.30%. The difference in median abnormal returns (−14.04% versus −5.89%) is of the same magnitude. These results are confirmed in Panel B for *BHAR*. As outlined in Table 2.1, the consistently more negative longer-term stock price reactions following COVID SEOs are consistent with a market timing interpretation. In contrast, we do not find significantly lower post-announcement returns for COVID convertibles using both measures. For straight bonds, we find a weakly significant difference in the median post-announcement return for *BHAR* but not for *CAR*.

## 2.6 Does the COVID crisis affect corporate security offering uses of proceeds?

To examine $Q_4$, we investigate changes in relevant issuer characteristics in the year following the offering. Consistent with Kim and Weisbach (2008) and Walker and Yost (2008), we use capital expenditures, R&D, acquisitions, long-term debt reduction, changes in inventory, changes in cash, and changes in working capital to measure the use of proceeds. Capital expenditures, R&D, acquisitions, and increases in inventory capture investment purposes for the offering proceeds. As noted in Table 2.1, increases in cash and working capital are consistent with market timing, precautionary, or flight to quality motives.[15] For income and cash flow statement items (capital expenditures, R&D, acquisitions, and long-term debt reduction), we take the logarithm of one plus the total value of each variable since the issue date, normalized by total assets before the issue date. That is: $\text{Use of proceeds}=\ln[(\sum_{i=1}^{t} V_i/\text{total assets}_0)+1]$ where $V$ is the variable being measured, quarter 0 is the fiscal quarter-end before the issue date, and quarter $t$ is the $t^{th}$ quarter after quarter 0. For balance sheet items (inventory, cash, and working capital), we take the logarithm of one plus changes in each variable normalized by total assets before the issue date, or: $\text{Use of proceeds}=\ln[((V_i\text{-}V_0)/\text{total assets}_0)+1]$. We aggregate all proceeds raised by the same firm within the same fiscal quarter. To avoid confounding effects, we exclude firm-quarter observations with different types of securities issued.

For each type of security offering, we estimate the following regression similar to models reported in Kim and Weisbach (2008) and Erel et al. (2012):

$$\text{Use of proceeds}=\beta_0+\beta_1\text{COVIDMonth}+\beta_2\text{Proceeds}+\beta_3\text{COVIDMonth}\times\text{Proceeds} +\beta_4\text{TotalAssets}+\text{FE}+\varepsilon \quad (2)$$

where *Proceeds* captures total proceeds raised from security offerings over the fiscal quarter. We take the logarithm of one plus the ratio of total proceeds to total assets to minimize the effect of outliers. The *COVIDMonth* dummy variable equals one if the fiscal quarter includes a COVID-period month. The key variable of interest is the *COVIDMonth*×*Proceeds* interaction term, which captures the impact of the COVID crisis on the use of proceeds. We also control for $TotalAssets_0$ and industry FE in the regressions. Table 2.11 presents the regression results for each type of security, omitting the coefficients on *TotalAssets* and industry FE for brevity. *t*-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses.

[15] Long-term debt reductions are less clear-cut in terms of inferred motive. Notably, this use of proceeds could be consistent with market timing (Hertzel and Li, 2010; Walker, Yost, and Zhao, 2016), but also with precautionary motives, to the extent that the firm frees up debt capacity to deal with future shocks to its cash flows.

<<Please insert Table 2.11 here>>

Panel A represents the regression results for SEOs. We consistently find significant positive coefficients on *COVIDMonth×Proceeds* for changes in cash and working capital across the different post-offering quarters, reinforcing a market timing interpretation for COVID SEOs. We also document significant negative coefficients on *COVIDMonth×Proceeds* for R&D expenditure across the different quarters, indicating that seasoned equity issuers are less likely to use the offering proceeds to fund R&D expenditures during the COVID period. Panel B shows that proceeds raised from COVID convertibles are more likely to be used to reduce long-term debt over the four quarters following issuance. However, we do not find any other consistent change in the use of proceeds for convertibles. Panel C represents the regression results for straight bonds. Again, we do not observe any consistent change in the use of proceeds between pre-COVID and COVID SBOs.

### 2.7 Robustness and additional tests

In this section, we report robustness and additional tests cementing the interpretations of our main results.

#### 2.7.1 The role of government interventions in driving COVID security offerings

The U.S. Government launched a series of interventions to support the flow of credit to businesses during the COVID crisis (Clarida, Duygan-Bump, and Scotti, 2021). Among these interventions, the Federal Reserve's Primary Market Corporate Credit Facility (PMCCF) and Secondary Market Corporate Credit Facility (SMCCF) are potentially relevant for our sample firms. The PMCCF facilitated the purchase of new (convertible) bonds and loans, while the SMCCF aided the trading of previously issued bonds. Since we focus on primary security offerings, it is the PMCCF rather than the SMCCF that is most pertinent to our research design, but we consider the latter scheme as well for completeness.[16]

[16] The PMCCF and SMCCF are not the only governmental corporate credit facilities offered during the COVID crisis. Notably, the U.S. Small Business Administration provided financial support to small businesses, defined as firms with no more than 500 employees, via the Payment Protection Program Liquidity Facility (PPPLF) starting on April 9, 2020, and ending on May 31, 2021. Moreover, the Federal Reserve established the Main Street Lending Program (MSLP) to support lending to firms that are too small to qualify for the PMCCF and SMCCF but too large to qualify for the loans and grants available through the PPPLF. The MSLP purchased 95 percent of eligible loans from lenders (mostly banks), thereby sharing the credit risk. PPPLF and MSLP aimed to support credit to

Table 2.12, Panel A provides details on these two government interventions, including eligible firms, eligible assets, and the beginning and end dates of the schemes. O'Hara and Zhou (2021), Falato, Goldstein, and Hortacsu (2021), Kargar, Lester, Lindsay, Liu, Weill, and Zuniga (2021), Boyarchenko, Cox, Crump, Danzig, Kovner, Shachar, and Steiner (2022a), Boyarchenko, Kovner, and Shachar (2022b), and Gilchrist, Wei, Yue, and Zakrajsek (2024) show that the PMCCF and SMCCF improved bond market functioning and liquidity. It is, therefore, worth considering whether the abnormal (convertible) bond issuance activities during the COVID period could be ascribed to the introduction of these government schemes.

<<Please insert Table 2.12 here>>

We note that the results of two previous tests cast doubt on this conjecture. Firstly, both credit facilities ceased new purchase activities at the end of 2020. Therefore, bond issuance activities from 2021 onward cannot be attributed to these facilities. January 2021, the cutoff month we used earlier to distinguish the *COVIDPeriod1* and *COVIDPeriod2* dummy variables, marks the transition between these periods. Therefore, next to distinguishing more broadly between the earlier and later stages of the COVID crisis, our findings in Table 2.5, Panel B also enable us to assess the impact of the PMCCF and SMCCF government interventions on COVID security issuance activities. As noted earlier, these earlier results indicate firmly that firms still engage in abnormal convertible and straight bond offerings even during the *COVIDPeriod2* not covered by the two government interventions. Secondly, another important characteristic of the PMCCF and SMCCF is that their support pertains uniquely to investment grade firms. If these government interventions are the primary driver for the increased bond issuance during the COVID period, we would therefore expect to see an increase in offerings only among investment grade firms. However, our earlier findings in Table 2.5, Panel C indicate that the non-investment grade firms, who are ineligible for corporate credit facilities, also engage in abnormal (convertible) bond issuance during COVID. In fact, for convertible bonds, the abnormal increase in offerings during the crisis holds only for non-investment grade

firms only via the loan market, whilst this paper focuses on security offerings. Moreover, our sample consists of publicly listed, large to very large companies, whilst the PPPLF and MSLP cover small and medium-sized companies, respectively. For these reasons, we rule out that the PPPLF and the MSLP drive the abnormal (convertible) bond issuance of our sample firms during the COVID period and focus instead on the PMCCF and SMCCF.

firms. Together, these two previous tests suggest that the observed abnormal (convertible) bond issuance activities during COVID are not caused by government interventions.

As an additional test, we exploit the fact that, as noted in Table 2.12, Panel A, the PMCCF and SMCCF facilities targeted relatively short-maturity debt, i.e., primary market debt of up to four years in maturity and secondary market debt of up to five years in maturity, respectively. We examine whether we observe a higher occurrence of bonds with shorter maturities during the initial stage of the COVID crisis in which these credit facilities were in place (*COVIDPeriod1*), compared with the pre-COVID period as well as the later stage of the COVID crisis in which these facilities ceased to exist (*COVIDPeriod2*). Panel B reports the monthly average and median *Maturity* of both types of bond offerings during these subperiods.

The average maturity for convertible bonds during *COVIDPeriod1* is 5.34 years, significantly lower than the pre-COVID average of 6.30 years but still above the maximum maturity covered by the two credit facilities. The average maturity for convertible bonds during *COVIDPeriod2* is 5.39 years, insignificantly different from the *COVIDPeriod1* average. Medians tell a similar story. The decrease in the *COVIDPeriod1* convertible bond *Maturity* is consistent with a government intervention explanation. However, the fact that convertible bond issuers do not revert to their pre-COVID *Maturity* levels in *COVIDPeriod2,* in which these government interventions are no longer in place, is inconsistent with such an explanation. We note that COVID-period decreases in bond maturities may be driven by factors other than government interventions. For example, a flight to quality rationale may also imply a drop in COVID-period bond maturities, as investors prefer shorter-maturity, “safer” debt instruments (Erel et al., 2012).

Regarding straight bonds, the analysis indicates no significant differences in the *Maturity* of pre-COVID offerings and offerings made in *COVIDPeriod1*, with averages of 10.08 years and 10.76 years, respectively. In addition, straight bonds issued during *COVIDPeriod2* have an average *Maturity* of 8.78 years, significantly lower than the *COVIDPeriod1* average *Maturity*. This pattern does not align with the idea that increased straight bond issuance is motivated by the introduction of government interventions, as this would imply shorter straight bond maturities during *COVIDPeriod1* rather than *COVIDPeriod2*.

Overall, our findings indicate that the abnormal increase in (convertible) bond issuance during the COVID period cannot be attributed to the PMCCF or SMCCF.

### 2.7.2 Firms with positive versus negative cash flow effects from the COVID crisis

Whilst the COVID crisis unambiguously increased cash flow uncertainty, the direction of its effect on corporate cash flows varied, with some firms experiencing a higher demand for their products and services and others facing severe cash flow drops (De Vito and Gomez, 2020). In the next set of additional tests, we verify whether our baseline security choice results hold across firms with different cash flow implications from the COVID crisis.

We first focus on firms' actual cash flow changes following the onset of the COVID crisis. We zoom in on the first quarter of the pandemic, considering it a pivotal time to measure cash flow implications from COVID before firms have implemented potential remediating measures. We measure *CashFlow* as outlined in the Appendix B1. Figure 2.3 shows the distribution of *CashFlow* changes around the first quarter of the COVID period. We observe that some firms have high positive *CashFlow* changes, skewing the average above the median *CashFlow* change. In total, 44.03% of the sample firms experience a positive *CashFlow* change, while 55.97% of the firms observe a negative *CashFlow* change.

<<Please insert Figure 2.3 here>>

We next investigate the industry distribution of *CashFlow* changes over the first quarter of the COVID pandemic. As outlined in Table 2.13, Panel A, the COVID-induced shock has adverse cash flow impacts for most firms in Consumer NonDurables, Consumer Durables, and Energy industries, with 65.91%, 69.64%, and 72.28% of firms in these industries having negative *CashFlow* changes. In contrast, more than half of the firms in the Chemicals and Healthcare industries experience an increased *CashFlow* during the first quarter of the COVID period.

<<Please insert Table 2.13 here>>

We then conduct a subsample analysis to investigate if the COVID pandemic impacts security issuance activities differently for the firms with positive versus negative *CashFlow* changes, labeled *Positively Affected Firms* and *Negatively Affected Firms,* as defined in the Appendix B1. We hypothesize that firms suffering from negative cash flow shocks are more likely to experience near-term cash needs triggered by the COVID pandemic, leading them to raise external capital. Consistent with this prediction, Table 2.13, Panel B shows Wald tests indicating that, for straight bond offerings, the coefficient on the *COVIDPeriod* dummy for *Negatively Affected Firms* is significantly more positive than for firms with positively affected cash flows. This suggests that firms with negative cash flow consequences from the COVID crisis exhibit a higher abnormal straight bond issuance during the crisis than firms experiencing positive cash flow consequences. However, we observe abnormal increases in straight bond offerings and bank loans even for the *Positively Affected Firms*, as indicated by significant *COVIDPeriod* dummy variables even after controlling for the firm characteristics and macroeconomic conditions. By contrast, we find no abnormal seasoned equity or convertible bond issuance activity for both positively and negatively affected firms during the COVID crisis. We note that the sample that can be used for this subsample analysis is smaller than for the baseline security choice analysis in Table 2.5 (i.e., 212,688 firm-months compared with 275,479 firm-months in the baseline analysis) due to *CashFlow* changes not being available for some firms.

In addition to examining actual cash flow changes, we verify whether the abnormal increases in (convertible) bond offerings during COVID are restricted to firms that are more affected by social distancing requirements. Some firms, particularly those in high-tech industries, could adapt relatively easily to social distancing requirements by relying heavily on working-from-home practices. Conversely, social distancing requirements heavily disrupted the operations of firms in the food service, travel, and hospitality industries, as their operations inherently involve physical interaction with customers and among employees. Following Pagano and Zechner (2022) and Pagano et al. (2023), we assess a firm's resilience to social distancing requirements by using the "affected share" score proposed by Koren and Peto (2020). The affected share is inversely proportional to the fraction of workers in the firm's industry affected by social distancing restrictions. As outlined in the Appendix B1, we define *High Resilience Firms* as those with an "affected share" score below the median value of the sample and *Low Resilience Firms* as all other firms. We rerun the baseline security choice analysis separately for these two types of firms and display the results of this analysis in Table 2.13, Panel C. We find no evidence of abnormal SEOs for either type of firm. For convertibles, the *COVIDPeriod* dummy is only significant for low-resilience firms, not for high-resilience firms. Most importantly, we note abnormal increases in straight bonds and bank loans across both groups of firms, as evidenced by significant *COVIDPeriod* dummy variables, with the increase in bank loans significantly higher for low-resilience firms, according to the Wald test.

Overall, we conclude that our main security choice results, particularly those related to the abnormal straight bond increases during COVID, hold even for firms with positive cash flow changes and for high-resilience firms.

### 2.7.3 Alternative model specifications

In this section, we verify the robustness of our baseline results to the use of alternative methodology. We first confirm that our main security choice model and announcement returns regression results are robust using different combinations of industry FE and standard error clustering. We cannot include firm FE or fine-grained industry FE (e.g., Fama and French 36-industry fixed effects) in the security choice model because we do not achieve convergence in the estimations if we resort to these approaches. Given these constraints, our viable choices for FE structures encompass no FE or Fama and French 12-industry FE. In Table 2.14, Panel A, we report the results of the baseline security choice analysis with alternative fixed effects (all based on the Fama and French 12-industry classification) and standard error structures.

<<Please insert Table 2.14 here>>

Column (1) does not include any FE and uses robust standard errors. Column (2) includes industry FE and uses robust standard errors. Column (3) includes industry FE and clusters standard errors by the firm. Results for these alternative model specifications, and notably for our key variable of interest, *COVIDPeriod*, are entirely in line with the results in our baseline security choice analysis shown in Table 2.5. We acknowledge the argument provided by Breuer and deHaan (2023), who suggest that FE groups should be "nested" within the standard error clusters. For example, firm FE combined with industry-clustered standard errors is acceptable from an econometric viewpoint but not vice versa. Therefore, we do not use the specification in Column (3) as our baseline security choice analysis. In Panel B, we show that our SEO announcement return regression results are also robust when adopting analogous FE and standard error structures. In particular, the *COVIDPeriod* dummy variables are significant after controlling for the macroeconomic conditions, issuer characteristics, and issue characteristics, as indicated in Columns (1), (3), and (5). However, these dummy variables are no longer significant after we add a *ContaminatingNews* dummy variable, as shown in Columns (2), (4), and (6), consistent with our baseline results. We conclude that our findings remain robust under different model specifications.

We then show that the SEO announcement returns results are also robust to using a different estimation window in the event study (i.e., days −251 to −11 before the announcement date), using a value-weighted market index instead of an equal-weighted market index, and using the Fama and French (1993) three-factor model instead of the market model, as shown in Table 2.14 Panel C. In Columns (1), (3), and (5), we regress the SEO announcement returns on macroeconomic conditions, issuer characteristics, and issue characteristics. We find that SEO announcement returns are notably higher during the COVID period compared to the pre-COVID era, consistent with our baseline findings from Table 2.9. We then add a *ContaminatingNews* dummy in Columns (2), (4), and (6). Again, consistent with the results in Table 2.9, the *COVIDPeriod* dummy is no longer significant after controlling for a *ContaminatingNews* dummy variable. We conclude that our event study results are not sensitive to the estimation methods used.

**2.7.4 The GFC versus the COVID crisis**

Besides the COVID crisis, the financial market has witnessed another major global economic crisis in recent years, i.e., the GFC. The GFC is comparable to the COVID crisis in terms of its scope and severity. However, whilst the COVID crisis originated as a health crisis and represented an unexpected, exogenous shock to the real economy, which initially seemed unrelated to the availability of external financing, the GFC originated inside the financial sector and thereby represented an endogenous process (Fahlenbrach et al., 2021; Kargar et al., 2021). Recent studies show that the GFC and COVID crisis affected firms' dividend payout decisions differently; however, we are not aware of any direct comparison between security issuance behavior and security offering announcement returns across the crises.[17] Addressing this gap, we examine whether our main findings on security choices and stock price reactions during the COVID crisis resemble those observed during the GFC. This part of the study spans the period

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[17] Mauck and Pruitt (2021) find that, whilst the GFC led to an increase in dividend cuts and omissions predominantly for financial firms, the COVID pandemic led to an increase in dividend cuts and omissions across all sectors.

from January 2007 to June 2021, thereby explicitly including the GFC period (which we define as ranging from January 2008 to December 2009, consistent with Pelzl and Valderrama (2023)) for comparison. We first replicate our baseline security analysis over this extended sample, including the GFC crisis. Table 2.15, Panel A provides the results.

<<Please insert Table 2.15 here>>

In a similar vein as *COVIDPeriod*, the *GFCPeriod* dummy variable captures abnormal securities issuance during the GFC after controlling for the other determinants included in the model. Neither *GFCPeriod* nor *COVIDPeriod* is significant for SEOs after including the corporate financing determinants suggested by the existing corporate finance theories. However, the significant coefficients on *GFCPeriod* and *COVIDPeriod* for convertibles suggest firms issue more convertible bonds than existing corporate finance theories suggest during both crises. Finally, we observe no abnormal straight bond and bank loan issuance during the GFC period, in contrast with their abnormal issuance volumes during COVID.

We next investigate the stock price reaction to security offering announcements for the extended sample, including the GFC. Table 2.15, Panel B provides the results. Unlike the positive average SEO announcement effect observed during the COVID period, we observe negative average SEO announcement returns during the GFC period, significantly lower than the "normal" averages. Moreover, as shown in Panel C, we observe no significant differences in the presence of *ContaminatingNews* between the GFC and "normal" periods. Whilst a detailed analysis of the drivers of these GFC results is outside the scope of our study, a tentative explanation for the announcement returns findings for the GFC is that the GFC witnessed a substantial credit crunch, limiting firms' access to debt financing (Ivashina and Scharfstein, 2010; Kahle and Stulz, 2013; Benmelech and Bergman, 2018). As a result, firms may have used SEOs as a last resort financing option, with investors negatively updating their cash flow predictions following GFC SEO announcements.

In summary, our findings underscore the unique nature of the COVID period compared to the GFC period regarding firms' security offering choices and the stock price reactions to these offerings.

## 2.8 Summary and implications

We examine the impact of the COVID crisis on corporate security choice ($Q_1$), security offering announcement effects ($Q_2$), post-announcement returns ($Q_3$), and uses of proceeds ($Q_4$). Pre-COVID findings suggest seasoned equity offerings result from an urgent need for funding. Instead, our analysis indicates that COVID SEOs are timed opportunistically and often packaged with positive news, leading to an improved stock market reception. We do not find any strong evidence for the main convertible bond rationales, nor for more general corporate finance theories, for COVID convertibles. Notably, our results during the COVID period are largely inconsistent with existing convertible bond theories based on asymmetric information (Brennan and Kraus; Brennan and Schwartz, 1988; Stein, 1992). In a similar vein, we conclude that the abnormal increase in straight bond issuance since the onset of the COVID crisis is not explained by existing corporate finance theories. In further tests, we show that our findings are not attributable to increased government support facilitating credit during the COVID crisis and hold for firms with different cash flow effects from the crisis.

We furthermore show that the COVID crisis differs from the GFC with regards to security offering choices and the stock price reactions to these offerings' announcements. During the GFC period, we do not observe abnormal increases in straight bond offerings, nor do we observe positive stock price reactions to SEOs or an increase in the packaging of R&D news with SEO announcements. These differences can be interpreted in light of the GFC being a financial crisis with severe credit constraints. By contrast, the COVID crisis was a health crisis in which firms engaged in abnormal bond offering increases and cunningly timed their SEOs to occur together with favorable R&D-related news.

Our findings are relevant for corporate managers and investors evaluating corporate financing options and the shareholder value effects of these. Our study also has implications for future academic studies on corporate financing decisions. The corporate finance literature witnessed a burst of security choice analyses from the mid-1990s until approximately 2010, with contributions of Jung et al. (1996), Lewis et al. (1999), Erel et al. (2012), and Gomes and Phillips (2012), among others. Our evidence suggests that, during periods of significant disruption and uncertainty, such as the COVID crisis, firms exhibit behavior that is difficult to explain by firm-specific and macroeconomic empirical measures associated with these existing frameworks. In this context, the recent “imperfect managerial knowledge” rationale of DeAngelo (2022) could be potentially relevant. This capital structure theory argues that in a context with substantial uncertainty, managers simply try to secure reliable funding, resulting in the absence of a clear mapping between equity- and debt-related financing cost proxies and corporate finance decisions. This prediction seems to hold for the COVID convertible and straight bond offering increases, which are “abnormal” in the sense that they cannot be explained by firm and macroeconomic variables suggested by pre-COVID security choice theories and models. The inability of established corporate finance theories to account for the COVID-period increases in convertible and straight bond offerings suggests that further theory development is needed to model corporate financing decisions in a setting with severe, multidimensional shocks such as the COVID crisis.

So, what is next? We will need to wait for a few more years to know whether the pandemic caused structural shifts in firms’ security issuance behavior and the associated stock price reactions or whether these elements have reverted to pre-COVID patterns in the “(new) normal” period following the COVID crisis. In any case, it has been argued that “once in a lifetime” events like the COVID crisis will become much more common in the years to come due to the combined effects of increased population, climate change, political instability, global integration, and urbanization (Whiting, 2020; Hague, 2022). Our findings may, therefore, also be relevant for corporate financing decisions during future crises, which are equally likely to be complex and multifaceted in terms of the shocks they represent for firms.

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**Figure 2.1: Security issuance and bank loan proceeds, leverage, and cash ratios over the sample period**

This figure reports the monthly total proceeds of security offerings and bank loans and the monthly average corporate Leverage and Cash ratios from January 2010 to June 2021. The security offerings sample includes seasoned equity offerings, convertible bond offerings, and straight bond offerings. The grey dotted line represents the average of the pre-COVID period from January 2010 to February 2020 and the average of the COVID period from March 2020 to June 2021. The shaded areas correspond to the COVID period starting in March 2020. The Appendix B1 provides variable definitions and sources for *Leverage* and *Cash* ratio.

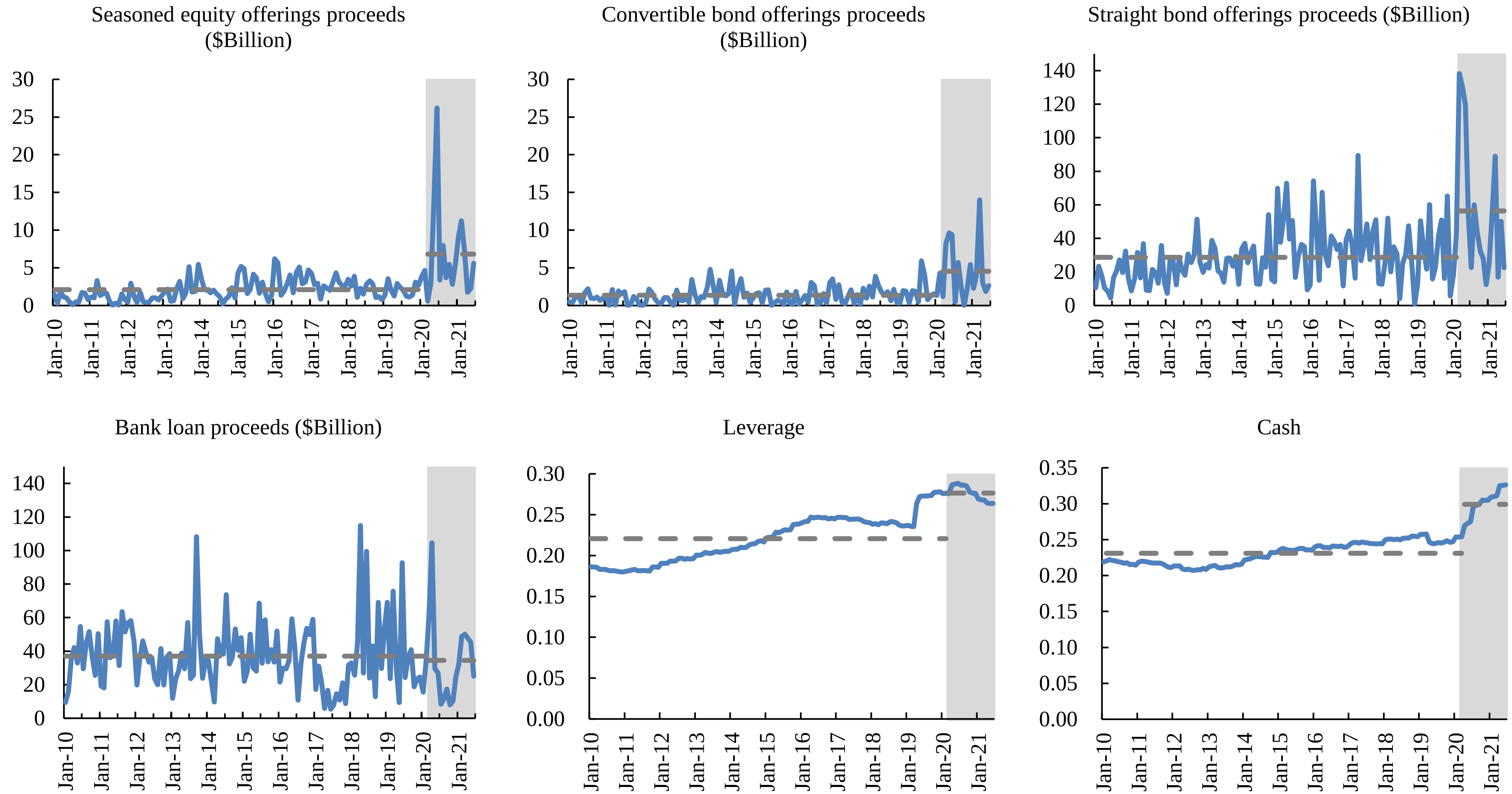

**Figure 2.2: Macroeconomic conditions during the pre-COVID and COVID period**

This figure shows macroeconomic conditions from January 2010 to June 2021. The grey dotted line represents the average of the pre-COVID period from January 2010 to February 2020 and the average of the COVID period from March 2020 to June 2021. The shaded areas correspond to the COVID period starting in March 2020. The Appendix B1 provides variable definitions and sources.

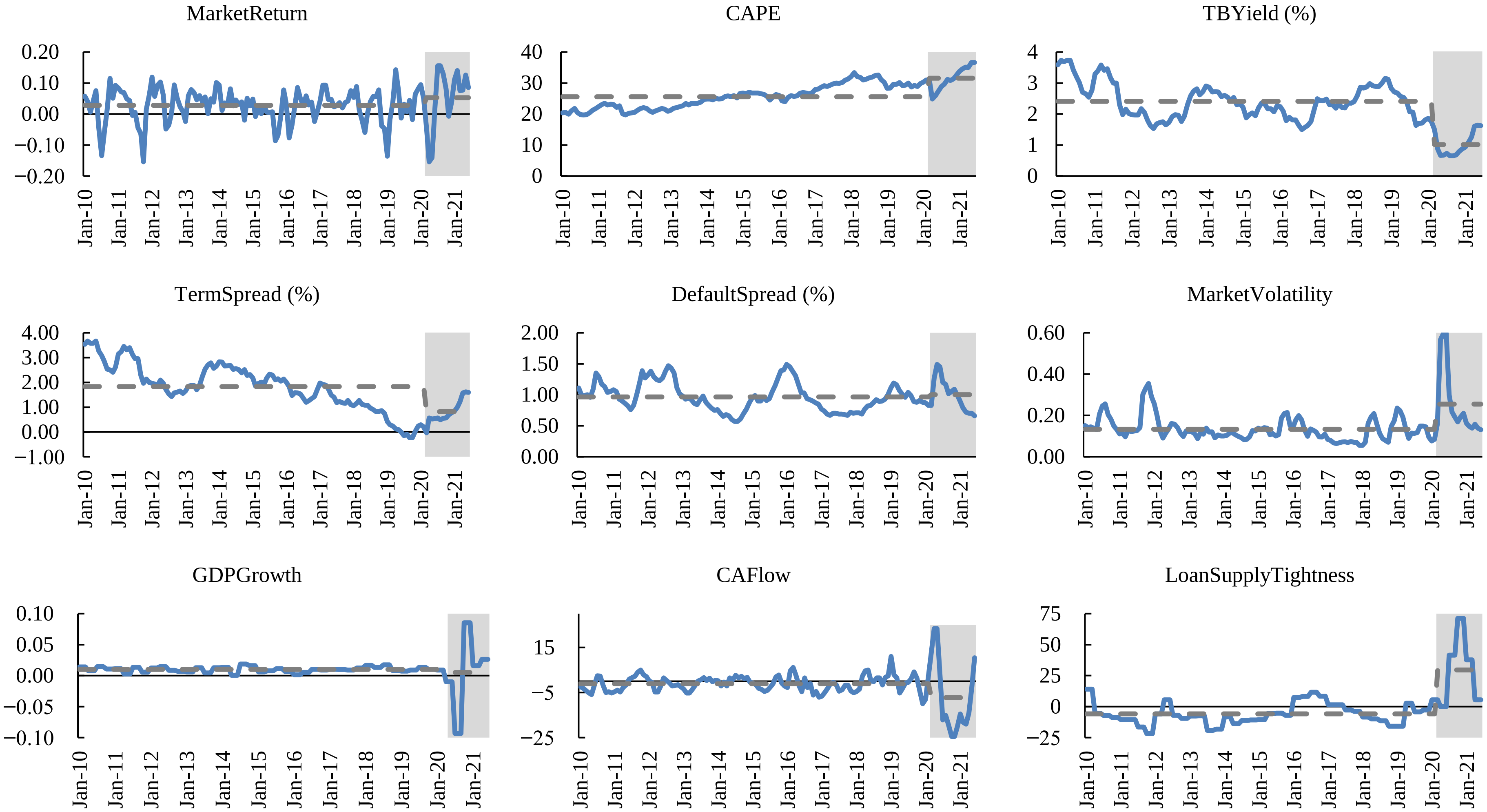

**Figure 2.3: Cash flow change around the first quarter of the COVID period distribution**

This figure provides the empirical distribution of *CashFlow* changes around the first quarter of the COVID period across six equally-spaced bins in our sample. *CashFlow* is the ratio of the sum of earnings before extraordinary items (IBQ) and depreciation (DPQ) to total assets (ATQ). The Appendix B1 provides variable definitions and sources.

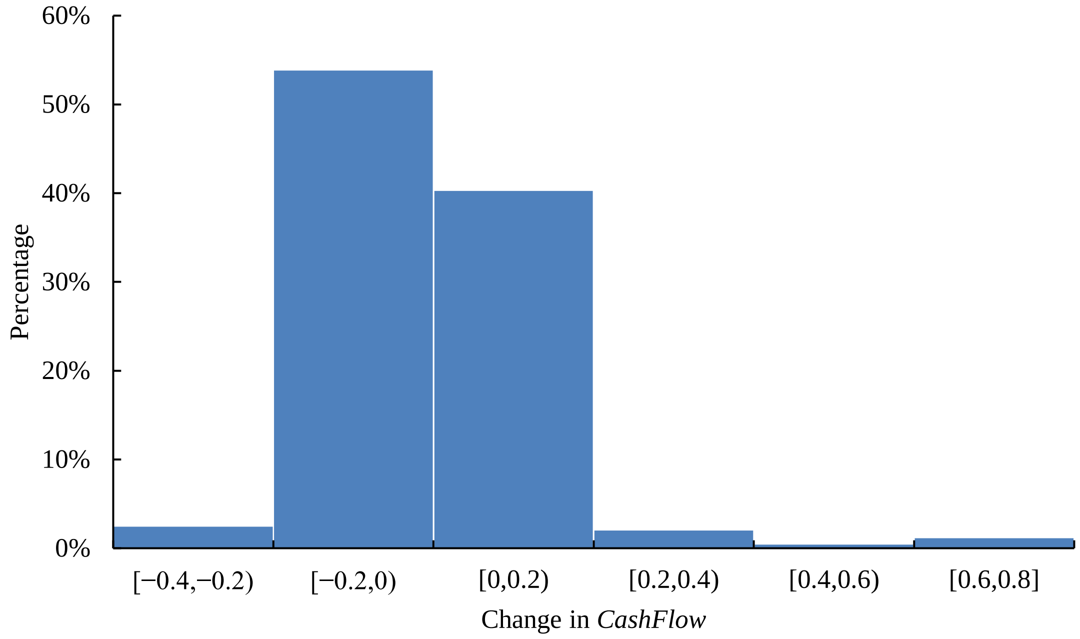

**Table 2.1: Predicted impact of the COVID crisis on corporate financing decisions and their outcomes**

| Theory | COVID-induced shocks | Impact of COVID-induced shocks on: | | | |
|---|---|---|---|---|---|
| | | Security choice: $Q_1$ | Announcement stock return: $Q_2$ | Longer-term stock return: $Q_3$ | Use of proceeds: $Q_4$ |
| Trade-off | Increased uncertainty, Reduced cash flows | Increased likelihood to issue equity-like instead of debt-like securities | No prediction | No prediction | No prediction |
| | Increased cash flows | Increased likelihood to issue debt-like instead of equity-like securities | | | |
| Pecking order | Increased information asymmetry about firm value between firm insiders and outsiders | Increased likelihood to issue debt-like instead of equity-like securities | Negative | No prediction | No prediction |
| Market timing | Favorable conditions for raising debt | Increased likelihood to issue debt-like instead of equity-like securities | No prediction | Negative | More likely to be used as cash, less likely to be invested |
| | Favorable conditions for raising equity | Increased likelihood to issue equity-like instead of debt-like securities | | | |
| Precautionary cash demand | Increased uncertainty, enhancing the benefits of cash as a safety cushion | Increased likelihood to issue equity-like instead of debt-like securities | Positive | No prediction | More likely to be used as cash, less likely to be invested |
| Risk uncertainty | Increased information asymmetry about firm risk between firm insiders and outsiders | Increased likelihood to issue convertible bonds instead of straight bonds | Negative | No prediction | No prediction |
| Backdoor equity | Increased information asymmetry about firm value between firm insiders and outsiders | Increased likelihood to issue convertible bonds instead of seasoned equity | Negative | No prediction | No prediction |
| Flight to quality | Keynesian uncertainty, higher investor risk aversion | Increased likelihood, particularly of investment grade firms, to issue debt-like instead of equity-like securities | No prediction | No prediction | More likely to be used as cash, less likely to be invested |

**Table 2.2: Descriptive statistics of pre-COVID and COVID security offerings and bank loans**

This table presents descriptive statistics of security offerings and bank loans (Loan) from January 2010 to June 2021. The security offering sample includes seasoned equity offerings (SEO), convertible bond offerings (CBO), and straight bond offerings (SBO). The pre-COVID period ranges from January 2010 to February 2020, and the COVID period ranges from March 2020 to June 2021. For each security type and each of the two periods, we report monthly averages of the number of offerings and total proceeds. The proportion of months in which firms choose to make a particular security offering or a bank loan (out of all firm-months) and the proportion of proceeds raised from each type of external financing are reported in parentheses. We employ an independent sample *t*-test to examine the differences between the COVID and the pre-COVID period issue numbers and volumes. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| | Number of offerings | | | | Total proceeds ($ Billion) | | | |
|---|---|---|---|---|---|---|---|---|
| | SEO | CBO | SBO | Loan | SEO | CBO | SBO | Loan |
| Pre-COVID period | 21.25 | 4.02 | 21.92 | 29.53 | 2.26 | 1.36 | 29.23 | 37.35 |
| | (1.06%) | (0.20%) | (1.10%) | (1.48%) | (3.45%) | (2.02%) | (41.50%) | (53.03%) |
| COVID period | 43.94 | 9.63 | 32.75 | 23.81 | 7.11 | 4.56 | 58.24 | 36.34 |
| | (2.24%) | (0.49%) | (1.67%) | (1.22%) | (8.03%) | (4.37%) | (52.72%) | (34.89%) |
| Difference | 22.69*** | 5.61** | 10.83** | −5.72* | 4.85*** | 3.20*** | 29.01** | −1.01 |
| | (1.18%***) | (0.29%**) | (0.57%**) | (−0.27%*) | (4.58%***) | (2.34%***) | (11.22%**) | (−18.15%***) |

**Table 2.3: Pre-COVID and COVID security offerings and bank loans by industry**

This table presents the industry distribution of security offerings and bank loans (Loan) from January 2010 to June 2021. We use the Fama and French 12-industry classification. The security offering sample includes seasoned equity offerings (SEO), convertible bond offerings (CBO), and straight bond offerings (SBO). The pre-COVID period ranges from January 2010 to February 2020; the COVID period ranges from March 2020 to June 2021. For each external financing option and subperiod, the proportions of the number of offerings made by each industry are reported in parentheses.

| Industry | Pre-COVID period | | | | COVID period | | | |
|---|---|---|---|---|---|---|---|---|
| | SEO | CBO | SBO | Loan | SEO | CBO | SBO | Loan |
| Consumer Non-Durables | 43 | 8 | 278 | 279 | 8 | 4 | 52 | 30 |
| | (1.66%) | (1.63%) | (10.40%) | (7.74%) | (1.14%) | (2.60%) | (9.92%) | (7.87%) |
| Consumer Durables | 36 | 9 | 60 | 121 | 6 | 2 | 12 | 12 |
| | (1.39%) | (1.84%) | (2.24%) | (3.36%) | (0.85%) | (1.30%) | (2.29%) | (3.15%) |
| Manufacturing | 107 | 33 | 339 | 544 | 22 | 9 | 75 | 56 |
| | (4.13%) | (6.73%) | (12.68%) | (15.10%) | (3.13%) | (5.84%) | (14.31%) | (14.70%) |
| Energy | 210 | 21 | 321 | 292 | 20 | 4 | 43 | 17 |
| | (8.10%) | (4.29%) | (12.00%) | (8.10%) | (2.84%) | (2.60%) | (8.21%) | (4.46%) |
| Chemicals | 26 | 8 | 137 | 186 | 8 | 0 | 25 | 15 |
| | (1.00%) | (1.63%) | (5.12%) | (5.16%) | (1.14%) | (0.00%) | (4.77%) | (3.94%) |
| Business Equipment & Software | 391 | 200 | 368 | 626 | 117 | 69 | 84 | 77 |
| | (15.08%) | (40.82%) | (13.76%) | (17.37%) | (16.64%) | (44.81%) | (16.03%) | (20.21%) |
| Telecommunication | 28 | 10 | 209 | 173 | 4 | 2 | 34 | 22 |
| | (1.08%) | (2.04%) | (7.82%) | (4.80%) | (0.57%) | (1.30%) | (6.49%) | (5.77%) |
| Wholesale & Retail | 57 | 18 | 286 | 473 | 31 | 10 | 68 | 58 |
| | (2.20%) | (3.67%) | (10.70%) | (13.13%) | (4.41%) | (6.49%) | (12.98%) | (15.22%) |
| Healthcare | 1,547 | 139 | 218 | 374 | 442 | 41 | 40 | 41 |
| | (59.68%) | (28.37%) | (8.15%) | (10.38%) | (62.87%) | (26.62%) | (7.63%) | (10.76%) |
| Other | 147 | 44 | 458 | 535 | 45 | 13 | 91 | 53 |
| | (5.67%) | (8.98%) | (17.13%) | (14.85%) | (6.40%) | (8.44%) | (17.37%) | (13.91%) |
| *N* | 2,592 | 490 | 2,674 | 3,603 | 703 | 154 | 524 | 381 |

**Table 2.4: Differences between pre-COVID and COVID firm characteristics**

This table reports the average values of sample firm characteristics from January 2010 to June 2021. The choice menu includes seasoned equity offerings (SEO), convertible bond offerings (CBO), straight bond offerings (SBO), bank loans (Loan), and not raising external financing (No Issue). The pre-COVID period ranges from January 2010 to February 2020, and the COVID period ranges from March 2020 to June 2021. The Appendix B1 provides variable definitions and sources. In part (3) ("Difference"), we employ an independent sample *t*-test to examine if the average value differs significantly between the COVID and pre-COVID periods. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| | Pre-COVID period (1) | | | | | COVID period (2) | | | | | Difference (3) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | No Issue | SEO | CBO | SBO | Loan | No Issue | SEO | CBO | SBO | Loan | No Issue | SEO | CBO | SBO | Loan |
| Tax ($\times 10^3$) | 3.61 | 0.04 | 1.55 | 5.38 | 4.93 | 1.27 | −0.55 | −0.95 | 2.21 | 1.60 | −2.34*** | −0.59** | −2.50*** | −3.17*** | −3.33*** |
| Leverage | 0.22 | 0.17 | 0.20 | 0.32 | 0.26 | 0.28 | 0.18 | 0.30 | 0.38 | 0.32 | 0.06*** | 0.01 | 0.10*** | 0.07*** | 0.06*** |
| InterestCoverage | 33.05 | 38.97 | 25.79 | 17.61 | 27.25 | 29.44 | 39.38 | 20.21 | 15.20 | 21.85 | −3.61*** | 0.41 | −5.58 | −2.41** | −5.40*** |
| Profitability | −0.02 | −0.14 | −0.04 | 0.01 | 0.01 | −0.03 | −0.13 | −0.04 | 0.01 | 0.00 | −0.01*** | 0.00 | 0.00 | −0.01*** | −0.01*** |
| Cash | 0.23 | 0.47 | 0.32 | 0.10 | 0.12 | 0.30 | 0.52 | 0.35 | 0.11 | 0.14 | 0.06*** | 0.05*** | 0.03 | 0.01** | 0.01* |
| Assets | 6.60 | 4.58 | 6.60 | 9.14 | 7.67 | 6.68 | 4.59 | 6.89 | 9.36 | 8.29 | 0.08*** | 0.02 | 0.29** | 0.23*** | 0.62*** |
| FirmAge | 2.64 | 1.93 | 2.34 | 3.12 | 2.82 | 2.70 | 1.92 | 2.14 | 3.26 | 2.98 | 0.06*** | −0.00 | -0.21** | 0.13*** | 0.16*** |
| FixedAssets | 0.23 | 0.18 | 0.17 | 0.32 | 0.27 | 0.22 | 0.15 | 0.19 | 0.30 | 0.27 | −0.01*** | −0.03*** | 0.02 | −0.01 | 0.00 |
| RatedFirm | 0.34 | 0.09 | 0.20 | 0.87 | 0.54 | 0.34 | 0.07 | 0.18 | 0.93 | 0.62 | −0.00 | −0.02* | −0.03 | 0.05*** | 0.09*** |
| ResidualVolatility | 0.41 | 0.68 | 0.42 | 0.25 | 0.32 | 0.61 | 0.93 | 0.62 | 0.42 | 0.50 | 0.20*** | 0.25*** | 0.19*** | 0.18*** | 0.18*** |
| StockReturn | 0.03 | 0.14 | 0.10 | 0.05 | 0.04 | 0.10 | 0.28 | 0.17 | 0.04 | 0.05 | 0.08*** | 0.14*** | 0.07** | −0.01 | 0.00 |
| MarkettoBook | 3.53 | 5.33 | 5.84 | 3.80 | 3.34 | 4.66 | 6.67 | 11.32 | 4.78 | 4.50 | 1.13*** | 1.34** | 5.48*** | 0.99* | 1.16** |
| CashFlowVolatility | 0.03 | 0.05 | 0.04 | 0.03 | 0.03 | 0.04 | 0.05 | 0.03 | 0.03 | 0.03 | 0.00*** | 0.00 | −0.00 | 0.00 | 0.00 |
| R&DExpenditure | 0.02 | 0.08 | 0.03 | 0.00 | 0.01 | 0.02 | 0.07 | 0.03 | 0.00 | 0.01 | 0.00*** | −0.01*** | −0.01 | −0.00 | 0.00 |
| DividendPaying | 0.33 | 0.03 | 0.10 | 0.66 | 0.45 | 0.28 | 0.04 | 0.08 | 0.66 | 0.51 | −0.05*** | 0.01 | −0.02 | −0.00 | 0.06** |

**Table 2.5: Impact of the COVID crisis on security choice**

This table presents the results of models examining the impact of the COVID crisis on corporate security choices. The choice menu includes seasoned equity offerings (SEO), convertible bond offerings (CBO), straight bond offerings (SBO), bank loans (Loan), and not raising external financing (the baseline option). Panel A presents the results of the baseline security choice model. Column (1) only includes the *COVIDPeriod* dummy, which takes a value of one for months between March 2020 and June 2021 and zero for months between January 2010 and February 2020. Column (2) includes the *COVIDPeriod* dummy, firm characteristics, and industry fixed effects (FE), defined using the Fama and French 12-industry classification. Column (3) includes the *COVIDPeriod* dummy, macroeconomic variables, and industry FE. Column (4) includes the *COVIDPeriod* dummy, firm characteristics, macroeconomic variables, and FE. Panel B replaces the *COVIDPeriod* dummy with two COVID period dummies, distinguishing between the first ten months (*COVIDPeriod1*) and the remaining months (*COVIDPeriod2*) of the pandemic. Panel C presents a subsample analysis for investment grade (Column (1)) and non-investment grade firms (Column (2)). Panels B and C include the same firm characteristics and macroeconomic conditions as those in Panel A, Column (4). The *p*-value for the difference in *COVIDPeriod* coefficients between subsamples is based on a Wald *Chi*-square test. The Appendix B1 provides variable definitions and sources. *t*-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level.

Panel A: Full sample

| | (1) | | | | (2) | | | | (3) | | | | (4) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | SEO | CBO | SBO | Loan | SEO | CBO | SBO | Loan | SEO | CBO | SBO | Loan | SEO | CBO | SBO | Loan |
| COVIDPeriod | 0.420*** | 0.430*** | 0.254*** | −0.051 | 0.309*** | 0.325*** | 0.231*** | −0.024 | −0.036 | 0.252*** | 0.379*** | 0.569*** | −0.028 | 0.217*** | 0.465*** | 0.598*** |
| | (12.15) | (7.27) | (4.31) | (−1.01) | (7.90) | (7.83) | (5.62) | (−0.87) | (−0.22) | (2.68) | (6.05) | (8.19) | (−0.20) | (2.73) | (10.45) | (8.34) |
| Tax | | | | | −6.737*** | −6.247*** | 3.437*** | 1.405 | | | | | −6.862*** | −6.430*** | 1.459 | −0.388 |
| | | | | | (−3.47) | (−2.58) | (2.72) | (1.32) | | | | | (−3.67) | (−2.78) | (1.15) | (−0.31) |
| Leverage | | | | | 0.064 | −0.176 | 0.239** | −0.219*** | | | | | 0.079 | −0.157 | 0.350*** | −0.091 |
| | | | | | (0.99) | (−1.12) | (2.01) | (−2.59) | | | | | (1.29) | (−0.95) | (2.94) | (−1.13) |
| InterestCoverage | | | | | −0.001 | −0.004*** | −0.002*** | 0.000 | | | | | −0.000 | −0.004*** | −0.002*** | 0.000* |
| | | | | | (−1.22) | (−10.00) | (−2.85) | (1.41) | | | | | (−1.18) | (−9.94) | (−2.89) | (1.73) |
| Profitability | | | | | −1.063*** | −0.847*** | 1.243* | 0.847** | | | | | −1.094*** | −0.944*** | 1.371* | 0.664** |
| | | | | | (−10.58) | (−3.51) | (1.69) | (2.47) | | | | | (−9.79) | (−4.06) | (1.86) | (2.11) |
| Cash | | | | | −0.401*** | −0.030 | −0.413*** | −0.805*** | | | | | −0.403*** | −0.027 | −0.435*** | −0.809*** |
| | | | | | (−3.64) | (−0.13) | (−3.03) | (−10.89) | | | | | (−3.60) | (−0.11) | (−3.16) | (−14.23) |
| TotalAssets | | | | | −0.103*** | 0.171*** | 0.299*** | 0.115*** | | | | | −0.104*** | 0.168*** | 0.302*** | 0.121*** |
| | | | | | (−4.33) | (13.40) | (13.63) | (9.68) | | | | | (−4.60) | (12.07) | (13.49) | (12.26) |
| Age | | | | | −0.220*** | −0.095** | 0.022 | −0.049*** | | | | | −0.219*** | −0.093** | 0.031 | −0.039*** |
| | | | | | (−12.25) | (−2.23) | (1.01) | (−5.30) | | | | | (−11.94) | (−2.17) | (1.39) | (−4.22) |
| FixedAssets | | | | | 0.199** | −0.018 | 0.232 | −0.003 | | | | | 0.204** | −0.017 | 0.201 | −0.047 |
| | | | | | (2.36) | (−0.11) | (1.40) | (−0.03) | | | | | (2.31) | (−0.10) | (1.19) | (−0.61) |
| RatedFirm | | | | | −0.011 | −0.338*** | 0.532*** | 0.126*** | | | | | −0.013 | −0.336*** | 0.529*** | 0.114*** |
| | | | | | (−0.14) | (−2.88) | (8.42) | (3.13) | | | | | (−0.17) | (−2.84) | (8.58) | (2.79) |
| ResidualVolatility | | | | | 0.109 | −0.080 | −0.233 | −0.017 | | | | | 0.095 | −0.164 | −0.302** | −0.001 |
| | | | | | (0.96) | (−0.74) | (−1.54) | (−0.21) | | | | | (0.78) | (−1.31) | (−2.05) | (−0.01) |
| StockReturn | | | | | 0.669*** | 0.420*** | 0.242*** | 0.100*** | | | | | 0.691*** | 0.546*** | 0.358*** | 0.183*** |
| | | | | | (20.02) | (4.11) | (3.71) | (2.89) | | | | | (22.26) | (5.07) | (5.63) | (3.90) |
| MarkettoBook | | | | | 0.004*** | 0.009*** | 0.002 | 0.001 | | | | | 0.004*** | 0.009*** | 0.003* | 0.003* |
| | | | | | (3.05) | (3.88) | (1.50) | (0.82) | | | | | (2.95) | (4.07) | (1.94) | (1.88) |

**Table 2.5 continued**

| | (1) | | | | (2) | | | | (3) | | | | (4) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | SEO | CBO | SB | Loan | SEO | CBO | SB | Loan | SEO | CBO | SB | Loan | SEO | CBO | SB | Loan |
| CashFlowVolatility | | | | | 2.245*** | −2.045 | −0.713 | 0.216 | | | | | 2.273*** | −1.339 | −0.591 | −0.449 |
| | | | | | (5.90) | (−1.23) | (−0.63) | (0.12) | | | | | (5.49) | (−1.07) | (−0.36) | (−0.43) |
| R&DExpenditure | | | | | 3.071*** | 2.115*** | −1.994*** | −2.520** | | | | | 3.068*** | 1.979*** | −1.614** | −2.099** |
| | | | | | (25.59) | (3.06) | (−2.75) | (−2.32) | | | | | (22.61) | (3.08) | (−2.01) | (−2.34) |
| DividendPaying | | | | | −0.403*** | −0.545*** | 0.029 | −0.051*** | | | | | −0.405*** | −0.558*** | 0.033 | −0.029 |
| | | | | | (−4.34) | (−6.83) | (0.41) | (−2.66) | | | | | (−4.23) | (−7.19) | (0.46) | (−1.50) |
| MarketReturn | | | | | | | | | 1.192*** | 0.548 | 0.364* | −0.392* | 0.452** | −0.135 | 0.089 | −0.632** |
| | | | | | | | | | (7.51) | (1.39) | (1.74) | (−1.67) | (2.15) | (−0.46) | (0.45) | (−2.56) |
| CAPE | | | | | | | | | 0.011 | −0.007 | −0.022*** | −0.036*** | 0.012 | −0.010 | −0.037*** | −0.039*** |
| | | | | | | | | | (1.21) | (−0.74) | (−6.63) | (−9.23) | (1.44) | (−0.97) | (−7.67) | (−8.41) |
| TBYield | | | | | | | | | −0.064 | −0.015 | −0.110*** | 0.086*** | −0.093** | −0.031 | −0.119*** | 0.088*** |
| | | | | | | | | | (−1.60) | (−0.19) | (−4.78) | (3.40) | (−2.11) | (−0.44) | (−3.99) | (3.25) |
| DefaultSpread | | | | | | | | | −0.346*** | −0.586*** | −0.171*** | 0.009 | −0.312*** | −0.553*** | −0.143*** | 0.030 |
| | | | | | | | | | (−3.82) | (−7.03) | (−5.37) | (0.23) | (−3.65) | (−6.50) | (−3.60) | (0.68) |
| TermSpread | | | | | | | | | 0.055 | −0.025 | −0.017 | −0.003 | 0.088 | −0.011 | 0.015 | 0.005 |
| | | | | | | | | | (0.95) | (−0.58) | (−0.73) | (−0.16) | (1.50) | (−0.27) | (0.60) | (0.29) |
| MarketVolatility | | | | | | | | | 1.663*** | 1.326*** | −0.132 | −0.180 | 1.579*** | 1.295*** | −0.112 | −0.224 |
| | | | | | | | | | (7.40) | (3.30) | (−0.66) | (−1.05) | (7.35) | (3.26) | (−0.50) | (−1.24) |
| GDPGrowth | | | | | | | | | −0.161 | −0.659 | −0.544* | 1.377** | 0.793 | −0.352 | −0.337 | 1.425** |
| | | | | | | | | | (−0.25) | (−1.55) | (−1.73) | (2.52) | (1.03) | (−0.82) | (−0.91) | (2.56) |
| CAFundFlow | | | | | | | | | −0.002 | 0.005 | 0.007*** | −0.004 | −0.000 | 0.008** | 0.006** | −0.003 |
| | | | | | | | | | (−0.81) | (1.63) | (3.51) | (−1.48) | (−0.14) | (2.34) | (2.56) | (−1.27) |
| LoanSupplyTightness | | | | | | | | | 0.002 | 0.001 | −0.002** | −0.007*** | 0.001 | 0.000 | −0.004*** | −0.007*** |
| | | | | | | | | | (1.45) | (0.58) | (−2.56) | (−7.57) | (0.48) | (0.15) | (−3.32) | (−6.95) |
| Constant | −3.166*** | −3.902*** | −3.151*** | −3.004*** | −2.495*** | −4.715*** | −5.755*** | −3.444*** | −3.812*** | −3.637*** | −1.741*** | −2.109*** | −2.658*** | −3.971*** | −4.505*** | −2.846*** |
| | (−14.45) | (−37.66) | (−34.78) | (−47.22) | (−18.79) | (−29.14) | (−19.93) | (−26.39) | (−14.03) | (−8.74) | (−17.87) | (−14.25) | (−9.02) | (−12.29) | (−21.75) | (−12.96) |
| Industry FE | No | | | | Yes | | | | Yes | | | | Yes | | | |
| *Log pseudolikelihood* | −60,286.14 | | | | −52,994.14 | | | | −57,911.44 | | | | −52,644.36 | | | |
| *N* | 275,479 | | | | 275,479 | | | | 275,479 | | | | 275,479 | | | |

**Table 2.5 continued**

Panel B: Initial and subsequent phases of the COVID crisis

| | SEO | CBO | SBO | Loan |
|---|---|---|---|---|
| COVIDPeriod1 | −0.100 | 0.091 | 0.465*** | 0.487*** |
| | (−0.69) | (0.99) | (9.89) | (5.84) |
| COVIDPeriod2 | 0.016 | 0.308*** | 0.464*** | 0.699*** |
| | (0.12) | (3.50) | (5.26) | (7.99) |
| Firm characteristics | Yes | | | |
| Macroeconomic condition | Yes | | | |
| Industry FE | Yes | | | |
| *Log pseudolikelihood* | −52,637.81 | | | |
| *N* | 275,479 | | | |

Panel C: Investment grade and non-investment grade firms

| | (1) Investment grade firms | | | | (2) Non-investment grade firms | | | |
|---|---|---|---|---|---|---|---|---|
| | SEO | CBO | SBO | Loan | SEO | CBO | SBO | Loan |
| COVIDPeriod | −0.532 | 0.257 | 0.215** | 0.474*** | −0.016 | 0.220*** | 0.591*** | 0.610*** |
| | (−1.38) | (0.27) | (2.31) | (2.84) | (−0.13) | (3.05) | (11.89) | (8.26) |
| Wald test *p*-value for difference in *COVIDPeriod* coefficients | 0.18 | 0.97 | 0.00 | 0.45 | | | | |
| Firm characteristics | Yes | | | | Yes | | | |
| Macroeconomic conditions | Yes | | | | Yes | | | |
| Industry FE | No | | | | No | | | |
| *Log pseudolikelihood* | −11,529.76 | | | | −41,113.54 | | | |
| *N* | 39,314 | | | | 236,165 | | | |

## Table 2.6: Differences between pre-COVID and COVID security choice determinants

Panel A presents the results of multinomial probit models estimated separately for the pre-COVID period (from January 2010 to February 2020) in Column (1) and the COVID period (from March 2020 to June 2021) in Column (2). The choice menu includes seasoned equity offerings (SEO), convertible bond offerings (CBO), straight bond offerings (SBO), bank loans (Loan), and not raising external financing (the baseline option). Industries are defined using the Fama and French 12-industry classification. *t*-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses. Panel B reports actual and predicted external financing choices during the COVID period. Predicted probabilities are calculated from the coefficients in the regression model shown in Column (1) of Panel A. The last column employs an independent sample *t*-test to examine if the average predicted frequencies per external financing option differ significantly from the actual frequencies in the COVID period. The Appendix B1 provides variable definitions and sources. ***, **, and * denote significance at the 1%, 5%, and 10% level.

Panel A: Security choice determinants for pre-COVID and COVID security offerings and bank loans

| | (1) Pre-COVID period | | | | (2) COVID period | | | |
|---|---|---|---|---|---|---|---|---|
| | SEO | CBO | SBO | Loan | SEO | CBO | SBO | Loan |
| Tax | −6.199*** | −3.993 | 1.942 | −0.033 | −11.526** | −18.405*** | −1.598 | −4.811 |
| | (−3.43) | (−1.57) | (1.38) | (−0.03) | (−2.53) | (−4.99) | (−0.46) | (−0.98) |
| Leverage | 0.105 | −0.269* | 0.348*** | −0.046 | −0.113 | 0.148 | 0.335*** | −0.522** |
| | (1.31) | (−1.66) | (2.67) | (−0.52) | (−1.01) | (0.45) | (2.58) | (−2.35) |
| InterestCoverage | −0.001 | −0.004*** | −0.002*** | 0.001* | −0.000 | −0.002* | −0.001 | −0.000 |
| | (−1.45) | (−9.75) | (−3.17) | (1.65) | (−0.66) | (−1.83) | (−1.31) | (−0.37) |
| Profitability | −1.164*** | −1.014*** | 1.423 | 0.737** | −0.712*** | −0.394 | 1.587*** | 0.168 |
| | (−9.28) | (−4.42) | (1.59) | (1.98) | (−3.35) | (−1.08) | (3.92) | (0.28) |
| Cash | −0.416*** | −0.016 | −0.424*** | −0.797*** | −0.440*** | −0.185 | −0.452 | −0.824*** |
| | (−3.27) | (−0.06) | (−2.79) | (−11.17) | (−4.03) | (−0.53) | (−1.45) | (−3.30) |
| TotalAssets | −0.092*** | 0.166*** | 0.301*** | 0.115*** | −0.155*** | 0.167*** | 0.298*** | 0.183*** |
| | (−3.63) | (12.23) | (12.66) | (10.41) | (−4.73) | (5.09) | (11.35) | (17.61) |
| Age | −0.207*** | −0.064 | 0.038 | −0.031*** | −0.296*** | −0.263*** | −0.025 | −0.108*** |
| | (−8.12) | (−1.50) | (1.56) | (−2.93) | (−8.80) | (−5.46) | (−0.55) | (−3.07) |
| FixedAssets | 0.197** | −0.116 | 0.205 | −0.069 | 0.184 | 0.382 | 0.220 | 0.166 |
| | (2.07) | (−0.54) | (1.30) | (−0.85) | (0.84) | (1.50) | (0.78) | (1.13) |
| RatedFirm | −0.040 | −0.298** | 0.504*** | 0.111** | 0.077 | −0.471*** | 0.718*** | 0.103 |
| | (−0.46) | (−2.45) | (9.42) | (2.30) | (1.07) | (−3.13) | (4.16) | (1.22) |
| ResidualVolatility | 0.101 | −0.122 | −0.376*** | −0.023 | 0.126 | −0.404** | −0.245 | 0.213* |
| | (0.89) | (−0.90) | (−2.91) | (−0.23) | (0.77) | (−2.17) | (−1.13) | (1.66) |
| StockReturn | 0.700*** | 0.538*** | 0.381*** | 0.218*** | 0.620*** | 0.542*** | 0.275 | 0.027 |
| | (25.29) | (3.75) | (5.20) | (4.06) | (6.61) | (5.07) | (1.64) | (0.21) |
| MarkettoBook | 0.004** | 0.006*** | 0.003* | 0.002 | 0.005*** | 0.014*** | 0.003** | 0.003 |
| | (2.29) | (2.68) | (1.77) | (1.22) | (2.97) | (5.89) | (2.13) | (0.81) |
| CashFlowVolatility | 2.824*** | −0.259 | −0.471 | −0.585 | 0.402 | −7.537*** | −1.890 | −1.457 |
| | (7.34) | (−0.13) | (−0.32) | (−0.73) | (0.38) | (−2.95) | (−0.97) | (−1.05) |
| R&DExpenditure | 3.232*** | 1.933*** | −1.414 | −2.107** | 2.295*** | 3.014** | −2.769 | −1.559 |
| | (20.83) | (3.08) | (−1.40) | (−2.22) | (8.05) | (2.54) | (−1.52) | (−1.06) |
| DividendPaying | −0.465*** | −0.572*** | 0.019 | −0.041** | −0.126 | −0.523*** | 0.066 | 0.103*** |
| | (−4.33) | (−6.66) | (0.27) | (−2.12) | (−1.23) | (−6.91) | (0.62) | (3.01) |
| MarketReturn | −0.320 | 0.388 | 0.053 | −0.669** | 1.211** | −6.854*** | −2.024** | 0.693 |
| | (−1.40) | (1.17) | (0.34) | (−2.27) | (1.99) | (−7.02) | (−2.20) | (0.89) |
| CAPE | −0.003 | −0.031*** | −0.032*** | −0.038*** | 0.166*** | 0.259*** | 0.012 | −0.086 |
| | (−0.35) | (−3.13) | (−5.33) | (−8.48) | (3.73) | (3.77) | (0.36) | (−1.13) |
| TBYield | −0.012 | 0.056 | −0.118*** | 0.080*** | −1.215*** | 0.169 | −0.832*** | −0.502 |
| | (−0.27) | (0.86) | (−3.27) | (2.93) | (−10.64) | (0.64) | (−2.60) | (−0.85) |
| DefaultSpread | −0.287*** | −0.463*** | −0.060 | 0.005 | −0.987*** | −0.763 | −1.722** | −2.621*** |
| | (−3.87) | (−5.26) | (−0.87) | (0.09) | (−4.44) | (−0.92) | (−2.06) | (−2.88) |
| TermSpread | 0.023 | −0.090** | 0.030 | 0.004 | −0.099 | −0.170 | −0.208 | −0.035 |
| | (0.42) | (−2.44) | (1.00) | (0.27) | (−0.34) | (−0.63) | (−1.64) | (−0.18) |
| MarketVolatility | 0.082 | −0.589** | −0.378 | 0.336 | 3.512*** | 5.781*** | 1.385 | 1.450 |
| | (0.24) | (−2.11) | (−1.10) | (1.31) | (3.31) | (3.71) | (0.98) | (0.96) |

**Table 2.6 continued**

| | (1) Pre-COVID period | | | | (2) COVID period | | | |
|---|---|---|---|---|---|---|---|---|
| | SEO | CBO | SBO | Loan | SEO | CBO | SBO | Loan |
| GDPGrowth | −7.167* | −5.065 | 0.653 | 2.428 | 0.761 | −9.060*** | −1.341 | 1.693 |
| | (−1.71) | (−0.77) | (0.19) | (1.16) | (0.94) | (−13.36) | (−1.34) | (1.11) |
| CAFundFlow | −0.009* | 0.023* | −0.005 | −0.009* | 0.018*** | −0.014 | −0.004 | 0.002 |
| | (−1.75) | (1.83) | (−0.94) | (−1.76) | (2.84) | (−1.45) | (−0.79) | (0.80) |
| LoanSupplyTightness | −0.002 | 0.000 | −0.003* | −0.006*** | 0.005 | 0.011* | −0.009 | −0.006 |
| | (−0.50) | (0.18) | (−1.81) | (−5.02) | (1.21) | (1.69) | (−1.41) | (−0.78) |
| Constant | −2.177*** | −3.413*** | −4.706*** | −2.888*** | −5.396*** | −12.392*** | −3.386* | 1.669 |
| | (−5.76) | (−8.82) | (−23.36) | (−12.65) | (−3.77) | (−5.82) | (−1.90) | (0.44) |
| Industry FE | Yes | | | | Yes | | | |
| *Log pseudolikelihood* | −44,938.51 | | | | −7,513.76 | | | |
| *N* | 244,169 | | | | 31,310 | | | |

Panel B: Actual versus predicted probabilities of security choices and bank loans in the COVID period

| | Actual | Predicted | Difference |
|---|---|---|---|
| SEO | 2.24% | 1.86% | 0.38% |
| CBO | 0.49% | 0.16% | 0.33%*** |
| SBO | 1.67% | 0.90% | 0.77%*** |
| Loan | 1.22% | 0.56% | 0.65%*** |

**Table 2.7: Differences between pre-COVID and COVID security offering announcement returns**

This table presents summary statistics of cumulative abnormal stock returns (*CAR*) measured over the window (−1, 1) relative to the announcement date of seasoned equity offerings (SEO), convertible bond offerings (CBO), and straight bond offerings (SBO). The market model parameters are estimated using the equal-weighted CRSP market index over the window (−240, −40) relative to the announcement date. The pre-COVID period ranges from January 2010 to February 2020, and the COVID period ranges from March 2020 to June 2021. We use a standardized cross-sectional test to examine if the average *CAR(*−1, 1*)* is equal to zero (Boehmer, Masumeci, and Poulsen, 1991). We use a Wilcoxon signed-rank test to examine if the median *CAR(*−1,1*)* is equal to zero. We also report the differences in average and median *CAR* between the COVID and pre-COVID periods. We use an independent sample *t*-test (Mann-Whitney U test) to examine if average (median) abnormal stock returns differ significantly across the two subperiods. The Appendix B1 provides variable definitions and sources. ***, **, and * indicate the statistical significance of the test at the 1%, 5%, and 10% levels, respectively.

| | N | Average | Median | Std. Dev | % with a negative value |
|---|---|---|---|---|---|
| SEO | | | | | |
| Pre-COVID period (1) | 2,567 | −5.16%*** | −4.58%*** | 16.13% | 70.94% |
| COVID period (2) | 670 | 2.50%* | −5.36%*** | 42.39% | 65.07% |
| Difference between (2) and (1) | | 7.66%*** | −0.78% | | |
| CBO | | | | | |
| Pre-COVID period (1) | 380 | −3.84%*** | −3.12%*** | 14.01% | 71.58% |
| COVID period (2) | 128 | −5.85%*** | −5.70%*** | 8.52% | 78.12% |
| Difference between (2) and (1) | | −2.01%* | −2.58%*** | | |
| SBO | | | | | |
| Pre-COVID period (1) | 1,502 | −0.09% | −0.08% | 3.96% | 51.46% |
| COVID period (2) | 217 | 0.30% | −0.28% | 7.00% | 51.15% |
| Difference between (2) and (1) | | 0.39% | −0.20% | | |

### Table 2.8: Contaminating news around SEO and convertible bond announcements

This table presents the nature and frequency of contaminating news for seasoned equity offering (SEO) and convertible bond offering (CBO) announcements. The pre-COVID period ranges from January 2010 to February 2020; the COVID period ranges from March 2020 to June 2021. We search the Factiva database for confounding announcements on the offering announcement date and the trading days immediately before and after this date. Corporate actions include mergers and acquisitions, stock splits, share repurchases, and dividend payments. The category "Other" includes all major company-specific news not covered in the previous categories, such as important contract announcements. In case there is more than one contaminating announcement, we consider the announcement that is mentioned first in the news coverage. Panel A contains the full SEO sample, Panel B contains SEO with issuers operating in the Healthcare, Medical Equipment, and Drugs Industry, and Panel C contains other SEO. We use the Fama and French 12-industry classification. Panel D provides analogous results for the convertible bond sample. We employ a Chi-square test to examine if the proportion of contaminating news differs significantly across the two subperiods. ***, **, and * indicate the statistical significance of the test at the 1%, 5%, and 10% levels, respectively.

Panel A: SEO

| Announcement types | Pre-COVID | | COVID | | Difference |
|---|---|---|---|---|---|
| | N | % | N | % | |
| Corporate actions | 59 | 2.30% | 18 | 2.69% | 0.39% |
| Financial results | 204 | 7.95% | 64 | 9.55% | 1.61% |
| Management team changes | 31 | 1.21% | 14 | 2.09% | 0.88% |
| Research and development progress | 133 | 5.18% | 117 | 17.46% | 12.28%*** |
| Other | 101 | 3.93% | 74 | 11.04% | 7.11%*** |
| *N* | 528 | 20.57% | 287 | 42.84% | 22.27%*** |

Panel B: SEO in the Healthcare, Medical Equipment, and Drugs industry

| Announcement types | Pre-COVID | | COVID | | Difference |
|---|---|---|---|---|---|
| | N | % | N | % | |
| Corporate actions | 12 | 0.79% | 3 | 0.72% | −0.07% |
| Financial results | 105 | 6.93% | 36 | 8.70% | 1.76% |
| Management team changes | 23 | 1.52% | 10 | 2.42% | 0.90% |
| Research and development progress | 129 | 8.51% | 114 | 27.54% | 19.02%*** |
| Other | 47 | 3.10% | 35 | 8.45% | 5.35%*** |
| *N* | 316 | 20.86% | 198 | 47.83% | 26.97%*** |

Panel C: SEO in other industries

| Announcement types | Pre-COVID | | COVID | | Difference |
|---|---|---|---|---|---|
| | N | % | N | % | |
| Corporate actions | 47 | 4.47% | 15 | 5.86% | 1.39% |
| Financial results | 99 | 9.41% | 28 | 10.94% | 1.53% |
| Management team changes | 8 | 0.76% | 4 | 1.56% | 0.80% |
| Research and development progress | 4 | 0.38% | 3 | 1.17% | 0.79% |
| Other | 54 | 5.13% | 39 | 15.23% | 10.10%*** |
| *N* | 212 | 20.15% | 89 | 34.77% | 14.61%*** |

Panel D: CBO

| Announcement types | Pre-COVID | | COVID | | Difference |
|---|---|---|---|---|---|
| | N | % | N | % | |
| Corporate actions | 24 | 6.32% | 7 | 5.47% | −0.85% |
| Financial results | 23 | 6.05% | 12 | 9.38% | 3.32% |
| Management team changes | 3 | 0.79% | 2 | 1.56% | 0.77% |
| Research and development progress | 5 | 1.32% | 2 | 1.56% | 0.25% |
| Other | 25 | 6.58% | 11 | 8.59% | 2.01% |
| *N* | 80 | 21.05% | 34 | 26.56% | 5.51% |

**Table 2.9: Impact of the COVID crisis on security offering announcement returns**

This table presents the results of OLS regressions testing the impact of the COVID crisis on seasoned equity offering (SEO) and convertible bond offering (CBO) announcement returns. The dependent variable is the cumulative abnormal return (*CAR)* measured over the window (−1,1) relative to the announcement date, estimated using a standard market model approach. Panel A examines SEO announcement returns, and Panel B examines CBO announcement returns. Column (1) only includes the *COVIDPeriod* dummy. Column (2) adds firm characteristics and industry fixed effects (FE), defined using the Fama and French 12-industry classification. Column (3) adds macroeconomic conditions. Column (4) adds issue characteristics. Column (5) adds a *ContaminatingNews* dummy equal to one if major confounding news is identified in the three trading days around the offering announcement date. Confounding news includes corporate actions, financial results, management team changes, research and development progress, and other major news about the firm's operations. Columns (6) and (7) replicate the analysis in Columns (4) and (5) but distinguish between the first ten months (*COVIDPeriod1*) and the remaining months (*COVIDPeriod2*) of the pandemic. *t*-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses. The Appendix B1 provides variable definitions and sources. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: SEO announcement returns

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| COVIDPeriod | 0.077*** | 0.085*** | 0.096** | 0.087** | 0.053 | | |
| | (3.58) | (4.27) | (3.16) | (2.98) | (1.81) | | |
| COVIDPeriod1 | | | | | | 0.093** | 0.058 |
| | | | | | | (3.12) | (1.73) |
| COVIDPeriod2 | | | | | | 0.061 | 0.029 |
| | | | | | | (1.29) | (0.69) |
| ContaminatingNews | | | | | 0.116*** | | 0.116*** |
| | | | | | (3.92) | | (3.93) |
| Tax | | 0.412*** | 0.401*** | 0.367** | 0.326*** | 0.361** | 0.320** |
| | | (4.06) | (3.82) | (3.21) | (3.48) | (2.96) | (3.23) |
| Leverage | | −0.010 | −0.009 | −0.008 | −0.007 | −0.009 | −0.008 |
| | | (−0.48) | (−0.49) | (−0.46) | (−0.49) | (−0.48) | (−0.50) |
| InterestCoverage | | −0.000** | −0.000** | −0.000** | −0.000** | −0.000*** | −0.000** |
| | | (−3.03) | (−3.19) | (−3.04) | (−2.59) | (−3.38) | (−2.88) |
| Profitability | | 0.012 | 0.011 | 0.024 | 0.030* | 0.024 | 0.030 |
| | | (0.96) | (0.87) | (1.52) | (1.84) | (1.50) | (1.82) |
| Cash | | 0.018 | 0.019 | 0.011 | 0.009 | 0.013 | 0.010 |
| | | (1.24) | (1.31) | (0.91) | (0.74) | (1.02) | (0.85) |
| TotalAssets | | 0.008** | 0.009** | 0.011* | 0.007 | 0.011* | 0.007 |
| | | (2.42) | (2.43) | (2.16) | (1.78) | (2.12) | (1.73) |
| Age | | −0.001 | −0.001 | 0.002 | 0.002 | 0.002 | 0.002 |
| | | (−0.15) | (−0.34) | (0.43) | (0.49) | (0.47) | (0.53) |
| FixedAssets | | −0.055 | −0.056 | −0.052 | −0.053* | −0.052 | −0.053* |
| | | (−1.52) | (−1.65) | (−1.61) | (−1.95) | (−1.58) | (−1.91) |
| RatedFirm | | −0.002 | −0.003 | −0.007 | −0.012 | −0.007 | −0.012 |
| | | (−0.11) | (−0.19) | (−0.32) | (−0.60) | (−0.33) | (−0.61) |
| ResidualVolatility | | −0.010 | −0.006 | −0.004 | −0.004 | −0.004 | −0.004 |
| | | (−1.37) | (−0.97) | (−0.51) | (−0.54) | (−0.51) | (−0.54) |
| StockReturn | | −0.005 | −0.008 | −0.016** | −0.016*** | −0.016** | −0.016*** |
| | | (−0.57) | (−1.16) | (−2.92) | (−3.51) | (−2.92) | (−3.56) |
| MarkettoBook | | −0.000*** | −0.000*** | −0.000*** | −0.000*** | −0.000*** | −0.000*** |
| | | (−7.29) | (−6.97) | (−4.31) | (−4.70) | (−4.07) | (−4.40) |
| CashFlowVolatility | | 0.129** | 0.135*** | 0.120** | 0.046 | 0.114** | 0.041 |
| | | (2.57) | (3.62) | (2.73) | (1.12) | (2.45) | (0.96) |
| R&DExpenditure | | 0.006 | 0.005 | 0.003 | 0.013 | 0.003 | 0.013 |
| | | (0.28) | (0.20) | (0.12) | (0.51) | (0.12) | (0.50) |

**Table 2.9 continued**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| DividendPaying | | −0.017 | −0.014 | −0.018 | −0.015 | −0.018 | −0.014 |
| | | (−1.61) | (−1.26) | (−1.49) | (−1.28) | (−1.44) | (−1.25) |
| MarketReturn | | | 0.031 | 0.034 | 0.020 | 0.027 | 0.014 |
| | | | (0.85) | (0.87) | (0.63) | (0.60) | (0.35) |
| CAPE | | | −0.003 | −0.005* | −0.005* | −0.004 | −0.003 |
| | | | (−1.31) | (−2.01) | (−1.83) | (−1.60) | (−1.64) |
| TBYield | | | −0.012 | −0.014* | −0.019** | −0.017** | −0.021*** |
| | | | (−1.72) | (−2.08) | (−2.91) | (−2.80) | (−3.75) |
| DefaultSpread | | | −0.065*** | −0.066*** | −0.076*** | −0.072*** | −0.081*** |
| | | | (−3.41) | (−3.81) | (−4.27) | (−5.22) | (−6.04) |
| TermSpread | | | −0.001 | 0.003 | 0.007 | 0.007 | 0.011 |
| | | | (−0.08) | (0.46) | (1.23) | (0.87) | (1.66) |
| MarketVolatility | | | −0.027 | −0.018 | 0.032 | 0.026 | 0.072 |
| | | | (−0.29) | (−0.18) | (0.32) | (0.26) | (0.77) |
| GDPGrowth | | | 0.138 | 0.150 | 0.155 | 0.318* | 0.310 |
| | | | (0.68) | (0.75) | (0.79) | (2.07) | (1.78) |
| IssueSize | | | | 0.022** | 0.022* | 0.023** | 0.022** |
| | | | | (2.38) | (2.26) | (2.45) | (2.33) |
| Secondary | | | | −0.007 | 0.003 | −0.006 | 0.003 |
| | | | | (−0.39) | (0.19) | (−0.36) | (0.20) |
| Shelf | | | | −0.027*** | −0.021** | −0.025*** | −0.020** |
| | | | | (−3.99) | (−2.84) | (−3.25) | (−2.49) |
| Constant | −0.052*** | −0.084** | 0.092 | 0.128 | 0.128 | 0.092 | 0.095 |
| | (−20.16) | (−3.14) | (0.95) | (1.28) | (1.26) | (0.99) | (1.08) |
| Industry FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| *Adj. R-squared* | 0.02 | 0.02 | 0.02 | 0.03 | 0.07 | 0.03 | 0.07 |
| *N* | 3,237 | 3,237 | 3,237 | 3,237 | 3,237 | 3,237 | 3,237 |

Panel B: CBO announcement returns

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| COVIDPeriod | −0.020** | −0.041** | 0.019 | 0.016 | 0.016 | | |
| | (−3.04) | (−2.63) | (0.28) | (0.32) | (0.32) | | |
| COVIDPeriod1 | | | | | | 0.068 | 0.067 |
| | | | | | | (1.31) | (1.36) |
| COVIDPeriod2 | | | | | | −0.029 | −0.029 |
| | | | | | | (−0.65) | (−0.67) |
| ContaminatingNews | | | | | 0.005 | | 0.004 |
| | | | | | (0.37) | | (0.28) |
| Tax | | 0.016 | 0.003 | 0.043 | 0.045 | 0.043 | 0.045 |
| | | (0.05) | (0.01) | (0.15) | (0.16) | (0.15) | (0.16) |
| Leverage | | −0.057** | −0.046* | −0.034* | −0.034* | −0.034* | −0.034* |
| | | (−2.48) | (−2.20) | (−1.95) | (−1.94) | (−1.92) | (−1.91) |
| InterestCoverage | | −0.000 | −0.000 | −0.000 | −0.000 | −0.000 | −0.000 |
| | | (−1.33) | (−1.54) | (−0.75) | (−0.71) | (−0.78) | (−0.75) |
| Profitability | | −0.030 | −0.024 | −0.027 | −0.027 | −0.028 | −0.028 |
| | | (−0.91) | (−0.71) | (−1.20) | (−1.20) | (−1.22) | (−1.22) |
| Cash | | −0.015 | −0.027 | −0.026 | −0.026 | −0.025 | −0.025 |
| | | (−0.25) | (−0.50) | (−0.52) | (−0.51) | (−0.52) | (−0.51) |
| TotalAssets | | 0.009 | 0.009 | −0.004 | −0.004 | −0.004 | −0.004 |
| | | (1.39) | (1.79) | (−0.36) | (−0.36) | (−0.38) | (−0.38) |

**Table 2.9 continued**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Age | | −0.003 | −0.004 | −0.003 | −0.003 | −0.002 | −0.002 |
| | | (−0.41) | (−0.48) | (−0.40) | (−0.40) | (−0.38) | (−0.38) |
| FixedAssets | | −0.068* | −0.079* | −0.066* | −0.065* | −0.066* | −0.065* |
| | | (−1.94) | (−2.13) | (−1.98) | (−2.06) | (−2.03) | (−2.13) |
| RatedFirm | | 0.011 | 0.011 | 0.015* | 0.015* | 0.016* | 0.016* |
| | | (1.11) | (1.00) | (2.12) | (2.08) | (2.24) | (2.19) |
| ResidualVolatility | | 0.058 | 0.064 | 0.082 | 0.082 | 0.083 | 0.083 |
| | | (0.96) | (1.09) | (1.37) | (1.38) | (1.37) | (1.38) |
| StockReturn | | −0.011 | −0.013 | −0.027* | −0.027* | −0.028* | −0.028* |
| | | (−0.77) | (−0.75) | (−2.07) | (−2.04) | (−2.04) | (−2.02) |
| MarkettoBook | | 0.001*** | 0.001*** | 0.001*** | 0.001*** | 0.001*** | 0.001*** |
| | | (8.34) | (7.50) | (4.33) | (4.05) | (4.37) | (4.08) |
| CashFlowVolatility | | 0.006 | 0.013 | 0.026 | 0.028 | 0.022 | 0.024 |
| | | (0.09) | (0.23) | (0.37) | (0.38) | (0.33) | (0.34) |
| R&DExpenditure | | −0.133 | −0.099 | −0.115 | −0.115 | −0.117 | −0.117 |
| | | (−1.69) | (−1.30) | (−1.58) | (−1.57) | (−1.60) | (−1.59) |
| DividendPaying | | 0.008 | 0.007 | 0.009 | 0.009 | 0.009 | 0.009 |
| | | (0.53) | (0.57) | (1.53) | (1.45) | (1.53) | (1.46) |
| MarketReturn | | | 0.129** | 0.140** | 0.139** | 0.129** | 0.128* |
| | | | (2.35) | (2.77) | (2.70) | (2.29) | (2.25) |
| CAPE | | | −0.003 | −0.001 | −0.001 | 0.000 | 0.000 |
| | | | (−0.57) | (−0.16) | (−0.15) | (0.02) | (0.03) |
| TBYield | | | 0.045 | 0.058* | 0.058* | 0.057* | 0.057* |
| | | | (1.55) | (2.03) | (2.05) | (2.02) | (2.05) |
| DefaultSpread | | | −0.064** | −0.044 | −0.044 | −0.042 | −0.042 |
| | | | (−2.64) | (−1.57) | (−1.60) | (−1.51) | (−1.55) |
| TermSpread | | | −0.007 | −0.010 | −0.010 | −0.008 | −0.007 |
| | | | (−0.59) | (−1.18) | (−1.24) | (−0.92) | (−0.97) |
| MarketVolatility | | | 0.114 | 0.100 | 0.100 | 0.082 | 0.082 |
| | | | (0.70) | (0.56) | (0.57) | (0.46) | (0.47) |
| CAFundFlow | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | | | (0.24) | (0.73) | (0.72) | (0.61) | (0.61) |
| GDPGrowth | | | −0.106 | −0.118* | −0.118* | −0.071 | −0.072 |
| | | | (−1.20) | (−1.96) | (−1.97) | (−0.83) | (−0.84) |
| CreditRating | | | | 0.004 | 0.004 | 0.004 | 0.004 |
| | | | | (1.42) | (1.43) | (1.46) | (1.47) |
| 144A | | | | 0.029 | 0.029 | 0.029 | 0.029 |
| | | | | (1.21) | (1.23) | (1.20) | (1.22) |
| IssueSize | | | | −0.018 | −0.018 | −0.019 | −0.019 |
| | | | | (−1.05) | (−1.04) | (−1.09) | (−1.08) |
| Maturity | | | | 0.001 | 0.001 | 0.001 | 0.001 |
| | | | | (1.20) | (1.26) | (1.21) | (1.27) |
| ConvPremium | | | | 0.003** | 0.003** | 0.003** | 0.003** |
| | | | | (2.89) | (2.91) | (2.87) | (2.90) |
| Constant | −0.038*** | −0.080 | −0.065 | −0.223* | −0.225* | −0.244* | −0.246* |
| | (−8.36) | (−1.30) | (−0.41) | (−1.87) | (−1.94) | (−2.11) | (−2.17) |
| Industry FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| *Adj. R-squared* | 0.00 | 0.01 | 0.03 | 0.19 | 0.18 | 0.19 | 0.19 |
| *N* | 508 | 508 | 508 | 506 | 506 | 506 | 506 |

**Table 2.10: Differences between post-announcement stock returns of pre-COVID and COVID security offerings**

This table presents summary statistics for cumulative abnormal stock returns (*CAR*, estimated using a standard market model approach) and buy-and-hold stock returns (*BHAR*, estimated using a Fama and French (1993) three-factor model measured over the window (2,60) relative to the announcement date seasoned equity offerings (SEO), convertible bond offerings (CBO), and straight bond offerings (SBO). The pre-COVID period ranges from January 2010 to February 2020, and the COVID period ranges from March 2020 to June 2021. We use a standardized cross-sectional test to examine if the average *CAR* and *BHAR* are equal to zero (Boehmer et al., 1991) and a Wilcoxon signed-rank test to examine if the median *CAR* and *BHAR)* are equal to zero. We assess differences between the COVID and pre-COVID periods using an independent sample *t*-test and Mann-Whitney U test to examine if average (median) abnormal stock returns differ significantly across the two subperiods. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

| | N | Average | Median | Std. Dev | % with a negative value |
|---|---|---|---|---|---|
| Panel A: CAR(2,60) using a market model | | | | | |
| SEO | | | | | |
| Pre-COVID (1) | 2,567 | −4.30%*** | −5.89%*** | 45.82% | 58.04% |
| COVID (2) | 670 | −15.79%*** | −14.04%*** | 52.61% | 63.28% |
| Difference btw. (2) and (1) | | −11.49%*** | −8.15%*** | | |
| CBO | | | | | |
| Pre-COVID (1) | 380 | −2.93%*** | −1.29%* | 22.22% | 53.16% |
| COVID (2) | 128 | −7.51%** | −3.84%** | 33.12% | 57.81% |
| Difference btw. (2) and (1) | | −4.58% | −2.55% | | |
| SBO | | | | | |
| Pre-COVID (1) | 1,501 | −1.96%*** | −1.14%*** | 17.79% | 53.76% |
| COVID (2) | 217 | −1.58%** | −0.31% | 22.07% | 50.69% |
| Difference btw. (2) and (1) | | 0.38% | 0.83% | | |
| Panel B: BHAR(2,60) using a Fama and French (1993) three-factor model | | | | | |
| SEO | | | | | |
| Pre-COVID (1) | 2,567 | −8.10%*** | −9.23%*** | 57.59% | 62.91% |
| COVID (2) | 670 | −23.35%*** | −18.38%*** | 79.67% | 67.91% |
| Difference btw. (2) and (1) | | −15.25%*** | −9.15%*** | | |
| CBO | | | | | |
| Pre-COVID (1) | 380 | −3.89%*** | −2.94%*** | 23.21% | 56.58% |
| COVID (2) | 128 | −7.11%** | −6.04%** | 41.68% | 61.72% |
| Difference btw. (2) and (1) | | −3.22% | −3.10% | | |
| SBO | | | | | |
| Pre-COVID (1) | 1,501 | −2.44%*** | −1.98%*** | 17.78% | 55.83% |
| COVID (2) | 217 | −5.16%*** | −4.00%*** | 23.91% | 59.45% |
| Difference btw. (2) and (1) | | −2.72% | −2.02%* | | |

**Table 2.11: Differences between uses of proceeds of pre-COVID and COVID security offerings**

This table presents OLS regression analyses of the impact of the COVID crisis on the uses of proceeds of seasoned equity offerings (SEO), convertible bond offerings (CBO), and straight bond offerings (SBO). We use capital expenditures, R&D, acquisitions, long-term debt reduction, changes in inventory, changes in cash, and changes in working capital to capture uses of proceeds. For each of these potential uses of proceeds, we estimate the following regression: Use of proceeds=$\beta_0+\beta_1$COVIDMonth+$\beta_2$Proceeds+$\beta_3$COVIDMonth × Proceeds+Controls+ε. The dependent variable for asset-based variables (inventory, cash, and working capital) is: Use of proceeds=$\ln[((V_t - V_0)/\text{total assets}_0) + 1]$, and for cash flow-based variables (capital expense, acquisition, R&D, reduction in long-term debt) is Use of proceeds=$\ln[(\sum_{i=1}^{t} V_i/\text{total assets}_0)+1]$ where *V* is the variable being measured, and quarter 0 is the quarter end before issuance. The independent variables include *COVIDMonth*, *Proceeds*, and their interaction term. We control for firm size (*TotalAssets*) and industry fixed effects, which we do not report in the table for brevity. Industries are defined using the Fama and French 12-industry classification. The Appendix B1 provides variable definitions and sources. *t*-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Variables | | COVIDMonth | | Proceeds | | COVIDMonth× Proceeds | | *N* | *R-squared* |
|---|---|---|---|---|---|---|---|---|---|
| | | $\beta_1$ | *t*-stat | $\beta_2$ | *t*-stat | $\beta_3$ | *t*-stat | | |
| Panel A: SEO | | | | | | | | | |
| ∑CapitalExpense | 1 | −0.00 | (−1.51) | 0.01 | (1.22) | −0.00 | (−0.82) | 3,205 | 0.38 |
| | 2 | −0.01 | (−1.31) | 0.03 | (1.27) | −0.00 | (-0.44) | 3,176 | 0.37 |
| | 3 | -0.01 | (-1.17) | 0.05 | (1.33) | 0.00 | (0.20) | 3,130 | 0.34 |
| | 4 | -0.01 | (-1.48) | 0.07 | (1.42) | 0.01 | (0.50) | 3,084 | 0.36 |
| ∑R&D | 1 | 0.01 | (1.36) | 0.11*** | (6.11) | -0.05*** | (-7.71) | 2,649 | 0.32 |
| | 2 | 0.02* | (2.12) | 0.21*** | (6.52) | -0.11*** | (-8.12) | 2,606 | 0.38 |
| | 3 | 0.03* | (1.93) | 0.29*** | (6.69) | -0.13*** | (-6.14) | 2,556 | 0.40 |
| | 4 | 0.03* | (1.98) | 0.37*** | (7.42) | -0.15*** | (-6.07) | 2,515 | 0.42 |
| ∑Acquisition | 1 | -0.01 | (-1.14) | 0.02 | (0.95) | 0.03 | (0.93) | 3,148 | 0.04 |
| | 2 | -0.01 | (-1.03) | 0.02 | (0.94) | 0.02 | (1.00) | 3,109 | 0.05 |
| | 3 | -0.00 | (-0.22) | 0.03 | (1.00) | 0.02 | (0.82) | 3,047 | 0.06 |
| | 4 | 0.00 | (0.21) | 0.03 | (0.86) | 0.02 | (0.87) | 2,991 | 0.07 |
| ∑LTDReduction | 1 | -0.01* | (-2.14) | -0.01** | (-3.16) | 0.01 | (1.12) | 3,184 | 0.09 |
| | 2 | -0.01** | (-2.56) | -0.01 | (-1.72) | 0.01 | (1.23) | 3,146 | 0.09 |
| | 3 | -0.02** | (-2.99) | -0.01 | (-1.79) | 0.01 | (0.96) | 3,088 | 0.10 |
| | 4 | -0.02** | (-2.77) | -0.02 | (-1.28) | 0.01 | (0.44) | 3,035 | 0.10 |
| ΔInventory | 1 | −0.00 | (−0.49) | 0.00 | (0.87) | 0.01 | (1.12) | 3,149 | 0.03 |
| | 2 | −0.00 | (−0.20) | 0.01 | (1.37) | 0.02 | (1.08) | 3,120 | 0.07 |
| | 3 | 0.00 | (0.62) | 0.02 | (1.31) | 0.01 | (1.10) | 3,074 | 0.08 |
| | 4 | 0.00 | (0.55) | 0.03 | (1.53) | 0.02 | (1.33) | 3,036 | 0.08 |
| ΔCash | 1 | 0.02*** | (4.35) | 0.87*** | (13.42) | 0.06** | (2.41) | 3,210 | 0.73 |
| | 2 | 0.04* | (1.86) | 0.85*** | (11.02) | 0.15*** | (6.98) | 3,182 | 0.58 |
| | 3 | 0.05* | (2.09) | 0.79*** | (9.69) | 0.17*** | (7.16) | 3,139 | 0.41 |
| | 4 | 0.07* | (1.96) | 0.69*** | (10.94) | 0.18*** | (5.90) | 3,096 | 0.32 |

**Table 2.11 continued**

| Variables | | COVIDMonth | | Proceeds | | COVIDMonth× Proceeds | | *N* | *R-squared* |
|---|---|---|---|---|---|---|---|---|---|
| | | $\beta_1$ | *t*-stat | $\beta_2$ | *t*-stat | $\beta_3$ | *t*-stat | | |
| Panel A: SEO | | | | | | | | | |
| ΔWC | 1 | 0.02*** | (3.99) | 0.93*** | (10.88) | 0.09** | (2.94) | 3,196 | 0.70 |
| | 2 | 0.05*** | (3.29) | 0.88*** | (10.19) | 0.16*** | (7.84) | 3,166 | 0.56 |
| | 3 | 0.08*** | (3.26) | 0.81*** | (9.46) | 0.16*** | (9.55) | 3,119 | 0.40 |
| | 4 | 0.10** | (3.24) | 0.71*** | (11.93) | 0.17*** | (6.24) | 3,071 | 0.30 |
| Panel B: CBO | | | | | | | | | |
| ∑CapitalExpense | 1 | −0.01** | (−2.45) | 0.01 | (1.77) | 0.00 | (0.79) | 639 | 0.11 |
| | 2 | −0.01* | (−2.10) | 0.02 | (1.62) | 0.00 | (0.29) | 638 | 0.10 |
| | 3 | −0.02* | (−1.85) | 0.04 | (1.80) | 0.00 | (0.11) | 630 | 0.07 |
| | 4 | −0.02* | (−2.04) | 0.05* | (2.20) | 0.01 | (0.36) | 622 | 0.10 |
| ∑R&D | 1 | 0.00 | (0.70) | 0.09*** | (4.66) | −0.04** | (−2.38) | 500 | 0.29 |
| | 2 | 0.01 | (0.95) | 0.15*** | (5.82) | −0.07** | (−2.85) | 489 | 0.32 |
| | 3 | 0.01 | (0.37) | 0.20*** | (8.32) | −0.08 | (−1.55) | 482 | 0.35 |
| | 4 | 0.01 | (0.46) | 0.25*** | (13.65) | −0.10 | (−1.68) | 474 | 0.36 |
| ∑Acquisition | 1 | −0.01 | (−0.85) | 0.02 | (0.73) | −0.00 | (−0.11) | 608 | 0.02 |
| | 2 | 0.02 | (1.38) | 0.05 | (1.18) | −0.06 | (−1.78) | 604 | 0.03 |
| | 3 | 0.00 | (0.43) | 0.09** | (2.51) | 0.01 | (0.42) | 593 | 0.04 |
| | 4 | −0.02 | (−1.09) | 0.09* | (1.90) | 0.09 | (0.98) | 582 | 0.05 |
| ∑LTDReduction | 1 | −0.03 | (−1.68) | 0.08 | (1.29) | 0.13*** | (4.11) | 612 | 0.05 |
| | 2 | −0.04 | (−1.77) | 0.07 | (1.08) | 0.17*** | (4.90) | 609 | 0.06 |
| | 3 | −0.05* | (−2.05) | 0.05 | (0.71) | 0.19*** | (5.70) | 597 | 0.06 |
| | 4 | −0.06* | (−2.16) | 0.03 | (0.40) | 0.20*** | (5.70) | 587 | 0.05 |
| ΔInventory | 1 | −0.00 | (−1.25) | −0.00 | (−0.57) | 0.01 | (1.36) | 615 | 0.06 |
| | 2 | −0.01 | (−1.21) | 0.01 | (1.55) | 0.01 | (0.95) | 614 | 0.06 |
| | 3 | −0.01 | (−0.88) | 0.02 | (1.53) | 0.01 | (0.66) | 607 | 0.06 |
| | 4 | −0.01 | (−0.91) | 0.02 | (1.19) | 0.02 | (0.73) | 603 | 0.08 |
| ΔCash | 1 | −0.05** | (−2.30) | 0.78*** | (7.62) | 0.16 | (1.27) | 640 | 0.57 |
| | 2 | −0.04** | (−2.73) | 0.76*** | (10.54) | 0.12** | (2.30) | 639 | 0.52 |
| | 3 | −0.04* | (−1.99) | 0.65*** | (5.47) | 0.11** | (2.44) | 631 | 0.39 |
| | 4 | 0.00 | (0.13) | 0.59*** | (3.34) | 0.02 | (0.14) | 623 | 0.28 |
| ΔWC | 1 | −0.02 | (−1.83) | 0.89*** | (16.46) | 0.05 | (0.59) | 626 | 0.53 |
| | 2 | −0.02* | (−1.88) | 0.81*** | (10.69) | 0.04 | (0.71) | 623 | 0.49 |
| | 3 | −0.00 | (−0.27) | 0.74*** | (8.23) | −0.02 | (−0.50) | 615 | 0.39 |
| | 4 | 0.02 | (0.71) | 0.63*** | (4.83) | −0.09 | (−0.53) | 609 | 0.27 |

**Table 2.11 continued**

| Variables | | COVIDMonth | | Proceeds | | COVIDMonth× Proceeds | | *N* | *R-squared* |
|---|---|---|---|---|---|---|---|---|---|
| | | $\beta_1$ | *t*-stat | $\beta_2$ | *t*-stat | $\beta_3$ | *t*-stat | | |
| Panel C: SBO | | | | | | | | | |
| ∑CapitalExpense | 1 | −0.01** | (−2.67) | 0.02 | (1.27) | −0.01 | (−0.84) | 3,078 | 0.41 |
| | 2 | −0.01** | (−2.81) | 0.06 | (1.20) | −0.04 | (−0.96) | 3,068 | 0.41 |
| | 3 | −0.01** | (−2.65) | 0.09 | (1.30) | −0.04 | (−0.99) | 3,056 | 0.42 |
| | 4 | −0.02** | (−2.43) | 0.11 | (1.38) | −0.03 | (−0.77) | 3,044 | 0.43 |
| ∑R&D | 1 | −0.00 | (−1.49) | 0.02** | (2.88) | 0.01 | (0.70) | 1,304 | 0.21 |
| | 2 | −0.00 | (−0.88) | 0.04** | (2.90) | 0.01 | (0.50) | 1,123 | 0.25 |
| | 3 | −0.00 | (−0.72) | 0.07** | (2.98) | 0.01 | (0.36) | 1,119 | 0.26 |
| | 4 | −0.00 | (−0.77) | 0.09** | (3.00) | 0.02 | (0.46) | 1,113 | 0.26 |
| ∑Acquisition | 1 | 0.00 | (0.55) | 0.27*** | (3.65) | −0.12 | (−1.58) | 2,825 | 0.12 |
| | 2 | 0.01 | (1.17) | 0.64*** | (6.13) | −0.28** | (−3.21) | 2,772 | 0.25 |
| | 3 | 0.01 | (0.69) | 0.67*** | (6.65) | −0.23** | (−2.38) | 2,733 | 0.25 |
| | 4 | 0.00 | (0.04) | 0.69*** | (5.85) | −0.17 | (−1.24) | 2,702 | 0.24 |
| ∑LTDReduction | 1 | −0.00 | (−0.00) | 0.32*** | (4.54) | 0.14 | (1.53) | 2,977 | 0.30 |
| | 2 | 0.00 | (0.17) | 0.43*** | (4.43) | 0.18* | (2.24) | 2,950 | 0.33 |
| | 3 | 0.00 | (0.54) | 0.44*** | (4.37) | 0.16* | (2.08) | 2,927 | 0.28 |
| | 4 | 0.00 | (0.30) | 0.47*** | (4.54) | 0.16 | (1.82) | 2,904 | 0.25 |
| ΔInventory | 1 | −0.00 | (−0.59) | 0.01 | (1.10) | 0.01 | (0.56) | 2,913 | 0.03 |
| | 2 | 0.00 | (0.81) | 0.11 | (1.23) | −0.05 | (−0.84) | 2,903 | 0.09 |
| | 3 | 0.01 | (1.23) | 0.11 | (1.26) | −0.04 | (−0.79) | 2,887 | 0.09 |
| | 4 | 0.01 | (1.48) | 0.10 | (1.21) | −0.01 | (−0.13) | 2,905 | 0.09 |
| ΔCash | 1 | 0.00 | (0.06) | 0.24*** | (5.10) | 0.02 | (0.35) | 3,081 | 0.12 |
| | 2 | 0.01 | (1.13) | 0.18** | (2.98) | 0.02 | (0.55) | 3,073 | 0.06 |
| | 3 | 0.01 | (0.69) | 0.17 | (1.39) | 0.02 | (0.20) | 3,059 | 0.04 |
| | 4 | 0.01 | (0.63) | 0.19 | (1.47) | −0.05 | (−0.57) | 3,048 | 0.04 |
| ΔWC | 1 | −0.01 | (−1.14) | 0.24*** | (4.19) | 0.05 | (0.86) | 2,942 | 0.12 |
| | 2 | 0.01 | (1.22) | 0.23* | (2.23) | −0.03 | (−0.44) | 2,933 | 0.09 |
| | 3 | 0.00 | (0.28) | 0.08** | (2.48) | 0.03 | (0.75) | 2,920 | 0.03 |
| | 4 | 0.00 | (0.54) | 0.07* | (1.99) | −0.02 | (−0.26) | 2,909 | 0.03 |

**Table 2.12: Role of government interventions in security choices during the COVID crisis**

Panel A describes potentially relevant Federal Reserve interventions supporting corporate credit during the COVID crisis. To verify the role of these interventions, Panel B presents average and median convertible bond offering (CBO) and straight bond offering (SBO) maturities from January 2010 to June 2021. The pre-COVID period ranges from January 2010 to February 2020. *COVIDPeriod1* ranges from March 2020 to December 2020 and *COVIDPeriod2* ranges from January 2021 to June 2021. We use an independent sample *t*-test (Mann-Whitney U test) to examine if average (median) maturities differ significantly across subperiods. The Appendix B1 provides variable definitions and sources. ***, **, and * denote significance at the 1%, 5%, and 10% level.

Panel A: Government interventions during the COVID crisis

| | Primary Market Corporate Credit Facility | Secondary Market Corporate Credit Facility |
|---|---|---|
| Eligible firms | Investment grade firms | Investment grade firms |
| Eligible assets | Corporate straight and convertible bonds and syndicated loans issued by an eligible firm, with a maturity of four years or less | Corporate straight and convertible bonds issued by an eligible firm, and sold to the Facility by an eligible seller, with a remaining maturity of five years or less. |
| Announcement date | March 23, 2020 | March 23, 2020 |
| End date | December 31, 2020 | December 31, 2020 |

Panel B: Security offering maturities (in years)

| | (1) CBO | | (2) SBO | |
|---|---|---|---|---|
| | Average | Median | Average | Median |
| Pre-COVID (1) | 6.30 | 5.05 | 10.08 | 8.52 |
| COVIDPeriod1 (2) | 5.34 | 5.02 | 10.76 | 9.68 |
| COVIDPeriod2 (3) | 5.39 | 5.02 | 8.78 | 8.06 |
| Difference between (2) and (1) | −0.96*** | −0.02** | 0.68 | 1.16 |
| Difference between (2) and (3) | −0.05 | 0.00 | 1.98*** | 1.62 |

**Table 2.13: Additional tests accounting for the cash flow impact of the COVID crisis**

Panel A presents the industry distribution of cash flow changes over the first quarter of the COVID pandemic, using the Fama and French 12-industry classification. Positively (Negatively) Affected Firms have a positive (negative) *CashFlow* change over the first quarter of the COVID period. Panel B presents the results of a subsample analysis for firms with positive (Column (1)) versus negative (Column (2)) *CashFlow* changes over the first quarter of the COVID pandemic, using a multinomial probit model. The choice menu includes seasoned equity offerings (SEO), convertible bond offerings (CBO), straight bond offerings (SBO), bank loans (Loan), and not raising external financing (the baseline option). Panel C presents the results of a subsample analysis for high (Column (1)) versus low (Column (2)) resilience firms, using a multinomial probit model. Resilience is measured inversely proportional to the fraction of workers affected by social distancing restrictions, using the industry-specific "affected share" score proposed by Koren and Peto (2020). High (Low) Resilience Firms are those whose "affected share" score is below (above) the median value of the sample. Firm characteristics and macroeconomic conditions included in Panels B and C are the same as those included in Table 2.5, Panel A, Column (4). The *p*-value for the difference in *COVIDPeriod* coefficients between subsamples is based on a Wald *Chi*-square test. The Appendix B1 provides variable definitions and sources. *t*-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level.

Panel A: Cash flow change over the first quarter of the COVID pandemic by industry

| Industry | Positively Affected Firms | | Negatively Affected Firms | |
|---|---|---|---|---|
| | N | % | N | % |
| Consumer NonDurables | 30 | 34.09% | 58 | 65.91% |
| Consumer Durables | 17 | 30.36% | 39 | 69.64% |
| Manufacturing | 92 | 40.00% | 138 | 60.00% |
| Energy | 28 | 27.72% | 73 | 72.28% |
| Chemicals | 31 | 50.82% | 30 | 49.18% |
| Business Equipment & Software | 185 | 46.25% | 215 | 53.75% |
| Telecommunication | 20 | 43.48% | 26 | 56.52% |
| Wholesale & Retail | 94 | 46.77% | 107 | 53.23% |
| Healthcare | 295 | 50.43% | 290 | 49.57% |
| Other | 91 | 36.40% | 159 | 63.60% |

Panel B: Impact of the COVID crisis on security choice: firms with positive versus negative cash flow changes

| | (1) Positively Affected Firms | | | | (2) Negatively Affected Firms | | | |
|---|---|---|---|---|---|---|---|---|
| | SEO | CBO | SBO | Loan | SEO | CBO | SBO | Loan |
| COVIDPeriod | −0.220 | −0.051 | 0.189** | 0.468*** | −0.219 | 0.097 | 0.428*** | 0.592*** |
| | (−1.28) | (−0.24) | (2.02) | (4.22) | (−1.20) | (0.86) | (4.81) | (6.59) |
| Wald test *p*-value for difference in *COVIDPeriod* coefficients | 1.00 | 0.58 | 0.09 | 0.10 | | | | |
| Firm characteristics | Yes | | | | Yes | | | |
| Macroeconomic conditions | Yes | | | | Yes | | | |
| Industry FE | Yes | | | | Yes | | | |
| *Log pseudolikelihood* | −16,219.61 | | | | −23,677.85 | | | |
| *N* | 88,492 | | | | 124,196 | | | |

Panel C: Impact of the COVID crisis on security choice: high versus low resilience firms

| | (1) High Resilience Firms | | | | (2) Low Resilience Firms | | | |
|---|---|---|---|---|---|---|---|---|
| | SEO | CBO | SBO | Loan | SEO | CBO | SBO | Loan |
| COVIDPeriod | 0.065 | 0.084 | 0.528*** | 0.520*** | −0.442 | 0.522*** | 0.421*** | 0.684*** |
| | (0.68) | (0.75) | (4.98) | (8.43) | (−1.15) | (2.99) | (7.60) | (8.37) |
| Wald test *p*-value for difference in *COVIDPeriod* coefficients | 0.19 | 0.05 | 0.40 | 0.07 | | | | |
| Firm characteristics | Yes | | | | Yes | | | |
| Macroeconomic conditions | Yes | | | | Yes | | | |
| Industry FE | No | | | | No | | | |
| *Log pseudolikelihood* | −27,892.61 | | | | −20,982.18 | | | |
| *N* | 153,103 | | | | 101,208 | | | |

## Table 2.14: Robustness tests with alternative model specifications

Panels A and B present the results of security choice and SEO announcement return analyses with alternative standard error and fixed effect (FE) structures. Industry FE is defined using the Fama and French 12-industry classification. In Panel A, the choice menu includes seasoned equity offerings (SEO), convertible bond offerings (CBO), straight bond offerings (SBO), bank loans (Loan), and not raising external financing (the baseline option). Column (1) does not include FE and uses robust standard errors. Column (2) includes industry FE and uses robust standard errors. Column (3) includes industry FE and clusters standard errors by the firm. In Panel B, Columns (1) and (2) do not include any FE and use robust standard errors. Columns (3) and (4) include industry FE and use robust standard errors. Columns (5) and (6) include industry FE and cluster standard errors by firm. Panel C reports announcement return analysis results using alternative event study methodologies. The dependent variable is the cumulative abnormal return (*CAR*) measured over the window (−1, 1) relative to the SEO announcement date. Columns (1) and (2) use the market model with an equal-weighted CRSP market index with an estimation window of (−251, −11) days before the announcement date. Columns (3) and (4) use market models with a value-weighted CRSP market index with an estimation window of (−240, −40) days before the announcement. Columns (5) and (6) use a Fama and French (1993) three-factor model with an estimation window of (−240, −40) days before the announcement. Columns (1), (3), and (5) include the *COVIDPeriod* dummy, issuer characteristics, macroeconomic conditions, and issue characteristics. In Columns (2), (4), and (6), we add a *ContaminatingNews* dummy. *t*-statistics are calculated using robust standard errors clustered at the industry level. All columns in Panel C contain industry FE. Firm characteristics and macroeconomic conditions included in Panel C are the same as those included in Table 2.5, Panel A Column (4). The Appendix B1 provides variable definitions and sources. ***, **, and * indicate the statistical significance of the test at the 1%, 5%, and 10% levels, respectively.

Panel A: Security choice analysis with different standard error and fixed effect structures

| | (1) | | | | (2) | | | | (3) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | SEO | CBO | SB | Loan | SEO | CBO | SB | Loan | SEO | CBO | SB | Loan |
| COVIDPeriod | −0.034 | 0.218* | 0.463*** | 0.599*** | −0.028 | 0.217* | 0.465*** | 0.598*** | −0.028 | 0.217* | 0.465*** | 0.598*** |
| | (−0.47) | (1.91) | (6.15) | (8.64) | (−0.38) | (1.90) | (6.18) | (8.61) | (−0.37) | (1.87) | (6.48) | (9.05) |
| Firm characteristics | Yes | | | | Yes | | | | Yes | | | |
| Macroeconomic conditions | Yes | | | | Yes | | | | Yes | | | |
| Standard errors | Robust | | | | Robust | | | | Clustered by firm | | | |
| Industry FE | No | | | | Yes | | | | Yes | | | |
| *Log pseudolikelihood* | −52,802.28 | | | | −52,644.36 | | | | −52,644.36 | | | |
| *N* | 275,479 | | | | 275,479 | | | | 275,479 | | | |

Panel B: SEO announcement return analysis with different standard error and fixed effect structures

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| COVIDPeriod | 0.085* | 0.052 | 0.087* | 0.053 | 0.087* | 0.053 |
| | (1.79) | (1.15) | (1.80) | (1.14) | (1.81) | (1.15) |
| ContaminatingNews | | 0.116*** | | 0.116*** | | 0.116*** |
| | | (8.71) | | (8.70) | | (8.88) |
| Firm characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Macroeconomic conditions | Yes | Yes | Yes | Yes | Yes | Yes |
| Standard errors | Robust | Robust | Robust | Robust | Clustered by firm | Clustered by firm |
| Industry FE | No | No | Yes | Yes | Yes | Yes |
| *Adj. R-squared* | 0.03 | 0.07 | 0.03 | 0.07 | 0.03 | 0.07 |
| *N* | 3,237 | 3,237 | 3,237 | 3,237 | 3,237 | 3,237 |

Panel C: SEO announcement return analysis with alternative event study methodologies

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Equal-weighted | Equal-weighted | Value-weighted | Value-weighted | Fama and French (1993) three-factor | Fama and French (1993) three-factor |
| COVIDPeriod | 0.086** | 0.051 | 0.078** | 0.044 | 0.078** | 0.044 |
| | (2.97) | (1.75) | (2.73) | (1.53) | (2.62) | (1.47) |
| ContaminatingNews | | 0.116*** | | 0.115*** | | 0.114*** |
| | | (3.92) | | (3.93) | | (3.99) |
| Firm characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Macroeconomic conditions | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| *Adj. R-squared* | 0.03 | 0.07 | 0.03 | 0.07 | 0.03 | 0.07 |
| *N* | 3,237 | 3,237 | 3,237 | 3,237 | 3,237 | 3,237 |

**Table 2.15: Security choice analysis for an extended sample period including the GFC**

This table presents the results of models examining the impact of the Global Financial Crisis (GFC) and COVID crisis on corporate security choice, using an extended sample from January 2007 to June 2021. The GFC period ranges from January 2008 to December 2009; the COVID period ranges from March 2020 to June 2021; and the remaining months are labeled the Normal period. Panel A presents the results of multinomial probit models. The choice menu includes seasoned equity offerings (SEO), convertible bond offerings (CBO), straight bond offerings (SBO), bank loans (Loan), and not raising external financing (the baseline option). Firm characteristics and macroeconomic conditions are the same as those included in Table 2.5, Panel A, Column (4). Industries are defined using the Fama and French 12-industry classification. *t*-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses. Panel B presents average cumulative abnormal stock returns (*CAR*) measured over the window (−1, 1) relative to the announcement date. The market model parameters are estimated using the equal-weighted CRSP market index over the window (−240, −40) relative to the announcement date. We use a standardized cross-sectional test to examine if the average *CAR* equals zero (Boehmer et al., 1991). We also report the differences in averages using an independent sample *t*-test. Panel C presents the nature and frequency of contaminating news for SEO announcements. We obtain information about confounding news from Factiva. We search for confounding announcements on the offering announcement date and the trading days immediately before and after the announcement. Corporate actions include mergers and acquisitions, stock splits, share repurchases, and dividend payments. The category "Other" includes all major company-specific news not covered in the previous categories, such as important contract announcements. In case there is more than one contaminating announcement, we take the announcement that is mentioned first in the news coverage. We employ a *Chi*-square test to examine if the proportion of contaminating news differs significantly across the two subperiods. The Appendix B1 provides variable definitions and sources. ***, **, and * indicate the statistical significance of the test at the 1%, 5%, and 10% levels, respectively.

Panel A: Corporate security choice

| | SEO | CBO | SBO | Loan |
|---|---|---|---|---|
| GFCPeriod | 0.032 | 0.206** | 0.075 | 0.017 |
| | (0.91) | (2.57) | (1.03) | (0.27) |
| COVIDPeriod | 0.099 | 0.551*** | 0.510*** | 0.600*** |
| | (0.95) | (6.15) | (9.05) | (12.56) |
| Firm characteristic | Yes | | | |
| Macroeconomic condition | Yes | | | |
| Industry FE | Yes | | | |
| *Log pseudolikelihood* | −67,938.62 | | | |
| *N* | 367,577 | | | |

Panel B: Security offering announcement returns

| | (1) Normal | | (2) GFC | | (3) COVID | | Difference (2)-(1) | Difference (3)-(1) |
|---|---|---|---|---|---|---|---|---|
| | N | Average | N | Average | N | Average | | |
| SEO | 2,707 | −5.03% | 371 | −6.48% | 670 | 2.50% | −1.45%** | 7.53%*** |
| CBO | 462 | −3.57% | 72 | −7.09% | 128 | −5.85% | −3.52%*** | −2.28%** |
| SBO | 1,710 | −0.06% | 433 | −0.04% | 217 | 0.30% | 0.02% | 0.36% |

Panel C: Contaminating news around SEO announcements

| Types of announcements | (1) Normal | | (2) GFC | | (3) COVID | | Difference (2)-(1) | Difference (3)-(1) |
|---|---|---|---|---|---|---|---|---|
| | N | % | N | % | N | % | | |
| Corporate actions | 62 | 2.29% | 9 | 2.43% | 18 | 2.69% | 0.14% | 0.40% |
| Financial results | 210 | 7.76% | 34 | 9.16% | 64 | 9.55% | 1.41% | 1.79% |
| Management team changes | 32 | 1.18% | 5 | 1.35% | 14 | 2.09% | 0.17% | 0.91% |
| Research and development progress | 140 | 5.17% | 24 | 6.47% | 117 | 17.46% | 1.30% | 12.29%*** |
| Other | 113 | 4.17% | 18 | 4.85% | 74 | 11.04% | 0.68% | 6.87%*** |
| Total | 557 | 20.58% | 90 | 24.26% | 287 | 42.84% | 3.68% | 22.26%*** |

# Chapter 3. The spillover effects of management narratives for seasoned equity issuance decisions

### 3.1 Introduction

Understanding the factors influencing firm equity financing decisions is crucial in corporate finance. Market timing is considered a key determinant of the seasoned equity financing decision, with managers seeking to issue highly-priced shares (Baker and Wurgler, 2002; Graham and Harvey, 2001). Another stream of the literature suggests that meeting a near-term cash need can be a crucial reason that firms make seasoned equity offerings as they discover attractive new investment opportunities or face financial difficulties (David McLean, 2011; DeAngelo et al., 2010; Huang and Ritter, 2021). Research on equity financing decisions typically assumes that firms make capital structure choices independently, without regard to the actions or characteristics of their peers. As such, the role of peers in affecting capital financing decisions remains largely understudied. However, peer firms play an important role in shaping a number of corporate policies, such as investment decisions (Bustamante and Frésard, 2021), payout decisions (Adhikari and Agrawal, 2018), and so on. In addition, existing evidence suggests that peer firms may matter in capital financing decisions.

Leary and Roberts (2014) contend that firms do not independently make financing decisions. Firms may derive insights about optimal capital structure or financing models by observing peer financing. Alternatively, the learning could be related to industry growth opportunities. Graham and Harvey (2001) provide the survey evidence and indicate that a significant number of CFOs acknowledge the importance of peer firm financing decisions for their own financing decisions. Aghamolla and Thakor (2022) further illustrate this dynamic within the drug development industry and find that in the drug development industry, a private firm's decision to go public can trigger IPO decisions among its peers. The most closely related paper to my work is Billet et al. (2023). They show that firms increase their SEOs when their peers conduct an SEO within the prior six months. So far, the literature on equity finance decisions documents a "true" peer effect where firms simply observe and mimic other corporate finance decisions. My paper argues that firms can also become better informed about industry investment or financing opportunities using publicly available information about their peers and then adjust their equity financing decisions.

Managers may lack complete information regarding industry growth opportunities and challenges, which can hinder their ability to make optimal financing decisions, especially in complex economic and policy environments. To bridge this information gap, managers seek information that adds to their knowledge. A peer firm can be a source of information, which may possess unique insights due to variations in prior investments, information-gathering practices, and in-house expertise. Financial reports represent a prominent information source. As a mandated section in a firm's annual report filed with the Securities and Exchange Commission (SEC), the Management Discussion and Analysis (MD&A) section delivers managerial commentary about trends and events expected to affect liquidity, capital resources, and future operations materially. Firms will change their MD&A after changes in operations, capital resources, and other major activities, which are informative about future earnings, cash flows, investments, and firm value. MD&As do not merely rehash information found elsewhere but provide incremental information to other information resources. It contains a wealth of non-financial and forward-looking information and serves as a valuable complement to financial information as "soft" information, enabling outsiders to capture and grasp decision-useful information (Li, 2010). In addition, an annual report is publicly available so a firm's MD&A can be easily accessed by outsiders. With standardized format and content requirements, MD&A ensures reliability and comparability, making it a robust source for external analysis. Therefore, outsiders can utilize the firm's MD&A section and make their own decisions. In particular, previous studies show that investors utilize a firm's MD&A narratives to form their risk perceptions about the firm (Kravet and Muslu, 2013), predict the firm's future earnings (Barron et al., 1999), and make investment decisions (Loughran and Mcdonald, 2011; Muslu et al., 2015). Recent studies also document the firm use of peers' MD&A narratives and show that firms increase their investment and boost investment efficiency when average peer MD&A narratives become more optimistic (Cho and Muslu, 2021; Durnev and Mangen, 2020). These findings suggest that peers' MD&A narratives can help a firm make decisions based on improved information about industry-wide investment opportunities and challenges.

Firms can strategically utilize MD&A narratives from other firms in their financing decisions to enhance their understanding of financial information and better navigate industry-wide opportunities and challenges. This is especially valuable when using MD&A, which is disclosed by firms that operate within the same product market sector. To finance investment opportunities identified in peers' MD&A sections, firms may favor equity capital over debt capital. This preference is driven by the greater flexibility that equity capital provides to issuers, along with the limited restrictions it imposes on fund usage (Fama and French 2002; Jung, Kim, and Stulz 1996; Myers 2003). Furthermore, given the considerable uncertainty typically associated with the investment opportunities outlined in peers' MD&A narratives, I hypothesize that firms will be more likely to raise equity, particularly as the tone of peers' disclosures becomes increasingly positive, in order to capitalize on these potential investment opportunities. Yet, the literature to date does not examine the usefulness of a firm's peers' publicly available narratives in corporate finance decisions. This paper fills this gap by investigating the extent to which firms are influenced by their peers' perspectives on the future trends of their product market in the MD&A when making financing decisions, using a comprehensive sample of U.S. firms between 1997 and 2020.[18]

To answer this question, I analyze whether the changing tone of peer firms' MD&A narratives affects a firm's equity financing decisions. We assess the content of MD&As by analyzing their tone, which enables us to transcend the diverse terminology and definitions that firms employ to express comparable concepts. This approach focuses on the underlying meanings rather than the specific language (Cole and Jones, 2005). I assess the tone of the MD&A sections using the Loughran and McDonald's (2011) financial positive and negative dictionaries. The MD&A tone is calculated as an average across firms within the same industry, with the focal firm excluded from this calculation. I identify a firm's peers using product market peer groups developed by Hoberg and Phillips (2016), which are constructed based on firm pairwise similarity scores from text analysis of firm 10-K product descriptions.

The baseline tests show that, on average, the likelihood of equity issuance is positively associated with the changing positive tone of its peers' MD&A narrative, with the changing MD&A tone of its peers being the average changing MD&A tone of all other firms in the same product markets. However, this peer influence does not exist in the bond financing decisions. Further tests show that this association is stronger when a firm operates in a more competitive product market, as measured by total similarity and the number of its peers.

Several additional empirical tests are performed. First, I expect the financing decision to be associated with the changing tone of new and current peers. This relationship should be weaker for past peers because their product descriptions have significantly diverged from those

[18] Sample starts with the year 1998 because I require the previous two years' filings to be on EDGAR and the year 1996 is the first fiscal year for which almost all companies filed the 10-K electronically. The sample ends in 2020 since I examine the post issuance activities.

of the focal firm and thus should not provide as relevant information as new and current peers. Results indicate that firms' seasoned equity financing decisions are less sensitive to the changing tone of firms that are no longer their peers and more sensitive to the changing positive tone of current and new peers matters for a firm’s equity financing decisions. Second, examine the leader-follower model, where learning is much more likely among followers than leaders. According to the information-based theory (Foucault and Fresard, 2014), firms intend to learn from leaders, which enables them to garner additional information about better growth opportunities and challenges. Leaders are likely better informed about product and capital markets. On the other hand, followers often struggle to access valuable information, making the MD&A narrative of market leaders more valuable to them. Findings reveal that a firm’s equity financing decisions are only significantly associated with the leader peers (i.e., larger, have more market share, and more tangible), consistent with the leader-follower model. This finding is consistent with a learning motivation for the identified peer effect. Thirdly, I investigate the role of content. Different MD&A content should impact the identified spillover effect differently. Firms may find that the tone of specific content is more informative. Specifically, I focus on the changing tone of three types of content sentences: investment-related sentences, numerical sentences, and forward-looking sentences. I find that changing the tone in numerical sentences drives the baseline findings, confirming the role of MD&A as supplementary qualitative information alongside quantitative information. Finally, I examine the use of proceeds and post-issuance returns to corroborate my main finding. Issuers are more likely to use proceeds to finance research and development (R&D) when their peers become more positive in their MD&A disclosure, consistent with the conjecture that firms raise capital to finance the potential investment opportunities revealed by increased positive peers’ tone. Real option theory predicts that firms with great investment opportunities will have a lower post-issuance return (Carlson et al., 2006; Lyandres et al., 2008). In line with the investment story, I find that post-issue abnormal stock returns show more negative trends for issuers whose peers become more optimistic. To verify robustness, I also employ an alternative industry classification and various empirical settings, yielding consistent results supporting the positive association between firms’ seasoned equity financing decisions and peers’ changing positive tone.

This study contributes to the literature in several ways. Firstly, this paper sheds new light on the corporate peer effect by showing the impact of peers’ changing tone in textual disclosures on seasoned equity issuance decisions. Indeed, previous studies typically focus on peer effects from explicitly imitating peers’ activities or information obtained through private and public quantitative information. For example, Billett et al. (2023) show that firms are more likely to issue SEO when their peers issue SEO in the past six months. Bradley and Yuan (2013) indicate that firms are more likely to issue seasoned equity if the market reacts favorably to their peer's SEO announcement. This paper indicates that firms use peers' publicly available narratives when making financing decisions. Specifically, in addition to the peer's security issuance activities and peer change in Tobin Q, the peers' MD&A tone is likely incremental information to the firm's security issuance decision.

Secondly, this paper contributes to the growing literature within economics and finance that examines the determinants of seasoned equity financing decisions. Previous studies explain the firms' equity financing decision based on trade-off theory, pecking order theory, market timing theory, and the precautionary demand for cash theory (Baker and Wurgler, 2002; DeAngelo et al., 2010; Kraus and Litzenberger, 1973; Myers and Majluf, 1984). The role of peers in affecting capital financing decisions has often been ignored in previous studies. One related study is Leary and Roberts (2014), which examines whether firms make corporate financing decisions by imitating peers' capital structures. I advance this literature by providing a novel determinant of corporate financing decisions: publicly available textual disclosures of peer firms and exploring how firms use peers' textual disclosures to make better-informed corporate financing decisions.

Finally, this paper provides additional evidence on the proprietary costs of disclosure. Although theoretical frameworks suggest that disclosures may undermine a firm's competitive position in product markets (Darrough and Stoughton, 1990; Verrecchia, 1983), empirical evidence supporting this view is very limited. Previous studies have examined how firms strategically manage disclosures to mitigate proprietary costs (Ellis et al., 2012; Lang and Sul, 2014; Verrecchia, 1983). My paper shows that firms' disclosure can influence their peers' financing decisions. These financing choices may influence the competitive dynamics among peers.

The remainder of the paper is structured as follows. Section 3.2 provides a literature review and develops testable predictions. Section 3.3 describes the data and defines the main variables. Section 3.4 provides empirical results on the equity financing decision, uses of proceeds, and post-issuance stock return. Section 3.5 delivers a battery of robustness checks. Section 3.6 concludes.

### 3.2 Literature review and Hypothesis development

The literature on peer effects shows that a firm's decision-making can be influenced by its peers. Many previous studies have focused on a firm's explicit imitation of peer actions and outcomes, such as capital structure (MacKay and Phillips, 2005; Leary and Roberts, 2014), initial public offering (Aghamolla and Thakor, 2022), SEO (Billett et al., 2023), stock splits (Kaustia and Rantala, 2015), dividend payment (Adhikari and Agrawal, 2018; Grennan, 2019), tax avoidance (Bird et al., 2018; Kubick et al., 2015), investments (Bustamante and Frésard, 2021), and management compensation (Bizjak et al., 2011). Another branch of research documents that firms use private information about peers to make decisions. For example, firms with private connections among executives and directors share a similar tax-avoidance strategy (Brown and Drake, 2014), disclosure policy (Cai et al., 2014), corporate governance practice (Foroughi et al., 2017), and capital investments (Fracassi, 2016) owing to private connections among executives and directors. In addition, existing studies also perceive peers' stock prices and restatement as a major source of peer information (Durnev and Mangen, 2009; Foucault and Fresard, 2014). These findings indicate that mimicking or learning from peers is prevalent and associated with financially prudent decision-making and reduced costs. Indeed, the above studies typically ascribe peer effects to either deliberate replication of peer activities or spillovers of private and public quantitative information. However, little attention has been paid to whether firms utilize peers' publicly available narratives when making corporate decisions.

Annual 10-K disclosure is a credible channel through which managers convey superior information about firm conditions to outsiders. Among all 10-K sections, MD&A is arguably the most closely read and important component that delivers managerial commentary about trends and events expected to affect liquidity, capital resources, and future operations materially (Securities and Exchange Commission, 1989, 2003; Tavcar, 1998). The SEC intends for the MD&A section to offer investors a perspective through the eyes of management, providing a transparent view and guidance regarding the content of MD&A disclosures. The length of the MD&A section has increased over time, making it potentially a rich depository of corporate narratives (Cho and Muslu, 2021). The existing literature suggests that 10-K disclosure, especially the MD&A section, has become a standard resource for outsiders seeking a comprehensive understanding of the firm's decisions and insight into future projections (Brown and Tucker, 2011; Drake et al., 2016; Loughran and Mcdonald, 2016). The content and sentiment of 10-K reports enable investors to form their risk perceptions about the firm

(Campbell et al., 2014; Kravet and Muslu, 2013), predict a firm's future earnings (Barron et al., 1999; Cole and Jones, 2004; Li, 2010), and invest based on the improved information (Loughran and Mcdonald, 2011; Muslu et al., 2015).

At the industry level, peers' MD&A tone reflects the prospect of an industry. Additionally, peers' MD&A tone can serve as a reference guide for comprehending the macro-environment (Cho and Muslu, 2021). The MD&A disclosures contain a wealth of non-financial and prospective information, enabling firms to gain better insights into potential opportunities and challenges. This is particularly valuable when considering peers' MD&A, which is disclosed by firms operating within the same market sector and subject to the same industrial regulations. Firms can utilize peers' MD&A tone to reduce information collection costs, correct cognitive biases, and prevent losses incurred by uninformed choices. If the average tone of peers' MD&A becomes positive, it suggests a favorable macroeconomic condition or industry prospect. Firms are inclined to increase their investment and boost investment efficiency when peer MD&A tone becomes more positive (Cho and Muslu, 2021; Durnev and Mangen, 2020). With more investment opportunities, firms are more likely to use equity to finance (Myers, 2003). Numerous studies have empirically validated this theory, such as Wu and Wang (2005) and Wu and Au Yeung (2012).

To sum up, given the informativeness and availability of peers' MD&A, I hypothesize that a firm will raise equity capital according to the changing tone of peer textual disclosure to seize investment opportunities:

**Hypothesis:** *The likelihood of equity issuance is positively associated with the increased positive tone of peer narratives.*

## 3.3 Data

### 3.3.1 Sample

I obtain 10-K filings, financial statements, and stock prices between 1997 and 2020 from the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system, Compustat, and CRSP databases, respectively. Following Loughran and McDonald (2011), I discard 10-K filings for which I cannot confidently identify an MD&A or that have fewer than 250 MD&A words, as they are too short to provide useful information from textual analysis.[19] I then merge

[19] After electronically gathering 10-Ks including 10-K, 10-K405, 10KSB, 10KSB40, 10-KT, and 10KT405, I exclude 10,057 filing for which have less than 250 words in MD&A or for which I cannot confidently identify an MD&A. Appendix C2 provides the step to identify the MD&A section.

the EDGAR data with Compustat and exclude observations that lack data to link with Compustat and CRSP, to identify product market peers, and to construct empirical variables. I delete utilities (SIC codes 4900–4999) and financial firms (SIC codes 6000–6999) that may face regulatory restrictions on their capital structure. I further restrict the sample to firms listed on the New York Stock Exchange (NYSE), NYSE American, and NASDAQ with a CRSP share code of 10 or 11 (ordinary shares).

The SEO sample selection process begins with all SEOs issued by U.S. industrial firms in the SDC database. Following Lyandres, Sun, and Zhang (2008), I delete units and purely secondary share offerings in which firms do not raise capital, and I only include the main tranche of each issue when there are multiple tranches to avoid double counting. I then match firm-year observations with the SEO sample. Following Erel, Julio, Kim, and Weisbach (2012), I collapse firms' SEO at the year level. I only include the first offering in the case of multiple SEOs issued by one firm in one fiscal year (Fu and Huang, 2016). The final sample comprises 47,497 firm-year observations from 6,660 unique firms, where 3,234 firm-year with SEO issued by 1,719 firms.

I define firms' potential peers as the product market peers identified using Hoberg and Phillips' (2010, 2016) network industry classification (TNIC) data, constructed based on the similarity of product descriptions of 10-Ks (Item 1 or Item 1A). The rationale behind this approach is rooted in the notion that managers often consider other firms as peers based on the similarity of their products. Therefore, the level of product similarity plays a crucial role in identifying peers. The main advantage of the TNIC data, in contrast to traditional measures such as SIC codes, is that it is time-varying and nontransitive. Under this classification system, each firm has its own set of distinct peers. This identification results in an average (median) of 49 (18) peers, similar to those reported by Cho and Maslu (2021). I also identify industries using the SIC 3-digit codes as an alternative to product market peers, as discussed in Section 3.5. The main variables used in this study are described in Appendix C1.

### 3.3.2 Variable construction

I capture the content of MD&As using their tone, which allows me to abstract from the many different terms and definitions employed by different firms to convey similar information (Cole and Jones, 2005). In light of earlier studies on managerial tone, I measure the tone of a firm's MD&A narrative using the 2020 version of Loughran and McDonald's (2011) financial positive and negative dictionaries.[20] For each firm year, I obtain the number of positive and negative words per 100 words in the MD&A section of 10-K reports and calculate the changes in tone, labeled as Δ*Firm Positive* and Δ*Firm Negative*. I focus on changes rather than levels since the level of tone in corporate disclosure may be an inherent firm characteristic. Following Cho and Maslu (2021), positive tone and negative tone are included separately because they differ in credibility (Hutton et al., 2003), timeliness (Kothari et al., 2009), and information content (Darrough and Stoughton, 1990). These changing tones may reveal industry-wide opportunities and challenges. The main variables of interest are changes in peer positive and negative tone (Δ*Peer Positive* and Δ*Peer Negative*), calculated as the average change in positive and negative tone across all peers' MD&A narrative for each firm-year observation.

Besides the change in MD&A tone, I include several control variables that prior studies identify as associated with the firm's equity issuance decision (see, e.g., Frank and Goyal, 2009; Graham and Harvey, 2001; Leary and Roberts, 2014). First, I control for the following firm characteristics: change in firm size (Δ*Firm Size*) and change in Tobin Q (Δ*Firm Tobin*), which reflect future and current growth expectations, change in leverage (Δ*Firm Leverage*), change in tangibility (Δ*Firm Fixed Assets*), change in cash (Δ*Firm Cash*), change in profitability (Δ*Firm Profitability*), which reflect financial constraints and resources, change in R&D expenditure (Δ*Firm R&D*) and stock returns (*Firm Stock Return*) which capture the market timing opportunities. Second, I control for the following peer firm characteristics: average change in firm size (Δ*Peer Firm Size*), average change in Tobin (Δ*Peer Tobin*), average change in leverage (Δ*Peer Leverage*), average change in tangibility (Δ*Peer Fixed Assets*), average change in cash (Δ*Peer Cash*), average change in profitability (Δ*Peer Profitability*), average change in R&D expenditure (Δ*Peer R&D*), stock returns (*Peer Stock Return*), and peer SEO issuance activities (*Peer SEO*) which captures firm's explicit imitation of peers' equity issuance activities.

### 3.3.3 Descriptive statistics

Table 3.1 reports descriptive statistics for MD&A tone and firm characteristics, discussed in 3.3.2.

<<Please insert Table 3.1 here>>

To minimize the effect of outliers, I winsorize all continuous variables at the 1st and 99th percentiles. Table 3.1 shows that, within the MD&A section, positive words account for 0.9%

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[20] The Loughran McDonald word list has been developed for the context of 10-K, unlike other word lists such as Diction (Loughran and McDonald, 2015); it contains 347 positive words and 2345 negative words.

while negative words account for 2.1%, calculated as the average across all peers for each firm year. These proportions closely align with the average tone observed for the focal firm. The key variables of interest, $\Delta$*Peer Positive* and $\Delta$*Peer Negative,* have averages of $-0.008$ and 0.034, respectively. It implies that peer firms, on average, decrease positive and increase negative words over time. In a similar trend, changes in positive and negative tone in a firm's MD&A narrative (i.e., $\Delta Firm\ Positive$ and $\Delta Firm\ Negative$) have averages of $-0.008$ and 0.039, respectively. Regarding firm characteristics, peer characteristics are similar to their firm counterpart, although aggregation reduces their standard deviation.

Table 3.2 reports the differences in empirical variables between SEO and non-SEO firms.

<<Please insert Table 3.2 here>>

In line with my hypothesis, ΔPeer Positive is higher for those who issue SEO in the following year. In addition, ΔFirm Positive and ΔFirm Negative are higher for those SEO issuers than firms that do not issue SEO in the next year, suggesting tone management.

## 3.4 Empirical results

### 3.4.1 Seasoned equity financing decision

To test whether changing peer tone prompts a firm's SEO decision, I utilize a change regression on the decision to issue an SEO, following Xu (2012) and Cho and Muslu (2021).

$$\text{SEO}_{t+1}=\beta_0+\beta_1\Delta\text{Peer Positive}_t+\beta_2\Delta\text{Peer Negative}_t+\beta_3\Delta\text{Controls}+\varepsilon \qquad (1)$$

where $SEO_{t+1}$ is a dummy equal to 1 if the firm issues an SEO in a given year, t+1, and zero for the rest of the Compustat firms in that year. $\Delta$*Peer Positive*$_t$ and $\Delta$*Peer Negative*$_t$ are average changes in the positive tone and negative tone of peers' MD&A narratives from year t−1 to t, respectively. The one-year lag between the dependent and independent variables of Equation (1) allows a firm to acquire and respond to information obtained from the changing tone of peer narratives. Lagged annual changes of firm positive tone, firm negative tone, peer characteristics, firm characteristics, and peer SEO issuance activities variables, as discussed in Section 3.3.2, are included as control variables. Following prior literature, I include year fixed effects in all regressions and report heteroscedasticity-consistent standard errors clustered by industry. Table 3.3 presents the results of estimating Equation (1).

<<Please insert Table 3.3 here>>

Column (1) only includes the change in MD&A tone and year fixed effect. The coefficient for $\Delta$*Peer Positive*$_t$, 0.049, is significant on the 1% level, while the coefficient for $\Delta$*Peer Negative*$_t$, -0.001, is not significant. This result suggests that peers' increasing positive tone increases the likelihood of firms' SEO issuance, which is consistent with the hypothesis. However, this significant effect of $\Delta$*Peer Positive*$_t$, could be caused by shifts in peer or firm characteristics. We, therefore, add control variables outlined in Section 3.3.2. to the model in Column (2). The respective coefficient for $\Delta$*Peer Positive*$_t$, 0.031, is also significant. Peers' changing negative tone still does not significantly impact SEO issuance decisions. In addition, I include peer SEO issuance activities to control for the firm's explicit imitation of peer SEO issuance activities. *PeerSEO*$_t$ has a significant coefficient of 0.513, indicating that firms are motivated by peers' SEO issuance to issue SEOs. This finding provides evidence of a firm's explicit imitation of peer financing decisions. All results are robust using the number of SEOs issued as dependent variables (as shown in Column (3)), using logit and probit models (as shown in Columns (4) and (5)), and using level (instead of change) as control variables. Taken together, these findings indicate that a changing positive tone of peer narratives impacts a firm seasoned equity issuance activities.

This peer effect is also economically significant. When $\Delta$Peer Positive$_t$ increases by one standard deviation (0.099), the likelihood of issuing SEO increases by $0.031\times0.099=0.3\%$, corresponding to 4.5% of the mean value of SEO (0.068).

Finally, I estimate a multinomial probit model to analyze firms' choice between seasoned equity, bonds, or no external financing. The findings confirm my results that firms are more likely to issue seasoned equity in response to an increase in peers' positive MD&A tone. However, this peer influence does not exist in the bond financing decisions, as shown in Column (6). These results, taken together, support the idea that firms prefer to finance investment opportunities with equity, not bonds, as Myers (1977) suggested.

#### ***3.4.1.1 The role of product market competition***

I then analyze whether this association between a firm's equity issuance activities and peers' changing MD&As tone varies with competition in the product market. Previous literature shows that peer effects are stronger when a firm and its peer compete fiercely and try to win customers (Adhikari and Agrawal, 2018; Cao et al., 2019; Durnev and Mangen, 2020). When firms operate in a more competitive environment, they may pay attention to peers' actions and disclosure in order to maintain their competitive parity with peers. Competition may shape a firm's financing decisions in an effort to obtain a number of competitive advantages in the product market. SEOs serve distinct roles in corporate financing strategies to overcome competitive pressures. In particular, SEOs offer necessary liquidity that supports ongoing investment and innovation. The decision to raise additional equity through an SEO affects not only the issuing firm but also its competitors, influencing the broader competitive landscape of the product market. Raising seasoned equity will result in an increase in cash infusion for issuers. Unlike debt financing, equity capital has fewer constraints and grants management greater investment flexibility. As a result, firms can further develop their existing project portfolio (such as allocating more resources to existing drug development) and broaden their project portfolio (such as developing new drugs). Therefore, I expect the relationship between firm equity financing decisions and peer changing MD&A tone to be stronger when the firm faces more intense competition. I include the *Number of Peers* and *Total Similarity* to account for the effect of competition. The number of peers is the number of product market peers based on Hoberg and Phillips' (2010, 2016) network industry classification data. Total similarity measures firms' exposure to product market competition based on how similar a firm's products are to those of its peers.

<<Please insert Table 3.4 here>>

Table 3.4 shows the results of the analysis of how competition affects the relationship between firm equity financing decisions and peer-changing MD&A tone.

The coefficient on $\Delta$*Peer Positive* $\times$ *Competition* and $\Delta$*Peer Negative* $\times$ *Competition* shows how the association between the probability of SEO issuance and the tone of its peers' MD&As is affected by competition. Both interaction terms, $\Delta$*Peer Positive*$\times$*Number of Peers* and $\Delta$*Peer Positive* $\times$*Total* Similarity, are significantly positive, suggesting that the association between a firm SEO issuance and the tone of its peers' MD&As is stronger when a firm faces higher competition. My expectation is supported by the data.

#### *3.4.1.2 The heterogeneous analysis of peer characteristics*

In the subsequent tests, I enhance the identification process and broaden the scope of empirical evidence by re-estimating Equation (1) using distinct groups of peers characterized by different characteristics.

##### **3.4.1.2.1 Do firms respond to the MD&A of peers that cease to be peers?**

As discussed before, one of the significant advantages of using TNIC to identify peers is its ability to capture the dynamic nature of product markets. The set of peers for each firm is changing each year in TNIC industries. Capitalizing on such annual changes, I define three peer groups for each firm-year observation: peers for $year_{t-1}$ that cease to be peers for $year_t$ (past peers), peers for both $year_{t-1}$ and $year_t$ (current peers), and peers for $year_t$ that were not peers for $year_{t-1}$ (new peers), following Jayaraman et al. (2021). In this case, the SEO issuance decision should be associated with the changing tone of new and current peers. This relationship should be weaker for past peers because product descriptions of past peers have significantly diverged from those of the firm and thus should not provide as relevant information as the product descriptions of new and current peers. I test this prediction by replacing ΔPeer $\text{Positive}_t$ and ΔPeer $\text{Negative}_t$ with the respective average for new, current, and past peer groups. Table 3.5 reports the results.

<<Please insert Table 3.5 here>>

Consistent with my expectation, in Column (1), changing the positive tone of past peers is insignificant, suggesting that the main findings of Table 3.3 are muted for past peers. In columns (2) and (3), I find that the coefficients on Δ*Peer Positive* for current and new peers remain significantly positive. Overall, the evidence corroborates my main results and alleviates concerns that the observed impact of peers' MD&A narrative on firm SEO decisions is merely the result of the mechanical relationship between the focal firm and its product market peers.

#### 3.4.1.2.2 Leader-follower model

To shed light on the potential mechanisms behind peer effects in seasoned equity issuance, I examine heterogeneity in the coefficient on peer changing MD&A tone, $\beta_1$, from Equation (1). Specifically, I investigate if this relationship is driven by a leader-follower model in which less successful firms are sensitive to more successful firms but not vice versa. Less successful firms often struggle to access valuable peer information. According to Leary and Roberts (2014), market followers are more likely to imitate their peer firms' financing decisions. Therefore, these market followers may find greater value in their peers' MD&A narrative because of its accessibility. Larger and easier-to-value firms and firms with more market share are likely better informed about product and capital markets. I partition the peer into two sub-groups by firm size, market share, and asset tangibility. Specifically, a peer is defined as a leader if its size exceeds the focal firm and is otherwise defined as a follower peer. In the same fashion, leaders and followers are defined by their market shares (sales revenue) and asset tangibility relative to the focal firm. Table 3.6 estimates the regression among each leader and follower sample.

<<Please insert Table 3.6 here>>

The coefficient on leader peers' ΔPeer Positive is significantly positive and much larger in magnitude than that on follower peers' ΔPeer Positive. The implication is that firms are more sensitive to the changing positive tone of peers that are larger, have more market share, and are more tangible than them, consistent with the leader-follower model. That is, a firm pays more attention to peers who are perceived to have superior information, indicating that firms react to peers' changing tone in the MD&A section based on learning motivations.

#### *3.4.1.3 Role of content*

I then examine the relationship between firms' equity financing decisions and peer's changing tone of different sentences. Firms may pay more attention to the sentences that discuss specific content. In addition, firms may also find that the tone of specific content is more informative since specific information will reduce uncertainties. Bayesian belief revision per unit of noisy information is less than that in response to one unit of precise information (Holthausen and Verrecchia, 1988). Prior studies have employed different proxies for specific content within textual disclosures. Hope, Hu, and Lu (2016) utilize numbers (including percentages, monetary amounts, times, and dates) and show that investors are sensitive to specific risk disclosures. In addition, Muslu, Radhakrishnan, Subramanyam, and Lim (2015) demonstrate that forward-looking disclosure in the MD&A section helps investors forecast a firm future earnings performance. Therefore, numerical and forward-looking narratives from peers' MD&A sections can help firms have a better idea about industry-wide opportunities and challenges. Additionally, sentences discussing investment may contain salient information, such as industry-wide opportunities and challenges regarding future investments. Firms should make financing decisions based on the changing tone of peer narratives related to investments. Therefore, the content of the peer narrative should affect the identified peer influence.

Following Cho and Muslu (2021), I focus on three types of content sentences: investment-related sentences, numerical sentences, and forward-looking sentences. MD&A sections are divided into content sentences and other sentences utilizing the word list established by Cho and Muslu (2021). In the sample, 21 percent of MD&A sentences contain industry/investment words, 64 percent of MD&A sentences contain numerical words, and 29 percent of MD&A sentences contain forward-looking words, consistent with Cho and Muslu (2021). I re-estimate Equation (1) by replacing ΔPeer Positive, ΔPeer Negative, ΔFirm Positive, and ΔFirm Negative with the respective changing tone for content and other sentences (such as forward-looking and non-forward-looking MD&A sentences) and report the results in Table 3.7.

<<Please insert Table 3.7 here>>

Column (1) shows results with the investment content category. Inconsistent with my expectation, the coefficient for ΔPeer Positive of Other is significant, while the coefficient for ΔPeer Positive of Content is not significant. The changing tone of investment-related sentences may contain more informative content for firms. However, this could be attributed to the fact that only 21% of the sentences contain investment-related words.

Column (2) presents the results for the numerical content category. The coefficient for ΔPeer Positive of Content is significant, whereas ΔPeer Positive of Other is not significant. This finding suggests that changes in tone in numerical sentences primarily contribute to the baseline findings, supporting the significance of soft information.

Column (3) shows results with the forward-looking content category. The coefficient for ΔPeer Positive of Other is significant, while the coefficient for ΔPeer Positive of Content is not significant. However, the ΔPeer Positive of Content is not statistically different from ΔPeer Positive of Other. Overall, it remains unclear whether the changing tone in forward-looking sentences is the driver of the identified peer influence.

**3.4.2 Use of proceeds**

To investigate post-issuance investment, I follow Kim and Weisbach (2008) and Walker and Yost (2008) and examine post-SEO changes in capital expenditures, R&D, acquisitions, long-term debt reduction, changes in inventory, and changes in cash to measure the use of proceeds. Capital expenditures, R&D, acquisitions, and increases in inventory capture investment purposes for the offering proceeds. Increases in cash are consistent with the motive of market timing. Finally, long-term debt reduction is less clear-cut in terms of inferred motive. It is potentially attributable to long-term debt strengthening the monitoring of managers (Jensen, 1986) or market timing (Hertzel and Li, 2010; Walker et al., 2016).

For income statement and cash flow statement items (capital expenditures, R&D, acquisitions, and long-term debt reduction), I take the log of one plus the total value of each variable since the issue date normalized by total assets before the issue date: Use of proceeds=$\ln[(\sum_{i=1}^{t} V_i/\text{total assets}_{-1})+1]$, where V is the variable being measured, year −1 is the fiscal year-end before the issue date, and year t is the number of years after the issuance year. For balance sheet items (inventory, cash, and working capital), I take the log of one plus changes in each variable normalized by total assets before the issue date: Use of proceeds=$\ln[((V_t - V_0)/\text{total assets}_{-1})+1]$. I aggregate all proceeds raised by the same firm within the same fiscal year. I estimate the following regression similar to those reported by Kim and Weisbach (2008) and Erel et al. (2012), using the following Specification:

$$\text{Use of proceeds}=\beta_0+\beta_1\text{LogProceeds}+\beta_2\Delta\text{Peer Positive}+\beta_3\Delta\text{Peer Negative}$$
$$+\beta_4\Delta\text{Peer Positive}\times\text{LogProceeds}+\beta_5\Delta\text{Peer Negative}\times\text{LogProceeds}+\text{Controls}+\varepsilon \quad (2)$$

where LogProceeds captures the total proceeds raised from seasoned equity issuance over the fiscal year. I take the log of one plus the ratio of total proceeds to total assets to minimize the effect of outliers. The key variables of interest are the ΔPeer Positive × LogProceeds and ΔPeer Negative× LogProceeds interaction terms, which capture the impact of the changes in peer tone on the use of proceeds. I also control for year and industry fixed effects in the regressions. Industry fixed effects are based on FIC 500 industry fixed effects as defined in Hoberg and Phillips (2016). Table 3.8 presents the regression results, omitting the coefficients on LogProceeds, ΔPeerPositive, ΔPeerNegative, LogAssets, year, and industry dummies for brevity.

<<Please insert Table 3.8 here>>

*t*-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses.

I find significant positive coefficients on $\Delta Peer\ Positive \times LogProceeds$ for R&D expenditure, further cementing the conjecture that issuers raise seasoned equity to finance investment opportunities when peers become more positive in their MD&A disclosure. I also document significant negative coefficients on $\Delta Peer\ Positive \times LogProceeds$ for acquisition. The results suggest that proceeds raised from SEO whose peers become more positive are less likely to be used for acquisition.

### 3.4.3 Long-term stock performance

The last set of tests focuses on the relationship between peers' changing tone in the MD&A section and post-issuance stock price performance. Real option theory predicts that firms with great investment opportunities will experience a lower post-issuance return as they invest after the issuance (Carlson et al., 2006; Lyandres et al., 2008). If a firm responds to peers' increased positive tone by issuing SEO and then using the proceeds for investment, these issuers should experience lower post-issuance stock returns. I measure issuers' long-term stock return using the buy-and-holding approach to validate my hypothesis.[21] Specifically, buy-and-hold abnormal returns (*BHAR*) is calculated as the difference between buy-and-hold returns to SEO firms compared to its peers who do not issue SEO over a 72-month window (i.e., [−36, 36]) around the issuance month:

$$\mathrm{BHAR}_{\mathrm{i},\tau} = \prod_{t=1}^{\tau}[1 + R_{i,t}] - \prod_{t=1}^{\tau}[1 + MR_{i,t}] \qquad (3)$$

[21] The BHAR approach is largely free of rebalancing bias, has a strong power to detect abnormal return, and more robust then than the calendar time method (Asparouhova et al., 2013; Loughran and Ritter, 2000; Lyon et al., 1999). Moreover, I want to isolate the impact of peer changing tone on long-term stock return. I can only conduct multiple regression on BHAR not calendar time methods.

where $\mathrm{BHAR}_{i,\tau}$ is BHARs for firm i for length τ months, $R_{i,t}$ is the return for firm i in month t, and $MR_{i,t}$ is peer return in month t, and month t is the number of months after the issuance month. I focus on 36-month BHARs, which are reported in two periods: one begins in the first month following the SEO issuance (i.e., [1, 36]), and the other begins in the seventh month following the SEO issuance (i.e., [7, 42]).[22] I also report 12-month and 24-month BHARs for robustness checks. To examine my hypothesis, I classify issuers into two groups based on whether ΔPeer Positive is above the median per year.

Table 3.9 Panel A presents BHARs for the full sample and high and low peer positive tone samples, respectively.

<<Please insert Table 3.9 here>>

I find significantly negative mean BHARs for all issuers, ranging from −8.0% to – 33.4% for all horizons, except *BHAR*[1,36] for low-$\Delta\text{Peer Positive}_t$ group. These results provide additional evidence of SEO underperformance, which has been documented in previous studies. The last column shows the difference in mean BHAR between high-$\Delta\text{Peer Positive}_t$ and low-$\Delta\text{Peer Positive}_t$ groups. The results send a clear message: The long-run abnormal returns of stocks in the high-$\Delta\text{Peer Positive}_t$ group are significantly lower than those in the low $\Delta\text{Peer Positive}_t$ group, indicating a relative stock underperformance of SEO issuers whose peers increase their positive tone in their MD&A narrative, consistent with my expectations.

Following Fu and Huang (2016), I then implement the following regression model to investigate the effects of peer changing tone on long-run stock returns:

$$BHAR = \beta_1\Delta\text{Peer Positive}_t+\beta_2\Delta\text{Peer Negative}_t+\beta_3\text{Controls}+\varepsilon \tag{4}$$

where BHAR is the 12-month, 24-month, and 36-month buy-and-hold abnormal return relative to peers. The explanatory variables of interest are peers' changing positive and negative tones. Other control variables include the firm’s changing tone, firm size, Tobin’s Q, leverage, fixed assets, cash, profitability, stock return, stock volatility, proceeds, industry (classified as the FIC 500 industry), and year dummies. Table 3.9 Panel B shows that $\Delta \textit{Peer Positive}_t$ has a negative impact on long-term abnormal returns even after controlling for various firm and issue characteristics. Increased positive peer tone, which suggests the investment opportunities, contributes to post-issue underperformance even after controlling for the potential mispricing

[22] To minimize the effect of underwriter price stabilization practices, I also examine the BHAR 7-42, following . Previous studies, such as Loughran and Ritter (1995), always find no SEO underperformance in the first six month after the issuance. Underwriters may buy share in the open market to create demand, which could potentially affect our results.

effect, supporting the real-investment explanations of low long-run post-issuance stock price underperformance put forward by Li et al. (2009) and Carlson et al. (2006).

### 3.5 Robustness tests

In the baseline results, peers are identified using TNIC. Most studies define peer groups based on pre-defined industry classifications, such as Standard Industry Classification (SIC), North American Industry Classification System (NAICS), and Global Industry Classification Standard (GICS) (e.g., Beatty et al., 2013). Prior studies have demonstrated that these pre-defined industry classifications are noisy proxies for the peer group and often fail to accurately group firms operating within the same product market. Additionally, these industry classifications are rarely updated, failing to capture the evolving nature of product markets.[23] Therefore, I use TNIC in the main results. However, consistent with previous literature, I define peer groups based on three-digit SIC industry groups in the robustness check. Next, I re-estimate the main analyses using a three-digit SIC industry definition; the results are presented in Table 3.10.

<<Please insert Table 3.10 here>>

Overall, my results hold. Specifically, the results in Columns (1) and (2) show that the estimated coefficient of $\Delta Peer\ Positive_t$ is significantly positive, suggesting that firms are more likely to issue SEO when peer firms become more optimistic in their MD&A. Moreover, I examine if this association is moderated by competition. In particular, I measure competition using three variables computed at the level of the 3-digit SIC code: (1) entry costs, (2) industry size, and (3) product substitutability, following Karuna (2007). Entry costs (*EntryCosts*) are defined as the natural logarithm of the weighted average of the gross value of property, plant, and equipment (PPE) for each firm within an industry, with the weights based on each firm's market share within that industry. PPE serves as a proxy for the minimal level of investments required to enter an industry to commence production. Larger initial investments generally have greater barriers to entry. Industry size (*IndustrySize*) is calculated as the natural logarithm of total industry sales, which reflects the density of consumers in an industry. Product substitutability (*ProductSubstitutability*) is calculated as the ratio of industry operating costs to total industry sales. A higher ratio indicates greater substitutability of products, as it represents

[23] I am not the first to argue that SIC classifications are an imperfect proxy for defining peer groups. Prior studies indicates that SIC codes often misclassify firms by failing to account for heterogeneity within groups (e.g., Clarke (1989); Bhojraj et al., (2003); Brickley and Zimmerman (2010))

the inverse of the price-cost margin. When products are more substitutable, firms face constraints in charging higher prices without risking the loss of customers. Column (3) includes these competition fundamentals and their interaction term with $\Delta$*Peer Positive*$_t$ and $\Delta$*Peer Negative*$_t$. The coefficient on interaction term shows how the relationship between the firm's seasoned equity issuance activities and the changing tone of its peer's MD&As is affected by *EntryCosts*, *IndustrySize*, and Product *ProductSubstitutability*. The coefficient on the interaction between *EntryCosts* and $\Delta$*Peer Positive*$_t$ is significantly negative at -0.042, suggesting that the relationship between peer-changing positive tone is stronger when firms operate in industries with lower entry costs.

### 3.6 Conclusion

In this study, I investigate if peers' changing tone wields any influence on the firm's SEO issuance. I show that the increased positive tone of peers' MD&A narrative encourages firms to issue SEOs. Competition moderates this peer influence. In addition, the firm responds to the changing positive MD&A tones of both new and current peers but not to those of past peers. Firms are sensitive to the changing tone of peers who are larger, have more market share, and are more tangible than them. Further tests suggest that the changes in tone in numerical sentences drive the association between peer changing tone and equity financing decisions. Regarding the post-issuance activities, I document that issuers whose peers have increased their positive tone are more likely to use the SEO proceeds to finance R&D. I also document a lower post-issuance stock return for those whose peers have increased their positive tone.

My evidence suggests that a firm bases its financing decision on the changing tone of peers' MD&A narrative, which will then change the product market and competitive landscape, potentially disadvantaging the disclosing firm. This paper provides empirical support for the proprietary costs of disclosure and suggests that firms should consider such proprietary costs when making the annual report, especially the MD&A section.

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**Table 3.1: Descriptive Statistics**

This table reports the descriptive statistics for season equity offering (SEO), management discussion and analysis (MD&A) tone, peer characteristics, and firms' characteristics and their changes. I present means, 25th percentile, median, 75th percentile, standard deviations, and the number of observations for each variable. A variable pertaining to peers is calculated as the average, across all peers, of each peer's value for that variable. Appendix C1 provides variable definitions and sources. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| | Level | | | | | | Change | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | 25% | Median | 75% | St.dev. | Obs. | Mean | 25% | Median | 75% | St.dev. | Obs. |
| Peer Positive | 0.928 | 0.772 | 0.884 | 1.076 | 0.217 | 47,497 | -0.008 | -0.048 | -0.001 | 0.035 | 0.099 | 47,497 |
| Peer Negative | 2.088 | 1.738 | 2.011 | 2.310 | 0.516 | 47,497 | 0.034 | -0.095 | 0.016 | 0.161 | 0.284 | 47,497 |
| Firm Positive | 0.923 | 0.634 | 0.852 | 1.137 | 0.408 | 47,497 | -0.008 | -0.125 | -0.006 | 0.114 | 0.233 | 47,497 |
| Firm Negative | 2.098 | 1.485 | 1.966 | 2.557 | 0.852 | 47,497 | 0.039 | -0.219 | 0.013 | 0.277 | 0.511 | 47,497 |
| Peer SEO | 0.087 | 0.000 | 0.034 | 0.125 | 0.127 | 47,497 | | | | | | |
| Peer Firm Size | 5.778 | 4.785 | 5.734 | 6.656 | 1.221 | 47,497 | 0.074 | 0.000 | 0.066 | 0.140 | 0.140 | 47,497 |
| Peer Tobin | 2.320 | 1.500 | 2.009 | 2.917 | 1.109 | 47,497 | -0.132 | -0.366 | -0.065 | 0.193 | 0.855 | 47,497 |
| Peer Leverage | 0.160 | 0.077 | 0.130 | 0.233 | 0.110 | 47,497 | 0.009 | -0.007 | 0.007 | 0.023 | 0.034 | 47,497 |
| Peer Fixed Assets | 0.234 | 0.099 | 0.153 | 0.304 | 0.192 | 47,497 | 0.002 | -0.008 | 0.001 | 0.011 | 0.021 | 47,497 |
| Peer Cash | 0.260 | 0.094 | 0.208 | 0.387 | 0.193 | 47,497 | -0.009 | -0.028 | -0.006 | 0.010 | 0.038 | 47,497 |
| Peer Profitability | 0.018 | -0.026 | 0.079 | 0.130 | 0.171 | 47,497 | -0.007 | -0.028 | -0.005 | 0.015 | 0.052 | 47,497 |
| Peer R&D | 0.087 | 0.001 | 0.038 | 0.139 | 0.106 | 47,497 | 0.002 | -0.002 | 0.000 | 0.005 | 0.025 | 47,497 |
| Peer Stock Return | 0.184 | -0.086 | 0.102 | 0.361 | 0.461 | 47,497 | | | | | | |
| Firm Size | 5.608 | 4.144 | 5.545 | 6.998 | 1.962 | 47,497 | 0.066 | -0.069 | 0.032 | 0.162 | 0.303 | 47,497 |
| Firm Tobin | 2.186 | 1.142 | 1.589 | 2.513 | 1.754 | 47,497 | -0.102 | -0.356 | -0.018 | 0.266 | 1.324 | 47,497 |
| Firm Leverage | 0.159 | 0.000 | 0.100 | 0.274 | 0.177 | 47,497 | 0.008 | -0.018 | 0.000 | 0.019 | 0.083 | 47,497 |
| Firm Fixed Assets | 0.234 | 0.065 | 0.151 | 0.329 | 0.226 | 47,497 | 0.002 | -0.016 | 0.000 | 0.017 | 0.049 | 47,497 |
| Firm Cash | 0.242 | 0.043 | 0.149 | 0.371 | 0.250 | 47,497 | -0.008 | -0.040 | -0.001 | 0.032 | 0.101 | 47,497 |
| Firm Profitability | 0.027 | 0.002 | 0.096 | 0.153 | 0.247 | 47,497 | -0.007 | -0.038 | -0.001 | 0.029 | 0.131 | 47,497 |
| Firm R&D | 0.073 | 0.000 | 0.010 | 0.094 | 0.131 | 47,497 | 0.002 | 0.000 | 0.000 | 0.001 | 0.061 | 47,497 |
| Firm Stock Return | 0.157 | -0.273 | 0.034 | 0.380 | 0.722 | 47,497 | | | | | | |

**Table 3.2: Univariate analysis**

This table reports the mean and median values of empirical variables and differences in these empirical variables between the SEO issued year and the non-SEO issued year. I also use an independent sample *t*-test (Mann-Whitney U test) to examine if the average (median) value differs significantly. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| | SEO (1) | | Non-SEO (2) | | Diff in mean | Diff in median |
|---|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | (1) − (2) | (1) − (2) |
| ΔPeer Positive | 0.002 | 0.009 | -0.009 | -0.002 | 0.011*** | 0.011*** |
| ΔPeer Negative | 0.036 | 0.016 | 0.034 | 0.016 | 0.002 | -0.001 |
| ΔFirm Positive | 0.001 | 0.005 | -0.008 | -0.007 | 0.009** | 0.012*** |
| ΔFirm Negative | 0.018 | 0.004 | 0.040 | 0.013 | -0.022** | -0.010 |
| Peer SEO | 0.204 | 0.164 | 0.079 | 0.029 | 0.125*** | 0.134*** |
| ΔPeer Firm Size | 0.090 | 0.083 | 0.073 | 0.065 | 0.016*** | 0.019*** |
| ΔPeer Tobin | -0.043 | -0.004 | -0.138 | -0.068 | 0.095*** | 0.064*** |
| ΔPeer Leverage | 0.014 | 0.013 | 0.008 | 0.006 | 0.006*** | 0.007*** |
| ΔPeer Fixed Assets | 0.005 | 0.002 | 0.002 | 0.001 | 0.003*** | 0.002*** |
| ΔPeer Cash | -0.012 | -0.010 | -0.009 | -0.006 | -0.003*** | -0.003*** |
| ΔPeer Profitability | -0.011 | -0.012 | -0.007 | -0.004 | -0.005*** | -0.007*** |
| ΔPeer R&D | 0.003 | 0.000 | 0.002 | 0.000 | 0.001 | 0.000*** |
| Peer Stock Return | 0.224 | 0.174 | 0.181 | 0.099 | 0.043*** | 0.076*** |
| ΔFirm Size | 0.097 | 0.058 | 0.064 | 0.031 | 0.033*** | 0.027*** |
| ΔFirm Tobin | 0.215 | 0.127 | -0.125 | -0.023 | 0.340*** | 0.150*** |
| ΔFirm Leverage | 0.008 | 0.002 | 0.001 | 0.000 | 0.007*** | 0.002*** |
| ΔFirm Fixed Assets | 0.020 | 0.000 | 0.007 | 0.000 | 0.013*** | 0.000*** |
| ΔFirm Cash | -0.023 | -0.008 | -0.007 | 0.000 | -0.017*** | -0.007*** |
| ΔFirm Profitability | -0.034 | -0.010 | -0.005 | -0.001 | -0.029*** | -0.010*** |
| ΔFirm R&D | 0.018 | 0.000 | 0.001 | 0.000 | 0.017*** | 0.000*** |
| Firm Stock Return | 0.317 | 0.080 | 0.145 | 0.031 | 0.172*** | 0.049*** |

**Table 3.3: SEO financing decision**

This table presents the regression analysis of the relationship between peer changing tone and firm seasoned equity financing decisions. In Column (1), the dependent variable is a dummy variable that equals one if a firm issues SEO during year t+1. The explanatory variable of interest is ΔPeer Positive and ΔPeer Negative, the average change between t and t-1 of each peer's MD&A tone. Peer Positive (Peer Negative) is the number of positive (negative) words per 100 words in a firm's MD&A section, measured using the 2020 version of the word list from Loughran and McDonald (2011). Firms' potential peers are product market peers identified using Hoberg and Phillips' (2010, 2016) network industry classification data. Column (2) adds peer and firm characteristics. Column (3) uses the number of SEOs issued in year t+1 as the dependent variable. Columns (4) and (5) use the logit and probit models instead of the linear probability model and report the coefficient estimates, respectively. Columns (6) and (7) report coefficient estimates for a multinomial probit model. The dependent variable includes SEO and bonds. The base outcome is not issuing SEO and bonds in year t+1. All specifications include year fixed effect, controlling for unobservable economy-wide time-specific effects that may affect all firms. Appendix C1 provides variable definitions and sources. *t*-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses. Industry classifications are based on fixed effects of the FIC 500 industry, as defined by Hoberg and Phillips (2016). ***, **, and * denote significance at the 1%, 5%, and 10% level.

| | Linear probability model | | | Logit model | Probit model | Multinomial probit model | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | SEO | SEO | Number of SEO | SEO | SEO | SEO | Bond |
| ΔPeer Positive | 0.049*** | 0.031*** | 0.038*** | 0.632** | 0.318*** | 0.446*** | 0.071 |
| | (2.95) | (2.72) | (2.74) | (2.52) | (2.71) | (2.75) | (0.39) |
| ΔPeer Negative | -0.001 | -0.001 | -0.003 | 0.078 | 0.034 | 0.052 | 0.025 |
| | (-0.09) | (-0.10) | (-0.43) | (0.63) | (0.55) | (0.62) | (0.37) |
| Peer SEO | | 0.513*** | 0.630*** | 5.577*** | 2.929*** | 3.885*** | -0.366 |
| | | (3.76) | (3.78) | (7.99) | (6.94) | (7.32) | (-0.79) |
| ΔPeer Firm Size | | -0.099*** | -0.127*** | -1.081*** | -0.527*** | -0.610** | 0.688*** |
| | | (-2.69) | (-2.80) | (-3.32) | (-2.96) | (-2.49) | (3.34) |
| ΔPeer Tobin | | 0.009*** | 0.012*** | 0.151*** | 0.081*** | 0.128*** | 0.176*** |
| | | (4.50) | (5.14) | (3.48) | (3.88) | (4.42) | (4.50) |
| ΔPeer Leverage | | 0.245*** | 0.286*** | 3.895*** | 1.857*** | 2.556*** | 0.655 |
| | | (3.00) | (3.00) | (3.70) | (3.48) | (3.57) | (1.23) |
| ΔPeer FixedAssets | | 0.035 | 0.028 | 1.836 | 0.957 | 1.458 | 1.559 |
| | | (0.41) | (0.24) | (1.19) | (1.25) | (1.35) | (1.49) |
| ΔPeer Cash | | -0.230*** | -0.281*** | -3.731*** | -1.822*** | -2.116*** | 2.874*** |
| | | (-2.77) | (-2.66) | (-3.54) | (-3.54) | (-2.93) | (4.78) |
| ΔPeer Profitability | | -0.108* | -0.154** | -1.902*** | -0.890*** | -1.142** | 0.359 |
| | | (-1.92) | (-1.97) | (-2.90) | (-2.67) | (-2.43) | (0.83) |
| ΔPeer R&D | | 0.094 | 0.094 | 1.730 | 0.986* | 1.521** | 1.066 |
| | | (1.13) | (0.71) | (1.48) | (1.82) | (2.04) | (1.38) |
| Peer Stock Return | | 0.001 | 0.001 | 0.060 | 0.021 | -0.004 | -0.258*** |
| | | (0.17) | (0.11) | (0.50) | (0.35) | (-0.05) | (-3.05) |

**Table 3.3 continued**

| | Linear probability model | | | Logit model | Probit model | Multinomial probit model | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | SEO | SEO | Number of SEO | SEO | SEO | SEO | Bond |
| ΔFirm Positive | 0.006 | 0.005 | 0.005 | 0.069 | 0.037 | 0.042 | -0.064 |
| | (0.97) | (0.89) | (0.71) | (0.79) | (0.83) | (0.69) | (-1.22) |
| ΔFirm Negative | -0.007*** | -0.003 | -0.006* | -0.071 | -0.034 | -0.055* | -0.079*** |
| | (-2.76) | (-1.23) | (-1.67) | (-1.63) | (-1.55) | (-1.83) | (-3.14) |
| ΔFirm Size | | 0.045*** | 0.047*** | 0.653*** | 0.334*** | 0.487*** | 0.234*** |
| | | (6.56) | (4.97) | (5.95) | (6.93) | (6.59) | (2.60) |
| ΔFirm Tobin | | 0.008** | 0.009* | 0.103*** | 0.050*** | 0.076*** | 0.051*** |
| | | (2.08) | (1.68) | (3.20) | (3.01) | (3.33) | (4.55) |
| ΔFirm Leverage | | 0.069*** | 0.073*** | 1.023*** | 0.512*** | 0.677*** | -0.093 |
| | | (5.02) | (3.69) | (4.10) | (4.69) | (4.47) | (-0.61) |
| ΔFirm Fixed Assets | | 0.066** | 0.091** | 1.152*** | 0.525** | 0.781*** | 0.532 |
| | | (2.04) | (2.15) | (2.75) | (2.52) | (2.64) | (1.59) |
| ΔFirm Cash | | -0.071*** | -0.100*** | -1.094** | -0.576** | -0.778** | 0.165 |
| | | (-3.50) | (-7.10) | (-2.20) | (-2.57) | (-2.50) | (1.49) |
| ΔFirm Profitability | | -0.068*** | -0.083*** | -0.812*** | -0.396*** | -0.538*** | -0.046 |
| | | (-2.93) | (-2.89) | (-7.94) | (-5.28) | (-4.95) | (-0.44) |
| ΔFirm R&D | | 0.280*** | 0.354*** | 2.715*** | 1.339*** | 1.890*** | 0.413** |
| | | (12.49) | (13.52) | (3.20) | (4.10) | (4.14) | (2.43) |
| Firm Stock Return | | 0.018*** | 0.016*** | 0.233** | 0.124*** | 0.172*** | 0.022 |
| | | (4.62) | (2.87) | (2.35) | (3.04) | (3.06) | (0.78) |
| Constant | 0.069*** | 0.019*** | 0.020*** | -4.356*** | -2.323*** | -3.148*** | -2.250*** |
| | (3.60) | (7.41) | (6.26) | (-29.50) | (-30.76) | (-30.63) | (-27.73) |
| Year fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 47,497 | 47,497 | 47,497 | 47,497 | 47,497 | 47,497 | 47,497 |
| Adj. R-squared / Pseudo R-squared / Wald chi-squared | 1.4% | 9.0% | 9.0% | 14.3% | 14.3% | 12545.0 | |

## Table 3.4: Role of competition

This table presents the regression analysis of the role of competition. The dependent variable is a dummy variable that equals one if the firm issues SEO during year t+1. The explanatory variable of interest is the interaction term between the competition measure and ∆Peer Positive and ∆Peer Negative, the average change between t and t-1 of each peer MD&A tone. Competition measures include number of peers and total similarity. The number of peers is the number of product market peers based on Hoberg and Phillips' (2010, 2016) network industry classification data in the sample in year t. Total similarity is the sum of the pairwise similarity scores between the firm and all peers in the sample in year t. All specifications are estimated using the full set of control variables and year fixed effect, which are not tabulated. Appendix C1 provides variable definitions and sources. *t*-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses. Industry classifications are based on fixed effects of the FIC 500 industry, as defined by Hoberg and Phillips (2016). ***, **, and * denote significance at the 1%, 5%, and 10% level.

| | (1)<br>Number of peers | (2)<br>Total similarity |
|---|---|---|
| ∆Peer Positive | 0.013 | 0.027** |
| | (1.27) | (2.42) |
| ∆Peer Negative | 0.007 | 0.007 |
| | (1.44) | (1.54) |
| ∆Peer Positive*Competition | 0.003*** | 0.017*** |
| | (6.16) | (2.73) |
| ∆Peer Negative*Competition | -0.001*** | -0.010*** |
| | (-2.83) | (-2.92) |
| Competition | 0.001*** | 0.009*** |
| | (5.81) | (18.42) |
| Peer control | Yes | Yes |
| Firm control | Yes | Yes |
| Year fixed effect | Yes | Yes |
| Observations | 47,497 | 47,497 |
| Adj. R-squared | 11.0% | 11.8% |

**Table 3.5: Dynamic Peer Groups and the impact of changing peer tone in firm SEO issuance decision**

This table reports the regression analysis of the relationship between seasoned equity financing decisions and peer changing MDA tone conditional on the dynamic peer group. The dependent variable is a dummy variable that equals one if the firm issues SEO during year t+1. I define three peer groups for each firm-year observation: peers for year t−1 that cease to be peers for year t (past peers), peers for both year t−1 and year t (current peers), and peers for year t that were not peers for year t−1 (new peers). Firm-year observations with no past, current, and new peers are excluded, reducing the sample size to 39,389, 42,557, and 38,597. All specifications are estimated using the full set of control variables and year fixed effect, which are not tabulated. Appendix C1 provides variable definitions and sources. *t*-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses. Industry classifications are based on fixed effects of the FIC 500 industry, as defined by Hoberg and Phillips (2016). ***, **, and * denote significance at the 1%, 5%, and 10% level.

| | (1)<br>Past | (2)<br>Current | (3)<br>New |
|---|---|---|---|
| ΔPeer Positive | -0.005 | 0.041** | 0.034** |
| | (-0.24) | (1.99) | (2.12) |
| ΔPeer Negative | 0.014* | 0.005 | -0.010 |
| | (1.71) | (0.54) | (-0.97) |
| Peer SEO | 0.195*** | 0.506*** | 0.164*** |
| | (2.84) | (3.77) | (3.59) |
| Peer control | Yes | Yes | Yes |
| Firm control | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes |
| Observations | 39,389 | 42,557 | 38,597 |
| Adj. R−squared | 4.7% | 9.8% | 4.8% |

**Table 3.6: Leader-follower model**

This table presents the regression analysis of the relation between seasoned equity financing decisions and peer changing MDA tone conditional on whether the peer is a follower or a leader. The dependent variable is a dummy variable that equals one if the firm issues SEO during year t+1. In Column (1), follower and leader are defined based on firm size: a peer is defined as a leader if its size is larger than the focal firm and is otherwise defined as a follower. Similarly, followers and leaders are defined by their market shares (sales revenue) relative to the focal firm in Column (2) and defined based on their asset tangibility relative to the focal firm in Column (3). All specifications are estimated using the full set of control variables and year fixed effect, which are not tabulated. Appendix C1 provides variable definitions and sources. *t*-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses. Industry classifications are based on fixed effects of the FIC 500 industry, as defined by Hoberg and Phillips (2016). ***, **, and * denote significance at the 1%, 5%, and 10% level.

| | (1) Defined by size | | (2) Defined by market share | | (3) Defined by asset tangibility | |
|---|---|---|---|---|---|---|
| | Leader | Follower | Leader | Follower | Leader | Follower |
| ΔPeer Positive | 0.031** | 0.001 | 0.031*** | -0.001 | 0.021** | 0.016 |
| | (2.30) | (0.08) | (2.80) | (-0.14) | (2.02) | (1.62) |
| ΔPeer Negative | 0.009** | -0.004 | 0.011*** | -0.002 | -0.005 | 0.006 |
| | (2.28) | (-0.69) | (2.90) | (-0.46) | (-1.12) | (1.03) |
| Peer control | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm control | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 43,588 | 40,949 | 43,540 | 40,234 | 42,373 | 41,943 |
| Adj. R−squared | 9.2% | 9.4% | 9.3% | 7.9% | 8.6% | 8.1% |

## Table 3.7: Role of content

This table presents the regression analysis of the relation between a firm seasoned equity financing decision and peer changing tone conditional on sentence content. The dependent variable is a dummy variable that equals one if the firm issues SEO during year t+1. The key independent variable is the peers' changing positive and negative tone of the content sentences. Specifically, I examine three types of content sentences: investment-related, numerical, and forward-looking. The sentence is identified as investment-related, numerical, and forward-looking if it contains keywords. The word list is provided in Appendix C3. All specifications are estimated using the full set of control variables and year fixed effect, which are not tabulated. Appendix C1 provides variable definitions and sources. *t*-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses. Industry classifications are based on fixed effects of the FIC 500 industry, as defined by Hoberg and Phillips (2016). ***, **, and * denote significance at the 1%, 5%, and 10% level.

| | (1) Investment | (2) Numerical | (3) Forward-looking |
|---|---|---|---|
| ΔPeer Positive of Content | 0.005 | 0.032*** | 0.012 |
| | (0.88) | (3.20) | (1.19) |
| ΔPeer Negative of Content | 0.001 | 0.006 | 0.005 |
| | (0.40) | (1.39) | (1.42) |
| ΔPeer Positive of Other | 0.032*** | 0.009 | 0.027*** |
| | (2.71) | (1.27) | (2.73) |
| ΔPeer Negative of Other | 0.005 | 0.002 | 0.003 |
| | (1.03) | (0.53) | (0.71) |
| ΔFirm Positive of Content | -0.001 | 0.007* | -0.001 |
| | (-0.47) | (1.91) | (-0.41) |
| ΔFirm Negative of Content | -0.001 | -0.002 | -0.002* |
| | (-1.06) | (-0.66) | (-1.65) |
| ΔFirm Positive of Other | 0.008* | -0.001 | 0.007 |
| | (1.77) | (-0.34) | (1.48) |
| ΔFirm Negative of Other | -0.001 | -0.001 | 0.001 |
| | (-0.51) | (-0.43) | (0.52) |
| Peer control | Yes | Yes | Yes |
| Firm control | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes |
| Observations | 47,497 | 47,497 | 47,497 |
| Adj. R−squared | 10.0% | 10.0% | 10.0% |
| Test of coefficients ($\chi^2$ statistic is in parentheses) | | | |
| ΔPeer Positive of Content - ΔPeer Positive of Other | -0.027** | 0.023** | -0.015 |
| | (4.72) | (4.79) | (0.97) |
| ΔPeer Negative of Content - ΔPeer Negative of Other | -0.004 | 0.004 | 0.002 |
| | (0.37) | (0.45) | (0.15) |

## Table 3.8: Use of proceeds

This table presents regression analyses of the impact of peer changing tone on the uses of proceeds of seasoned equity offerings. I use capital expense, R&D, acquisitions, long-term debt reduction, changes in inventory, and changes in cash capture uses of proceeds. Specifically, for each of these potential uses of proceeds, I estimate: Use of proceeds=$\beta_0+\beta_1$LogProceeds+$\beta_2$ΔPeer Positive+$\beta_3$ΔPeer Negative+$\beta_4$ΔPeer Positive × LogProceeds+$\beta_5$ΔPeer Negative × LogProceeds +$\beta_6$Firm size+ Fixed Effects+$\varepsilon$. The dependent variable for asset-based variables (inventory and cash) is: Use of proceeds=$ln[((V_t - V_{-1})/\text{total assets}_{-1}) + 1]$, and for cash flow-based variables (capital expense, acquisition, R&D, reduction in long-term debt) is Use of proceeds=$\ln[(\sum_{i=0}^{t} V_i/\text{total assets}_{-1})+1]$ where $V$ is the variable being measured, and year −1 is the year-end before issuance. The independent variables include ΔPeer Positive, ΔPeer Negative, *LogProceeds*, their interaction term (i.e., ΔPeer Positive × *LogProceeds* and ΔPeer Negative × *LogProceeds*), and *Firm Size*. I control for industry and year fixed effects. Industry fixed effects are based on FIC 500 industry fixed effects as defined in Hoberg and Phillips (2016). Appendix C1 provides variable definitions and sources. *t*-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses. For brevity, I present results only for the variables of interest and indicate significant coefficients on ΔPeer Positive × *LogProceeds* and ΔPeer Negative × *LogProceeds*) in bold. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Variables | Year | ΔPeer Positive × LogProceeds | | ΔPeer Negative × LogProceeds | | N | $R^2$ |
|---|---|---|---|---|---|---|---|
| | | $\beta_4$ | t-stat | $\beta_5$ | t-stat | | |
| ∑Capital Expense | 1 | -3.404 | (-1.420) | -1.324 | (-1.594) | 1,963 | 6.0% |
| | 2 | -3.206 | (-1.108) | -1.486 | (-1.639) | 1,640 | 4.6% |
| | 3 | -1.619 | (-0.626) | -1.220 | (-1.244) | 1,402 | 4.2% |
| ∑R&D | 1 | 5.625 | (1.405) | 0.586 | (0.278) | 1,958 | 28.0% |
| | 2 | **13.995**** | (2.153) | 0.591 | (0.220) | 1,636 | 30.0% |
| | 3 | **20.080**** | (2.189) | 0.479 | (0.158) | 1,395 | 31.2% |
| ∑Acquisition | 1 | **-3.155**** | (-2.200) | -0.188 | (-0.519) | 1,912 | 4.2% |
| | 2 | -7.888 | (-1.323) | 0.679 | (0.630) | 1,581 | 3.0% |
| | 3 | **-14.267*** | (-1.886) | -0.347 | (-0.220) | 1,346 | 4.1% |
| ∑LTD Reduction | 1 | 2.157 | (1.600) | -0.255 | (-0.609) | 1,918 | 6.2% |
| | 2 | 2.105 | (0.905) | -0.630 | (-0.991) | 1,588 | 9.2% |
| | 3 | 0.002 | (0.001) | -1.349* | (-1.750) | 1,346 | 10.8% |
| ΔInventory | 1 | 0.271 | (0.229) | -0.355 | (-1.401) | 1,963 | 3.8% |
| | 2 | -1.557 | (-0.970) | -0.144 | (-0.426) | 1,640 | 3.1% |
| | 3 | -0.167 | (-0.107) | 0.108 | (0.279) | 1,401 | 2.2% |
| ΔCash | 1 | 16.883 | (1.358) | -3.264 | (-1.215) | 1,967 | 9.8% |
| | 2 | 13.112 | (1.110) | -4.446* | (-1.704) | 1,647 | 9.7% |
| | 3 | 2.713 | (0.306) | 3.379 | (1.191) | 1,411 | 8.9% |

**Table 3.9: Long-term stock performance**

This table presents 1-year, 2-year, and 3-year buy-and-hold abnormal stock returns (BHARs) of issuing firms in relation to matched non-issuers during the three years after the offering. 3-year BHARs are reported for two periods: months 1-36 and months 7-42. Panel A presents the buy-and-hold returns of the issuer in excess of the buy-and-hold return for non-issuers matched peers. I first classify issuers into two groups based on whether ΔPeer Positive is above or below the median per year. I use a t-test to examine if the mean BHARs equal zero. I also report the difference in BHARs between the high peer changing positive tone SEOs and low peer changing positive tone SEOs and use an independent sample t-test to examine if BHAR differs significantly across the two subsamples. Panel B reports regression results of long-run abnormal returns. The dependent variable is months 1-12, months 1-24, months 1-36, and months 7-42 BHARs relative to non-issuer matched peers. All specifications are estimated using industry and year fixed effect, which are not tabulated. Industry fixed effects are based on FIC 500 industry fixed effects as defined in Hoberg and Phillips (2016). Appendix C1 provides variable definitions and sources. t-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: BHAR

| | Full | Low | High | Diff |
|---|---|---|---|---|
| BHAR_1_12 | -9.15%*** | -7.99%*** | -10.31%*** | -2.33% |
| BHAR_1_24 | -15.63%*** | -8.98%** | -22.27%*** | -13.30%*** |
| BHAR_1_36 | -20.99%*** | -10.94% | -31.19%*** | -20.25%*** |
| BHAR_7_42 | -24.49%*** | -15.60%*** | -33.40%*** | -17.80%*** |

Panel B: Regression

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | BHAR_1_12 | BHAR_1_24 | BHAR_1_36 | BHAR_7_42 |
| ΔPeer Positive | -0.383* | -0.675* | -1.266*** | -1.203*** |
| | (-1.71) | (-1.73) | (-3.04) | (-3.02) |
| ΔPeer Negative | 0.008 | 0.022 | 0.254 | -0.004 |
| | (0.10) | (0.15) | (1.47) | (-0.03) |
| ΔFirm Positive | -0.058 | -0.095 | 0.094 | 0.018 |
| | (-1.12) | (-0.85) | (0.34) | (0.08) |
| ΔFirm Negative | 0.033 | 0.158* | -0.078 | -0.085 |
| | (1.35) | (1.88) | (-0.60) | (-0.84) |
| Firm size | 0.001 | 0.015 | 0.059* | 0.049* |
| | (0.08) | (0.63) | (1.93) | (1.72) |
| Tobin | 0.001 | 0.000 | -0.018 | 0.007 |
| | (0.16) | (0.04) | (-0.77) | (0.31) |
| Leverage | -0.064 | 0.086 | -0.162 | -0.212 |
| | (-1.17) | (0.83) | (-0.89) | (-0.64) |
| Fixed Assets | 0.293** | 0.404 | 0.129 | 0.203 |
| | (2.42) | (1.41) | (0.38) | (0.53) |
| Cash | -0.034 | 0.029 | 0.149 | 0.120 |
| | (-0.57) | (0.26) | (1.20) | (0.83) |
| Profitability | 0.113** | 0.458*** | 0.540*** | 0.545*** |
| | (2.39) | (6.70) | (3.80) | (4.09) |
| R&D | -0.063 | 0.379* | 0.848** | 0.582* |
| | (-0.94) | (1.69) | (2.38) | (1.84) |
| Stock Return | 0.000 | -0.039* | -0.043** | -0.057*** |
| | (0.04) | (-1.76) | (-2.17) | (-2.75) |
| Stock Volatility | -0.194* | 0.313 | 0.598** | 0.433 |
| | (-1.87) | (1.37) | (2.04) | (1.54) |
| Proceeds | 0.017 | 0.059 | -0.008 | -0.062** |
| | (1.47) | (1.11) | (-0.17) | (-2.07) |
| Constant | -0.068 | -0.386** | -0.640*** | -0.566*** |
| | (-0.86) | (-2.05) | (-2.66) | (-2.81) |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Industry fixed effect | Yes | Yes | Yes | Yes |
| Observations | 3,219 | 2,792 | 2,350 | 2,181 |
| Adj. R-squared | 1.5% | 1.7% | 2.5% | 2.0% |

**Table 3.10: Identifying peers using SIC**

This table presents the regression analysis of the relationship between peer changing tone and firm seasoned equity financing decisions where peers are identified based on SIC industry classification. In Column (1), the dependent variable is a dummy variable that equals one if the firm issues SEO during year t+1. The explanatory variable of interest is ΔPeer Positive and ΔPeer Negative, the average change between t and t-1 of each peer's MD&A tone. Peer Positive (Peer Negative) is the number of positive (negative) words per 100 words in a firm's MD&A section, measured using the 2020 version of the word list from Loughran and McDonald (2011). Firms' potential peers are all firms in the same 3-digit SIC code as the firm, excluding the latter. Column (2) adds peer and firm characteristics. Column (3) adds competition measures: industry size, entry costs, and product substitutability. All specifications are estimated using the full set of control variables and year fixed effect, which are not tabulated. Appendix C1 provides variable definitions and sources. t-statistics, calculated using robust standard errors clustered at the industry level, are reported in parentheses. Industry classifications are based on the 3-digit SIC code. ***, **, and * denote significance at the 1%, 5%, and 10% level.

| | (1) | (2) | (3) |
|---|---|---|---|
| ΔPeer Positive | 0.033** | 0.030* | 0.034 |
| | (2.02) | (1.89) | (0.27) |
| ΔPeer Negative | -0.004 | 0.003 | 0.081 |
| | (-0.41) | (0.54) | (1.08) |
| ΔPeer Positive*IndustrySize | | | 0.031 |
| | | | (1.40) |
| ΔPeer Negative*IndustrySize | | | -0.006 |
| | | | (-0.74) |
| ΔPeer Positive*EntryCosts | | | -0.043*** |
| | | | (-2.65) |
| ΔPeer Negative*EntryCosts | | | -0.003 |
| | | | (-0.72) |
| ΔPeer Positive*ProductSubstitutability | | | 0.000 |
| | | | (0.97) |
| ΔPeer Negative*ProductSubstitutability | | | 0.000 |
| | | | (1.02) |
| Firm changing tone | Yes | Yes | Yes |
| Peer controls | No | Yes | Yes |
| Firm controls | No | Yes | Yes |
| Competition controls | No | No | Yes |
| Year fixed effect | Yes | Yes | Yes |
| Observations | 52,179 | 52,179 | 52,179 |
| Adj. R−squared | 1.39% | 3.45% | 4.46% |

# Chapter 4. Investor base, short selling, and announcement returns: Evidence from the convertible bond market

## 4.1 Introduction

Convertible bonds are hybrid securities with both debt and equity attributes that not only offer investors coupon income but also give them an option to convert their bonds into stocks. The convertible bond market has witnessed exceptionally high levels of new issuance since the outbreak of the COVID-19 crisis.[24] According to Bloomberg data, more than $100 billion of U.S. convertible bonds have been issued in 2020, a new issuance record since 2007.[25] This surge remained in 2021.[26]

Empirical studies document that convertible bond announcement returns are negative between the announcement returns reported for straight debt and equity. These findings are consistent with the information asymmetry theory proposed by Myers and Majluf (1984). Previous studies have further explored potential determinants of convertible bond announcement returns. Some of these studies focus on either the supply side of the convertible bond market (see, for example, Lewis et al. (1999)) while others examine macroeconomic conditions (see, for example, Dutordoir and Van de Gucht (2007)). This paper extends the literature by examining whether the demand side of the convertible bond market also influences convertible bond announcement effects.

This paper shows that the convertible bond market has undergone two significant shifts in its investor base over the past decades: first, from traditional long-only investors (e.g., mutual funds, insurance companies, and pension funds) to convertible arbitrage hedge funds, then back

[24] See Howcroft and Ramnarayan (2020): "Convertible bond issues surge in coronavirus-hit market", Reuters: https://www.reuters.com/article/health-coronavirus-convertiblebonds/convertible-bond-issues-surge-in-coronavirus-hit-market-idUSL8N2DW3NI (retrieved on May 23, 2021).
[25] See Kim (2021): "Convertible-bond market braces for a 2021 that's good, not great", Bloomberg: https://www.bloomberg.com/news/articles/2021-01-04/convertible-bond-market-braces-for-a-2021-that-s-good-not-great (retrieved on May 23, 2021).
[26] See Murugaboopathy (2021): "Global Companies Raise Massive Cash Through Convertible Bonds at Start of 2021", Reuters: https://www.reuters.com/article/us-global-markets-convertibles-graphic/global-companies-raise-massive-cash-through-convertible-bonds-at-start-of-2021-idUSKBN2AH1C4 (retrieved on May 23, 2021).

to traditional long-only investors again. Around the beginning of the 21st century, convertible arbitrage hedge funds became the principal buyers of convertible bonds, contrasting with the 1990s when traditional long-only investors dominated the convertible bond market. Specifically, about three-quarters of newly issued convertible bonds were taken up by convertible arbitrage hedge funds between 2000 and 2008 (Brown et al., 2012). However, the convertible bond investor base has shifted from convertible arbitrage hedge funds to traditional long-only investors over the past two decades. The turning point was the global financial crisis (GFC) when the convertible arbitrage hedge fund industry experienced a significant contraction, driven by large losses and net asset outflows (Dick-Nielsen and Rossi, 2020; Hutchinson and Gallagher, 2010; Mitchell and Pulvino, 2012). The asset under management value of convertible arbitrage hedge funds sharply decreased since the GFC, as shown in Figure 4.1. In the meantime, the importance of hedge funds in the convertible bond market declined substantially. The convertible bond market has witnessed a sharp decrease in the number of hedge fund holders (Spiegeleer, 2011). Specifically, according to Barclay data, the proportion of convertible bonds held by hedge funds shrunk from 74% to 53% from the beginning of 2008 to the third quarter of 2009. Since the end of the GFC, traditional long-only investors have re-dominated the convertible bond market.[27] Specifically, hedge funds only buy 20-25%, and the traditional long-only investors buy the remaining 75-80% of the convertible bond market.[24]

Unlike the traditional long-only investors, who buy and hold convertible bonds, convertible arbitrage hedge funds generally buy convertible bonds and short the underlying stocks to hedge the embedded equity component (Agarwal et al., 2011; Choi et al., 2009). This buy-and-hedge strategy exerts downward pressure on stock prices around the convertible bond announcement date. Consequently, the convertible bond announcement effect is negatively impacted by the magnitude of arbitrage-induced short-selling activities by hedge funds. Shifts in the investor base of the convertible bond market influence the announcement effect. Given the twists and turns in the convertible bond investor base, there exists a unique opportunity to examine the proposition that arbitrage-induced short-selling activity by hedge funds determines

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[27] See Parlamis (2015): "Structural changes in the US convertibles market: Implications for convertible arbitrage", Pine River Capital: https://pinerivercapital.com/Content/perspectives/PRCM%20Structural%20Changes%20in%20the%20US%20Convertibles%20 Market%20-%20Parlamis%200115%20ap.pdf (retrieved on May 23, 2021).

the convertible bond announcement effect. As convertible bond financing grows in size and importance as a corporate financing vehicle, it becomes imperative to understand the shareholder wealth effects of convertible bond offerings and identify their determinants.

I examine the impact of change in investor base on convertible bond announcement effects using a sample of 2,083 convertible bonds announced between April 1, 1986, and June 30, 2021. I document a more negative announcement effect when the convertible arbitrage hedge funds dominated the convertible bond market from January 1, 2000, to December 31, 2009 (labeled as the *CAHedgeFundPeriod*). Specifically, the convertible bond offering announced during the *CAHedgeFund* period induced an average announcement return of −5.19%. In contrast, convertible bond announcement returns are significantly higher when traditional investors dominate the convertible bond market, with an average announcement return of −3.41%. This difference in announcement returns remains significant even after controlling for standard convertible bond announcement return determinants, including issue-specific, issuer-specific, and macroeconomic conditions. I conjecture that differences in announcement returns are attributable to fluctuations in the magnitude of arbitrage-related short selling. I measure the arbitrage-induced short selling following the methodology of previous studies (e.g., Choi et al., 2009). Specifically, I regress daily short-selling activities on potential determinants that influence convertible arbitrageurs' likelihood of short-selling the issuer's stock. I use the predicted value from this regression to measure arbitrage-induced short selling for each convertible bond offering. I find that cross-period differences in announcement returns disappear after controlling for arbitrage-induced short-selling measures. This result holds robustly across a range of convertible arbitrage strategies. I also document a price reversal after the convertible bond issuance, supporting that the more negative convertible bond announcement effect is attributed to the price pressure caused by short-selling activities from convertible arbitrage hedge funds.

This paper contributes to the literature that examines the convertible bond announcement effect. To the best of my knowledge, there is no paper that investigates the pattern of U.S. convertible bond announcement returns after the GFC. I aim to fill this gap by leveraging post-GFC data and examining the impact of shifts in the investor base on the convertible bond announcement effect. Duca et al. (2012) show that convertible bond announcement returns became more negative after 2000, while the equity and straight debt announcement returns remained relatively stable over the same period. They suggest that the increase in arbitrage-related short-selling of hedge funds after 2000 explains the decrease in the convertible bond announcement effect. However, they use monthly short-interest data to measure short-selling activities, which may not accurately capture short-selling transactions during the few days around the convertible bond issue date. I utilize daily equity lending data to understand the short-selling pattern near the issuance date and examine the impact of changes in the buyer side of the convertible bond market on announcement returns. Additionally, I document another shift in the convertible bond investor base. This paper also investigates the crisis period convertible bond announcement effects. The information asymmetry is heightened during the crisis period (Dissanaike et al., 2014). In addition, the cost of financial distress may increase with the decrease in a firm's financial condition caused by the crisis. However, no study has focused on convertible bond announcement returns during the crisis period. I document a more negative market reaction to convertible bond offerings during the crisis period relative to non-crisis periods. The study contributes to the studies investigating the impact of changing economic conditions on convertible bond announcement returns.

The remainder of the paper is organized as follows. Section 4.2 discusses shifts in the buy-side of the convertible bond market. Section 4.3 develops the hypotheses. Section 4.4 describes the data. Section 4.5 analyzes the impact of change in the buyer side of the convertible bond market on the convertible bond announcement return and post-issuance return. Section 4.6 is the conclusion.

### 4.2 The changing investor base of convertible bonds

The convertible bond market has experienced two significant shifts in its investor base over the past decades.

Until the end of the last century, a significant fraction of convertible bonds were bought by traditional long-only investors who sought diversification benefits and indirect participation in the stock market (Lummer and Riepe, 1993). However, the convertible arbitrage industry has proliferated and become the predominant buyer of the convertible bond market since the rise of convertible arbitrage hedge funds (Loncarski et al., 2009). Previous studies have clearly documented the rapid growth of the convertible arbitrage industry. For example, Choi et al. (2009) report that assets managed by convertible arbitrage hedge funds have increased steadily since the early 2000s. In addition, Brown et al. (2012) show that convertible arbitrage hedge funds played a critical role in funding the convertible bond market and bought about three-quarters of newly issued convertible bonds between 2000 and 2008.

However, the convertible arbitrage hedge fund industry experienced a significant contraction during the GFC, driven by large losses and net asset outflows (Dick-Nielsen and Rossi, 2020; Hutchinson and Gallagher, 2010; Mitchell and Pulvino, 2012). According to data from the TASS Hedge Fund Database, convertible arbitrage hedge funds experienced heavy capital redemptions from investors during the GFC, as shown in Panel A of Table 4.1. Furthermore, the convertible arbitrage strategy was among the worst-performing hedge fund strategies during the GFC. According to the Hedge Fund Research (HFR) database, the convertible arbitrage index dropped by more than 30 percent in 2008, marking the largest loss since HFR began tracking the convertible arbitrage strategy in 1990. In comparison, the HFRI Fund Weighted Composite Index lost 19 percent in 2008.[28] Figure 4.1 displays the quarterly assets under management (AUM) value for convertible arbitrage hedge funds from the Barclay Hedge database, covering the period from January 2000 to June 2021.

<<Please insert Figure 4.1 here>>

As shown in Figure 4.1, the convertible arbitrage industry has taken heavy hits since the GFC, with a dramatic decrease in the size of assets under management since 2008, and remained relatively low over the past decade relative to the pre-GFC level. In the meantime, convertible arbitrage hedge funds gradually lost their dominant position in the convertible bond market while traditional long-only investors grew to control the convertible bond market (Spiegeleer, 2011).[27] The convertible bond market has witnessed a sharp decrease in the convertible bond offering bought by hedge funds during the GFC. According to Barclay data, the proportion of

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[28] Also see Walker and Baum (2008): "Convertible-bond arbitrage loses its shirt; Deprived of leverage, hedge fund strategy set for its worst year", Wall Street Journal: https://www.wsj.com/articles/SB122688700899932417 (retrieved on 23 May 2021).

convertible bonds held by hedge funds shrunk from 74% to 53% from the beginning of 2008 to the third quarter of 2009. The investor base has shifted from convertible arbitrage hedge funds toward traditional long-only investors following the GFC. The popular financial press also shares a similar view and suggests that convertible arbitrage hedge funds only buy a small proportion (20-25%) of convertible bonds, and their holdings concomitantly decrease.[29]

I also examine the convertible arbitrage hedge fund industry's media coverage to gain more insight into the convertible arbitrage hedge fund industry. I searched the Factiva database for newspaper articles that mentioned "convertible arbitrage" or related terms from 1986 to 2020. Figure 4.2 depicts the yearly number of convertible arbitrage-related newspaper articles in the Factiva database.[30]

<<Please insert Figure 4.2 here>>

The number of articles experienced a considerable increase since 2000 and remained at a high level until 2008, followed by a sharp decrease after 2009. This pattern supports the idea that convertible arbitrage hedge funds have become less active in the 2010s.

The exact date from which traditional long-only investors outnumber convertible arbitrage hedge funds is hard to determine as hedge funds disclose limited information on their investment. Based on my evidence, this shift in investor base happened circa the end of 2009.

I also examine the crisis period convertible arbitrage announcement effect. Specifically, the crisis period includes the *GFC* period and the *COVID* period. Following Beber and Pagano (2013), I use the date Lehman Brothers collapsed (i.e., September 15, 2008), which is the most salient turning point that led to the financial crisis, as the start date of the *GFC* period. Following previous studies (Li et al., 2016), I use December 31, 2009, as the end date of the *GFC* period. According to the International Monetary Fund annual report, the COVID-19 recession is the worst global economic crisis since the Great Depression in the 1930s

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[29] See Ostroff and Davies (2020): "Investors Binge on Convertible Bonds as Issuance Soars", Wall Street Journal: https://www.wsj.com/articles/investors-binge-on-convertible-bonds-as-issuance-soars-11604324846 (retrieved on 23 May 2021).

[30] Following the methodology of Duca et al. (2012), convertible arbitrage related articles include any newspaper article containing the terms "convertible arbitrage", "convertible debt arbitrage", "convertible bond arbitrage", "convertible arbitrageur", "convertible debt arbitrageur", "convertible bond arbitrageur", "convertible arbitrageurs", "convertible debt arbitrageurs", or "convertible bond arbitrageurs" in Factiva database. I also adjust for duplicate newspaper articles.

(International Monetary Fund, 2020). The first sign of this recession was the U.S. stock market collapse, which began in early March (Mazur et al., 2021). Therefore, I use March 1, 2020, as the start date of the COVID period.

I label the period from January 1, 2000, to December 31, 2009, as the *CAHedgeFund* period, when convertible arbitrage hedge funds dominate the convertible bond market. It contains two subperiods: the *Arbitrage* period ranges from January 1, 2000, to September 14, 2008, and the *GFC* period ranges from September 15, 2008, to December 31, 2009. On the other hand, I label the period ranging from April 1, 1986, to December 31, 1999, and from January 1, 2010, to February 29, 2020, as the *TraditionalInvestor* period, when traditional long-only investors dominate the convertible bond market. It also contains two subperiods: the *LongOnly* period ranges from April 1, 1986, to December 31, 1999, and from January 1, 2010, to February 29, 2020, and the *COVID* period ranges from March 1, 2020, to June 30, 2021.

### 4.3 Hypothesis development

Convertible arbitrage hedge funds usually establish short positions in the underlying stock around the convertible bond issue date (Choi et al., 2009). The level of hedge fund involvement in the convertible bond market is substantially higher during the *CAHedgeFund* period than during the *TraditionalInvestor* period. Accordingly, the amount of arbitrage-related short-selling associated with *CAHedgeFund* period convertible bonds should be higher than *TraditionalInvestor* period convertible bonds; therefore, I form the following hypothesis:

**Hypothesis 1:** *CAHedgeFund period convertible bond offerings are associated with more arbitrage-induced short-selling than the TraditionalInvestor period convertible bond offerings are.*

In the presence of downward demand curves for the underlying stock, an increase in the supply of shares associated with short-selling transactions would lead to a temporary downward price pressure (Bechmann, 2004; Liu and Wu, 2014). These supply shocks are expected to negatively affect stock returns around convertible bond issue dates (Loncarski et al., 2009; Schultz, 2008). Moreover, as most convertible bonds in my sample are issued within one trading day of the announcement date, arbitrage-related short-selling activities are also expected to affect convertible bond announcement returns negatively. The quick placement of recent convertible bond offerings results from the fact that most convertible bonds (i.e., 57.42%) are structured under 144A, allowing issuers and qualified institutional investors to trade convertible bonds without registration directly. Given the different levels of convertible arbitrage hedge fund involvement in the convertible bond market, I make the following hypothesis:

**Hypothesis 2:** *CAHedgeFund period convertible bonds are associated with more negative announcement returns than the TraditionalInvestor period convertible bonds.*

Any observed difference in announcement return between the *TraditionalInvestor* period and *CAHedgeFund* period convertible bonds may be attributable to the intertemporal fluctuation in other convertible bond announcement effect determinants rather than the arbitrage-related short selling. To isolate the impact of the arbitrage-related short selling on convertible bond announcement return, I examine the following prediction:

**Hypothesis 3:** *The differences in convertible bond announcement return between the CAHedgeFund period and the TraditionalInvestor period are attributable to arbitrage-induced short selling.*

Moreover, the negative stock price effect will dissipate once the market fully absorbs uninformed supply shocks caused by the convertible arbitrage short selling. The stock prices would revert to the fundamental level within a few days after the issuance. Given that the *CAHedgeFund* period convertible bond is likely to be associated with more arbitrage-induced short selling, I form the following hypothesis:

**Hypothesis 4:** *Convertible bonds announced during the CAHedgeFund period have a more positive post-issuance stock return than those announced during the TraditionalInvestor period.*

The uncertainty of the firm's value and information asymmetry is arguably more pronounced in the crisis than in the "normal" period, which may lead to a more negative announcement return. In addition, the probability of financial distress may increase with the decrease in a firm's financial condition caused by the crisis. I thus propose the following hypothesis:

**Hypothesis 5:** *Crisis period convertible bonds are associated with more negative announcement returns than non-crisis period convertible bonds.*

## 4.4 Data

### 4.4.1 Sample construction

I collected a sample of U.S. convertible bond offerings announced between April 1, 1986, and June 30, 2021, from the Securities Data Corporation New Issues database (SDC). I exclude offerings made by utilities (SIC codes 4900–4999) and financial firms (SIC codes 6000–6999), which may face regulatory restrictions. In line with previous studies (see, for example, Duca et al. (2012); Kim and Purnanandam (2014); Kim (2016)), I only include the standard type of convertible bond offerings. In particular, units, warrants, preferred stocks, exchangeable bonds, and mandatory convertible bonds are deleted from the convertible bond offering sample. I then eliminate privately placed non-Rule 144A convertible bond offerings because previous studies have documented essential dissimilarities in the announcement effects of public and private security offerings. I include Rule 144A convertible bond offerings since they are more similar to the public than private offerings, following Gomes and Phillips (2012). I then identify the announcement date for each security offering. Following Jegadeesh et al. (1993), Krishnaswami and Yaman (2007), Kim and Purnanandam (2014), and Mehmood et al. (2018), I use the filing date as the announcement date for the non−144A and non-shelf offerings and use the issue date as the announcement date for Rule 144A offerings and Rule 415 shelf offerings.[31] I manually collect announcement dates from Factiva for offerings that do not have available announcement dates on SDC. I exclude security offerings without an identifiable announcement date on either SDC or Factiva. Additionally, I exclude convertible bond offerings that lack a conversion price or maturity date. In cases where there are multiple tranches of convertible bond offerings, I only include the main tranche of each security offering to avoid double counting (Hanselaar et al., 2019).

[31] Kim and Purnanandam (2014) argue that the firm's intention to issue security offering is generally announced on the filing date.

I then match the observed convertible bond offering with accounting data from the CRSP-Compustat Merged database (CCM) and stock price data from the Center for Research in Security Prices (CRSP) monthly file. First, I restrict my attention to firms listed on the New York Stock Exchange (NYSE), NYSE American, and NASDAQ with a CRSP share code of 10 or 11.[32] Second, I require issuers to have at least 240 days of pre-announcement stock price data available on the CRSP; I also expect them to have accounting data measured at fiscal year-end preceding the announcement date available on the CCM. Applying these criteria yields a final sample of 2,083 convertible bond offerings. Notably, I have 830 convertible bond offerings during the CA Hedge Fund period and 1,253 convertible bond offerings during the Traditional Investor period.

### 4.4.2 Measure for arbitrage-related short selling

To test my hypothesis, I construct a measure for arbitrage-induced short-selling associated with each convertible bond offering. The short-selling data is sourced from the Markit Securities Finance data, available daily from January 2006 to December 2019. The number of shares on loan is a good proxy for the short interest and is commonly used in previous studies on short selling, such as Cohen et al. (2007). Short selling is defined as the change in daily total balance quantity on the issue date, scaled by the shares outstanding, labeled as $SS/SO$. As the total balance quantity is the settlement data that captures short-selling transactions initiated two or three trading days ago, I shift the observations backward by two or three trading days. Figure 4.3 shows the short-selling activities measured over days $[-15,15]$ around the convertible bond issue date.

<<Please insert Figure 4.3 here>>

As shown in Figure 4.3, the short selling near the issue date for the *Arbitrage* period and the *GFC* period convertible bond offerings are higher than *LongOnly* period offerings. In contrast, the short selling on days that are relatively far from the issue date are similar among the three sub-periods.

However, a portion of the short-selling around the convertible bond issue date may also come from the valuation short-selling of the fundamental traders who view the convertible

[32] NYSE American is formerly known as AMEX.

bond offering as a stock overvaluation signal (Asquith et al., 2005; Choi et al., 2009; De Jong et al., 2011). To disentangle arbitrage and valuation short selling, I regress short selling ($SS/SO$) on three different sets of potential arbitrage demand determinants identified in previous theoretical and empirical studies: issuer-specific characteristics, issue-specific characteristics, and capital supply. I use the predicted value of this regression for each convertible bond as a proxy for arbitrage-related short-selling associated with that offering.

Convertible arbitrage hedge funds are attracted to convertible bonds whose underlying stock is more accessible to establish and maintain short positions. Specifically, stocks with greater liquidity and higher institutional ownership are more accessible for hedge funds to borrow at a relatively lower cost (Asquith et al., 2005; D'avolio, 2002). Therefore, I include the Amihud (2002) illiquidity measure (*Amihud*) and proportion of institutional ownership (*InstitOwnership*) in my analysis. I collect institutional ownership data from the Thomson Reuters database. Furthermore, hedge funds dislike convertible bonds issued by dividend-paying firms since hedge funds need to reimburse the lender for any dividends paid to the shareholders, which introduces an additional cost for hedge funds (Calamos, 2011; Choi et al., 2009; Dechow et al., 2001). I thus include an indicator for dividend-paying stocks (*DividendPaying*). Lastly, Brown et al. (2012) show that hedge funds prefer underlying stocks to be highly volatile. A higher stock return volatility would increase the expected profit from the embedded call option. Therefore, the analysis also includes stock return volatility (*StockVolatility*).

In addition to issuer-specific characteristics, arbitrage-induced short selling is also influenced by issue-specific characteristics. I anticipate that convertible bond offerings requiring hedge funds to short a larger number of shares for hedging purposes will be associated with a higher amount of arbitrage-induced short selling. Given that a typical convertible arbitrage hedge fund employs a delta-neutral hedging strategy, I include a variable *(DeltaNeutral/SO)* that measures the required number of shares shorted by hedge funds to achieve a delta-neutral hedge. This is scaled by the number of outstanding shares as measured 20 trading days before the announcement date.

I also examine two-directional hedging strategies, bullish gamma hedge, and bearish gamma hedge, to ensure the robustness of my findings. The bullish gamma hedge aims to capitalize on an expected increase in the stock price and yields greater returns when the stock price rises. Conversely, the bearish gamma hedge seeks to profit from an expected decrease in the stock price. I construct variables to measure the expected number of shares to be shorted under the bullish gamma *(GammaBull/SO)* and bearish gamma *(GammaBear/SO)* hedging strategies, following the method of Fabozzi et al. (2008). Specifically, for the under bearish (bullish) gamma hedging strategy, hedge funds need to short the underlying stocks by 0.09 more (less) than the Delta under the delta-neutral hedging strategy. Furthermore, I expect that the amount of arbitrage-induced short selling is positively related to the convertible bond gamma value (*Gamma*). Gamma measures the sensitivity of the convertible bond's Delta to the changes in the underlying stock price. Calamos (2011) argues that convertible arbitrage hedge funds prefer to buy convertible bonds with a high gamma. Positions with a high gamma need to be rebalanced more frequently, which provides convertible arbitrage hedge funds with increased opportunities to derive incremental profits. In addition, hedge funds may prefer convertible bond offerings with no call provision or strong call protection because they dislike being exposed to the risk of forced conversion (Brown et al., 2012; Calamos, 2011). In their study, Van Marle and Verwijmeren (2017) find that about 94% of convertible bonds bought by hedge funds are sold within three years of issuance. Therefore, hedge funds would be indifferent between convertible bonds that are not callable and whose call protection period is more than three years (Grundy and Verwijmeren, 2018). my analysis includes an indicator for the convertible bond offerings that are callable within the first three years of the bond's life (*Callable*). Lastly, I expect convertible bond arbitrageurs to be more interested in convertible bond offerings with lower conversion premiums, as these offerings tend to have lower interest rates and credit risks (Calamos, 2011; Choi et al., 2009; Hackney et al., 2020). Conversion premium (*ConvPremium*) is measured as the excess of the conversion price over the stock price measured on trading day −5.

Finally, I include convertible arbitrage hedge funds' capital supply in the regression analysis of $SS/SO$ ratio on potential arbitrage-induced short-selling determinants. Choi et al.

(2010) show that the magnitude of arbitrage short selling is positively related to capital flow into hedge funds. Arbitrage-induced short-selling becomes easier for hedge funds when they have more available capital to invest. I collect hedge fund flow data from the TASS database and select the hedge fund with convertible arbitrage as their primary investment category. Following Goetzmann et al. (2003), I calculate the hedge fund flow (*CAFlow*) using the change in the total assets over the quarter prior to the convertible bond issuance, adjusted for the fund return.

Panel A of Table 4.1 presents the summary statistics for these potential determinants of arbitrage-induced short selling.

<<Please insert Table 4.1 here>>

Appendix D1 provides detailed descriptions of the explanatory variables used in this paper. All continuous variables are winsorized at the 1st and 99th percentiles. Overall, the results reveal significant differences in determinants of arbitrage-induced short selling between the *CAHedgeFund* period and the *TraditionalInvestor* period, as indicated by the *t*-test for pairwise differences in means presented in the final column. Compared to the *TraditionalInvestor* period, issuers from the *CAHedgeFund* period typically have stocks with higher liquidity, volatility, and institutional ownership. They are also less likely to pay dividends. Conversely, the average number of shares that need to be shorted under hedging strategies is lower for *CAHedgeFund* period convertible bond offerings than those from the *TraditionalInvestor* period. Additionally, the average gamma value for *CAHedgeFund* period convertible bond offerings is lower than those in the *TraditionalInvestor* period. I also observe that a smaller proportion of convertible bonds are callable within the first three years of the bond's life during the *CAHedgeFund* period compared to the *TraditionalInvestor* period. Convertible bond offerings from the *CAHedgeFund* period have higher conversion premiums than those from the *TraditionalInvestor* period. Regarding capital supply, convertible arbitrage hedge funds experienced a larger capital outflow during the *TraditionalInvestor* period compared to the *CAHedgeFund* period.

Table 4.1 Panel B presents the regression results of $SS/SO$ on a set of arbitrage-induced short-selling determinants. Column (1) assumes convertible arbitrage hedge funds adopt a delta-neutral hedging strategy. Consistent with my expectations, short-selling activities are significantly higher when the underlying stock is more liquid, the number of shares needed to be shorted for a delta-neutral position is greater, and the offering is callable within the first three years of the bond's life. In Columns (2) and (3), I replicate the regression analysis in Column (1) but assume convertible arbitrage hedge funds follow bearish gamma and bullish gamma hedging strategies in lieu of Delta neutral strategy. The results in Columns (2) and (3) are similar to the results in Column (1), indicating my results are robust to alternative hedging strategies.

I use the predicted value of the regression in Column (1) of Table 4.1 Panel A for each convertible bond as a proxy for arbitrage-related short-selling associated with that offering. Specifically, I multiply the estimated coefficients by the value of explanatory variables in Column (1) of Table 4.1 Panel A. The result value is labeled as *ArbDemand*/*SO_DeltaNeutral*. Notice that I only require offerings with all explanatory variables available but do not require offerings to have the short-selling data available. Table 4.2 reports the summary statistics of estimated arbitrage-related short-selling and control variables.

<<Please insert Table 4.2 here>>

Consistent with Hypothesis 1, *CAHedgeFund* period convertible bond offerings are associated with more arbitrage-induced short-selling than the *TraditionalInvestor* period convertible bond offerings are, as shown in Table 4.2.

### 4.4.3 Control variables

To disentangle the effect of arbitrage-related short selling from issue-specific characteristics, issuer-specific characteristics, and macroeconomic conditions, I include a set of control variables based on previous theoretical and empirical studies. Balance sheet and income statement variables are obtained from the CCM database measured at the fiscal year-end preceding the announcement date unless indicated otherwise. Stock price data are obtained from the CRSP database. The trading days are measured relative to the announcement date. Issue-specific characteristics are obtained from the SDC database and estimated at the issue date unless indicated otherwise. Macroeconomic conditions are extracted from the Datastream database and measured over the quarter before the convertible bond issue date unless indicated otherwise.

I first control for various issuer-specific characteristics in my analysis. Since convertible bonds consist of both equity and debt components, issuers with high equity-related or debt-related financing costs are likely to experience more substantial negative announcement returns. Consequently, factors influencing equity-related or debt-related financing costs are also expected to affect convertible bond announcement returns (Dutordoir and Van de Gucht, 2007). Following Lewis et al. (1999, 2003), the amount of cash holding (*Cash*) and the pre-announcement stock price run-up (*StockRunUp*) are used as proxies for equity-related financing costs. I calculate the stock return between −60 and −2 days before the convertible bond announcement date. I use the ratio of cash and short-term investments to total assets to measure the cash holding. A firm with a higher amount of cash holding or pre-announcement stock run-up is more likely to be perceived as overvalued by the market and face more adverse selection costs (Lucas and McDonald, 1990; Myers and Majluf, 1984). Therefore, I expect these firms will have a more substantial negative announcement return. Furthermore, I use the ratio of income tax payments to total assets (*Tax*), the ratio of long-term debt to total assets (*Leverage*), the ratio of earnings before interest, tax, depreciation, and amortization to total assets (*Profitability*), and the interest coverage ratio (*InterestCoverage*) to capture debt-related financing costs. Lewis et al. (1999, 2003) argue that a firm with a high leverage level, lower tax ratio, and lower profitability faces high debt-related financing costs. Therefore, I expect that convertible bonds issued by these firms would have more substantial negative announcement returns. The interest coverage ratio is calculated as the ratio of the operating income after depreciation burden to interest expense plus one and bounded at 0 and 100, following Blume et al. (1998). A firm with lower interest coverage ability is expected to face higher debt-related costs as it faces a higher risk of financial distress (Krishnaswami and Yaman, 2008; Loncarski et al., 2008). In addition to equity-specific and debt-specific financing costs, I also control for variables that impact both equity- and debt-related financing costs. Specifically, I include stock return volatility (*StockVolatility*), market-to-book ratio (*MarkettoBook*), fixed asset ratio (*FixedAssets*), firm size (*LogAssets*), and firm age (*LogAge*).

I use the annualized stock return volatility over a period of (−240, −40) relative to the announcement date to measure the firm risk. Firms with volatile stock returns are predicted to face more uncertainty and hence have higher levels of information asymmetry (Altınkılıç and Hansen, 2000; Corwin, 2003; Lee and Masulis, 2009). Therefore, I expect issuers with higher stock return volatilities to face higher financing costs and have more substantial negative announcement returns. The Market-to-book ratio is a reasonable proxy for growth opportunities, positively impacting the convertible bond announcement return (Jung et al., 1996). On the other hand, firms with higher market-to-book ratios face higher moral hazard costs, leading to more substantial negative announcement returns (Lewis et al., 1999, 2003). Hence, I have no clear expectations about the overall impact of the market-to-book ratio on convertible bond announcement returns. The fixed asset ratio is calculated as the ratio of property, plant, and equipment to total assets. Fixed assets are more accessible for investors to evaluate, and hence firms with more fixed assets experience fewer asymmetric information problems (Goyal and Wang, 2013). Larger firms, measured as the natural logarithm of inflation-adjusted total assets, tend to have lower information asymmetries and adverse selection costs (Brennan and Schwartz, 1988; Frank and Goyal, 2009; Guo and Mech, 2000). Firm age is measured as the natural logarithm of one plus the number of years listed. Younger firms tend to have less information available to investors and face higher levels of information asymmetry (Helwege and Liang, 1996; Jung et al., 1996). Therefore, fixed asset ratio, firm size, and firm age are expected to positively impact convertible bond announcement returns.

Next to issuer-specific characteristics, I also include a number of issue-specific characteristics. First, I include Delta (*Delta*) as a proxy for the convertible bond's equity component size. A higher delta value indicates that the convertible bond price is more sensitive to changes in its underlying stock price, implying a larger equity component. Convertible bonds that are more equity-like signal stronger firm overvaluation and tend to exhibit stronger negative announcement returns (Myers and Majluf, 1984). Second, I control the offering's credit rating (*CreditRating*). A higher value of CreditRating means a worse credit rating and, hence, a higher credit risk associated with the offering. Therefore, I expect a negative relation between credit rating and convertible bond announcement return. Third, I include the convertible bond offering size (*Proceeds*), measured as the ratio of offering proceeds to total assets. Krasker (1986) generalizes the Myers-Majluf model and shows that large offering sizes induce higher external financing costs, leading to a more substantial negative announcement return. Empirical evidence confirms this view and shows that offering size negatively affects the convertible bond announcement return (Dutordoir and Van de Gucht, 2007; Lewis et al., 1999; Mikkelson and Partch, 1986). Lastly, I include an indicator for the offerings made under Rule 144A private placement (*144A*) and an indicator for offerings made within one trading day of the announcement date (*Issue=Announcement*) in my analysis. Rule 144A permits issuers and qualified institutional investors to trade convertible bonds directly without registration, facilitating a quicker placement of these bonds. Given that the announcement dates for these convertible bonds are close to their issue dates, the announcement returns may capture the downward stock price pressure associated with arbitrage short selling. As a result, the announcement returns for Rule 144A offerings and issues where the announcement date equals the issue date tend to be more negative compared to their counterparts.

Finally, macroeconomic conditions could affect the convertible bond issuers' cash flow, investment opportunities, and risk perceptions, affecting the announcement returns of convertible bond offerings (Bayless and Chaplinsky, 1996; Dutordoir and Van de Gucht, 2007; Krishnaswami and Yaman, 2007). To capture macroeconomic conditions, I use five economic-wide financing factors suggested by previous studies, including interest rates, terms spreads, default spreads, market run-ups, and market return volatilities. I use the level of interest rates (*InterestRate*) as proxies for the economy-wide debt-related financing cost (Dittmar and Dittmar, 2008). I measure the term spread as the yield difference between the 10-year and 3-month Treasuries and the default spread as the yield difference between the BAA- and AAA-rated corporate bonds. The term spread is a credible indicator of macroeconomic conditions and expected growth opportunities (Dotsey, 1998; Stock and Watson, 1989). Furthermore, the default spread is a reasonable proxy for the financial distress costs (Bayless and Chaplinsky, 1991; Korajczyk and Levy, 2003). Therefore, I expect interest rates, terms spread, and default spread to impact convertible bond announcement returns negatively. In addition, I also include the pre-issue stock market run-up (*MarketRunups*), calculated as the market index (i.e., S&P

500) return over the quarter preceding the convertible bond issue date. A larger pre-issue market run-up is a credible signal of expected growth opportunities, which lowers the economy-wide adverse selection costs (Choe et al., 1993; Korajczyk and Levy, 2003). Investors react less negatively to the convertible bond offering after a stock market run-up. Therefore, I expect the market run-up to affect convertible bond announcement returns positively. Finally, I include stock market volatilities (*MarketVolatilities*), defined as the annualized standard deviation of S&P 500 return over the quarter before the convertible bond announcement date. Market volatility is an indicator of information asymmetry and risk uncertainty. I expect a negative relationship between market return volatilities and convertible bond announcement returns.

Table 4.2 shows that issuer characteristics differ across the sub-periods. The evidence regarding the relative magnitude of external financing costs between *CAHedgeFund* period issuers and *TraditionalInvestor* period issuers is mixed. *CAHedgeFund* period issuers exhibit significantly higher stock returns, volatility, leverage ratio, total assets, age, profitability, and interest coverage ratio while maintaining significantly lower cash holdings. Except for stock returns, volatility, and leverage ratio, these differences suggest that *CAHedgeFund* period issuers generally face lower external financing costs than *TraditionalInvestor* period issuers. I also discover significant differences in issuer-specific characteristics between the two crisis periods. For example, compared with *GFC* period issuers, *COVID* period issuers have higher market-to-book ratios (8.64 compared with 1.29). This finding supports the view that many high-growth firms opportunistically issue convertible bonds to finance their growth during the *COVID* period.[33]

Issue characteristics also significantly differ between the *CAHedgeFund* and *TraditionalInvestor* periods. Convertible bonds announced during the *CAHedgeFund* period are more equity-like than the *TraditionalInvestor* period convertible bonds (with a delta value of 0.81 compared with 0.75). Furthermore, the offering size of *CAHedgeFund* period convertible bonds is significantly smaller than the *TraditionalInvestor* period offerings. In

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[33] See Gregory (2020): "Convertible market looks to kick on after coming of age", Global Capital: https://www.globalcapital.com/article/b1ppxbxyvthsw3/convertible-market-looks-to-kick-on-after-coming-of-age (retrieved on May 23, 2021).

addition, I document higher proportions of *CAHedgeFund* period convertible bonds that are issued under Rule 144A and for which the announcement and issue date coincide. About 98.6% of convertible bond issuers in the COVID period announced their offering within one day of the issue date. This can be attributed to the increase in the percentage of Rule 144A offerings.

Finally, I also document significant differences in macroeconomic conditions across the sub-periods. The interest rates are relatively lower during the *CAHedgeFund* period than the *TraditionalInvestor* period, suggesting that *CAHedgeFund* period convertible bond issuers face lower economy-wide borrowing costs. Notably, the interest rate during the *COVID* period is relatively low, with an average rate of 0.98. In addition, I document higher default spreads and higher market volatilities during two crisis periods, indicating higher market-level financial distress and uncertainty.

Overall, Table 4.2 suggests that I need to control for these variables when analyzing the differences in convertible bond announcement returns between the *CAHedgeFund* period and the *TraditionalInvestor* period.

### 4.5 Main results

#### 4.5.1 Convertible bond announcement effects

I calculate the abnormal stock returns around the announcement dates by employing the event study methodology described by Brown and Warner (1985). I use the CRSP equally-weighted market index as a proxy for the market return and estimate market model regressions over the period from 240 days to 40 days prior to the announcement date. I measure the cumulative announcement-period stock returns (*CARs*) over the window (−1, 1) relative to the announcement date, labeled as *CARs*(−1, 1). Table 4.3 presents univariate results for security offering announcement returns.

<<Please insert Table 4.3 here>>

I assess the statistical significance of the announcement return using the Patell (1976) test (means) and the non-parametric sign test (medians). I also report the difference in announcement returns between the *CAHedgeFund* period and the *TraditionalInvestor* period and employ an independent sample *t*-test (means) and Mann-Whitney U rank test (medians) to examine if announcement returns differ significantly.

In line with Hypothesis 2, convertible bonds issued during the *TraditionalInvestor* period have a significantly less negative announcement effect than those issued during the *CAHedgeFund* period. *CAHedgeFund* period convertible bonds are associated with significant negative average *CARs*(−1, 1) of −5.19%, while convertible bonds issued during the *TraditionalInvestor* period have an average announcement return of −3.41%. Specifically, the announcement return during the *Arbitrage* period is 173 basis points lower than during the *LongOnly* period. Regarding the two crisis periods, convertible bonds realized a less negative announcement return in the COVID period than in the GFC period (−5.84% compared with −9.53%).

### 4.5.2 Determinants of convertible bond announcement returns

I then investigate whether the observed cross-period differences in the convertible bond announcement returns are attributable to fluctuations in the arbitrage-related short selling. I regress the announcement return on period dummies, estimated arbitrage-related short selling, and control variables. Table 4.4 presents the results of the regression analysis for *CARs*(−1, 1).

<<Please insert Table 4.4 here>>

Column (1) includes two period dummy variables: *CAHedgeFund* Period and *Crisis* Period. *CAHedgeFund* Period is a dummy variable that equals one if the offering is made between January 1, 2000, and December 31, 2009, when convertible arbitrage hedge funds dominated the convertible bond market. The *Crisis* Period is a dummy variable that equals one if the offering is made over the *GFC* period (ranging from September 15, 2008, to December 31, 2009) and the *COVID* period (ranging from March 1, 2020, to June 30, 2021), when a crisis occurred. Both period dummy variables are significantly negative, consistent with the univariate analysis. Specifically, the announcement return during the *CAHedgeFund* Period is significantly lower than during the *TraditionalInvestor* period. Convertible bonds issued during crisis periods exhibit more negative announcement returns than those issued during non-crisis periods, supporting Hypothesis 5.

Column (2) includes a set of control variables mentioned in Section 4.4.3 and industry fixed effects. Consistent with Hypothesis 2, I observe that the announcement returns of convertible bonds issued during the *CAHedgeFund* period are higher than those issued during the *TraditionalInvestor* period after controlling for a set of issue-specific, issuer-specific, and macroeconomic conditions. On the other hand, the difference in announcement return between the crisis periods and the "normal" period is no longer significant. I find a significant negative impact of equity component size, proxied by *Delta*, on announcement return. In line with De Jong et al. (2011), I also obverse that the market-to-book ratio significantly positively affects *CARs*(−1, 1). Contrary to my expectations, I document the positive impact of interest rates on convertible bond announcement returns. Nevertheless, this finding is consistent with what has been reported in Duca et al. (2012).

Hypothesis 3 conjectures that differences in announcement return between the *CAHedgeFund* and *TraditionalInvestor* periods disappear after controlling for arbitrage-related short selling. To examine my hypothesis, I include ArbDemand/SO and its interaction term with the *CAHedgeFund* period in Column (3). As my hypothesis predicts, the coefficients on the *CAHedgeFund* dummy variable become insignificant after controlling for the arbitrage-related short selling. Furthermore, the coefficients of *ArbDemand/SO* with the *CAHedgeFund* dummy variable are significantly negative. These findings suggest that highly negative convertible bond announcement returns during the *CAHedgeFund* period are likely driven by extensive arbitrage-related short selling.

In Columns (4) and (5), I replicate the regression analysis in Column (3) but assume convertible arbitrage hedge funds instead follow bearish gamma and bullish gamma hedging strategies. Specifically, I reestimate the *ArbDemand/SO* using the coefficients from Columns (2) and (3) of Panel B in Table 4.1. The results in Columns (4) and (5) are similar to those in Column (3), indicating that my findings are robust in assuming a range of convertible arbitrage strategies.

**4.5.3 Post-issuance stock return**

If the observed negative announcement effect can be attributed to convertible arbitrage short-selling activities, it suggests a potential stock price reversal following the issuance of convertible bonds. Given the variance in arbitrage-related short-selling activities between the *CAHedgeFund* period and the *TraditionalInvestor* period, I expect a more pronounced positive stock price reversal during the *CAHedgeFund* period than the *TraditionalInvestor* period. As a stock price reversal occurs within days after the uninformed arbitrage-related supply shocks, I estimate the *CARs* over short event windows (Harris and Gurel, 1986; Jain et al., 2019; Mitchell et al., 2004). Specifically, I calculate *CARs* over the window (2,5) and (2, 10) following the convertible bond issue dates, labeled as *CARs*(2,5) and *CARs*(2, 10). Table 4.5 reports the results of event studies for the post-issuance stock return.

<<Please insert Table 4.5 here>>

In line with Hypothesis 4, convertible bonds issued during the *CAHedgeFund* period have a significantly more positive post-issuance abnormal return. Specifically, the average abnormal return over the window (2,10) following convertible bond issuance during the *Arbitrage* period is 0.34%. On the other hand, during the *TraditionalInvestor* period, convertible bonds realized a significantly negative post-issuance abnormal return of −0.38%, consistent with Lewis et al. (2001), who documented poor stock price performance after the convertible bond issuance. CARs(2, 5) tells a similar story. I observe a more substantial stock price reversal during the *CAHedgeFund* period. These findings suggest that a portion of the more negative announcement returns for the convertible bonds issued during the *CAHedgeFund* period can be attributed to the arbitrage-induced short-selling activities.

I then regress the post-issuance abnormal return on the estimated arbitrage-related short-selling. I also include the illiquidity measure, which is expected to positively impact the price reversal (Bagwell, 1992). Consistent with my expectation, the interaction term of estimated arbitrage-related short selling and the *CAHedgeFund* Period dummy is significantly positive for both estimation windows. In addition, the *CAHedgeFund* Period dummy no longer has a significantly positive impact on *CARs*(2,10) after including the arbitrage-related short-selling measures. My findings are robust enough to assume a range of convertible arbitrage strategies.

## 4.5 Conclusion

Over the past decades, the convertible bond market has undergone two significant shifts in its investor base: from traditional long-only investors to convertible arbitrage hedge funds since 2000 and then back to traditional long-only investors after the GFC. This paper examines the impact of these shifts on convertible bond announcement returns. I document a more negative announcement effect during the *CAHedgeFund* period, when convertible arbitrage hedge funds dominated the convertible bond market from January 1, 2000, to December 31, 2009. Specifically, the average announcement return during the *CAHedgeFund* period is −5.19%, significantly lower than the average announcement return during the *TraditionalInvestor* period of −3.41%. This difference disappears after controlling for arbitrage-induced short selling associated with various hedging strategies. Additionally, I observe a price reversal after the *CAHedgeFund* period convertible bond issuances, supporting the idea that the more negative convertible bond announcement effect is attributed to the price pressure caused by short-selling activities from the convertible arbitrage hedge funds.

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**Figure 4.1: Aggregate net asset value of convertible arbitrage hedge funds**

This figure shows the quarterly aggregate asset under management of convertible arbitrage hedge funds and proceeds of convertible bonds from 1993Q1 to 2020Q2. The shaded areas correspond to the CA Hedge Fund period from January 1, 2000, to December 31, 2009.

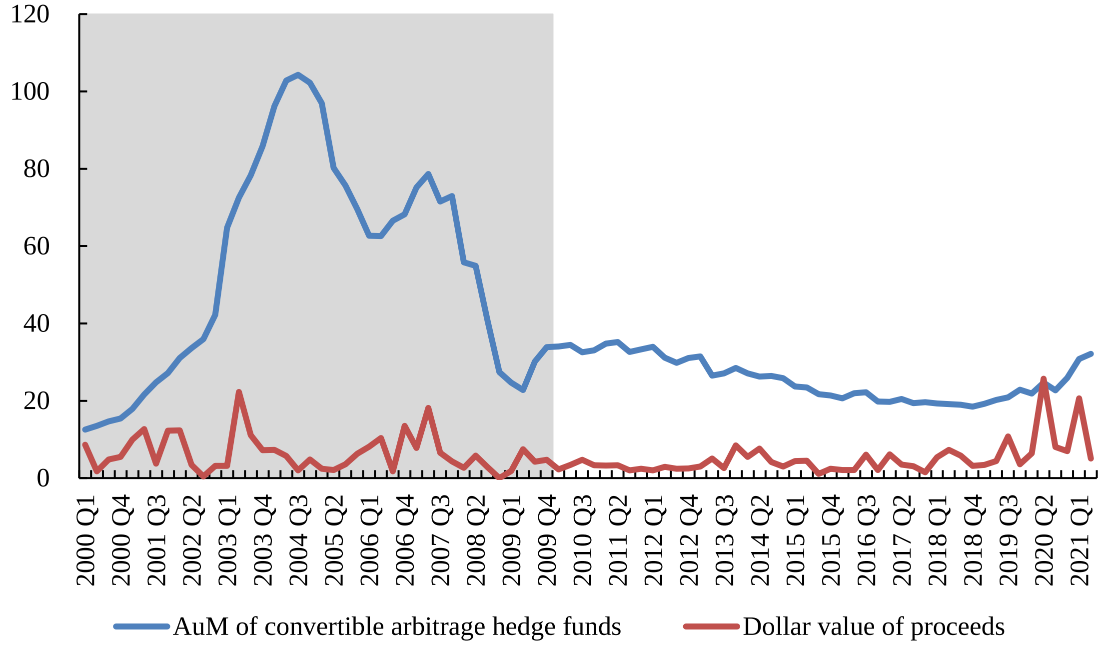


**Figure 4.2: The number of convertible arbitrage-related articles in Factiva**

This figure shows the annual number of convertible arbitrage-related newspaper articles from 1986 to 2020 in the Factiva database. Following the methodology of Duca et al. (2012), convertible arbitrage-related articles include any newspaper article containing the terms convertible arbitrage, convertible debt arbitrage, convertible bond arbitrage, convertible arbitrageur, convertible debt arbitrageur, convertible bond arbitrageur, convertible arbitrageur, convertible debt arbitrageur, or convertible bond arbitrageur in Factiva database. To avoid double-counting, I also adjust for duplicate newspaper articles. The shaded areas correspond to the *CAHedgeFund* period from January 1, 2000, to December 31, 2009.

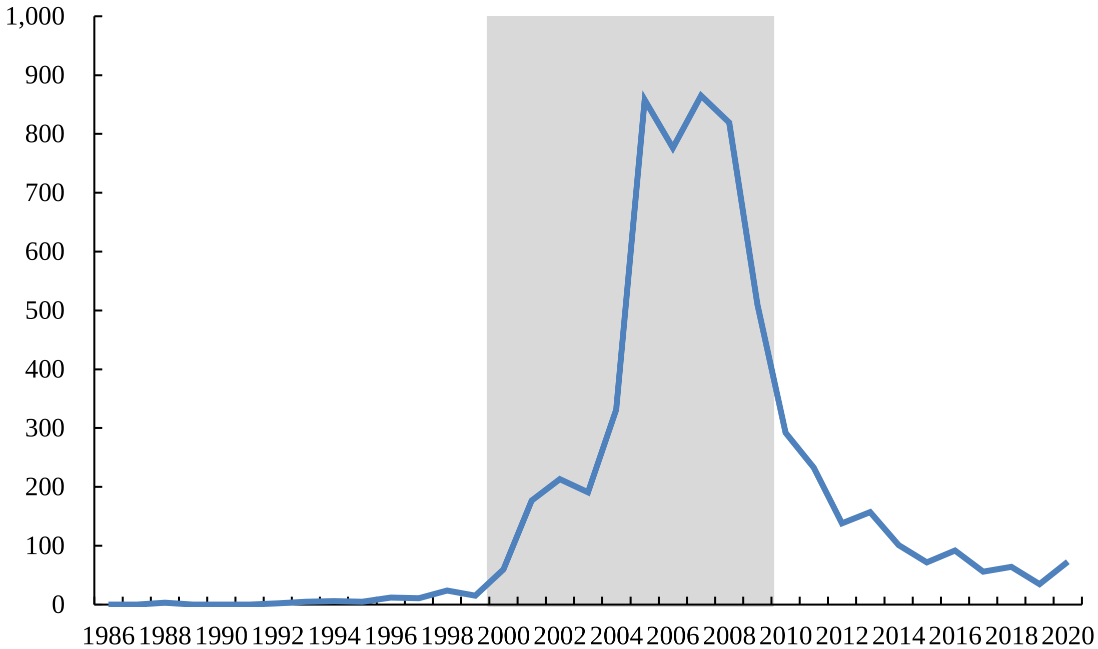
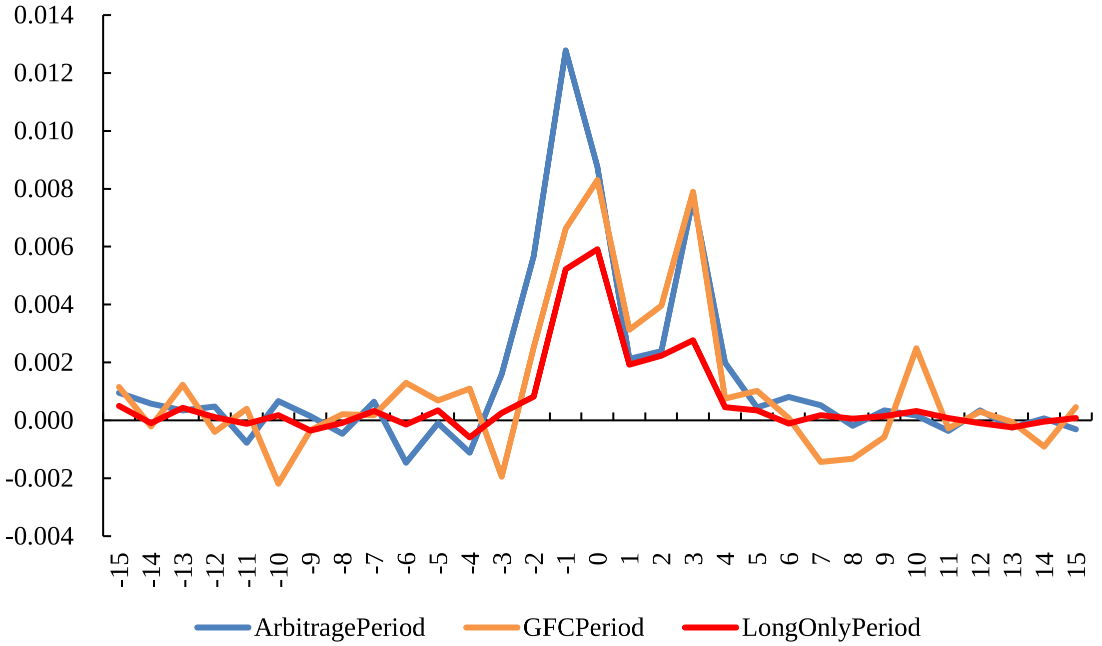


**Figure 4.3: Short selling around the convertible bond issue date**

This figure reports average daily short selling (scaled by the number of shares outstanding) measured over days [−15,15] relative to the convertible bond issue date from January 2006 to December 2019. The *Arbitrage* period ranges from January 1, 2006, to September 14, 2008, and the *GFC* period ranges from September 15, 2008, to December 31, 2009. Both periods referred to when convertible arbitrage hedge funds dominated the convertible bond market. The *LongOnly* period ranges from January 1, 2010, to December 31, 2019, when traditional long-only investors dominated the convertible bond market.



## Table 4.1: Arbitrage-related short selling

Panel A presents summary statistics of potential determinants of arbitrage-related short selling. The *Arbitrage* period ranges from January 1, 2000, to September 14, 2008, and the *GFC* period ranges from September 15, 2008 to December 31, 2009. Both periods were when convertible arbitrage hedge funds dominated the convertible bond market, defined as the *CAHedgeFund* period. The *LongOnly* period ranges from April 1, 1986, to December 31, 1999, from January 1, 2010, to February 29, 2020, and the *COVID* period ranges from March 1, 2020, to June 30, 2021. Both periods refer to the period when traditional long-only investors dominated the convertible bond market, defined as the *TraditionalInvestor* period. In the last column, I employ an independent sample *t*-test and an $\chi^2$-test to examine if the mean value of continuous variables and dummy variables (i.e., DividendPaying and Callable) differ significantly between the *CAHedgeFund* period and the *TraditionalInvestor* period. Variables are winsorized at the 1 percent and 99 percent levels. Panel B presents the regression results of the short-selling on potential determinants of arbitrage short-selling. t-statistics, calculated using heteroskedasticity-robust standard errors, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. N is the number of observations.

Panel A: Summary statistics of potential determinants of arbitrage-related short-selling

| | (1) Arbitrage Period | (2) GFC Period | (3) CAHedgeFund Period | (4) LongOnly Period | (5) COVID Period | (6) TraditionalInvestor Period | Difference (3)-(6) |
|---|---|---|---|---|---|---|---|
| Amihud | 0.010 | 0.067 | 0.014 | 0.074 | 0.004 | 0.066 | −0.051*** |
| DividendPaying | 0.193 | 0.328 | 0.204 | 0.252 | 0.156 | 0.241 | −0.037*** |
| InstOwn | 0.711 | 0.784 | 0.716 | 0.583 | 0.868 | 0.615 | 0.101*** |
| StockVolatility | 0.568 | 0.985 | 0.600 | 0.487 | 0.665 | 0.507 | 0.094*** |
| DeltaNeutral/SO | 0.103 | 0.141 | 0.106 | 0.136 | 0.074 | 0.129 | −0.023*** |
| GammaBear/SO | 0.114 | 0.157 | 0.118 | 0.151 | 0.084 | 0.143 | −0.026*** |
| GammaBull/SO | 0.092 | 0.125 | 0.094 | 0.120 | 0.065 | 0.114 | −0.020*** |
| Gamma | 0.008 | 0.013 | 0.009 | 0.012 | 0.010 | 0.012 | −0.003*** |
| Callable | 0.084 | 0.000 | 0.077 | 0.371 | 0.000 | 0.329 | −0.252*** |
| ConvPremium | 29.408 | 18.131 | 28.539 | 21.914 | 25.947 | 22.368 | 6.171*** |
| CAFundFlow | −2.058 | −9.657 | −2.644 | −3.298 | −1.755 | −3.124 | 0.480* |

Panel B: Regression analysis of $SS/SO$ on arbitrage demand determinants

| | (1) | (2) | (3) |
|---|---|---|---|
| Amihud | −0.008*** | −0.008*** | −0.008*** |
| | (−2.80) | (−2.80) | (−2.81) |
| DividendPaying | −0.001 | −0.001 | −0.001 |
| | (−0.53) | (−0.56) | (−0.48) |
| InstitOwnership | 0.003 | 0.003 | 0.003 |
| | (1.40) | (1.39) | (1.41) |
| StockVolatility | −0.002 | −0.002 | −0.002 |
| | (−0.79) | (−0.79) | (−0.81) |
| DeltaNeutral.SO | 0.019** | | |
| | (2.17) | | |
| GammaBear.SO | | 0.017** | |
| | | (2.20) | |
| GammaBull.SO | | | 0.021** |
| | | | (2.18) |
| Gamma | 0.049 | 0.048 | 0.050 |
| | (0.99) | (0.97) | (1.01) |
| Callable | −0.004** | −0.004** | −0.004** |
| | (−2.43) | (−2.43) | (−2.43) |
| ConvPremium | −0.000 | −0.000 | −0.000 |
| | (−1.03) | (−1.02) | (−1.01) |
| CAFlow | −0.000 | −0.000 | −0.000 |
| | (−1.36) | (−1.36) | (−1.36) |
| Constant | 0.003 | 0.003 | 0.003 |
| | (1.25) | (1.23) | (1.25) |
| Observations | 637 | 637 | 637 |
| R-squared | 0.03 | 0.03 | 0.03 |

**Table 4.2: Summary statistics for issuer-specific, issue-specific, macroeconomics variables and estimated arbitrage-related short-selling**

This table reports summary statistics for potential determinants of convertible bond announcement effects. The *Arbitrage* period ranges from January 1, 2000, to September 14, 2008, and the *GFC* period ranges from September 15, 2008, to December 31, 2009. These two periods were when convertible arbitrage hedge funds dominated the convertible bond market, defined as the *CAHedgeFund* period. The *LongOnly* period ranges from April 1, 1986, to December 31, 1999, from January 1, 2010, to February 29, 2020, and the *COVID* period ranges from March 1, 2020, to June 30, 2021. These two periods referred to when traditional investors dominated the convertible bond market, which is defined as the *TraditionalInvestor* period. In the last column, I employ an independent sample $t$-test and an $\chi^2$-test whether continuous and dummy variables (i.e., 144A and Issue=Announcement) differ significantly between the *CAHedgeFund* and *TraditionalInvestor* periods. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Variables (except estimated arbitrage-related short selling) are winsorized at the 1 percent and 99 percent levels.

| | (1) ArbitragePeriod | (2) GFCPeriod | (3) CAHedgeFundPeriod | (4) LongOnlyPeriod | (5) COVIDPeriod | (6) TraditionalInvestorPeriod | Difference (3)-(6) |
|---|---|---|---|---|---|---|---|
| *Estimated arbitrage-related short-selling* | | | | | | | |
| ArbDemand/SO_DeltaNeutral | 0.006 | 0.008 | 0.006 | 0.005 | 0.006 | 0.005 | 0.001*** |
| ArbDemand/SO_GammaBear | 0.006 | 0.008 | 0.006 | 0.005 | 0.006 | 0.005 | 0.001*** |
| ArbDemand/SO_GammaBull | 0.006 | 0.008 | 0.006 | 0.005 | 0.006 | 0.005 | 0.001*** |
| *Issuer-specific* | | | | | | | |
| StockRunUp | 0.186 | 0.389 | 0.202 | 0.166 | 0.201 | 0.170 | 0.032** |
| Cash | 0.232 | 0.146 | 0.226 | 0.236 | 0.325 | 0.246 | −0.021** |
| Tax | 0.018 | 0.008 | 0.017 | 0.018 | 0.001 | 0.017 | 0.001 |
| Leverage | 0.243 | 0.303 | 0.247 | 0.220 | 0.314 | 0.231 | 0.017* |
| StockVolatility | 0.568 | 0.985 | 0.600 | 0.487 | 0.665 | 0.507 | 0.094*** |
| MarkettoBook | 3.419 | 1.292 | 3.255 | 4.122 | 8.644 | 4.631 | −1.376*** |
| FixedAssets | 0.246 | 0.331 | 0.253 | 0.254 | 0.215 | 0.249 | 0.003 |
| Asset | 3.629 | 6.257 | 3.832 | 1.988 | 2.987 | 2.101 | 1.731*** |
| FirmAge | 15.996 | 23.842 | 16.601 | 13.887 | 13.622 | 13.857 | 2.744*** |
| Profitability | 0.062 | 0.071 | 0.063 | 0.050 | −0.028 | 0.042 | 0.021*** |
| InterestCoverage | 23.523 | 15.900 | 22.935 | 20.603 | 17.685 | 20.275 | 2.661* |
| *Issue-specific* | | | | | | | |
| Delta | 0.816 | 0.785 | 0.813 | 0.751 | 0.714 | 0.747 | 0.066*** |
| CreditRating | 10.535 | 9.641 | 10.466 | 10.729 | 9.021 | 10.537 | −0.071 |
| Proceeds | 0.310 | 0.152 | 0.298 | 0.409 | 0.391 | 0.407 | −0.109*** |
| 144A | 0.828 | 0.328 | 0.789 | 0.379 | 0.844 | 0.432 | 0.357*** |
| Issue=Announcement | 0.978 | 0.969 | 0.977 | 0.635 | 0.986 | 0.674 | 0.303*** |
| *Macroeconomic conditions* | | | | | | | |
| InterestRate | 4.539 | 3.155 | 4.432 | 5.040 | 0.980 | 4.583 | −0.151* |
| TermSpread | 1.653 | 2.989 | 1.756 | 1.673 | 0.717 | 1.565 | 0.191*** |
| DefaultSpread | 0.957 | 2.221 | 1.055 | 0.943 | 1.098 | 0.961 | 0.094*** |
| MarketRunups | 0.027 | 0.086 | 0.031 | 0.049 | 0.029 | 0.047 | −0.016*** |
| MarketVolatilities | 0.157 | 0.292 | 0.167 | 0.133 | 0.329 | 0.155 | 0.012*** |

## Table 4.3: Analysis of abnormal stock returns around the convertible bond announcement date

This table presents the summary statistics of cumulative abnormal returns (CARs) measured over the window (−1,1) relative to the convertible bond announcement dates, labeled as CARs(−1,1). The market model parameters are estimated using daily returns and the equal-weighted CRSP market index over the window (−240, −40) relative to the announcement date. The Arbitrage period ranges from January 1, 2000, to September 14, 2008, and the GFC period ranges from September 15, 2008, to December 31, 2009. These two periods were when convertible arbitrage hedge funds dominated the convertible bond market, defined as the CA Hedge Fund period. On the other hand, the LongOnly period ranges from April 1, 1986, to December 31, 1999, and from January 1, 2010, to February 29, 2020, and the COVID period ranges from March 1, 2020 to June 30, 2021. These two periods were when traditional long-only investors dominated the convertible bond market, defined as the Traditional Investor period. CrisisPeriod contains the GFC period (from September 15, 2008, to December 31, 2009) and the COVID period (from March 1, 2020 to June 30, 2021). I use the Patell (1976) Z-test to examine if the average CARs are equal to zero and the Sign test to examine if median CARs are equal to zero. I employ an independent sample *t*-test and Mann-Whitney U rank test to examine if the mean and median of CARs(−1,1) differ significantly across two sub-periods. ***, **, and * indicate the statistical significance of the test at the 1%, 5%, and 10% levels, respectively. N is the number of observations.

| | N | Average | Median | Std. Dev | % of Negative Value |
|---|---|---|---|---|---|
| CAHedgeFundPeriod (1) | 830 | −5.189%*** | −4.547%*** | 7.803% | 76.988% |
| ArbitragePeriod | 766 | −4.827%*** | −4.408%*** | 7.431% | 76.632% |
| GFCPeriod | 64 | −9.529%*** | −9.453%*** | 10.489% | 81.250% |
| TraditionalInvestorPeriod (2) | 1,253 | −3.410%*** | −2.746%*** | 9.861% | 70.710% |
| LongOnlyPeriod | 1,112 | −3.102%*** | −2.548%*** | 9.784% | 69.874% |
| COVIDPeriod | 141 | −5.841%*** | −5.759%*** | 10.158% | 77.305% |
| Differences (1)-(2) | | −1.779%*** | −1.801%*** | | |
| CrisisPeriod (3) | 205 | −6.993%*** | −6.923%*** | 10.379% | 78.537% |
| NormalPeriod (4) | 1,878 | −3.805%*** | −3.209%*** | 8.938% | 72.630% |
| Differences (3)-(4) | | −3.188%*** | −3.715%*** | | |

**Table 4.4: Regression analysis of convertible bond announcement return**

This table presents regression results of convertible bond announcement return. The dependent variable is cumulative abnormal return measured over the window (−1,1) relative to the announcement date. Columns (1) only include period dummies: *CAHedgeFund* period and *Crisis* period. *CAHedgeFund* period is a dummy variable that equals one if the offering is made between January 1, 2000, and December 31, 2009, when convertible arbitrage hedge funds dominated the convertible bond market. *Crisis* period is a dummy variable that equals one if the offering is made over the GFC period (from September 15, 2008, to December 31, 2009) and the COVID period (from March 1, 2020, to June 30, 2021). Columns (2) add issuer-specific, issue-specific, and macroeconomic conditions. In Columns (3), (4), and (5), *ArbDemand/SO_DeltaNeutral, ArbDemand/SO_ GammaBear*, and *ArbDemand/SO_ GammaBull* are included, which are the estimated arbitrage-related short-selling relative to the share outstanding for each convertible bond, calculated using the coefficients from the regression in Columns (1), (2), and (3) of table 4.1 Panel B, respectively. Industry fixed effects are defined using the Fama-French 12-industry classification. *t*-statistics, calculated using heteroskedasticity-robust standard errors, are in parentheses. N is the number of observations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *Period dummy* | | | | | |
| CAHedgeFundPeriod | −0.019*** | −0.011* | −0.013 | −0.013 | −0.013 |
| | (−4.89) | (−1.88) | (−1.27) | (−1.27) | (−1.28) |
| CrisisPeriod | −0.034*** | −0.001 | 0.006 | 0.006 | 0.006 |
| | (−4.50) | (−0.13) | (0.65) | (0.65) | (0.65) |
| *Estimated arbitrage-related short-selling* | | | | | |
| ArbDemand/SO_DeltaNeutral | | | −4.889*** | | |
| | | | (−5.29) | | |
| CAHedgeFundPeriod * ArbDemand/SO_DeltaNeutral | | | 0.562 | | |
| | | | (0.38) | | |
| ArbDemand/SO_ GammaBear | | | | −4.899*** | |
| | | | | (−5.34) | |
| CAHedgeFundPeriod * ArbDemand/SO_ GammaBear | | | | 0.565 | |
| | | | | (0.39) | |
| ArbDemand/SO_ GammaBull | | | | | −4.875*** |
| | | | | | (−5.28) |
| CAHedgeFundPeriod * ArbDemand/SO_ GammaBull | | | | | 0.588 |
| | | | | | (0.40) |
| *Issuer-specific* | | | | | |
| StockRunUp | | 0.006 | 0.002 | 0.002 | 0.002 |
| | | (0.87) | (0.31) | (0.30) | (0.31) |
| Cash | | −0.026 | −0.029 | −0.029 | −0.029 |
| | | (−1.11) | (−1.26) | (−1.26) | (−1.26) |
| Tax | | 0.018 | −0.019 | −0.019 | −0.019 |
| | | (0.23) | (−0.25) | (−0.25) | (−0.24) |
| Leverage | | −0.014 | −0.010 | −0.010 | −0.010 |
| | | (−1.08) | (−0.74) | (−0.74) | (−0.74) |
| StockVolatility | | −0.032 | −0.041* | −0.041* | −0.042* |
| | | (−1.49) | (−1.83) | (−1.83) | (−1.84) |
| MarkettoBook | | 0.001** | 0.001** | 0.001** | 0.001** |
| | | (2.56) | (2.10) | (2.09) | (2.11) |
| FixedAssets | | −0.002 | −0.005 | −0.005 | −0.005 |
| | | (−0.17) | (−0.43) | (−0.44) | (−0.43) |
| LogAssets | | 0.003 | 0.002 | 0.002 | 0.002 |
| | | (0.84) | (0.61) | (0.60) | (0.62) |
| LogAge | | −0.003 | −0.002 | −0.002 | −0.002 |
| | | (−1.07) | (−0.69) | (−0.70) | (−0.68) |
| Profitability | | 0.009 | 0.010 | 0.011 | 0.010 |
| | | (0.40) | (0.48) | (0.49) | (0.47) |
| InterestCoverage | | −0.000 | −0.000 | −0.000 | −0.000 |
| | | (−0.55) | (−0.36) | (−0.36) | (−0.36) |

**Table 4.4 continued**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *Issue-specific* | | | | | |
| Delta | | −0.077*** | −0.059** | −0.060** | −0.058** |
| | | (−2.94) | (−2.10) | (−2.13) | (−2.06) |
| CreditRating | | 0.002** | 0.001** | 0.001** | 0.001** |
| | | (2.39) | (2.24) | (2.25) | (2.23) |
| Proceeds | | 0.013 | 0.016 | 0.017 | 0.016 |
| | | (1.27) | (1.56) | (1.57) | (1.56) |
| 144A | | 0.012** | 0.013** | 0.013** | 0.013** |
| | | (2.14) | (2.34) | (2.34) | (2.34) |
| Issue=Announcement | | −0.005 | 0.003 | 0.003 | 0.003 |
| | | (−0.74) | (0.42) | (0.42) | (0.41) |
| *Macroeconomic conditions* | | | | | |
| InterestRate | | 0.007*** | 0.005*** | 0.005*** | 0.005*** |
| | | (5.08) | (3.30) | (3.30) | (3.31) |
| TermSpread | | 0.001 | 0.000 | 0.000 | 0.000 |
| | | (0.58) | (0.20) | (0.20) | (0.20) |
| DefaultSpread | | −0.005 | 0.002 | 0.002 | 0.002 |
| | | (−0.61) | (0.20) | (0.20) | (0.20) |
| MarketRunups | | 0.010 | 0.027 | 0.027 | 0.027 |
| | | (0.29) | (0.77) | (0.77) | (0.76) |
| MarketVolatilities | | −0.005 | −0.068* | −0.069* | −0.068* |
| | | (−0.15) | (−1.80) | (−1.81) | (−1.79) |
| Constant | −0.030*** | −0.031 | 0.001 | 0.001 | −0.000 |
| | (−10.50) | (−0.81) | (0.02) | (0.04) | (−0.00) |
| Industry fixed effect | No | Yes | Yes | Yes | Yes |
| Observations | 2,083 | 2,083 | 2,083 | 2,083 | 2,083 |
| R-squared | 0.02 | 0.09 | 0.11 | 0.11 | 0.11 |

## Table 4.5: Post-announcement returns of convertible bond offerings

Panel A and B present the summary statistics of cumulative abnormal returns (*CARs*) measured over the window (2,5) and (2,10) relative to the convertible bond announcement dates, labeled as *CARs*(2,5) and *CARs*(2,10). The market model parameters are estimated using daily returns and the equal-weighted CRSP market index over the window (−240, −40) relative to the announcement date. The Arbitrage period ranges from January 1, 2000, to September 14, 2008, and the GFC period ranges from September 15, 2008, to December 31, 2009. These two periods were when convertible arbitrage hedge funds dominated the convertible bond market, defined as the CA Hedge Fund period. On the other hand, the LongOnly period ranges from April 1, 1986, to December 31, 1999, and from January 1, 2010, to February 29, 2020, and the COVID period ranges from March 1, 2020, to June 30, 2021. These two periods were when traditional long-only investors dominated the convertible bond market, defined as the Traditional Investor period. I use the Patell (1976) Z-test to examine if the average *CARs* are equal to zero and the Sign test to examine if median *CARs* are equal to zero. I also report the difference in *CARs* between the pre-COVID period and the COVID-19 crisis period. I employ an independent sample *t*-test and Mann-Whitney U rank test to examine if the mean and median of *CARs*(−1,1) and *CARs*(2,10) differ significantly across two sub-periods. Panel C presents the regression results of post-announcement return of convertible bond offerings. *ArbDemand/SO* is the estimated arbitrage-related short-selling relative to the share outstanding for each convertible bond, calculated using the coefficients from the regression in Columns (1), (2), and (3) of Table 4.1 Panel B, respectively. Industry fixed effects are defined using the Fama-French 12-industry classification. t-statistics, calculated using heteroskedasticity-robust standard errors, are in parentheses. N is the number of observations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

| Panel A: CARs(2,5) | | | | | |
|---|---|---|---|---|---|
| | N | Average | Median | Std. Dev | % of Negative Value |
| CAHedgeFundPeriod (1) | 830 | 0.338%* | 0.24%*** | 6.443% | 46.988% |
| ArbitragePeriod | 766 | 0.437%** | 0.253%*** | 6.380% | 46.867% |
| GFCPeriod | 64 | −0.849% | 0.162% | 7.100% | 48.438% |
| TraditionalInvestorPeriod (2) | 1,251 | −0.033% | −0.193% | 5.687% | 51.476% |
| LongOnlyPeriod | 1,110 | −0.025% | −0.208% | 5.478% | 51.799% |
| COVIDPeriod | 141 | −0.094% | 0.478% | 7.144% | 48.936% |
| Differences (1)-(2) | | 0.371%** | 0.435%** | | |
| Panel B: CARs(2,10) | | | | | |
| CAHedgeFundPeriod (1) | 830 | 0.339%* | 0.117%* | 9.564% | 49.639% |
| ArbitragePeriod | 766 | 0.515%** | 0.231%** | 9.475% | 48.956% |
| GFCPeriod | 64 | −1.769% | −2.001% | 10.428% | 57.812% |
| TraditionalInvestorPeriod (2) | 1,251 | −0.378%* | −0.321% | 8.549% | 53.073% |
| LongOnlyPeriod | 1,110 | −0.306% | −0.328% | 8.042% | 53.507% |
| COVIDPeriod | 141 | −0.943% | −0.102% | 11.829% | 49.645% |
| Differences (1)-(2) | | 0.717%** | 0.439%** | | |

**Table 4.5 continued**

Panel C: Regression analysis of post-announcement returns of convertible bond offerings

| | CARs(2,5) | | | | CARs(2,10) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| CAHedgeFundPeriod | 0.004 | −0.016** | −0.016** | −0.016** | 0.007* | −0.016 | −0.016 | −0.016 |
| | (1.29) | (−2.28) | (−2.27) | (−2.29) | (1.65) | (−1.50) | (−1.49) | (−1.50) |
| CrisisPeriod | −0.005 | −0.006 | −0.006 | −0.006 | −0.012 | −0.015* | −0.015* | −0.015* |
| | (−0.89) | (−1.22) | (−1.22) | (−1.22) | (−1.43) | (−1.77) | (−1.77) | (−1.76) |
| Amihud | | −0.093 | −0.087 | −0.102 | | 0.652 | 0.650 | 0.653 |
| | | (−0.13) | (−0.13) | (−0.15) | | (0.69) | (0.69) | (0.70) |
| ArbDemand/SO_DeltaNeutral | | −0.004 | | | | −0.011 | | |
| | | (−0.31) | | | | (−0.53) | | |
| CAHedgeFundPeriod * ArbDemand/SO_DeltaNeutral | | 3.314*** | | | | 3.690** | | |
| | | (3.10) | | | | (2.28) | | |
| ArbDemand/SO_ GammaBear | | | −0.004 | | | | −0.011 | |
| | | | (−0.31) | | | | (−0.53) | |
| CAHedgeFundPeriod * ArbDemand/SO_ GammaBear | | | 3.292*** | | | | 3.664** | |
| | | | (3.09) | | | | (2.27) | |
| ArbDemand/SO_ GammaBull | | | | −0.004 | | | | −0.011 |
| | | | | (−0.31) | | | | (−0.53) |
| CAHedgeFundPeriod * ArbDemand/SO_ GammaBull | | | | 3.322*** | | | | 3.683** |
| | | | | (3.11) | | | | (2.28) |
| Constant | 0.000 | 0.001 | 0.001 | 0.001 | −0.002 | −0.006 | −0.006 | −0.006 |
| | (0.11) | (0.17) | (0.16) | (0.18) | (−1.02) | (−0.54) | (−0.54) | (−0.54) |
| Industry fixed effect | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Observations | 2,081 | 2,081 | 2,081 | 2,081 | 2,081 | 2,081 | 2,081 | 2,081 |
| R-squared | 0.00 | 0.01 | 0.01 | 0.01 | 0.00 | 0.01 | 0.01 | 0.01 |

# Chapter 5. Summary and Conclusions

This thesis consists of three Chapters that explore security issuance activities, specifically focusing on corporate financing determinants external to the firm itself. Chapter 2 investigates the impact of the COVID pandemic on security issuance activities. The COVID crisis represents a combination of disaggregated sectoral demand and supply shocks. It employs a comprehensive model to analyze firms' choices between SEOs, convertibles, straight bonds, and bank loans, utilizing data from all U.S. industry firms spanning January 2010 to June 2021. This Chapter documents substantial increases in corporate security offerings during the COVID pandemic. The findings reveal that SEOs during the COVID pandemic were opportunistically timed and frequently packaged with news, which led to an improved market reception. In contrast, the surge in convertible and straight bond issuances during the pandemic cannot be explained by traditional corporate finance theories and government interventions. The evidence suggests that security choice models from the pre-COVID era may no longer be adequate to explain security offerings during periods of significant disruption and uncertainty, such as the COVID-19 crisis.

Chapter 3 examines the impact of peers’ MD&A narratives on firms’ seasoned equity issuance activities. This Chapter explores whether peers’ publicly available information affects firms’ financing decisions. The analysis reveals that firms are more likely to issue seasoned equity when their peers' MD&A narratives become more positive, especially for firms in competitive product markets. Additionally, firms respond to the changes in MD&A tones from both new and current peers but not from past peers. Firms are sensitive to the changing tone of peers who are larger, have more market share, and are more tangible than them. These findings indicate that this peer effect is based on learning motivations. Further tests suggest that the changes in tone in numerical sentences drive this peer effect. Regarding the post-issuance activities, issuers whose peers have increased their positive tone are more likely to use the SEO proceeds to finance R&D. This Chapter also documents a lower post-issuance stock return for those whose peers have increased their positive tone. The findings indicate that MD&A narratives serve as a significant source of industry-wide information that influences financing decisions.

Chapter 4 examines the impact of shifts in the investor base on convertible bond announcement returns from April 1986 to June 2021. The convertible bond market has witnessed significant changes in its investor base, which have affected the announcement effects of these bonds. This Chapter highlights that the demand side of the security market influences market reactions to convertible bond announcements. The cross-period differences in announcement returns disappear after controlling for arbitrage-induced short-selling measures. This result holds robustly across a range of convertible arbitrage strategies. There is a price reversal after the convertible bond issuance, supporting that the more negative convertible bond announcement effect is attributed to the price pressure caused by short-selling activities from convertible arbitrage hedge funds.

The findings documented in this thesis are relevant for corporate managers and also have implications for future academic studies on corporate financing decisions. Chapter 2 highlights the inability of established corporate finance theories to explain the surge in convertible and straight bond offerings during the COVID period. This observation underscores the need for developing new theories to better understand financing decisions in times of major disruptions and uncertainties. These new theories could also be important for addressing future crises, which are equally likely to be complex and multidimensional in terms of the shocks they represent for firms. Chapter 3 reveals that a firm's financing decisions are influenced by changes in the tone of peers' MD&A narratives. This influence can alter the competitive landscape and market dynamics, potentially putting the disclosing firm at a disadvantage. Firms should carefully consider the trade-off between the benefits and the costs associated with disclosing information when preparing their annual reports, particularly the MD&A section. Chapter 4 documents the significant impact of demand-side short-selling actions associated with convertible bond announcements on their returns. Firms may need to consider external factors such as the demand side of the security market when evaluating security issuances.

## Appendix B1: Variable description

This Appendix defines the variables in our analysis in alphabetical order and provides their sources. All balance sheet and income statement variables are measured at the fiscal quarter end preceding the given month (in the security choice analysis) or at the fiscal year-end preceding the announcement date (in the announcement returns analysis) unless noted otherwise.

| Variable | Definition | Source |
|---|---|---|
| 144A | Dummy variable equal to one if an offering is made under the Securities and Exchange Commission's Rule 144A. | SDC |
| Age | Natural logarithm of one plus the number of years the firm has been publicly listed. | CRSP |
| CAFundFlow | Capital flows into convertible arbitrage hedge funds over the quarter preceding the given month. | Trading Advisor Selection System |
| CAPE | Campbell and Shiller's (1988) CAPE ratio in the month preceding the given month, calculated as the ratio of the S&P 500 Index to the average of the last ten years of inflation-adjusted earnings. | www.econ.yale.edu/~shiller/data.htm |
| Cash | Ratio of cash and short-term investment (CHEQ) to total assets (ATQ). | CCM |
| CashFlow | Ratio of the sum of earnings before extraordinary items (IBQ) and depreciation (DPQ) to total assets (ATQ). | CCM |
| CashFlowVolatility | Industry cash flow standard deviation over the last four years (with a minimum of three years) preceding the given month. The industry is measured on a two-digit Standard Industry Classification (SIC) code level. | CCM |
| ContaminatingNews | Dummy variable equal to one if major confounding news is identified in the three trading days around the offering announcement date. Confounding news includes corporate actions, financial results, management team changes, research and development progress, and other major news about the firm's operations. | Manual search in Factiva |
| ConvPremium | Excess of the CBO's conversion price over the stock price measured on trading day −5. | SDC and CRSP |
| COVIDMonth | Dummy variable equal to one if the fiscal quarter includes any month between March 2020 and June 2021. | |
| COVIDPeriod | Dummy variable equal to one for months from March 2020 until June 2021. | |
| COVIDPeriod1 | Dummy variable equal to one for months from March 2020 until December 2020. | |
| COVIDPeriod2 | Dummy variable equal to one for months from January 2021 until June 2021. | |
| CreditRating | Moody's credit rating or equivalent S&P credit rating of the CBO as of the issue date. I assign a Moody's rating of Baa2 to unrated bonds. I assign a value of one to Moody's Aaa ratings and add a value of one to each subsequent rating. | SDC |
| DefaultSpread | Average yield difference between BAA- and AAA-rated corporate bonds over the month preceding the given month. | Federal Reserve Economic Data |
| DividendPaying | Dummy variable equal to one if a firm paid out a dividend (DVPSXQ) over the fiscal quarter preceding the given month. | CCM |
| FixedAssets | Ratio of property, plant, and equipment (PPENTQ) to total assets (ATQ). | CCM |
| GDPGrowth | Gross domestic product growth over the quarter preceding the given month. | |
| GFCPeriod | Dummy variable equal to one for months from January 2008 until December 2009. | |
| High Resilience Firms | The firms whose "affected share" score is below the median value of the sample, using the "affected share" score proposed by Koren and Peto (2020). | https://zenodo.org/records/4016325 |

**Appendix B1 continued**

| Variable | Definition | Source |
|---|---|---|
| InterestCoverage | Ratio of operating income before depreciation (OIBDP) to interest expenses (XINTQ) plus one. The missing value of XINTQ is set to zero. Following Blume et al. (1998), any ratio greater than 100 is capped at 100, and any negative interest coverage ratio is set at zero. | CCM |
| IssueSize | Ratio of offering proceeds to total assets (ATQ). | SDC and CCM |
| LoanSupplyTightness | Net percentage of domestic banks tightening standards for commercial and industrial loans to large and middle-market firms over the quarter preceding the given month. Following Erel et al. (2012), I focus on the net percentage of domestic respondents who claim that they are tightening standards for commercial and industrial loans. | Federal Reserve Economic Data |
| Leverage | Ratio of long-term debt (DLTTQ) to total assets (ATQ). | CCM |
| Low Resilience Firms | The firms whose "affected share" score is above the median value of the sample, using the "affected share" score proposed by Koren and Peto (2020). | https://zenodo.org/records/4016325 |
| Maturity | Years until maturity of the bond offering as of the issue date. | SDC |
| MarketReturn | Return on the S&P 500 index over the quarter prior to the given month. | Compustat |
| MarkettoBook | Market value of equity (PRC×SHROUT) measured five trading days preceding the given month, divided by the book value of equity (CEQQ). | CRSP and CCM |
| MarketVolatility | Annualized market return volatility, calculated using the daily S&P 500 index return over the quarter prior to the given month. | Compustat |
| Negatively Affected Firms | The firms that have had a negative cash flow change over the first quarter of the COVID period. | CCM |
| Positively Affected Firms | The firms that have had a positive cash flow change over the first quarter of the COVID period. | CCM |
| Proceeds | Natural logarithm of one plus the total proceeds raised in the fiscal quarter normalized by the total assets. | SDC and CCM |
| Profitability | Ratio of net income (NIQ) to total assets (ATQ). | CCM |
| RatedFirm | Dummy variable equal to one if the firm has an S&P domestic long-term issuer credit rating. | Compustat |
| ResidualVolatility | Standard deviation of residuals obtained from a market model regression based on daily stock returns, using the CRSP equally-weighted market index to proxy for the market return, over the quarter preceding the firm-month. | CRSP |
| R&DExpenditure | Ratio of research and development expense (XRDQ) to total assets (ATQ), with missing values set to zero. | CCM |
| Secondary | Dummy variable equal to one if an SEO includes a tranche offered by existing shareholders. | SDC |
| Shelf | Dummy variable equal to one for shelf-registered security offerings. | SDC |
| StockReturn | Stock return over the quarter preceding the given month. | CRSP |
| Tax | Ratio of income tax (TXTQ) to total assets (ATQ). | CCM |
| TBYield | Average yield on ten-year U.S. Treasury Bonds over the month preceding the given month. | Federal Reserve Economic Data |
| TermSpread | Average yield difference between ten-year Treasury Bonds and three-month Treasury Bills over the month preceding the given month. | Federal Reserve Economic Data |
| TotalAssets | Natural logarithm of total assets (ATQ), deflated by the Consumer Price Index. | CCM and Federal Reserve Economic Data |
| ΔCash | Natural logarithm of one plus the change in cash (CHEQ) normalized by the total assets (ATQ). | CCM |
| ΔInventory | Natural logarithm of one plus the change in inventory (INVTQ) normalized by the total assets (ATQ). | CCM |

**Appendix B1 continued**

| Variable | Definition | Source |
|---|---|---|
| ΔInventory | Natural logarithm of one plus the change in inventory (INVTQ) normalized by the total assets (ATQ). | CCM |
| ΔWC | Natural logarithm of one plus the change in working capital (WCAPQ) normalized by total assets (ATQ). | CCM |
| ∑Acquisition | Natural logarithm of one plus total acquisition (AQC) since issuance normalized by the total assets (ATQ). | CCM |
| ∑CapitalExpense | Natural logarithm of one plus total capital expenditure (CAPX) since issuance normalized by the total assets (ATQ). | CCM |
| ∑LTDReduction | Natural logarithm of one plus total long-term debt reduction (DLTR) since issuance normalized by the total assets (ATQ). | CCM |
| ∑R&D | Natural logarithm of one plus total research and development expenditure (XRDQ) since issuance normalized by total assets (ATQ). | CCM |

## Appendix C1 Variable Definitions

This Appendix defines the variables in my analysis and provides their sources. All balance sheet and income statement variables are measured at the fiscal year end preceding the given year (in the security choice analysis) or at the fiscal year end preceding the issue date (in the use of proceeds and post-issuance stock return analysis) unless noted otherwise.

| Variable | Calculation | Source |
|---|---|---|
| *Change in MD&A Tone* | | |
| ΔPeer Positive | Average ΔFirm Positive of peers. | Own calculations |
| ΔPeer Negative | Average ΔFirm Negative of peers。 | Own calculations |
| ΔFirm Positive | Change in the number of positive words contained in the firm's MD&A divided by the total number of words. | Own calculations |
| ΔFirm Negative | Change in the number of negative words contained in the firm's MD&A divided by the total number of words. | Own calculations |
| *Change in Firm Characteristics* | | |
| ΔPeer Cash | Average change in peers' cash and short-term investment (CHE) divided by total assets (AT). | Compustat |
| ΔPeer Frim Size | Average change in peers' natural logarithm of total assets (AT), deflated by the Consumer Price Index. | Compustat and Federal Reserve Economic Data |
| ΔPeer Fixed Assets | Average change in peers' property, plant, and equipment (PPENT) divided by total assets (AT). | Compustat |
| ΔPeer Leverage | Average change in peers' long-term debt (DLTT) divided by total assets (AT). | Compustat |
| ΔPeer Profitability | Average change in peers' operating income before depreciation (OIBDP) divided by total assets (AT). | Compustat |
| ΔPeer R&D | Average change in peers' research and development expense (XRD) divided by total assets (AT). | Compustat |
| ΔPeer Tobin | Average change in peers' Tobin's Q, which is defined as total assets [AT] - book value of equity [CEQ]+market value of equity [CSHO×PRCC] divided by total assets [AT]. | Compustat |
| Peer SEO | The proportion of peers that issue SEO in the year. | SDC |
| Peer Stock Return | Average peers' stock return over the year. | CRSP |
| *Change in Firm Characteristics* | | |
| ΔFirm Cash | Change in the firm's cash and short-term investment (CHE) divided by total assets (AT). | Compustat |
| ΔFirm Firm Size | Change in the firm's natural logarithm of total assets (AT), deflated by the Consumer Price Index. | Compustat and Federal Reserve Economic Data |
| ΔFirm Fixed Assets | Change in the firm's property, plant, and equipment (PPENT) divided by total assets (AT). | Compustat |
| ΔFirm Leverage | Change in the firm's long-term debt (DLTT) divided by total assets (AT). | Compustat |
| ΔFirm Profitability | Change in the firm's operating income before depreciation (OIBDP) divided by total assets (AT). | Compustat |
| ΔFirm R&D | Change in the firm's research and development expense (XRD) divided by total assets (AT). | Compustat |
| ΔFirm Tobin | Change in the firm's Tobin's Q, which is defined as total assets [AT] - book value of equity [CEQ]+market value of equity [CSHO×PRCC] divided by total assets [AT]. | Compustat |
| Firm Stock Return | Stock return over the past year. | CRSP |
| *Competitiveness* | | |

| Variable | Calculation | Source |
|---|---|---|
| EntryCosts | Natural logarithm of the weighted average of the gross value of the cost of property, plant, and equipment (PPENT) for firms in the industry, weighted by each firm's market share (SALES). | Compustat |

**Appendix C1 continued**

| Variable | Calculation | Source |
|---|---|---|
| IndustrySize | Natural logarithm of total industry sales (SALES). | Compustat |
| ProductSubstitutability | The ratio of industry operating costs (COGS+XSGA+DPACT) to total industry sales (SALES). | Compustat |
| Total similarity | The sum of the pairwise similarities between the firm and all peers in the sample in the given year. | Hoberg's website |
| *Use of proceeds* | | |
| ΔCash | Natural logarithm of one plus the change in cash (CHE) normalized by the total assets (AT) measured at the fiscal quarter end before issuance. | Compustat |
| ΔInventory | Natural logarithm of one plus the change in inventory (INVT) normalized by the total assets (AT) measured at the fiscal quarter end before issuance. | Compustat |
| ∑Acquisition | Natural logarithm of one plus total acquisition (AQC) since issuance normalized by the total assets (AT) measured at the fiscal quarter end before issuance. | Compustat |
| ∑CapitalExpense | Natural logarithm of one plus total capital expenditure (CAPX) since issuance normalized by the total assets (AT) measured at the fiscal quarter end before issuance. | Compustat |
| ∑LTDReduction | Natural logarithm of one plus total long-term debt reduction (DLTR) since issuance normalized by the total assets (AT) measured at the fiscal quarter end before issuance. | Compustat |
| ∑R&D | Natural logarithm of one plus total research and development expense (XRD) since issuance normalized by the total assets (AT) measured at the fiscal quarter end before issuance. | Compustat |
| Firm size | Natural logarithm of total assets (AT), deflated by the Consumer Price Index. | CCM and Federal Reserve Economic Data |
| LogProceeds | Natural logarithm of one plus the total proceeds raised in the fiscal quarter normalized by the total assets (AT). | SDC and Compustat |

## Appendix C2 Measuring Tone of MD&A Disclosures

Following Loughran and McDonald (2011), I took the following steps with each 10-K filing:

- Step 1: Download and clean 10-k filings
    - Remove ASCII-Encoded segments
    - Remove <DIV>, <TR>, <TD>, and <FONT> tags
    - Remove all XML and XBRL
    - Remove SEC Header/Footer
    - Replace \  and \  with a blank space.
    - Replace \&AMP and \&#38 with “&”
    - Remove all remaining extended character references
    - Tag Exhibits
    - Remove Markup Tags
    - Excess line feeds are removed
- Step 2: Remove the 10-K filing if the total number of words with two or more letters is fewer than 2,000.
- Step 3: Parse the MD&A section.
    - Extract Item 7 (or Item 6 for small firms)) and Item 7A if applicable.
- Step 4: Remove the 10-K filing if the total number of words in the MD&A section is fewer than 250.
- Step 5: Remove stop words
- Step 6: Calculate the MD&A tone

## Appendix C3 Word list

| Category | Words |
|---|---|
| Investment | industry, market, demand, economic, customer, growth, invest, expansion, expand, capital expenditure, capital expenditures, capex, capx. |
| Numerical | one, two, three, four, five, six, seven, eight, nine, ten, eleven, twelve, thirteen, fourteen, fifteen, sixteen, seventeen, eighteen, nineteen, twenty, thirty, forty, fifty, sixty, seventy, eighty, ninety, hundred, thousand, million, billion, and any Arabic numeral expressions including monetary expressions, year, and percentages. |
| Forward-looking | Words: will, future, aim, anticipate, assume, commit, estimate, expect, forecast, foresee, hope, intend, plan, project, seek, target, and past and future tense of these words.<br><br>Phrase: next fiscal, next month, next period, next quarter, next year, incoming fiscal, incoming month, incoming period, incoming quarter, incoming year, coming fiscal, coming month, coming period, coming quarter, coming year, upcoming fiscal, upcoming month, upcoming period, upcoming quarter, upcoming year, subsequent fiscal, subsequent month, subsequent period, subsequent quarter, subsequent year, following fiscal, following month, following period, following quarter, following year. |

## Appendix D1: Variable Description

This Appendix defines the variables in alphabetical order. Balance sheet and income statement variables are obtained from the CCM database and measured at the fiscal year-end preceding the announcement date unless indicated otherwise. Stock price data are obtained from the CRSP database. The trading days are measured relative to the announcement date. Issue-specific characteristics are obtained from the SDC database and estimated at the issue date unless indicated otherwise. Macroeconomic conditions are collected from the Datastream database and measured over the quarter prior to the convertible bond issue date unless indicated otherwise.

| Variable name | Calculation |
|---|---|
| *144A* | A dummy variable equals one if the offering is made under Rule 144A. |
| *Amihud* | Amihud's (2002) illiquidity measure is calculated as the daily average ratio of absolute stock returns to dollar trading volumes over the window (−120, −20) relative to the convertible bond announcement date ($\times 10^6$). |
| ArbDemand/SO_DeltaNeutral | Estimated arbitrage-related short-selling relative to the share outstanding, assuming convertible arbitrageurs follow a delta-neutral hedging strategy. |
| ArbDemand/SO_GammaBear | Estimated arbitrage-related short-selling relative to the share outstanding, assuming convertible arbitrageurs follow a bearish gamma hedging strategy. |
| ArbDemand/SO_GammaBull | Estimated arbitrage-related short-selling relative to the share outstanding, assuming convertible arbitrageurs follow a bullish gamma hedging strategy. |
| *CAFlow* | The percentage capital flows into the convertible arbitrage hedge flow over the quarter prior to the convertible bond issuance. I collect hedge fund flow data from the TASS database. |
| CAHedgeFundPeriod | A dummy variable equals one if the offering is announced between January 1, 2000, and December 31, 2009, when convertible arbitrage hedge funds dominated the convertible bond market. |
| *Callable* | A dummy variable equals one if the offering is callable within the first three years of the bond's life. |
| *Cash* | The ratio of cash and short-term investment (CHE) to total assets (AT). |
| *ConvPremium* | The excess (expressed as a percentage) of the convertible bond offering's conversion price over the stock price measured on trading day −5. |
| *CrisisPeriod* | A dummy variable equals one if the offering is announced over the GFC period (from September 15, 2008, to December 31, 2009) and the COVID period (from March 1, 2020, to June 30, 2021). |
| *CreditRating* | Moody's credit ratings or equivalent S&P credit ratings of the convertible bond at the issue date. Consistent with Loncarski et al. (2009), I assign Moody's rating of Baa2 to unrated convertible bonds. In line with Chan and Chen (2007), I assign a value of one to Moody's Aaa ratings and add a value of one to each subsequent rating. That is, the lowest rating offering Moody's rating of Ca) is assigned with a value of 20. |
| *DefaultSpread* | The yield difference between the BAA- and AAA-rated corporate bonds. |
| *Delta* | The sensitivity of convertible bond price to the change in its underlying stock price, calculated as: $$Delta = e^{-\delta T}N(d_1) = e^{-\delta T}N\left\{\frac{\ln\left(\frac{S}{X}\right) + \left(r - \delta + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}\right\}$$ where N(·) is the cumulative probability under a standard normal distribution; S is the stock price measured on trading day −5 relative to the announcement date; X is the conversion price; r is the 10-year U.S. Treasury bond yield; $\delta$ is the continuously compounded dividend yield; $\sigma$ is the annualized stock return volatility; T is the time between the issue date and the maturity date. |
| *DeltaNeutral/SO* | The required number of shares needed to be shorted by the bondholder to obtain a delta-neutral position at the issue date, scaled by the number of shares outstanding measured on trading day −20 relative to the announcement date. The DeltaNeutral is calculated as: $$DeltaNeutral = \frac{(Number\ of\ convertibles\ issues)(Face\ value)(Delta)}{Conversion\ price}$$ |
| *DividendPaying* | A dummy variable equals one if the firm paid a dividend (DVPSX_F) over the previous fiscal year and zero otherwise. |
| *FixedAssets* | The ratio of property, plant, and equipment (PPENT) to total assets (AT). |

**Appendix D1 continued**

| Variable name | Calculation |
| --- | --- |
| *Gamma* | The sensitivity of convertible bond delta to the change in its underlying stock price, calculated as: $$Gamma = e^{-\delta T} N'(d_1) = e^{-\delta T} \frac{\varphi\left\{\frac{\ln\left(\frac{S}{X}\right) + \left(r - \delta + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}\right\}}{S\sigma\sqrt{T}}$$ where $\varphi(\cdot)$ is the probability distribution function of standard normal distribution, and other variables are the same as the variables defined in Delta. |
| *GammaBear/SO* | The required number of shares needed to be shorted by the bondholder to obtain a gamma bear hedge at the issue date, scaled by the number of shares outstanding measured on trading day −20 relative to the announcement date. The GammaBear is calculated as: $$\text{GammaBear} = \frac{(Number\ of\ convertibles\ issues)(Face\ value)(Delta + 0.09)}{Conversion\ price}$$ |
| *GammaBull/SO* | The required number of shares needed to be shorted by the bondholder to obtain a gamma bull hedge at the issue date, scaled by the number of shares outstanding measured on trading day −20 relative to the announcement date. The GammaBull is calculated as: $$\text{GammaBull} = \frac{(Number\ of\ convertibles\ issues)(Face\ value)(Delta - 0.09)}{Conversion\ price}$$ |
| *InstitOwnership* | The percentage of shares held by 13F institutions reported in the Thomson-Reuters Institutional Holdings database. |
| *InterestCoverage* | The ratio of operating income after depreciation (OIADP) to interest expense (XINT) plus one. Following Blume et al. (1998), any interest coverage ratio greater than 100 is bounded at 100, and any negative interest coverage ratio is set to 0. |
| *InterestRate* | The 10-year U.S. treasury bond yield. |
| *Issue=Announcement* | A dummy variable that equals one if the convertible bond is issued within one trading day of the announcement date. |
| *Leverage* | The ratio of long-term debt (DLTT) to total assets (AT). |
| *LogAge* | The natural logarithm of the number of years the firm has been listed plus one (i.e., log(1+age)). |
| *LogAsset* | Natural log of total assets of a firm (AT), deflated by the Consumer Price Index. |
| *MarketRunups* | The total return on the S&P 500 index over the quarter prior to the issue date. |
| *MarkettoBook* | The market value of equity (calculated as closing price (PRCC_F) multiplied by the number of common shares outstanding (CSHO)), divided by the book value of equity (CEQ). |
| *MarketVolatilities* | Annualized market return volatility, calculated using the daily S&P 500 index return over the quarter prior to the issue date. |
| *Profitability* | The ratio of earnings before interest, tax, depreciation, and amortization (EBITDA) to the total assets (AT). |
| *Proceeds* | Amount of capital raised at a convertible bond offering scaled by total assets (AT). |
| *StockRunUp* | Stock return over the window (−60, −2) relative to the announcement date. |
| *StockVolatility* | Annualized stock return volatility, calculated from daily stock returns over the window (−240, −40) relative to the announcement date. |
| *Tax* | The ratio of income taxed (TXT) to total assets (AT). |
| *TermSpread* | The difference between the 10-year U.S. Treasury bond yield and 3-month U.S. Treasury bill yield. |

## Appendix D2: Pearson correlation matrix of variables

Panel A and Panel B report correlation among variables included in Tables 4.1 and 4.4.

| Panel A: Correlations among variables included in estimated arbitrage-related short-selling | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| $SS/SO$ | | | | | | | | | | | |
| Amihud | −0.05 | | | | | | | | | | |
| DividendPaying | −0.02 | −0.02 | | | | | | | | | |
| InstOwn | 0.04 | −0.36 | −0.03 | | | | | | | | |
| StockVolatility | 0.00 | 0.13 | −0.28 | −0.12 | | | | | | | |
| DeltaNeutral/SO | 0.12 | 0.43 | −0.12 | −0.32 | 0.16 | | | | | | |
| GammaBear/SO | 0.12 | 0.43 | −0.11 | −0.32 | 0.15 | 1.00 | | | | | |
| GammaBull/SO | 0.12 | 0.43 | −0.13 | −0.32 | 0.17 | 1.00 | 1.00 | | | | |
| Gamma | 0.06 | 0.12 | −0.11 | −0.11 | 0.04 | 0.14 | 0.15 | 0.13 | | | |
| Callable | −0.06 | 0.20 | 0.16 | −0.41 | −0.11 | 0.22 | 0.21 | 0.22 | −0.16 | | |
| ConvPremium | −0.09 | −0.07 | −0.05 | 0.14 | −0.04 | −0.35 | −0.35 | −0.35 | −0.04 | −0.11 | |
| CAFundFlow | −0.05 | −0.08 | −0.07 | 0.14 | −0.10 | −0.10 | −0.10 | −0.10 | 0.13 | −0.19 | 0.02 |

**Appendix D2 continued**

Panel B: Correlations among variables included in announcement return analysis

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) | (21) | (22) | (23) | (24) | (25) | (26) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CAR(−1,1) | | | | | | | | | | | | | | | | | | | | | | | | | | |
| CAPeriod | −0.10 | | | | | | | | | | | | | | | | | | | | | | | | | |
| CrisisPeriod | −0.10 | −0.06 | | | | | | | | | | | | | | | | | | | | | | | | |
| ArbDemand/SO_DeltaNeutral | −0.19 | 0.10 | 0.11 | | | | | | | | | | | | | | | | | | | | | | | |
| ArbDemand/SO_GammaBear | −0.19 | 0.10 | 0.11 | 1.00 | | | | | | | | | | | | | | | | | | | | | | |
| ArbDemand/SO_GammaBull | −0.19 | 0.10 | 0.11 | 1.00 | 1.00 | | | | | | | | | | | | | | | | | | | | | |
| StockRunUp | 0.00 | 0.05 | 0.08 | −0.06 | −0.06 | −0.06 | | | | | | | | | | | | | | | | | | | | |
| Cash | −0.09 | −0.04 | 0.04 | 0.10 | 0.10 | 0.10 | 0.11 | | | | | | | | | | | | | | | | | | | |
| Tax | 0.08 | 0.01 | −0.15 | −0.13 | −0.13 | −0.13 | −0.04 | −0.12 | | | | | | | | | | | | | | | | | | |
| Leverage | −0.05 | 0.04 | 0.11 | 0.04 | 0.04 | 0.04 | 0.03 | −0.14 | −0.16 | | | | | | | | | | | | | | | | | |
| StockVolatility | −0.18 | 0.19 | 0.30 | −0.02 | −0.02 | −0.02 | 0.25 | 0.20 | −0.20 | 0.05 | | | | | | | | | | | | | | | | |
| MarkettoBook | 0.06 | −0.09 | 0.10 | −0.04 | −0.04 | −0.04 | 0.04 | 0.25 | −0.04 | −0.08 | 0.01 | | | | | | | | | | | | | | | |
| FixedAssets | 0.01 | 0.01 | 0.00 | −0.13 | −0.13 | −0.13 | −0.02 | −0.43 | −0.02 | 0.24 | 0.00 | −0.13 | | | | | | | | | | | | | | |
| LogAssets | 0.03 | 0.23 | 0.10 | −0.04 | −0.04 | −0.04 | −0.07 | −0.35 | −0.04 | 0.22 | −0.14 | −0.08 | 0.22 | | | | | | | | | | | | | |
| LogAge | 0.02 | 0.11 | 0.03 | 0.04 | 0.04 | 0.04 | −0.08 | −0.26 | 0.00 | 0.09 | −0.20 | −0.13 | 0.10 | 0.42 | | | | | | | | | | | | |
| Profitability | 0.12 | 0.06 | −0.08 | −0.10 | −0.10 | −0.10 | −0.03 | −0.55 | 0.45 | −0.05 | −0.33 | −0.08 | 0.22 | 0.29 | 0.19 | | | | | | | | | | | |
| InterestCoverage | 0.01 | 0.04 | −0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.21 | 0.23 | −0.46 | −0.02 | 0.05 | −0.18 | −0.15 | −0.07 | 0.12 | | | | | | | | | | |
| Delta | −0.12 | 0.20 | −0.08 | 0.04 | 0.04 | 0.05 | 0.12 | 0.08 | 0.03 | −0.01 | 0.39 | −0.03 | 0.02 | −0.28 | −0.29 | −0.05 | 0.01 | | | | | | | | | |
| CreditRating | 0.06 | −0.01 | −0.16 | −0.17 | −0.17 | −0.17 | 0.01 | −0.22 | 0.07 | 0.17 | 0.04 | −0.09 | 0.18 | −0.01 | −0.04 | 0.15 | −0.15 | 0.22 | | | | | | | | |
| Proceeds | 0.00 | −0.14 | −0.04 | 0.06 | 0.06 | 0.06 | 0.13 | 0.53 | 0.01 | −0.21 | 0.16 | 0.23 | −0.28 | −0.65 | −0.34 | −0.36 | 0.22 | 0.16 | −0.07 | | | | | | | |
| 144A | −0.04 | 0.35 | 0.07 | 0.22 | 0.21 | 0.21 | 0.04 | 0.16 | −0.08 | −0.04 | 0.09 | 0.08 | −0.19 | 0.10 | 0.01 | −0.05 | 0.14 | −0.02 | −0.27 | 0.02 | | | | | | |
| Issue=Announcement | −0.12 | 0.37 | 0.15 | 0.32 | 0.32 | 0.32 | −0.01 | 0.21 | −0.19 | 0.04 | 0.13 | 0.07 | −0.16 | 0.24 | 0.06 | −0.17 | 0.07 | −0.12 | −0.38 | −0.03 | 0.59 | | | | | |
| InterestRate | 0.16 | −0.03 | −0.45 | −0.35 | −0.35 | −0.35 | 0.04 | −0.28 | 0.29 | −0.03 | −0.18 | −0.12 | 0.23 | −0.11 | −0.03 | 0.30 | −0.04 | 0.23 | 0.38 | −0.02 | −0.42 | −0.61 | | | | |
| TermSpread | −0.02 | 0.08 | −0.06 | −0.01 | −0.01 | −0.01 | 0.04 | −0.06 | 0.02 | −0.01 | 0.13 | −0.13 | 0.07 | 0.01 | 0.08 | 0.04 | 0.01 | 0.05 | 0.08 | −0.10 | −0.01 | −0.05 | 0.01 | | | |
| DefaultSpread | −0.08 | 0.13 | 0.43 | 0.03 | 0.03 | 0.03 | 0.06 | −0.12 | 0.02 | 0.05 | 0.20 | −0.10 | 0.09 | 0.11 | 0.12 | 0.04 | −0.09 | 0.01 | 0.03 | −0.16 | −0.15 | −0.03 | −0.08 | 0.20 | | |
| MarketRunups | 0.03 | −0.11 | 0.03 | 0.13 | 0.13 | 0.13 | 0.33 | −0.01 | 0.06 | 0.00 | 0.04 | −0.01 | 0.01 | −0.06 | −0.02 | 0.04 | 0.02 | 0.04 | 0.03 | 0.03 | −0.05 | −0.09 | 0.10 | 0.07 | 0.11 | |
| MarketVolatilities | −0.08 | 0.07 | 0.57 | −0.18 | −0.18 | −0.18 | −0.01 | −0.01 | −0.06 | 0.08 | 0.23 | 0.05 | 0.03 | 0.13 | 0.02 | −0.03 | −0.04 | −0.02 | −0.07 | −0.06 | 0.07 | 0.13 | −0.23 | −0.09 | 0.48 | −0.29 |