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Timing Manipulation in Firm Disclosures

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Timing Manipulation in Firm Disclosures

A dissertation submitted in partial satisfaction of
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in Management

by

Wenyu Meng

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ABSTRACT OF THE DISSERTATION

Timing Manipulation in Firm Disclosures

by

Wenyu Meng

Doctor of Philosophy in Management

University of California, Los Angeles, 2022

Professor Avanidhar Subrahmanyam, Chair

Do CEOs time firm disclosures around their stock sales? I identify evidence of their manipulation in the timing of mandatory disclosures, whose high litigation risk deters CEOs from delivering misleading or fraudulent information. To disentangle timing of disclosures around predetermined sales from timing of sales around scheduled disclosures, I show that a CEO's exogenously strengthened intention to sell (after option vesting dates) is followed by disclosures with a heightened negative tone, but not preceded by disclosures with a heightened positive tone. When a CEO's urgency to sell (before option expiration dates) constrains her flexibility to time sales around disclosures, the negative tone of post-sale disclosures intensifies further, but the positive tone of pre-sale disclosures does not intensify. These results suggest that a CEO follows a passive strategy in mandatory disclosures: she withholds negative information to prevent the stock price from falling, instead of accelerating or generating positive information to push up the stock price before her sales.

The dissertation of Wenyu Meng is approved.

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2022

To Pluto Jr.,

my fluffy companion, my love, and my light,

without whom I would not survive this lonely, two-year-long COVID lockdown.

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1 Introduction

An efficient financial market is built upon the integrity of firm disclosures. Concerns about information asymmetry may discourage outside investors from holding firms' shares and in return, impair market liquidity and escalate funding frictions. Diamond and Verrecchia (1991) provide theoretical support for this reasoning by showing that public disclosure helps reduce the cost of capital as it eases the information asymmetry problem. Public policy-makers have long recognized the importance of regulating firm disclosures and attempted to mitigate and dissuade insider opportunism, leading to a number of regulations.

In the United States, Section 16(b) of the Securities Exchange Act of 1934, SEC Regulation FD (Fair Disclosure) in 2000, and Sections 403 and 409 of the Sarbanes-Oxley Act (SOX) of 2002 all aim to curtail insiders' information abuse and ensure an accurate and timely information flow into the financial market.[1] Indeed, the Securities and Exchange Commission (SEC) enforces these rules to combat inaccurate disclosures and fraud.[2] In this paper, I focus on mandatory disclosures, which I define as those publicized through Form 8-Ks.[3] The stringent monitoring of this class of disclosures weakens a CEO's ability to manipulate content, and therefore helps in securing the truthfulness of the information disclosed

[1] Section 16(b) of the Securities Exchange Act of 1934 authorizes a firm to claim back the "short-swing profit," if a company insider realizes a profit from the purchase and sale, or sale and purchase, of the company's equity securities within a period of fewer than six months. Regulation Fair Disclosure was enacted in October 2000 in an effort to prevent public companies from selectively disclosing material nonpublic information to market professionals and certain shareholders. Section 403 requires insiders to file a Form 4 to the SEC within two business days once they have equity transactions. Section 409 requires publicly traded firms to disclose material information "on a rapid and current basis" regarding changes in financial condition or operations. A firm is obliged to file a Form 8-K within four business days once a triggering event occurs. All types of material events that require a timely disclosure are specified in the Form 8-K.

[2] If a CEO fabricates positive news or mitigates negative news, she is liable to be charged with delivering fraudulent and misleading information. For example, in September 2018, SeaWorld Entertainment Inc. and its former CEO were fined $5 million for misleading investors about the impact the documentary film Blackfish had on the firm's reputation and business. More examples of the SEC investigations can be found at: https://www.sec.gov/news/pressreleases.

[3] There is no clear boundary as to how to divide voluntary and mandatory disclosures. In this paper, I classify all the disclosures filed through Form 8-Ks as mandatory disclosures, as compared to all other disclosures filed through voluntary channels, such as management forecasts and discretionary news. Different from voluntary disclosures that involve little litigation concern, mandatory disclosures are truthful and costly to file.

through this channel.

Unlike information content that can be investigated ex post, the arrival time of information is still at a CEO's discretion. The objective of this paper is to question the "timeliness" of disclosures and examine whether a CEO exploits the timing of disclosures for her personal gains. For instance, when a negative material event occurs, the firm is required to disclose this information through a Form 8-K to the SEC within four business days in compliance with Section 409 of SOX. If its CEO has some exogenous need for sale slightly after the designated deadline, she may be incentivized to postpone the disclosure so as to cash out before the stock price falls. I provide evidence to show that this manipulation in the timing of mandatory disclosures exists among CEOs of publicly traded firms in the United States.

Following a well-established textual analysis mechanism in Loughran and McDonald (2011), I construct a content score for each disclosure. It is defined as the minus percentage of negative words in this disclosure.[4] If a disclosure narrates information with more negative words (e.g., termination, penalties, and misstatement), it is considered as delivering more negative information. Depending on this measure, I find a CEO presents an information pattern clearly aligned with her personal interest. The information disclosed before her stock sales is more positive than her firm's usual level, while the information disclosed after the sales is more negative. This relation, however, is not sufficient to reach the conclusion of a CEO's manipulation, as her sale decision intertwines with information. A predetermined sale date with manipulation in the timing of disclosures and a flexible sale date that accommodates the fixed schedule of disclosures can produce the same favorable information pattern around stock sales. This entails a causal effect test to untwist a CEO's sale decision from its dependence on information.

To identify an exogenous variation in a CEO's intention to sell, I develop an instrument from the vesting dates of her executive option grants. The method is inspired by Edmans, Goncalves-Pinto, Groen-Xu, and Wang (2018), who use the vesting date of a share grant

[4]The specific structuring of the disclosure content measure varies slightly according to the different setups of my tests.

as their instrument. The vesting date of an option is its earliest exercisable date, on which a CEO's exposure to equity holdings rises sharply, thus escalating her under-diversification concern. This stronger motive to diversify implies the CEO's higher likelihood of stock sales. Indeed, her higher propensity to sell driven by newly vested options successfully captures her actual sales. At the same time, the vesting date of an option is determined on its grant date, which is long before the option vests. Since it is impossible to forecast what material event will take place in the far future, a vesting date is a predetermined date independent of information. This backs the exclusion restriction assumption. Therefore, I use a CEO's propensity to sell predicted from her option vesting dates as the instrument for her endogenous sale decisions. Its variation represents an exogenous strengthening in her intention to sell because it stems from her diversification need rather than information, and thus enables me to focus on her strategic timing of disclosures around "predetermined" sales.

I find evidence of a CEO's timing manipulation, and it exists only selectively. On the one hand, my event study identifies a pronounced negative tone in the disclosures subsequent to a CEO's option vesting dates. Furthermore, the 2SLS regression results show that a CEO's stronger intention to sell is followed by disclosures with a heightened negative tone. As a CEO has no incentive to suppress the stock price after cashing out, this implies that the subsequently disclosed negative information existed before her stock sale, and she withholds it until the sale. The setting of mandatory disclosures also averts the reverse causality issue that the subsequent negative disclosure reports her sale, because routine information, like a CEO's personal transactions, is not filed with the SEC through Form 8-Ks. On the other hand, my event study identifies no salient positive tone in the disclosures prior to a CEO's option vesting dates. The 2SLS regression results also show that a CEO's stronger intention to sell is not preceded by disclosures with a heightened positive tone. This suggests that no positive disclosure arises in advance of her stronger incentive to sell. A CEO decelerates the disclosures of negative information but does not accelerate those of positive information. This asymmetry makes sense, since the CEO may have no truthful positive information to speed up its disclosure.

Apart from timing, the word choice of a disclosure also leaves a CEO some discretionary space to exploit. A CEO may manipulate its tone with fewer negative words before her stock sales to cash out at a higher price. Additionally, she may originate positive events, such that the disclosed positive information is not fake, thus involving no litigation cost. The CEOs in my sample do not manipulate the wording of disclosures as expected, because I find no significantly positive tone in the disclosures preceding a CEO's exogenous need for sale. A publicly traded firm is required to file a Form 8-K to the SEC whenever an event that falls into the "material event" category occurs. The firm may use established templates when disclosing information through this channel, leaving its CEO limited space to exploit. The insignificant results also provide support for my assumption that a CEO's ability to generate positive information through fabricating or originating good news is mostly constrained in mandatory disclosures.

I also find that a CEO's urgency to sell makes a difference in disclosures. Referring to the threshold proposed in Malmendier and Tate (2005), I define an "expiring option" as an option with less than one year remaining life. The approaching deadline of a CEO's expiring option fuels her urgency to sell and limits her flexibility to time sales based on information. Under this circumstance, she is more incentivized to manipulate information in favor of her stock sales. To measure the incremental difference in disclosures due to this urgency, I split the disclosures around sales into two mutually exclusive groups: overlapping and non-overlapping. When a CEO's intention to sell overlaps with her urgency to sell, the CEO is more prone to disclosing positive information and withholding negative information before this sale. The "overlapping" group consists of the disclosures that tend to reflect this manipulation. Given a CEO's stock sale date and her exercise or expiration date of an expiring option, if a disclosure is filed in the overlapping interval of the pre-sale and pre-exercise (post-sale and post-exercise) windows, it is expected to report in a more positive (negative) tone. [5]

The negative tone of post-sale disclosures intensifies further in the "overlapping" group, when compared to the "non-overlapping" group. Consistent with the asymmetry I discover in the causal effect test, the positive tone of pre-sale disclosures does not intensify. These findings add to the evidence of a CEO's timing manipulation. Without manipulation, a CEO takes information as given. When she knows the forthcoming negative news, the optimal decision for her is always to cash out, irrespective of her holdings of expiring options. Therefore, in the absence of manipulation, the disclosures of the "overlapping" and "non-overlapping" groups should be reported with a similar tone. As I verify the statistical significance of the difference between the post-sale disclosures of the two groups, this is solid evidence of manipulation. Moreover, it is timing manipulation achieved by withholding negative information. As suggested by Murphy (2013), a CEO of a public firm usually has an incentive package that is connected with the firm's stock price, so there is no reason for her to deliberately disclose more negative information after her stock sales. She would rather disclose more positive information before sales if she may tailor the content or wording of disclosures to her personal needs.

The basis of timing manipulation is "a predetermined sale with a flexible timing of disclosures." My instrument develops from a situation that exogenously strengthens a CEO's intention to sell and simulates her predetermined sales. Likewise, a CEO's urgency to sell arises from her predetermined option expiration dates and constrains her ability to time sales freely. Collectively, I unveil a new scope in CEO opportunism. Unlike the strategies that actively push up the stock price, such as accelerating or generating positive information, a CEO's disclosure strategy is more passive when information must be truthful. She only withholds negative information to prevent the stock price from falling before her stock sales. The favorable information pattern of the disclosures around a CEO's stock sales is therefore a joint outcome of her timing of sales and timing of disclosures, with the former accounting

[5] A more detailed definition of "overlapping" and its mathematical description is in Chapter 3.

for the positive information gathering before her sales and the latter contributing to the negative information gathering after her sales.

The key presumption of a CEO's timing strategy is that, the withheld information elicits negative market responses when it is disclosed after her stock sales.[6] Otherwise, her manipulation is not worthwhile. To validate this implication, I divide the post-sale cumulative abnormal returns (CARs) by whether or not their associated stock sales are followed by any disclosure. Since the market can closely track a CEO's sales, the sale itself may depress the stock price, yielding a negative post-sale CAR. Consequently, I use the post-sale CARs without any disclosure as the baseline and examine their incremental difference from those with at least one disclosure. This difference is positively correlated with the extra information disclosed after stock sales, thus linking disclosures to stock performance.[7] One standard deviation enhancement in a CEO's intention to sell drives down the information positivity of its subsequent disclosures by some extent that is associated with an annualized CAR of -3.66%. If the CEO disclosed negative information as it occurred before her sales, she would have sold her stocks at a lower price. She earns an annualized profit of $92,500 per sale as she applies this timing strategy.[8]

[6] The validation tests of my disclosure content score corroborate this relation: the higher percentage of negative words of a disclosure predicts a lower post-file CAR; when this percentage is established as a daily firm characteristic, it also predicts the risk-adjusted return in both panel and Fama-MacBeth regressions.

[7] In the case of general news, this correlation may also arise from a reverse direction. For example, if a CEO sells at a large scale, the stock price may plummet, making the media report the price drop with more negative words. The mandatory disclosures in my setup basically void this possibility. Routine information like stock price drops is not reported to the SEC through Form 8-Ks, thus not covered in my disclosure sample. On the other hand, the negative events that must be reported to the SEC, such as direct financial obligations, material impairment losses, and terminations of material definitive agreements, will not take place simply due to a CEO's personal sale.

[8] The average worth of a CEO's stock sales per sale date is $2,527,313 for CEOs of publicly traded firms in the U.S. from 2008 to 2018 in my sample.

2 Literature review

2.1 Textual analysis

I employ textual analysis techniques to quantify the information of each disclosure. The pioneering work by Tetlock (2007) and Tetlock, Saar-Tsechansky, and Macskassy (2008) contributes new insights into the influence of the press media. The use of negative words in firm-specific news stories, as classified by Harvard General Inquirer (GI), can predict a firm's accounting earnings and stock returns. To overcome the limitations in the general-purpose classifications via Harvard Dictionary, Loughran and McDonald (2011) form alternative bags of words that better reflect textual content in the financial contexts. There are also some other studies (e.g., Kothari, Li, and Short, 2009; Da, Engelberg, and Gao, 2015; Gurun and Butler, 2012; Garcia, 2013) that establish textual indices to examine their predictability in financial metrics and stock performance.[9] Developing a disclosure content measure from text has an advantage over the methods in previous studies of strategic disclosure, as they rely on a reverse engineering process. These studies deduce the nature of information content backward from its ex post outcome. For instance, Aboody et al. (2008), Brockman et al. (2008), and Brockman et al. (2010) denote a voluntary management forecast as positive (negative) if the abnormal return after its publication is positive (negative). The textual analysis deciphers the information content straightaway by the use of words.

In this paper, I do not aim to authenticate the causal role of textual analysis on the stock price, as stated in Loughran and McDonald (2011): "The existing literature on financial text does not actually determine the causal link between tone and returns... Our results and others', however, suggest that textual analysis can contribute to our ability to understand the impact of information on stock returns, and even if tone does not directly cause returns, it might be an efficient way for analysts to capture other sources of information." I simply

[9]For more details on textual analysis, please see Loughran and McDonald (2016).

extend the application of their bag of negative words to Form 8-K disclosures. The disclosure content measure I establish from this class of disclosures does produce strong return predictability. Further, it would be a complicated problem to prove the causal role of textual analysis. Regulation FD requires a firm to notify the SEC of material events before any other channel, such that material nonpublic information should originate from 8-K disclosures. However, information flows into the stock market through numerous channels. I also need to specify which component of a disclosure causes the stock price to move: information content (Engelberg and Pontiff, 2018), dissemination process (Engelberg and Parsons, 2011; Peress, 2014; Barber and Odean, 2008; Da, Engelberg, and Gao, 2011; Ahern and Sosyura, 2014; Edmans et al., 2018), or word preference (Dougal, Engelberg, Garcia, and Parsons, 2012).[10] Regardless of the answer, my disclosure content measure is a mixture of all these aspects and strongly correlates with the stock return. This suffices my argument that a CEO withholds negative information to cash out before the price drops.

2.2 Strategic disclosure and CEO opportunism

The studies of strategic disclosure can be traced back to Noe (1999), and one primary strand is about a CEO's opportunism around the grant date of her executive option. Aboody and Kasznik (2000) and Daines, McQueen, and Schonlau (2018) confirm a V-shaped curve of the CARs around a scheduled grant. Aboody and Kasznik (2000) argue that a CEO consciously conveys more pessimistic views in private talks with analysts to deliberately suppress the stock price before option grants, so as to receive a higher number of options. In contrast, Narayanan, Schipani, and Seyhun (2006), Heron and Lie (2007), Narayanan

[10] Engelberg and Pontiff (2018) propose that the arrival of news revises investors' biased expectations before disclosures and explains the return anomalies on news days. Engelberg and Parsons (2011) and Peress (2014) identify the causal effect of mass media on trading volume. Barber and Odean (2008) find that individual investors are mostly net buyers of attention-grabbing stocks, Da et al. (2011) construct an attention measure that predicts the stock returns, Ahern and Sosyura (2014) find evidence in stock mergers that fixed exchange ratio bidders tend to originate dramatically more news stories to temporarily boost their stock prices during the period when the ratio is determined, and Edmans et al. (2018) show a positive correlation between the number of news releases, which works as a proxy for market attention, and future stock returns. Dougal et al. (2012) study the fixed effect of news columnists and argue that the writing style of journalists has a causal effect on aggregate market outcomes.

and Seyhun (2008), and Bebchuk, Grinstein, and Peyer (2010) show that the return pattern around an option grant has gradually vanished since the adoption of SOX in 2002, suggesting that a CEO's opportunism from option grants has abated drastically, under the scrutiny and enforcement of the SEC.[11] Departing from option grants, Aboody, Hughs, Liu, and Su (2008) and Brockman, Martin, and Puckett (2010) investigate a CEO's strategic disclosure that tailors to her option exercises, and Brockman, Khurana, and Martin (2008) and Rahman, Oliver, and Faff (2020) switch their focus to a CEO's stock purchases.

The major contribution of this paper is that I show evidence of a CEO's manipulation in the timing of mandatory disclosures for her stock sales. I refer to mandatory disclosures as those filed through Form 8-Ks. These disclosures are subject to stringent monitoring, and the SEC investigates those suspected of breaching federal securities laws. Probably due to this belief, researchers seldom pay attention to the CEO opportunism behind mandatory disclosures. Even if the content in this class of disclosures is truthful, a CEO may still modify the timing. Many studies claim a CEO's strategic disclosure in voluntary disclosures, without specifying whether she manipulates the timing or content, because it is hard to tell the difference when content manipulation carries little legal repercussions.[12]

To the best of my knowledge, the study closest to this paper is Edmans et al. (2018), who also explore a CEO's timing strategy. They argue that a CEO increases the amount of discretionary news in her sale month to attract market attention. One principal difference is that they add to the literature on voluntary disclosures, whereas I look at mandatory disclosures. To specifically examine a CEO's manipulation in the timing of disclosures, I avoid voluntary disclosures, as the CEO can also manipulate the content of disclosures in that setting. In fact, Edmans et al. (2018) also find that the amount of negative news

[11] I also studied stock performance around a CEO's option grant. The result agrees with the conclusions of Narayanan et al. (2006), Heron and Lie (2007), Narayanan and Seyhun (2008), and Bebchuk et al. (2010), that the negative CAR before an option grant disappears, based on my 2008-2018 sample.

[12] For example, a CEO may express an optimistic view on future prospects in the management forecast, and even if the firm's performance turns sour later, it is quite impossible to have her liable for personal opinions. Similarly, discretionary news covers almost all kinds of general firm news that leaves space for a CEO to manipulate information. To generate good news, she may initiate a new project and hint at its promising future, despite its primitive stage.

decreases before a CEO's sale month, but it does not bounce back in or after the sale month. So it seems that the CEO makes pre-sale negative news disappear, rather than reallocating it from the pre-sale month to the post-sale month. This implies the possibility of content manipulation. Regarding our stories, I show that a CEO withholds negative information to prevent the stock price from dropping before she cashes out. In contrast, Edmans et al. (2018) suggest that a CEO increases the amount of positive news in her sale month to push up the stock price for her sales.

2.3 Insider opportunism and regulatory implications

On one strand of the literature, researchers search for possible sources of private information that benefits insiders in their trades (e.g., Aboody and Lev, 2000; Cline, Gokkaya, and Liu, 2017; Goergen, Renneboog, and Zhao, 2019). Alternative to my hypothesis of a strategic timing of disclosures based on a predetermined sale intention, Hong and Li (2019) show that corporate insiders alter their routine sale and purchase schedule when they foresee information disclosures. Unlike this paper, they study all officers, board members, and beneficial owners of a firm, who have less autonomy in timing firm disclosures when compared to CEOs. Regarding the efficacy of regulations, Seyhun (1992a) evaluates the insider trading sanctions related to the Securities Exchange Act of 1934. He finds no additional deterrent effect on either the profitability or the volume of insider trading. Since the adoption of Regulation FD and SOX, however, Ke, Huddart, and Petroni (2003), Cheng and Lo (2006), Huddart, Ke, and Shi (2007), and Ertimur, Sletten, and Sunder (2014) show that a CEO will refrain from insider opportunism if it involves a higher risk of legal jeopardy. Cohen, Malloy, and Pomorski (2012) also find evidence of legal deterrence, as insiders downscale their opportunistic trading activities in the wake of tightening scrutiny. I affirm the efficacy of the existing regulations on "accurate disclosures," that the SEC's investigations do intimidate and discourage a CEO from content manipulation. On the other hand, when it comes to the requirement of "timely disclosures", I identify an insider trading strategy that is still plausible through a CEO's manipulation in the timing of disclosures.

The rest of this paper is organized as follows: In Section 3, I introduce the data sources. In Section 4, I discuss how I extract information from firm disclosures. In Sections 5 and 6, I present the evidence of a CEO's manipulation in the timing of firm disclosures from two different perspectives. Concluding remarks are in Section 7. The supplemental evidence and robustness checks are in the Appendix.

3 Data

3.1 Insider transaction data

I build up my sample primarily from Thomson Reuters Insiders Data, which collects insider transactions. Section 403 of SOX requires insiders who conduct any equity transaction to notify the SEC through a Form 4 disclosure within two business days. I focus on a CEO's stock sales, supplemented by her option grants for constructing my instrument and her option exercises for identifying exercises or expirations of expiring options. My secondary data sources include the Center for Research on Security Prices (CRSP), the Institutional Brokers Estimate System (IBES), Compustat, Execucomp, ISS Director, and SEC Analytics.

Unlike the sale transactions that are all sorted out clearly in Insiders Data, the option part needs further work. Insiders Data records only exercise transactions, as a CEO is not required to report her expired options to the SEC. Though not exercised in the end, the approaching deadline of her expired option before its expiration still imposes a higher tension and thus incentivizes the CEO to manipulate information. So I add this subset to the exercises of expiring options in Insiders Data. I deduce the expired options from Insiders Data and Execucomp. Insiders Data instantly keeps a live record of a CEO's option exercises, whereas Execucomp summarizes her option holdings in the proxy statement once a year. I first filter out all option grants from Insiders Data that also show up in Execucomp. If an option disappears from Execucomp after appearing there for years, I then check Insiders Data and search for the transactions that may explain its disappearance.[13] Finally, I consider an

[13]The disappearance might be related to several transaction codes in Insiders Data: M = Exercise of in-the-money or at-the-money derivative security acquired pursuant to Rule 16b-3 plan; D = Disposition to the issuer of issuer equity securities pursuant to Rule 16b-3(e); J = Other acquisition or disposition; W = Acquisition or disposition by will or laws of descent distribution; X = Exercise of in-the-money or at-the-money derivative security; O = Exercise of out-of-the-money derivative security; C = Conversion of derivative security; S = Open market or private sale of non-derivative or derivative security. Theoretically, the codes of "X," "O," "C," and "S" are not related to executive options, but I also take them into account. Since the transactions are self-reported, a CEO might make classification errors. This leaves a smaller sample of expired options, but with a higher accuracy.

option as “expired” if all other reasons like exercise, conversion, or disposition are not found in Insiders Data.

One challenge in linking Thomson Reuters’ data to other commonly used databases is that Thomson Reuters has its own company and person identifiers. Fortunately, it also reports NCUSIP, a CUSIP code filed with the SEC together with transaction information. To establish a firm-level linkage between Insiders Data and Compustat, I look for each firm’s historical record of NCUSIPs from CRSP and IBES, and then assign the firm GVKEY via PERMNO. To match Insiders Data’s person ID with Execucomp’s executive code, I first compute the string distance between each name pair, filter out those with a distance under an acceptable threshold, and then manually check each pair to guarantee the accuracy. I focus on all public firms traded on the NYSE, AMEX, and NASDAQ and extract the insider transactions from January 1, 2008 to December 31, 2018. Enacted in December 2004, FAS 123(R) requires a firm to recognize an accounting expense when it grants executive stock options. Prior to the enactment, a firm disclosed its equity-based incentive awards voluntarily, and therefore most firms do not have available points in Execucomp before 2006. As it takes time for a firm to adapt to the new rule, I begin the sample period in 2008.[14]

3.2 Mandatory disclosure data

There is no clear cutoff between voluntary and mandatory disclosures in the literature (e.g., Lerman and Livnat, 2010; He and Plumlee, 2020). In this paper, I emphasize the trustworthiness of information and classify all firm disclosures through Form 8-Ks as mandatory disclosures. I gather the disclosure data from SEC Analytics. It contains the details of each firm’s 8-K disclosures from EDGAR.

[14]SEC Analytics is updated to September 2019 as of this data cleaning in January 2021, so I choose to end the sample at the end of 2018.

Table 1: Descriptive Statistics of the Main Datasets

Panel A reports the numbers of firms, CEOs, disclosures, sales, and other related transactions in each sample. The baseline sample is a combination of SEC Analytics and Thomson Reuters Insiders Data, which sorts out the data points that have available values in both Form 8-K disclosures and stock sale transactions. This intersection is denoted as Disclosure×Sale. ...×Option grant represents a subsection in Disclosure×Sale that also has available values for option grants. "Other" on its row reports the number of option grants. ...×Option exer/expr is the subsection in Disclosure×Sale that also has available values for option exercises or expirations. "Other" on its row reports the number of option exercises or expirations in this subsample. Panel B provides the disclosure metrics and firm characteristics of the baseline sample, Disclosure×Sale. Negative(%) (Positive(%)) denotes the percentage of negative (positive) words in a Form 8-K disclosure.

Panel A: Number of firms, CEOs, etc. in each sample

Number:	Firm	CEO	Disclosure	Sale	Other
Disclosure×Sale	1,647	2,465	128,625	33,386	
...×Option grant	1,247	1,988	100,893	28,164	43,940
...×Option exer/expr	1,220	1,843	101,223	27,992	20,362

Panel B: Summary statistics of firm characteristics of the sample Disclosure×Sale

	Mean	Min	Max	Median	Sd	Number
Negative(%)	0.61	0	9.46	0.33	0.78	128,625
Positive(%)	0.58	0	5.73	0.44	0.41	128,625
lnAsset	7.77	-3.73	14.68	7.67	1.74	39,747
lnSale	5.88	-8.47	11.79	5.80	1.67	39,699
lnMarketCap	7.67	0.70	13.69	7.54	1.62	39,697
lnBM	-0.77	-8.74	9.47	-0.74	0.95	39,697
ROA	0.01	-1.87	1.78	0.01	0.04	39,744
TobinQ	1.96	0.31	26.76	1.53	1.40	39,697
Book leverage	0.54	0.02	3.22	0.53	0.25	39,747
Sale growth	0.03	-2.77	7.31	0.02	0.19	39,687
lnTurnover	-0.65	-5.27	5.32	-0.67	0.67	39,664
lnIlliquidity	0.31	0	8.98	0.09	0.62	39,555

3.3 Summary statistics

Table 1 provides the summary statistics of my sample. Since SEC Analytics records From 8-K disclosures in CIK, and Thomson Reuters Insiders Data records insider transactions in CUSIP, part of the sample is lost in linking these two datasets. Some points further drop out of the sample when I try to match the insiders in Execucomp with those in Thomson Reuter Insiders Data. Since this paper generally explores the relationship between firm disclosures and its CEO's stock sales, my analyses start from a baseline sample, which covers the data points in the intersection of disclosures (SEC Analytics) and sales (Thomson Reuters Insiders Data).

In Panel A of Table 1, the sample size slides a little bit when I combine the baseline sample Disclosure $\times$ Sale with the "option grant" data or the "option exercise or expiration" data, since some firms may not have option transaction data in Thomson Reuters Insiders Data. The drop is quite small relative to the original size, so I only report the descriptive statistics of the baseline sample in Panel B of Table 1. The firm characteristics are calculated from quarterly Compustat data and therefore have fewer observations than the disclosures.

4 Chapter 1: Interpreting information in firm disclosures

4.1 Defining a disclosure content measure

Material information of a firm disclosed in an 8-K form is in the text format. In this paper, I apply the textual analysis techniques to this type of disclosures and establish a disclosure content measure that qualifies information to facilitate the following studies. I construct a content score, DiscCon, on the basis of the percentage of negative words in each disclosure. Roughly speaking, the value of DiscCon is negatively correlated with this percentage. The exact details of defining this DiscCon vary a bit with test settings. I will elaborate in more detail later when it comes to the specific test.

The DiscCon is developed solely from the use of negative words for several reasons. First, negative word classifications have strong correlations with other financial variables. Their effectiveness as a proxy for the nature of a text is well recognized.[15] Second, some psychology studies suggest that people are instinctively more sensitive to negative words.[16] Third, as Loughran and McDonald (2011) suggest, language habit matters. People sometimes structure negative statements by negating positive words (e.g., do not like), but seldom do the reverse when expressing positive feelings (e.g., do not dislike). That is to say, a sentence with positive words may intend to convey negative information, so the content measure developed from the use of positive words may mix positive with negative messages. Finally, the tests in Subsection 4.2 also show that my DiscCon measure reveals a much tighter relationship with stock performance when it is developed from negative words in a disclosure, as compared to that from positive words.

Loughran and McDonald (2011) point out that the widely used Harvard General Inquirer

[15] Tetlock (2007) finds that negative words have a much stronger correlation with stock returns and summarize common variation in the entire set of General Inquirer work categories better than any other single category, including positive words.

[16] For example, Rozin and Royzman (2001) find that there is a general bias in animals and humans to give greater weight to negative entities, in light of both innate predispositions and experience.

classifies words only for general purposes. The negative words are typically not considered negative in the financial context. To tackle this limitation, they form a new set of word lists that better reflect the nature of financial text.[17] The top frequently occurring negative words already identified in the Harvard Dictionary are like *loss, impairment, against, adverse, decline*, etc. This word list is complemented by some additional negative words in a financial context, like *claims, restated, restructuring, litigation, discontinued*, etc. One example of a disclosure with a lot of negative words looks as follows:

> EMULEX CORPORATION (March 31, 2014)
>
> Item 1.01 Entry Into A Material Definitive Agreement
>
> On March 31, 2014, Emulex Corporation (the "Company") and Broadcom Corporation ("Broadcom") entered into a <u>Dismissal</u> and <u>Standstill</u> Agreement (the "<u>Dismissal</u> Agreement") pursuant to which Emulex and Broadcom entered into certain understandings with respect to outstanding <u>claims</u> relating to and arising out of the patent <u>infringement</u> suit identified as Broadcom Corporation v. Emulex Corporation, Civil Action No. 8:09-cv-01058 (C.D. Cal.) (the "<u>Litigation</u>"), brought by Broadcom <u>against</u> Emulex.
>
> Pursuant to the terms of the <u>Dismissal</u> Agreement:
>
> (i) Emulex has agreed to pay Broadcom, a non-refundable, non-cancelable <u>dismissal</u> and <u>standstill</u> fee in the amount of $5 million;
>
> (ii) Emulex and Broadcom have agreed to <u>dismiss</u>, without <u>prejudice</u>, the <u>unresolved</u> <u>claims</u> by Broadcom in the <u>Litigation</u> which were scheduled to be considered in a retrial scheduled for September 2014 (the "<u>Dismissed</u> <u>Claims</u>");
>
> ...

A disclosure with a higher percentage of negative words has a lower value in my DiscCon measure and is deemed to present more negative information. Conversely, an example of a disclosure that contains no negative words looks as follows:

[17] Besides negative words, Loughran and McDonald (2011) also build up the supplemental lists of positive, litigious, uncertainty, strong modal, and weak modal words.

Apple Inc. (February 5, 2019)

Item 5.02 Departure of Directors or Certain Officers; Election of Directors; Appointment of Certain Officers; Compensatory Arrangements of Certain Officers. (b)

On February 5, 2019, Apple Inc. announced that Angela Ahrendts, Senior Vice President, Retail, would depart Apple, effective April 15, 2019. Ms. Ahrendts is succeeded by Deirdre O'Brien, who assumed the role of Senior Vice President, Retail + People, effective February 5, 2019.

Such a disclosure has no negative words and is regarded as the most positive case according to my establishment of a DiscCon measure.[18]

4.1.1 Normalization of the disclosure content measure

DiscCon is a continuous measure. In this paper, I do not set a universal threshold across firms to classify the disclosures as "positive" or "negative". Rather, I compare each disclosure's content score with its firm level. If its DiscCon is higher (lower) than its firm-specific benchmark, this disclosure delivers information in a more positive (negative) tone than usual, and I view it to convey positive (negative) information. A universal standard across firms can be problematic. Each firm may have its own preference on wording in filing disclosures. If it adopts a more aggressive strategy in public communications, it may consciously avoid using negative words in its disclosures. In addition, a publicly traded firm may have established templates for reporting the material events specified by regulations. Then, its list of negative words may accidentally have a higher or lower overlap with the one in Loughran and

[18] Readers might be concerned about misclassification, as the neutral information without mentioning negative words will also be considered positive according to my definition. This does not undermine my major findings. If the market attention hypothesis is valid, then the release of neutral information also drives up the stock price. It functions similarly to positive information, then a CEO will try to disclose this type of information before her stock sales or follow its release to execute her sales. Since a CEO's exogenous stronger intention to sell is not preceded by disclosures with a higher DiscCon, neither positive nor neutral information is predominantly disclosed before this date. On the other hand, if the market attention hypothesis is not valid, then the release of neutral information has no positive effect on the stock price. We will see this type of information randomly show up around a CEO's exogenously strengthened intention to sell. This should weaken the downward shift of DiscCon after such a date, but my results still remain significant.

McDonald (2011). As a consequence, the same percentage of negative words may represent fairly different extents of negative information among firms. To translate this percentage into a comparable measure across firms, I need a firm-specific benchmark so as to discuss its value on a relative basis.

The benchmark differs depending on how the DiscCon measure is applied, and I develop it into both time-varying and time-invariant versions.[19] On the one hand, when I study a disclosure's implication for the market, the stock return is placed on the left-hand side of the regression, and the DiscCon measure is my independent variable. This restrains me from controlling the heterogenous preferences on language among firms by simply adding firm-level fixed effect control variables. Without a firm-specific normalization ahead of regression analysis, the coefficient of the DiscCon measure would give an average level of stock return change that is associated with one percentage increase in the usage of negative words across firms. However, I believe firms' different extents of stock return sensitivities to their word selection should be kept as a unique firm feature and should not be averaged out. The market response reflects the interpretation of information from the perspective of outside investors who, I assume, rely on a time-varying benchmark. Here I normalize each percentage on the basis of a firm-specific rolling benchmark, which is derived from all the disclosures of this firm over the past year. This also averts the looking-forward problem.[20] A past rolling benchmark implies that an outside investor deciphers the information underlying a DiscCon score, with reference to her continuously updated impression of a firm's language. Since memory fades over time, I place a higher weight on more recently filed disclosures.

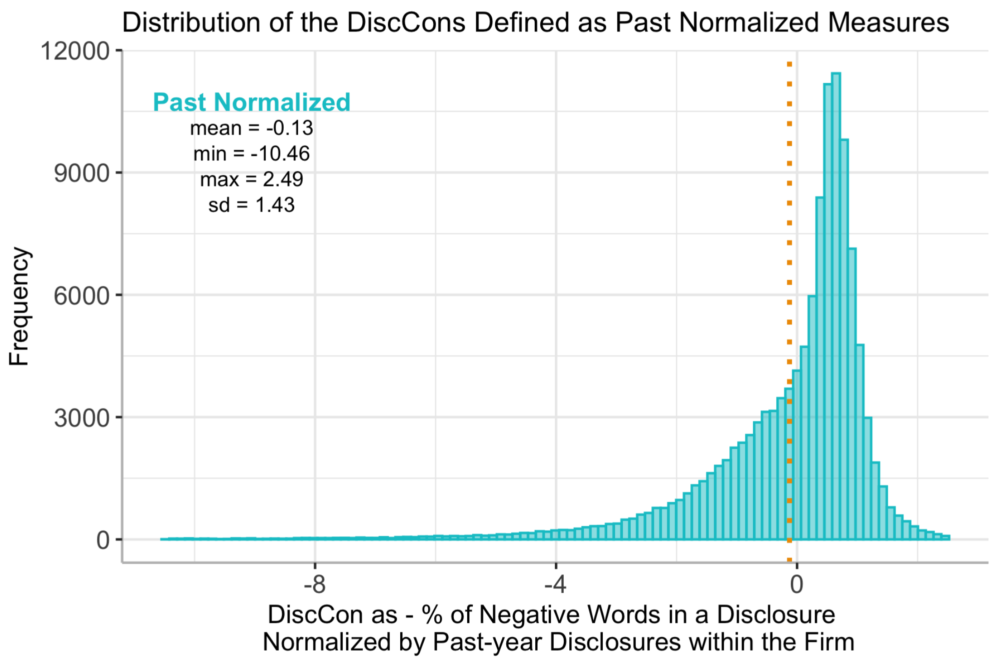
To normalize a disclosure filed on date ϕ, I first calculate the benchmark mean and standard deviation from all past disclosures weighted by their distances to this filing date ϕ.

[19] The specific methods together with their affiliated applications are summarized in Appendix A.5.1.

[20] If the normalization is based on a time-invariant benchmark mean and standard deviation, which involve all the available points of a firm, as in the case of Equation 7, the normalized DiscCon contains future information. This brings in the looking-forward problem when I test the return predictability of DiscCon.

Figure 1: Distribution of the DiscCons Defined as Past Normalized Measures

In this figure, I report the summary statistics and the distribution of the DiscCon measures defined as: $DiscCon \equiv -Neg_{PastNorm}$. $Neg_{PastNorm}$ is the percentage of negative words in a disclosure normalized by a past rolling benchmark. The benchmark mean and standard deviation for the normalization of a specific disclosure are computed from all the disclosures of its firm in the past year, with a higher weight on those released more recently. The orange dotted line denotes the overall mean of this past-normalized DiscCon measure covering all the disclosures in the sample. The distribution includes all the Form 8-K disclosures of the firms that are in the intersection of disclosure samples (SEC Analytics) and sale samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018.



The weight of each past disclosure released k days before date ϕ is calculated as follows:

$$w_{i,\phi-k} = \frac{(365 - k + 1) \cdot I_{i,\phi-k}}{\sum_{k=1}^{365} (365 - k + 1) \cdot I_{i,\phi-k}}, \tag{1}$$

where $I_{i,\phi-k} = 1$ if firm i has at least one disclosure on date $\phi - k$.

In Figure 1, I plot the distribution of the DiscCon measures defined by $-Neg_{PastNorm}$, and $Neg_{PastNorm}$ denote the percentage of negative words in a disclosure normalized by a past rolling benchmark. A disclosure with a positive (negative) "past-normalized" DiscCon can be interpreted as reporting relatively more positive (negative) information as compared to those filed last year. As it displays a long left tail, I take log transformation as follows to mitigate this issue before performing the regressions:

$$DiscCon_{Regression}^{X=DiscCon} \equiv -ln\left(|Neg_{PastNorm}|+1\right)\cdot Sign\left(Neg_{PastNorm}\right). \tag{2}$$

On the other hand, when I study how firm disclosures vary in connection with a CEO's personal interest, like her stock sale decision in Chapter 2 or her option exercise decision in Chapter 3, I regard disclosure positivity as my dependent variable and add a firm-level control to focus on within-firm variations. In this case, the DiscCon is interpreted by a time-invariant benchmark. That is, I assume each firm follows a consistent language in its disclosures so that information with a similar level of positivity will be reported with a similar percentage of negative words. I will discuss in more detail about how this time-invariant benchmark works in Chapters 2 and 3.

4.2 Market response to firm disclosures

To further support developing my disclosure content measure solely from the usage of negative words, I examine how the percentages of positive and negative words in a disclosure, normalized as $Pos_{PastNorm}$ and $Neg_{PastNorm}$, co-move with and predict stock performance.

4.2.1 Post-file analysis: Event study of abnormal returns on/after disclosures

I conduct an event study in this part to investigate whether the percentages of positive and negative words in a disclosure have significant correlation with its current and future stock performance. The regression is described as follows (ϕ denotes the filing date of a disclosure in the sample):

$$
\begin{aligned}
CAR_{i,\phi+t\sim\phi+T} \sim & \alpha + \beta \cdot Negative_{i,\phi} + \gamma \cdot Positive_{i,\phi} \\
& + \delta \cdot CAR_{i,\phi-10\sim\phi-1} \\
& + \eta_1 \cdot SUE_{i,\phi} + \eta_2 \cdot Cvrg_{i,\phi} \\
& + \eta_3 \cdot lnMakcap_{i,\phi} + \eta_4 \cdot lnBM_{i,\phi} \\
& + \eta_5 \cdot lnTurnover_{i,\phi} + \eta_6 \cdot lnIlliquidity_{i,\phi} \\
& + FirmFE_i + Year \times Month_\phi + \epsilon_{i,\phi},
\end{aligned} \tag{3}
$$

where $CAR_{i,\phi+t\sim\phi+T}$ cumulates the abnormal returns covering $[\phi+t, \phi+T]$ of firm i, rescaled to 100%. If $t = T = 0$, then $CAR_{i,\phi} = AR_{i,\phi}$ measures the abnormal return on the filing date ϕ. If $t = 1$ and $T \in [1, 5]$, then $CAR_{i,\phi+1\sim\phi+T}$ cumulates the abnormal returns covering $[1, T]$ trading days after the filing date ϕ. The abnormal return is based on a Fama-French four-factor model (momentum in addition to FF3 factors), with its parameters estimated from the daily returns of a 100-calendar-day window$[\phi - 130 \sim \phi - 31]$. The parameters have available values only if the covered window has no less than 30 data points and are adjusted by the Dimson method.

$Negative_{i,\phi}$ and $Positive_{i,\phi}$ are the negative and positive disclosure content measures of a disclosure of firm i filed on date ϕ, quantified as:

$$
\begin{aligned}
Negative_{i,\phi} &\equiv ln\left(|Neg_{PastNorm,i\phi}| + 1\right) \cdot Sign\left(Neg_{PastNorm,i\phi}\right) \\
Positive_{i,\phi} &\equiv ln\left(|Pos_{PastNorm,i\phi}| + 1\right) \cdot Sign\left(Pos_{PastNorm,i\phi}\right)
\end{aligned} \tag{4}
$$

with $Neg_{PastNorm,i\phi}$ ($Pos_{PastNorm,i\phi}$) denoting the percentage of negative (positive) words in this disclosure, normalized by a past rolling benchmark. Each disclosure has both negative and positive measures. $CAR_{i,\phi-10\sim\phi-1}$ cumulates the abnormal returns of a 10-trading-day window $[\phi - 10, \phi - 1]$. In the panel regression, I control the fixed effects of firms and $Year \times Month$s. In the Fama-MacBerh regression, the first-stage, cross-secitonal regression is conducted on a monthly basis. The months with less than 30 data points are removed from the test.

As shown in Table 2, the variable $Negative_{i,\phi}$ reports a significantly negative coefficient, so a higher percentage of negative words in an 8-K disclosure not only correlates with a lower abnormal return on its filing date, but predicts a lower CAR covering the period shortly after it. The market typically demonstrates its high sensitivity to material information. The coefficient has little incremental change from $AR_{i,\phi+1}$ (-0.073) to $CAR_{i,\phi+1\sim\phi+5}$ (-0.078) in the panel regression. This number is greater in the Fama-MacBeth regression, but is still less than half in size when compared to the coefficient of $AR_{i,\phi+1}$ (e.g., (0.114-0.077)/0.077). Since $CAR_{i,\phi+1\sim\phi+5}$ is the sum of $AR_{i,\phi+1}$ and $CAR_{i,\phi+2\sim\phi+5}$, the stock market almost finishes digesting the disclosed information in the first few trading days after its release date. The asymmetry in the results of $Positive_{i,\phi}$ and $Negative_{i,\phi}$ variables aligns with those of Loughran and McDonald's (2011). Therefore, the percentage of negative words works as a better proxy for the information content of a disclosure than that of positive words. This provides support for my use of the DiscCon measure solely from the bag of negative words.

Table 2: Event Study on the Abnormal Returns in Relation to Disclosures

This table reports the results of a post-file examination of whether the positive (negative) disclosure measure of an 8-K disclosure is correlated with positive (negative) abnormal returns on or shortly after its release date. $\%AR_{i,\phi}$ denotes the abnormal return on the filing date ϕ, and $\%CAR_{i,\phi+1,\phi+T}$ denotes the CAR covering the period of $[1,T]$ trading days after the filing date ϕ. The abnormal return is derived from a Fama-French four-factor model, whose parameters are estimated from the daily returns of a 100-calendar-day window $[\phi-130 \sim \phi-31]$. $Negative$ and $Positive$ are the disclosure measures quantified as $Negative \equiv ln\left(|Neg_{PastNorm}|+1\right) \cdot Sign\left(Neg_{PastNorm}\right)$ and $Positive \equiv ln\left(|Pos_{PastNorm}|+1\right) \cdot Sign\left(Pos_{PastNorm}\right)$. $Neg_{PastNorm}$ ($Pos_{PastNorm}$) is the percentage of negative (positive) words in an 8-K disclosure, normalized by a past rolling benchmark. T-statistics are reported in parentheses, with their standard errors adjusted in a two-way clustering at both the 4-digit SIC industry code and $Year \times Month$ levels for the panel regressions. The standard errors of Fama-MacBeth regressions are adjusted by the Newey-West method with a lag of one. The Fama-MacBeth regression has less than 132 data points (12 months×11 years), as I remove the months if they contain less than 30 points in the cross-sectional regression. The regression samples include all the 8-K disclosures of the firms that are in the intersection of disclosure samples (SEC Analytics) and sale samples (Thomson Reuter Insiders Data), ranging from from 2008 to 2018.

Regression:	Panel			Fama MacBeth		
DV (%):	$AR_{i,\phi}$	$AR_{i,\phi+1}$	$CAR_{i,\phi+1\sim\phi+5}$	$AR_{i,\phi}$	$AR_{i,\phi+1}$	$CAR_{i,\phi+1\sim\phi+5}$
	(1)	(2)	(3)	(4)	(5)	(6)
Negative	-0.061***	-0.073***	-0.078***	-0.071***	-0.077***	-0.114***
	(-3.62)	(-4.98)	(-2.90)	(-2.84)	(-4.55)	(-3.10)
Positiv	-0.001	-0.002	0.033	-0.007	-0.016	0.054*
	(-0.07)	(-0.12)	(1.23)	(-0.25)	(-0.82)	(1.88)
lnMakcap	-0.476***	-0.438***	-1.423***	-0.053***	-0.062***	-0.156***
	(-8.40)	(-8.61)	(-11.00)	(-4.05)	(-3.58)	(-4.59)
lnBM	0.044	0.058	0.323***	0.064**	-0.017	0.153**
	(1.26)	(1.56)	(4.46)	(2.55)	(-0.47)	(2.09)
lnTurnover	-0.039	-0.082**	-0.180**	-0.017	-0.087**	-0.211**
	(-0.96)	(-2.36)	(-2.22)	(-0.44)	(-2.45)	(-2.20)
lnIlliquidity	-0.292***	-0.298***	-1.039***	-0.226	-0.167	-0.590
	(-2.66)	(-3.06)	(-5.23)	(-0.58)	(-1.18)	(-0.95)
Cvrg	0.095*	0.096*	0.294***	0.078***	0.054*	0.227***
	(1.80)	(1.88)	(3.28)	(3.18)	(1.80)	(4.26)
SUE	0.090***	0.082***	0.100***	0.070***	0.079***	0.094***
	(7.96)	(7.57)	(7.11)	(11.37)	(14.67)	(11.80)
$CAR_{i,\phi-10\sim\phi-1}$	-0.005*	0.005**	0.034***	-0.002	0.005**	0.032***
	(-1.95)	(2.46)	(5.43)	(-0.65)	(2.21)	(5.51)
Obs	108,786	109,041	109,194	127	127	127
Adj. R^2	0.02	0.02	0.05	0.01	0.01	0.01
Firm	Y	Y	Y	N	N	N
Year×Month	Y	Y	Y	N	N	N

*,**, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.2.2 Full timeline analysis: Content measure as a daily firm characteristic

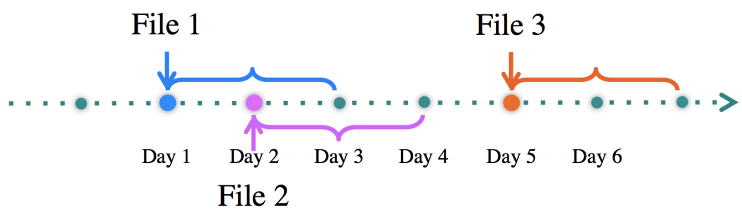
In this part, I examine the efficacy of the percentages of positive and negative words as proxies for positive and negative information in a disclosure. Here the disclosure content measure is established as a daily firm characteristic. The regression is described as follows (d denotes any available trading date of a firm in the sample):

$$\begin{aligned}\tilde{R}_{i,d} \sim & \alpha + \beta \cdot (File_{i,d} \times Negative_{i,d}) \\ & +\gamma \cdot (File_{i,d} \times Positive_{i,d}) + \theta \cdot File_{i,d} \\ & + \delta \cdot FF\alpha_{i,m_d-4\sim m_d-1} \\ & + \eta_1 \cdot idioVol_{i,m_d-4\sim m_d-1} + \eta_2 \cdot Cvrg_{i,d} \\ & + \eta_3 \cdot lnMakcap_{i,d} + \eta_4 \cdot lnBM_{i,d} \\ & + \eta_5 \cdot lnTurnover_{i,d} + \eta_6 \cdot lnIlliquidity_{i,d} \\ & + FirmFE_i + Year \times Month_d + \epsilon_{i,d},\end{aligned} \tag{5}$$

where $\tilde{R}_{i,d}$ is the daily risk-adjusted return of firm i on trading date d, rescaled to 100%. It is based on a Fama-French four-factor model (momentum in addition to FF3 factors), with its parameters estimated from the daily returns of a 4-calendar-month window $[m_d - 4, m_d - 1]$. m_d denotes the month of date d. The parameters have available values only if the covered window has no less than 30 data points and are adjusted by the Dimson method.

$Negative_{i,d}$ and $Positive_{i,d}$ denote the daily disclosure indices of firm i, developed from its 8-K disclosures in the following steps: (1) A disclosure filed on date ϕ has both negative and positive disclosure scores, $Negative_{i,\phi}$ and $Positive_{i,\phi}$, defined in equation 4. (2) Since it takes time for the stock market to reflect the information in a disclosure, I extend the "effective" period of its content measures. Figure 2 provides an example where I assume the disclosed information will be absorbed into the stock price in three trading days. Day 1 is covered by File 1 only, so its disclosure measure is simply File 1's measure. Days 2 and 3 are covered by both Files 1 and 2. The disclosure measure on these two days is the

Figure 2: Example Timeline for Defining a Daily Index of Disclosure Content



mean measure of File 1 and 2. (3) I set $T \in [0, 5]$ as the coverage length of each disclosure. $Negative_{i,d}$ ($Positive_{i,d}$) averages the $Negative_{i,\phi}$ ($Positive_{i,\phi}$) of all the disclosures whose filing date $\phi \in [d - T, d]$:

$$\begin{aligned} Negative_{i,d} &\equiv \frac{\sum_{\phi=d-T}^{d} Negative_{i,\phi} \cdot I_{i,\phi}}{\sum_{\phi=d-T}^{d} I_{i,\phi}} \\ Positive_{i,d} &\equiv \frac{\sum_{\phi=d-T}^{d} Positive_{i,\phi} \cdot I_{i,\phi}}{\sum_{\phi=d-T}^{d} I_{i,\phi}}, \end{aligned} \tag{6}$$

with $I_{i,\phi} = 1$ if firm i releases a Form 8-K disclosure on date ϕ.

$File_{i,d}$ is an indicator variable affiliated with $Negative_{i,d}$ and $Positive_{i,d}$. This variable is necessary because material events are not common. $File_{i,d} = 1$ if there exists an 8-K disclosure during $[d - T, d]$. A trading date with $File_{i,d} = 0$ has no available value of $Negative_{i,d}$ or $Positive_{i,d}$. Monthly updated $FF\alpha_{m_d-4\sim m_d-1}$ is the intercept term from the set of estimated parameters by which I calculate $\tilde{R}_{i,d}$. Monthly updated idiosyncratic firm risk control $idioVol_{m_d-4,m_d-1}$ is the standard deviation of the residuals from the regression by which I estimate the parameters for computing $\tilde{R}_{i,d}$. In the panel regression, I control the fixed effects of firms and $Year \times Months$. In the Fama-Macberh regression, the first-stage, cross-secitonal regression is conducted on a monthly basis. Given one month, if it has less than 30 data points, or the number of the data points with $File = 1$ is less than the total number of the available points in this month, this month is removed from the first-stage regression.

Table 3 presents the difference between the negative and positive words regarding their

Table 3: Relation between Firm Disclosures and Risk-adjusted Returns on a Daily Basis

This table shows the results of a test that examines whether the percentage of positive (negative) words relates to a positive (negative) stock return. The dependent variable, $\widetilde{R}_{id}$ (%), is a daily risk-adjusted return, with its parameters estimated from the daily returns of $[m_d - 4, m_d - 1]$ in a Fama-French four-factor model. m_d denotes the calendar month in which the date d locates. $File_{id} = 1$ only if there exists at least one 8-K disclosure during $[d - T, d]$. T is the length of the "effective" period that the stock market will reflect the information of a disclosure over this period. $Negative_{id}$ and $Positive_{id}$ are the mean negative and positive disclosure scores covering all the disclosures during $[d - T, d]$, with negative disclosure score defined as $Negative \equiv ln\left(|Neg_{PastNorm}| + 1\right) \cdot Sign\left(Neg_{PastNorm}\right)$ and positive disclosure score defined as $Positive \equiv ln\left(|Pos_{PastNorm}| + 1\right) \cdot Sign\left(Pos_{PastNorm}\right)$ for each disclosure. $Neg_{PastNorm}$ ($Pos_{PastNorm}$) is the percentage of negative (positive) words in an 8-K disclosure, normalized by a past rolling benchmark. T-statistics are reported in parentheses, with their standard errors adjusted in a two-way clustering at both the 4-digit SIC industry code and $Year \times Month$ levels for the panel regressions. The standard errors of Fama-MacBeth regressions are adjusted by the Newey-West method with a lag of one. The Fama-MacBeth regression has less than 132 data points (12 months×11 years), as I remove the months that contain less than 30 points in the first-stage, cross-sectional regression. Those with the number of $File = 1$ less than 1% of the sample of the first-stage regression are also removed from the test. The regression samples cover all the firms that are in the intersection of disclosure samples (SEC Analytics) and sale samples (Thomson Reuter Insiders Data), ranging from from 2008 to 2018.

Regression:	Panel			Fama MacBeth		
Coverage:	T = 0	T = 1	T = 5	T = 0	T = 1	T = 5
	(1)	(2)	(3)	(4)	(5)	(6)
File	0.067***	0.057***	0.015*	0.065***	0.052***	0.015*
	(5.51)	(5.43)	(1.70)	(6.87)	(7.21)	(1.94)
File×Negative	-0.041***	-0.040***	-0.011**	-0.040***	-0.038***	-0.010**
	(-3.96)	(-5.00)	(-2.01)	(-4.15)	(-5.35)	(-2.31)
File×Positive	0.007	0.000	0.002	0.007	-0.001	0.003
	(0.72)	(-0.04)	(0.62)	(0.67)	(-0.18)	(0.77)
lnMakcap	-0.081***	-0.081***	-0.081***	-0.007**	-0.007**	-0.006*
	(-8.70)	(-8.71)	(-8.69)	(-2.12)	(-2.18)	(-1.97)
lnBM	0.005	0.005	0.005	-0.003	-0.003	-0.003
	(1.19)	(1.20)	(1.19)	(-0.85)	(-0.91)	(-0.88)
lnTurnover	-0.008	-0.008	-0.008	-0.005	-0.005	-0.004
	(-1.17)	(-1.20)	(-1.18)	(-0.82)	(-0.87)	(-0.69)
lnIlliquidity	-0.028**	-0.028**	-0.028**	-0.014*	-0.014*	-0.013
	(-2.07)	(-2.08)	(-2.06)	(-1.66)	(-1.69)	(-1.48)
Cvrg	-0.014**	-0.014**	-0.014**	0.001	0.001	0.001
	(-2.01)	(-1.98)	(-2.01)	(0.09)	(0.12)	(0.11)
$FF\alpha_{i,m_d-4,m_{d-1}}$	-0.860	-0.862	-0.859	1.565	1.553	1.498
	(-0.58)	(-0.58)	(-0.57)	(1.00)	(0.99)	(0.97)
$idioVol_{i,m_d-4,m_d-1}$	-0.090	-0.086	-0.093	-0.514	-0.509	-0.540
	(-0.18)	(-0.17)	(-0.18)	(-1.57)	(-1.56)	(-1.64)
Obs	3,587,665	3,587,665	3,587,665	130	130	131
Adj. R^2	0.01	0.01	0.01	0.00	0.00	-0.00
Firm	Y	Y	Y	N	N	N
Year×Month	Y	Y	Y	N	N	N

*,**, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

relation with stock performance. Since the material events reported by the 8-K disclosures do not show up on a daily basis, a firm will not have available values for $Negative_{i,d}$ and $Positive_{i,d}$ unless it does disclose some information on or closely before this date d. The daily firm characteristics developed from 8-K disclosures do not take effect in its risk-adjusted returns until $File_{i,d} = 1$. The significantly negative coefficient of the interaction term $File_{i,d} \times Negative_{i,d}$ suggests that, conditioned on the real ocurrence of a disclosure on date d, a higher percentage of negative words is associated with a lower risk-adjusted return on or shortly after this disclosure. The market is responsive to the disclosures of material information. The coefficient of $File_{i,d} \times Negative_{i,d}$ declines from -0.04 to -0.01 in both panel and Fama-MacBeth regressions, when I extend the coverage period from 1 day to 6 days. That is to say, even if the market may take a longer time to fully digest a firm disclosure, the information will not elicit any market response as effectively as it does in the first few days.

In sum, a higher percentage of negative words in a disclosure is associated with a lower abnormal return on its filing date and predicts a lower post-file CAR over the next few days. When this percentage is established as a daily firm characteristic, it also presents a significantly negative correlation with the same-day as well as future risk-adjusted returns. This relation cannot be symmetrically replicated in the case of positive words. Many studies use the ratio of positive to negative percentage of a disclosure to measure its information content. Considering my findings here, the use of positive words only adds noise.

In this chapter, I establish a disclosure content measure that effectively quantifies the material information in 8-K disclosures. This measure eases my investigation on the clues of a CEO's timing manipulation, which is the major focus of the following chapters. I will set forth my empirical findings as follows. In Chapter 2, I study the relation between firm disclosures and its CEO's stock sales. This motivates me to further explore whether her sales affect disclosures. Then, I conduct a causal effect test to verify my hypothesis of a CEO's intentional modification in the timing of disclosures for her sales. This is achieved by identifying a CEO's exogenous need for diversification. In Chapter 3, I find out more evidence of a CEO's timing manipulation by examining her disclosures when she faces urgency to sell. Finally, I check the profitability of this timing strategy in Appendix A.1.

5 Chapter 2: Manipulation from diversification needs

5.1 Motivation: Firm disclosures around its CEO's stock sales

To sketch how a firm discloses material information when its CEO makes stock sale decisions, I perform an event study to specifically look at the disclosures around its CEO's stock sale transactions. Here in this paper, I focus on those within 10-business-day windows before and after a stock sale, which jointly cover about one calendar month for each sale.[21] I believe the event window should be neither too long nor too short. If the window is too long, for example, one month before or after a sale, then it means a CEO would not cash out until one month after the release of positive news. This almost voids her informational advantage, since the stock price may probably decline over this long period. In the meantime, the litigation risk of being caught concealing material information would also increase if negative news is withheld for too long.[22] Likewise, if the window is too short, for instance, one or two days before or after a sale, then again a CEO might not capture the price benefit from positive news, as the market requires time to fully digest the information. Meanwhile, the risk of being sued for insider trading would escalate if the CEO discloses negative news too quickly after her sales. As a result, I stick to a 10-day window in my tests, accompanied by a 5-day window as a robustness check in Appendix.[23]

[21] 8-K disclosures will not be interrupted by a temporary trading halt, so I place a 10-day threshold on the business day length rather than the trading day. More specifically, I impose a double-faceted criterion on the length of a window $K = min\left(K_{Calendar}, K_{Trading;Business}\right)$, where $K_{Calendar} = (7, 15)$ and $K_{Trading;Business} = (5, 10)$, two pairs respectively. A trading-day window is applied to CARs, while a business-day window is applied to disclosures. For example, if I want to sort out all the disclosures within a 10-business-day window around a sale date d, then the pre-sale (post-sale) period covers all the disclosures of $\left[max\left(d - 15_{Calendar}, d - 10_{Business}\right), d - 1\right]$ $\left(\left[d + 1, min\left(d + 15_{Calendar}, d + 10_{Business}\right)\right]\right)$. This constraint on the coverage in calendar days is necessary, because a firm's trading activity might be halted for a long time, then it simply adds noise if I take the points too far away from a sale into consideration. The disclosures are not affected by a trading halt, but are still exposed to other issues like natural disasters and long holidays.

[22] A CEO may be held accountable if she conceals material information from investors. For example, in June 2020, AmTrust Financial Services Inc. and its former CFO were charged for failing to disclose material facts about how the company estimated its insurance losses and reserves.

[23] The disclosure sample in the 5-business-day case is a little bit different from the 10-business-day case, as the disclosures tagged as both "pre-sale" and "post-sale" are removed from the sample. For example, if two sales are 10 business days away from each other, and there is one disclosure between them, 4 and 6 days from

Figure 3: Mean Positivity of the Disclosures Around a CEO's Stock Sales

In this figure, I plot $DiscCon\,(k) - k$, the mean DiscCon score of 8-K disclosures that are released k business days away from their closest sale dates. Each disclosure's content score, DiscCon, is constructed as $DiscCon_{Graph} \equiv -Neg_{Norm}$. Neg_{Norm} is the percentage of negative words in a disclosure normalized within its firm. The orange dotted line denotes the average DiscCon of each firm as well as the whole sample. A positive (negative) DiscCon signals a more positive (negative) tone in the disclosure as compared to the tones in other disclosures of its firm. It implies positive (negative) information in this disclosure. The solid line on the left (right) of $k = 0$ denotes the average level of the DiscCon scores covering all the disclosures within the event window $k \in [-10, -1]$ ($k \in [1, 10]$) business days from their designated sales. The mean is cross-sectionally weighted. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics) and sale samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018. Figure 14 in Appendix A.3 draws the pattern following a 5-business-day window.

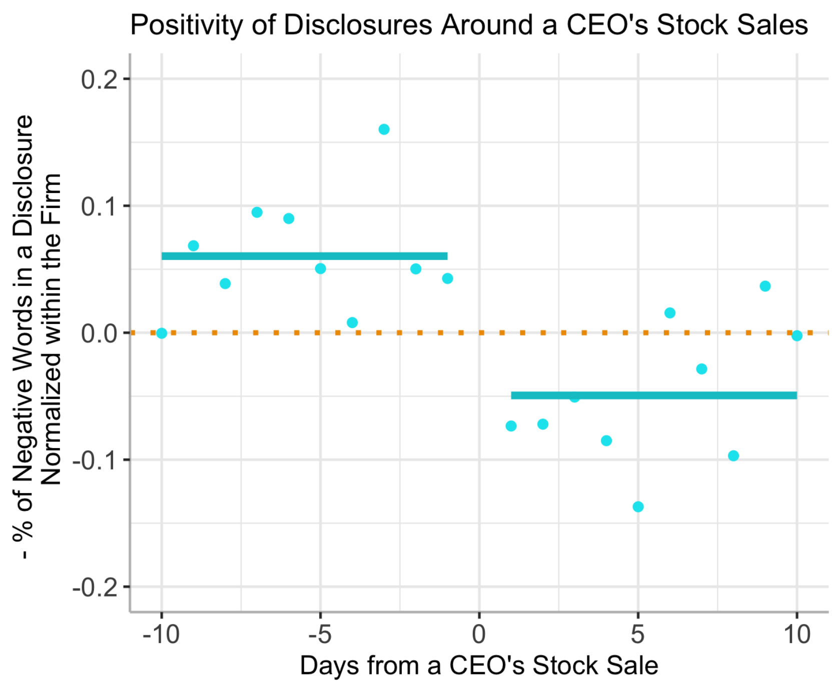


Figure 3 gives an overview of how the information positivity of firm disclosures vary as compared to the timing of its CEO's stock sales. Starting from one sale date, I first pick out the disclosures that are released within a 10-business-day window before or after it. When a disclosure drops into the event windows of more than one sale, it is matched with the closest sale, on the condition that these sales occur all before or after this disclosure. Otherwise, this disclosure is removed from the sample when it is tagged as both "pre-sale"

each sale respectively, then this disclosure is classified as "post-sale" in the 5-day case, but will be removed from the sample in the 10-day case, as it has conflicting classifications of "pre-sale" and "post-sale."

and “post-sale.” Next, each disclosure is assigned a value k, which is its distance in business days from its closest sale date. After repeating the steps above for every sale date in the sample, I group the disclosures by their k values and roll over the mean computation of the DiscCon scores across firms and CEOs for each k from -10 to 10.[24] In particular, as I need to sum up the DiscCon scores across firms, while firms may have heterogenous preferences on wording, recklessly adding up the raw percentages of negative words from different firms may bring in distortion. Therefore, I normalize the percentage values before taking average. The DiscCon score of each disclosure in this test is specifically defined as:

$$DiscCon_{Graph} \equiv -Neg_{Norm}, \tag{7}$$

where *Norm* denotes the normalization that each disclosure's percentage of negative words is standardized within its firm. This measure has a mean of 0 for each firm, so the DiscCons of the whole sample also average out at 0, which is the orange dotted line in Figure 3. A positive (negative) DiscCon signals a more positive (negative) tone in the disclosure as compared to the tones in other disclosures of the same firm. Figure 12 in Appendix A.2 reports the summary statistics and the distribution of this normalized DiscCon measure.

The scatter plots in Figure 3, $DiscCon\,(k) - k$, represent the mean DiscCon score of all the disclosures that are released k business days from their closest sales. The solid line on the left (right) of $k = 0$ depicts an average DiscCon level, which covers all the disclosures before (after) a CEO's stock sales within the event window. Since the disclosures filed before (after) a CEO's stock sales present a pronounced upshift (downshift) from the benchmark "0" in the mean DiscCon score, this suggests that the disclosures are predominately filed in a positive (negative) tone and thus deliver positive (negative) information before (after) her

[24]Considering the cross-sectional dependence, all the graphs in the paper report a mean that is cross-sectionally weighted. That is to say, the disclosures released on the same day are counted as one observation before computing the mean over time. Dahlquist and Jong (2008) show that the significant result in an event study sometimes is attributed to cross-sectional dependence. Firms may co-move with some common market condition on the same day. The equal weighting method applied in most event studies has its drawback that the observations from one same day may overweigh the whole sample. The cross-sectional weighting checks if the result remains significant over time.

sales.

To examine whether the upshift and downshift in Figure 3 are statistically significant, I also conduct a regression analysis to test this favorable pattern in a more meticulous manner. The results are in Appendix A.3. The fixed effect controls of firms and CEOs in the regression deal with the concerns of the heterogeneity in firms' preferences on wording and CEOs' inclination to manipulate information. I focus on the differences among disclosures within the same firm managed by the same CEO. In brief, the regression results confirm that the disclosures closely around a CEO's stock sales differ distinctly in their tones. The DiscCon score of a pre-sale (post-sale) disclosure tends to be higher (lower) than those of other disclosures at the 1% significance level,[25] meaning a disclosure filed before a CEO's stock sale typically imparts positive (negative) information.

The findings in this section, however, are simply the correlation between firm disclosures and its CEO's stock sales. A correlation does not form a compelling argument of manipulation, since a CEO may time her sale decisions in accordance with her preferential access to private information. A predetermined sale date with manipulation in the timing of disclosures and a flexible sale date customized for the fixed schedule of disclosures can both render the same favourable pattern in Figure 3. The objective in the following section is to vindicate a CEO's timing manipulation with more convincing evidence.

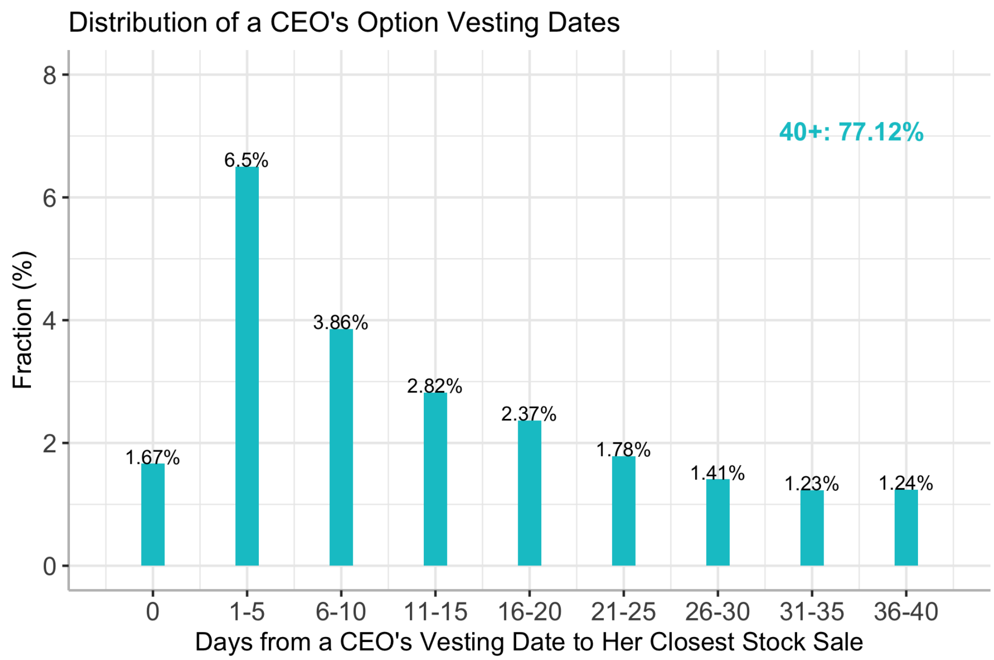
5.2 Hypothesis testing: Evidence of manipulation in timing

To disentangle a CEO's sale decision from its dependence on information, I develop an instrument from the vesting dates of her executive options and identify an exogenous variation in her intention to sell. Beginning from the validity, under-diversification has become a prevailing problem for CEOs in recent years. Murphy (2013) summarizes the composition of CEO compensation in S&P 500 firms from 1992 to 2011 and shows that the proportion of equity-based rewards has risen to over 50% of total compensation. The vesting date of an

[25] The counterpart of pre-sale (post-sale) disclosures refers to post-sale (pre-sale) disclosures and those filed without any sale around them.

Figure 4: Distribution of the Distances from a CEO's Vesting Dates to Her Closest Sales

In this graph, I show a general view of how soon a CEO sells her stocks when there are newly vested options. It plots the distribution of the distances from a CEO's option vesting dates to the closest stock sale dates of this CEO on or shortly afterwards. The sample of vesting dates is divided by the distance values, each labeled as "0," "1-5," "6-10," etc. on the x-axis. The y-axis is the fraction of each group in the whole sample. For example, the group of "0" means I first count the number of vesting dates that coincide with a CEO's stock sale dates and compute this number as a percentage of the total number of vesting dates in the sample. The distribution covers all the firms that are in the intersection of disclosure samples (SEC Analytics), sale samples, and option grant samples (Thomson Reuter Insiders Data) from 2008 to 2018.



option is its earliest exercisable date. A newly vested option on this date brings in an upward shift to a CEO's exposure to equity holdings and stirs up her diversification need. This will motivate the CEO to liquidate at least some stock shares and gives grounds for predicting her higher propensity to sell on and shortly after this date.

In Figure 4, I plot the distribution of the distances in days from CEOs' vesting dates to their closest subsequent sales. Out of all the active options that have available vesting dates, about 23% of options are followed by their CEOs' stock sales within 40 business days, roughly 2 calendar months, after their vesting dates. I split these options into several groups according to how soon a stock is sold subsequent to its latest option vesting date. The fraction number above each bar is the percentage of each group in the whole sample. For example, bar "0" indicates that about 1.67% of options get vested on the same day with their CEOs' stock sales. The distribution plot makes it quite clear that a CEO displays a stronger intention to sell on and closely after her option vesting dates. The fraction of options that are followed by stock sales within the first half of month almost doubles that within the second half of month. This fraction plummets and then stabilizes slightly above 1 % afterwards.

In the meantime, the vesting date of an option is independent of information, as it is determined on the option grant date, which is far earlier than the vesting date itself. Consequently, it is impossible to forecast whether and what type of information will occur around this date when the option is granted. Since the Form 8-K channel is supposed to disclose sensitive material information and is accessible to all investors via EDGAR, the market should be responsive to its disclosure. I carry out my studies in a daily frequency so as to precisely capture the dynamics of firm disclosures in relation to its CEO's intention to sell. Such a frequency also lowers the likelihood that a vesting date coincides with other scheduled firm events and thus reinforces the instrument's exclusion restriction assumption.[26]

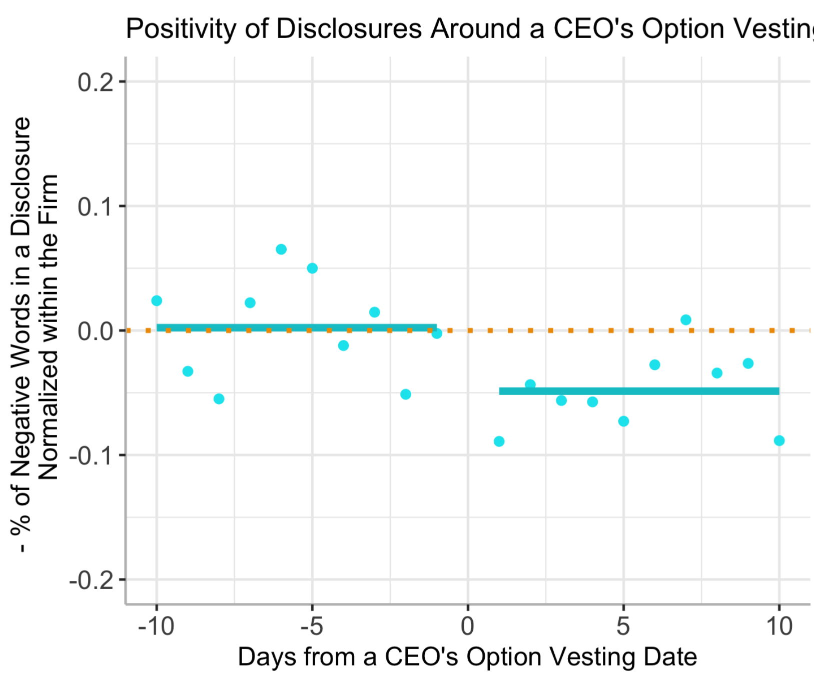
5.2.1 Firm disclosures around its CEO's option vesting dates

First, I redo the event study as in the "Motivation" part to depict how disclosures behave around a CEO's option vesting dates. The only difference is that I replace the actual sale dates, which may depend on information, with predetermined vesting dates. A vesting date exemplifies an exogenous shock to a CEO's intention to sell, which originates from her

[26] As shown in Figures 16 and 17 in the Appendix A.3, I display the timing of a CEO's option vesting in comparison to that of some other important firm events, such as 10-Ks, 10-Qs, and annual general meetings (AGMs), because a firm is likely to disclose material information around these events. As the basis of my causal effect test, the change in a CEO's intention to sell implied from her option vesting schedule should be independent of firm information. The high correlation with these informative events will challenge the exogeneity of a CEO's option vesting dates. Unlike these firm events that herd in particular months, a CEO has new options getting vested quite evenly in each month. Most of option vesting dates are at least 30 days away from their closest 10-K, 10-Q, and AGM dates, so a CEO's option vesting has little chance of coinciding with these firm events.

Figure 5: Mean Positivity of the Disclosures Around a CEO's Option Vesting Dates

In this figure, I plot $DiscCon\,(k) - k$, the mean DiscCon score of 8-K disclosures that are released k business days away from their CEO's option vesting dates. Each disclosure's content score, DiscCon, is constructed as $DiscCon_{Graph} \equiv -Neg_{Norm}$. Neg_{Norm} is the percentage of negative words in a disclosure normalized within its firm. The orange dotted line denotes the average DiscCon of each firm as well as the whole sample. A positive (negative) DiscCon signals a more positive (negative) tone in the disclosure as compared to the tones in other disclosures of its firm. It implies positive (negative) information in this disclosure. The solid line on the left (right) of $k = 0$ shows the average level of the content scores covering all the disclosures within the event window $k \in [-10, -1]$ ($k \in [1, 10]$) business days from their closest vesting dates. The mean is cross-sectionally weighted. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics), sale samples, and option grant samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018. Figure 18 in Appendix A.3 reports the case of a 5-business-day window.



escalated under-diversification concern and has nothing to do with information. Without manipulation, there should be no discernible information pattern around vesting dates.

Figure 5 , however, shows that the disclosures subsequent to vesting dates are still distinctly negative, signalling a CEO's manipulation. Since a CEO has no incentive to suppress the positivity of disclosures following her stock sales, the disclosed negative information existed before her sales, and the CEO withholds its disclosure until she cashes out. In addition, a CEO's personal transactions, such as stock sales, are not filed with the SEC through Form 8-Ks, thus not included in my disclosure sample. It is not the CEO's stock sale that gives rise to the subsequent negative information. On the other hand, a stronger intention to sell should have motivated a CEO to accelerate or generate positive information in advance, as argued in previous studies of voluntary disclosures. Nontheless, unlike Figure 3, which displays a positive tone of pre-sale disclosures, the tone of pre-vesting disclosures in Figure 5 is not different from the usual. This suggests that the positive information gathering before a CEO's stock sales is not a consequence of her sale decisions. Rather, her stock sales, when not predetermined, are typically timed upon the arrival of positive information.

5.2.2 Causal effect of a CEO's intention to sell on firm disclosures

The reduced form study above rests on the assumption that a CEO will immediately sell on a vesting date, although a sale can occur after it. To make the dates shortly after a vesting date also indicate the CEO's higher propensity to sell, I depart from the event study approach and employ a 2SLS regression that covers all available trading days of the firms in the sample. By establishing a daily measure for each firm that summarizes its disclosures, I investigate whether a date, if signaling an exogenous variation in a CEO's intention to sell, is associated with a dramatic change in the information disclosed around this date.

Particularly, the post-vesting window, which is described as "shortly after a vesting date", requires a clearer definition. I check the instruments developed from different lags, $L = \{0, 5, 10\}$, assuming a CEO will sell in response to a newly vested option exactly on its vesting date, on and within a 5-trading-day window after this date, or on and within a 10-trading-day window after this date, respectively. I expect the instrument from $L = 0$ to be weaker, since it may not effectively simulate a CEO's actual sales if she responds slower. At the same time, a post-vesting window of an unnecessarily long length also has drawbacks. The premise of my instrument is that a stock sale closely following a vesting date is driven by its CEO's diversification need rather than information. If this window is too long, for example, extending to one month, it becomes hard to tell whether a sale, far from a vesting date, still arises from the CEO's under-diversification concern.

Since the endogenous variable in the 2SLS regression is an indicator of a CEO's stock sales, I_{Sale}, its relation with vesting dates is probably nonlinear. A vesting date elevates a CEO's propensity to sell, but it cannot guarantee her sale on this date. Moreover, it may drive up her propensity to sell to different extents when her firm's characteristics vary.[27] To capture this nonlinearity, per the suggestions from Angrist and Pischke (2009), I add a preliminary regression, in which I develop my instrument, a CEO's propensity to sell, from her option vesting dates in a probit model. The preliminary and first-stage regressions take the following forms (d denotes an available trading date of firm i):

- Preliminary regression:

$$Pr\left(I_{Sale,id} = 1\right) \sim \Phi\left(\alpha_1 + \beta_1 \cdot I_{Vest,id} + \gamma_1 \cdot Controls_{id}\right), \tag{8}$$

- First-stage regression:

$$I_{Sale,id} \sim \alpha_2 + \beta_2 \cdot \hat{Pr}\left(I_{Sale,id} = 1\right) + \gamma_2 \cdot Controls_{id}, \tag{9}$$

where $I_{Sale,id}$ is a dummy variable that equals 1 if the CEO of firm i sells on trading date d. $I_{Vest,id}$ equals 1 if she has an option that turns exercisable within the trading-day window of $[d - L, d]$, with $L = \{0, 5, 10\}$. Since a CEO may not sell instantly when she has newly vested options, I extend this period for L more trading days after a vesting date to simulate her subsequent stock sales. $\Phi(\cdot)$ is a standard normal cumulative distribution function. $Pr\left(I_{Sale,id} = 1\right)$ denotes the probability that she sells on date d, and its fitted value, $\hat{Pr}\left(I_{Sale,id} = 1\right)$, is the instrument for the CEO's endogenous sale decision, $I_{Sale,id}$. To discern it from the fitted value of $I_{Sale,id}$ in the second-stage regression, I name $\hat{Pr}\left(I_{Sale,id} = 1\right)$ as the "propensity to sell" and $\hat{I}_{Sale,id}$ as the "intention to sell." $\hat{I}_{Sale,id}$ reflects a CEO's sale intention untied from information. It is predicted from $\hat{Pr}\left(I_{Sale,id} = 1\right)$ in a OLS model and

[27] For example, if a firm's stock price hits a historic high, and its CEO is almost certain to sell. In this case, a newly vested option strengthens the CEO's intention to sell by a smaller amount.

should be a continuous variable ranging from 0 to 1. All three regressions share the same set of controls, $Controls_{id}$, which are delineated below.[28]

The second-stage regression is formulated as follows:

$$
\begin{aligned}
DiscCon_{id}^{Period} \sim & \alpha + \beta \cdot \hat{I}_{Sale,id} \\
& + \delta_1 \cdot AGM_{Before,id} + \delta_2 \cdot AGM_{After,id} \\
& + \delta_1 \cdot SUE_{id} + \delta_2 \cdot PastReturn_{id} + \delta_3 \cdot idioVol_{id} \\
& + \eta_1 \cdot lnAsset_{id} + \eta_2 \cdot ROA_{id} + \eta_3 \cdot TobinQ_{id} \\
& + \eta_4 \cdot lnSale_{id} + \eta_5 \cdot SaleGwth_{id} \\
& + CEOFE_{id} + FirmFE_i + Year \times Month_d + \epsilon_{id},
\end{aligned}
\tag{10}
$$

where $DiscCon_{id}^{Period}$, with $Period \in \{Trailing, Leading\}$, is a daily disclosure score for firm i on trading day d. It averages the DiscCon scores of all the disclosures within a 10-business-day window of either $[d-10, d-1]$ for $Period = Trailing$ or $[d+1, d+10]$ for $Period = Leading$.[29] As illustrated below, I take two steps to establish this daily tracker of disclosures for each firm.

First, as a firm's disclosure is my dependent variable, I do not apply the normalization as in equation 7. Since the regression setting enables me to control the firm-level fixed effect, the heterogeneity in word preferences across firms no longer matters: I look for the deviation in the use of negative words within the same firm. If the DiscCon drops as compared to its firm's general level, then the information is reported in a more negative tone than usual, and I regard it as negative information. In Figure 13 of Appendix A.2, I plot the distribution of

[28]Readers might be concerned about the controls inside the cumulative distribution function in equation 8, under which circumstances, the controls also contribute to the instrument's variation. Since this variation follows a nonlinear relation with the controls, it cannot be excluded in the 2SLS regression. Then, it might be the controls that drive the instrument and generate the causal effect of a CEO's intention to sell on disclosures. To address this concern, I develop an instrument solely from the controls and redo the 2SLS regression. The new instrument is no longer valid, and all significant results are gone. Therefore, the instrument's nonlinear variation from the controls does not capture a CEO's actual sales and will not contaminate the causal effect I measure in the second-stage regression.

[29]As discussed earlier in the event studies, I adhere to a 10-business-day disclosure window in computing this moving average, and place the case of a 5-business-day window in the Appendix as a robustness check.

the DiscCon measures quantified by $-\%Neg$. Akin to Figure 1 and Figure 12, the measure has a long left tail if it is built upon a raw percentage, so I take log transformation before performing the regressions to adjust for this skewness:

$$DiscCon^{Y=DiscCon}_{Regression} \equiv -ln\left(\%Neg + 1\right). \tag{11}$$

More specifically, starting from a disclosure on a filing date ϕ, I quantify its information as $DiscCon_{i\phi} \equiv -ln\left(\%Neg_{i\phi} + 1\right)$, where $\%Neg_{i\phi}$ denotes the percentage of negative words in this disclosure.

Second, with the DiscCon score of each disclosure, $DiscCon_{i\phi}$, ready, $DiscCon^{Period}_{id}$ is computed as follows:

$$\begin{aligned} DiscCon^{Trailing}_{id} &\equiv \frac{\sum_{\phi=d-10}^{d-1} DiscCon_{i\phi} \cdot I_{i\phi}}{\sum_{\phi=d-10}^{d-1} I_{i\phi}} \\ DiscCon^{Leading}_{id} &\equiv \frac{\sum_{\phi=d+1}^{d+10} DiscCon_{i\phi} \cdot I_{i\phi}}{\sum_{\phi=d+1}^{d+10} I_{i\phi}}, \end{aligned} \tag{12}$$

with $I_{id} = 1$ if firm i has a disclosure on date d.

$Controls_{id}$ are firm characteristics. The date controls of $AGM_{id,Before}$ and $AGM_{id,After}$ are dummy variables, considering a CEO's information screening before an annual general meeting (Dimitrov and Jain, 2011). $AGM_{id,Before}$ ($AGM_{id.After}$) equals 1 if trading day d falls within the 10-business-day window before (after) firm i's annual general meeting. There are some additional factors that might affect a CEO's sale decision (Fos and Jiang, 2016; Edmans et al., 2018). The quarterly updated standardized unexpected earnings (SUE) score in IBES Summary is a commonly used measure for earnings surprises. A higher earnings surprise implies much better performance than what was anticipated. It may predict a price increase, which provokes a CEO's sale decision. The monthly updated $PastReturn$ is a one-year holding period return derived from the daily returns of $[m_d - 12, m_d - 1]$, with m_d denoting the month in which date d is located. Wary of the potential trading halts, I first compute the average daily return and then rescale it to a 252-trading-day length. The monthly updated $idioVol$ is the standard deviation of the residuals from the

Fama-French four-factor regression (Carhart, 1997), which considers the momentum effect in addition to the traditional SMB, HML, and market premium factors. The regression covers the daily returns of a four-calendar-month window $[m_d - 4, m_d - 1]$.[30] I also add quarterly fundamental controls of *lnAsset*, *ROA*, *TobinQ*, *lnSale*, and *SaleGwth*. See Appendix A.5.2 for more details of their definitions. Lastly, I control the fixed effects of firms, CEOs, and time, in consideration of the heterogeneity in the preferences on wording across firms, the inclinations to manipulate information across CEOs, and the market-wide shocks across $Year \times Months$.

Table 4 shows the results of the 2SLS regressions that are based on the instrument from $L = 10$. That is, a CEO's stock sales on and within 10 trading days after her option vesting dates are regarded as her reaction to the enhanced diversification need. The full sample includes all available trading days for each firm, but its size shrinks drastically when it intersects with $DiscCon^{Period}$. The total number drops from 1.97 million in column 1 to 0.74 millon in columns 2-5. Firms do not file 8-K disclosures daily, so the dependent variable $DiscCon^{Period}$ may miss some points throughout the sample period. Column 1 reports the significantly positive relation between I_{Vest} and $Pr\left(I_{Sale} = 1\right)$, so the dates of $I_{Vest} = 1$ are more likely to capture actual stock sales than those of $I_{Vest} = 0$. Consequently, a CEO's propensity to sell, $\hat{Pr}\left(I_{Sale} = 1\right)$, has an upshift in its value over the period of $[d_{Vest}, d_{Vest} + 10]$, with d_{Vest} denoting a vesting date. Since the process of generating the instrument, $\hat{Pr}\left(I_{Sale} = 1\right)$, does not involve $DiscCon^{Period}$, the fitted values are estimated from the full sample. After merging the data of $\hat{Pr}\left(I_{Sale} = 1\right)$ with the available points of $DiscCon^{Trailing}$ and $DiscCon^{Leading}$ respectively, I can launch the 2SLS regressions reported in columns 2 to 5.

The first-stage regression results, as presented in columns 2 and 4 of Table 4, both report a significantly positive relation between $\hat{Pr}\left(I_{Sale} = 1\right)$ and I_{Sale}. The F-statistics are also

[30] The parameters of the Fama-French four-factor model (α, β_{Mkt}, β_{SMB}, β_{HML}, β_{UMD}) have values only if the regression sample, which covers the daily returns of $[m_d - 4, m_d - 1]$, has ≥ 30 data points, with Dimson (1979) adjustment to address the potential problem of estimation bias if the number of sample points is too limited.

Table 4: Causal Effect of a CEO's Stronger Intention to Sell on Disclosures - Lag = 10

This table reports the results of a causal effect test that examines whether a CEO's intention to sell affects mandatory disclosures. $DiscCon_{id}^{Trailing}$ ($DiscCon_{id}^{Leading}$) is a daily DiscCon measure, defined as the mean DiscCon score of all the disclosures within a 10-business-day window before (after) date d, with each file's DiscCon quantified as $-ln\,(\%Neg+1)$. $I_{Vest,id}=1$ if its CEO has an executive option turning exercisable during $[d-10,d]$ period. $I_{Sale,id}=1$ if the CEO sells on date d. Column 1 generates the instruemnt $\hat{Pr}\,(I_{Sale,id}=1)$ from $I_{Vest,id}$, the fitted probability of $I_{Sale,id}=1$ on date d, in a probit model. Columns 2 and 4 report first-stage regression results to validate the vesting-implied instrument, given the limited samples of $DiscCon_{id}^{Trailing}$ and $DiscCon_{id}^{Leading}$. Columns 3 and 5 report second-stage regression results. T-statistics are reported in parentheses, with their standard errors adjusted in a two-way clustering at both the 4-digit SIC industry code and $Year \times Month$ levels. The test covers all firms that are in the intersection of disclosure samples (SEC Analytics), sale samples, and option grant samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018. *,**, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Regression:	Instrument	2SLS			
Sample:	Full	Trailing		Leading	
DV:	$Pr\,(I_{Sale}=1)$	I_{Sale}	$DiscCon^{Trailing}$	I_{Sale}	$DiscCon^{Leading}$
	(1)	(2)	(3)	(4)	(5)
I_{Vest}	0.284***				
	(41.60)				
$\hat{Pr}\,(I_{Sale}=1)$		0.276***		0.286***	
		(3.72)		(4.43)	
$\hat{I}_{Sale}$			-0.311		-5.092***
			(-0.28)		(-3.03)
lnAsset	-0.015***	-0.007**	-0.001	-0.005**	-0.019
	(-4.51)	(-2.32)	(-0.04)	(-2.12)	(-1.04)
ROA	0.121	0.053***	0.325***	0.040*	0.491***
	(0.90)	(2.65)	(2.60)	(1.92)	(2.65)
TobinQ	0.090***	-0.001	0.008**	-0.001	0.010
	(43.69)	(-0.69)	(2.42)	(-0.50)	(1.37)
lnSale	-0.013***	0.005**	0.024*	0.004*	0.042**
	(-3.76)	(2.10)	(1.90)	(1.74)	(2.46)
SaleGwth	0.172***	0.000	-0.002	-0.003	-0.009
	(8.06)	(-0.06)	(-0.17)	(-1.29)	(-0.55)
PastReturn	0.221***	0.006***	0.015	0.003**	0.034***
	(31.98)	(4.56)	(1.43)	(2.03)	(2.80)
SUE	0.009***	0.000	0.001	0.000	0.001
	(13.09)	(1.49)	(1.48)	(-0.27)	(1.58)
idioVol	-4.651***	-0.166***	-1.772***	-0.074	-2.117***
	(-10.50)	(-3.12)	(-4.13)	(-1.51)	(-3.90)
AGM_{Before}	0.097***	0.002**	0.021	0.002**	-0.002
	(6.45)	(2.09)	(1.54)	(2.13)	(-0.21)
AGM_{After}	0.162***	0.000	-0.015	0.002*	-0.013
	(11.73)	(-0.21)	(-1.45)	(1.95)	(-1.07)
Obs	1,970,785	741,685	741,685	738,072	738,072
χ^2 Test	0				
F-Test		20.17		23.87	
Firm, CEO, time	N	Y	Y	Y	Y

much greater than 10. This validates $\hat{Pr}\left(I_{Sale}=1\right)$ as a strong instrument to predict a CEO's sale decision, I_{Sale}, in both $DiscCon^{Trailing}$ and $DiscCon^{Leading}$ samples. In brief, there exists some exogenous increase in a CEO's propensity to sell on and closely after a vesting date, which then drives up her intention to sell, as implied by $\hat{I}_{Sale}$. Since this variation is independent of information, it allows me to examine the causal effect of the CEO's intention to sell on firm disclosures. The coefficient of $\hat{I}_{Sale}$ in column 3 does not significantly deviate from the null hypothesis of 0, suggesting that a CEO's strengthened intention to sell is not preceded by disclosures with a heightened positive tone. Conversely, the coefficient of $\hat{I}_{Sale}$ in column 5 exhibits a significantly negative relation with $DiscCon^{Leading}$, so a CEO's strengthened intention to sell is followed by disclosures with a heightened negative tone. This aligns with the implications from Figure 5 that a CEO withholds negative information in advance of her exogenously enhanced intention to sell, but does not disclose positive information beforehand, although the CEO should be induced to do so to maximize her profits from stock sales.

As demonstrated in Section 4.1.1, across all the Form 8-K disclosures in my sample, the use of negative words has an exceptionally long right tail. I take log transformation before the regressions to adjust for this skewness in the distribution. For this reason, to interpret the magnitude of the coefficient of $\hat{I}_{Sale}$, I need to convert the score back to a percentage term. Let Δ denote this coefficient and assume $\hat{I}_{Sale}$ changes from a to $a+\iota$:

$$-ln\left(\%Neg_{\hat{I}_{Sale}=a+\iota}+1\right)+ln\left(\%Neg_{\hat{I}_{Sale}=a}+1\right)=\Delta\iota. \tag{13}$$

This transforms to:

$$\%Neg_{\hat{I}_{Sale}=a+\iota}-\%Neg_{\hat{I}_{Sale}=a}=\left(e^{-\Delta\iota}-1\right)\left(\%Neg_{\hat{I}_{Sale}=a}+1\right). \tag{14}$$

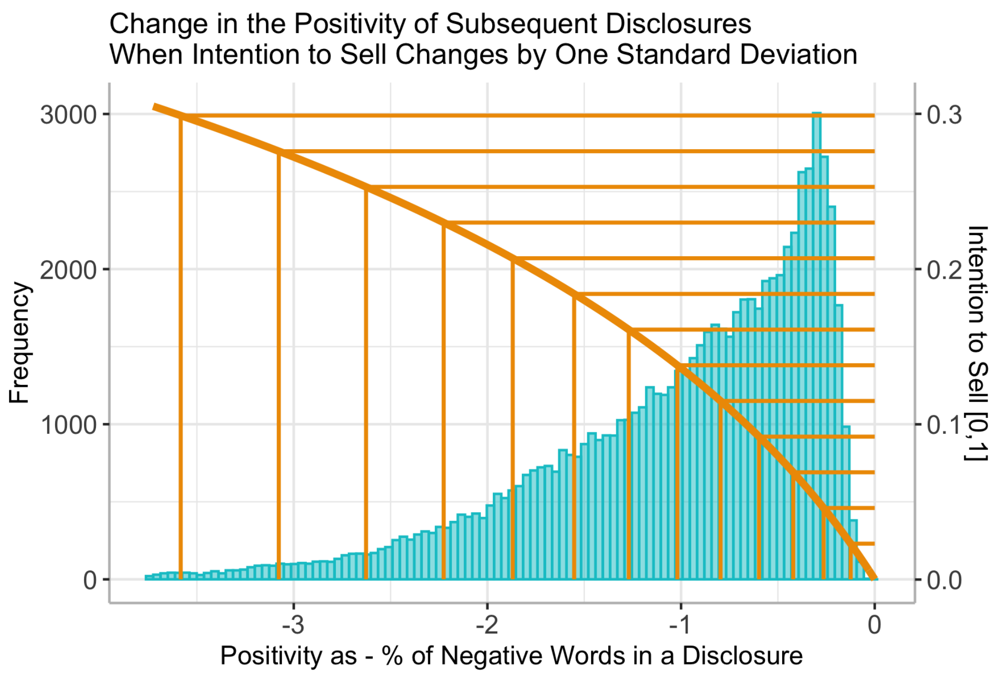
The equation above shows that it is difficult to determine the variation in the percentage of negative words of a disclosure in relation to the change in a CEO's intention to sell. For one thing, it depends on $\%Neg_{\hat{I}_{Sale}=a}$, so the starting point, a, matters. And for another, when Δ is negative, the positive slope of $e^{-\Delta\iota} - 1$ gets steeper as ι increases. Let $a = 0$ and $\iota = 1$, that is, I compute the change in the percentage of negative words in a disclosure when its CEO switches from the state of "absolutely no intention to sell" to that of "certain decision to sell". As reported in column 5 of Table 4, the value of Δ, -5.092, can be translated to a surge of at least 162 pps from $\%Neg_{\hat{I}_{Sale}=0}$ to $\%Neg_{\hat{I}_{Sale}=1}$. Note that the maximum value of a disclosure's percentage of negative words is 100%. Therefore, when $|\Delta|$ is much greater than 0, it is inappropriate to interpret the coefficient of $\hat{I}_{Sale}$ as if $\%Neg$ and ι follow a linear relation.

The orange curve in Figure 6 draws the nonlinear relation between a CEO's intention to sell and the information positivity of firm disclosures subsequent to it, as described in equation 14. In general, the disclosed information is in a more negative tone if it follows a stronger intention to sell. One standard deviation increase in the level of a CEO's intention to sell leads to an uneven decrease in the information positivity of subsequent disclosures. It depends on the starting level of her intention to sell. When the CEO initially has little incentive to sell, then even if newly vested options deepen her diversification needs, her probability of selling stocks is still low, so she is not likely to participate in the disclosure manipulation. In contrast, when the CEO has a strong incentive to sell, the additional diversification needs further ascertain her sale decision. This motivates her to take action and withhold negative information till after her sales. For reference purposes, I also plot the distribution of my disclosure content measure, which is quantified as $-\%Neg$, in this test setting.

The target of this paper is to light upon some signs of a CEO's manipulation, rather than measuring the exact size of the change in a disclosure's use of negative words, so I do not put stress on interpreting the magnitude of each coefficient. The significantly negative relation between $\hat{I}_{Sale}$ and $DiscCon^{Leading}$ is already sufficient to reveal a CEO's tendency to decelerate the disclosures of negative information when confronted with her forseeable

Figure 6: Interpreting the Causal Effect of a CEO's Sale Intention on Subsequent Disclosures

In this graph, I try to present a more visual explanation about the causal effect I have identified from the 2SLS regression in Table 4. The curve in orange draws the relation between a CEO's intention to sell and the information positivity of subsequent disclosures according to equation 14. A CEO's intention to sell, $\hat{I}_{Sale}$, is generated from equation 9. Information positivity is measured by $-\%Neg$, with $\%Neg$ representing the percentage of negative words in a disclosure. The vertical and horizontal lines help me to show the uneven change in information positivity of subsequent disclosures per one-standard-deviation change in a CEO's intention to sell. I also plot the distribution of my disclosure content measure, quantified as $-\%Neg$, in the background for reference. The test covers all firms that are in the intersection of disclosure samples (SEC Analytics), sale samples, and option grant samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018.



enhanced intention to sell.

5.2.3 Robustness check: Instruments established from different lags

As it is unclear as to how soon a CEO will respond to her option vesting, I check the instruments that are built upon different lags after vesting dates. In Table 5, I compare the results of the 2SLS regressions, which are based on post-vesting windows $L \in \{0, 5, 10\}$. $DiscCon^{Period}$ is still a daily moving average that covers all the disclosures within a 10-

Table 5: Instruments from Different Lags After a CEO's Option Vesting Dates

This table provides the results of the 2SLS regressions that rely on the instruments from different lag lengths, $L = \{0, 5, 10\}$ trading days, after option vesting dates. $I_{Vest,id} = 1$ if a CEO has an executive option turning exercisable during $[d - L, d]$ period. $I_{Sale,id} = 1$ if the CEO sells stock shares on date d. The instrument $\hat{Pr}\left(I_{Sale,id} = 1\right)$, the fitted probability of $I_{Sale,id} = 1$ from $I_{Vest,id}$, is generated by a probit model. Its relation with $I_{Vest,id}$ is reported in column 1. $DiscCon_{id}^{Trailing}$ ($DiscCon_{id}^{Leading}$) is a daily moving-average DiscCon measure, defined as the mean DiscCon score of all the disclosures within a 10-business-day window before (after) date d, with each file's DiscCon quantified as $-ln\left(\%Neg + 1\right)$. Columns 2 and 4 report the results of the first-stage regressions to validate the vesting-implied instrument, given the limited samples of $DiscCon_{id}^{Trailing}$ and $DiscCon_{id}^{Leading}$. Columns 3 and 5 report the second-stage regression results. T-statistics are reported in parentheses, with their standard errors adjusted in a two-way clustering at both the 4-digit SIC industry code and $Year \times Month$ levels. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics), sale samples, and option grant samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018. Table 12 in Appendix A.3 reports the results of the same set of 2SLS regression tests with the $DiscCon_{id}^{Trailing}$ and $DiscCon_{id}^{Leading}$ computed from a disclosure window of 5 business days. *,**, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Regression:		Instrument	2SLS			
Sample:		Full	Trailing		Leading	
DV:		$Pr\left(I_{Sale} = 1\right)$	I_{Sale}	$DiscCon^{Trailing}$	I_{Sale}	$DiscCon^{Leading}$
Lag:		(1)	(2)	(3)	(4)	(5)
	I_{Vest}	0.373***				
		(21.78)				
L = 0	$\hat{Pr}\left(I_{Sale} = 1\right)$		0.236**		0.177**	
			(2.11)		(2.08)	
	$\hat{I}_{Sale}$			-1.994		-5.376**
				(-1.29)		(-1.99)
	F-Test		20.15		23.83	
	I_{Vest}	0.315***				
		(39.00)				
L = 5	$\hat{Pr}\left(I_{Sale} = 1\right)$		0.323***		0.293***	
			(3.99)		(4.02)	
	$\hat{I}_{Sale}$			0.411		-3.227***
				(0.52)		(-2.65)
	F-Test		20.19		23.88	
	I_{Vest}	0.284***				
		(41.60)				
L = 10	$\hat{Pr}\left(I_{Sale} = 1\right)$		0.276***		0.286***	
			(3.72)		(4.43)	
	$\hat{I}_{Sale}$			-0.311		-5.092***
				(-0.28)		(-3.03)
	F-Test		20.17		23.87	
Obs		1,970,785	741,685	741,685	738,072	738,072
Firm, CEO, time		N	Y	Y	Y	Y

business-day window before or after an available trading date ($K = 10$).[31] I first re-examine the validity of each instrument for $DiscCon^{Trailing}$ and $DiscCon^{Leading}$ samples and report the results in columns 2 and 4. As expected in the case of $L = 0$, the instrument is weaker, because its solo increase on a vesting date cannot account for the stock sales that flock afterwards. A CEO may not sell immediately on her option vesting dates and require some time to react and execute her sale decisions. Similar to the results in Table 4, the regression in column 3 of Table 5 reports an insignificant coefficient of $\hat{I}_{Sale}$ with regard to $DiscCon^{Trailing}$, while that in column 5 reaffirms the significantly negative relation between $\hat{I}_{Sale}$ and $DiscCon^{Leading}$.

Set $L = 0$ aside for a moment, one intriguing pattern concerning each coefficient in columns 5 of Table 5 and Table 12 is that its magnitude grows as the coverage period extends: the coefficient's absolute value of (L, K) = (5,5) in Table 12 is around 2, those of (5,10) in Table 5 and (10,5) in Table 12 are around 3, and that of (10,10) in Table 5 is around 5. This says there is a continuous flow of negative information up to one month after a CEO's option vesting dates.[32] For example, (5,5) covers disclosures up to 10 days from a vesting date. Under this setting, only the disclosures in the period $[d_{Vest} + 1, d_{Vest} + 10]$ are attributed to a CEO's stronger intention to sell. Those after this cutoff, $d_{Vest} + 10$, are deemed irrelevant to the CEO's intensified diversification need from vesting dates, and thereby paired with a lower intention to sell. If the CEO sells stocks or discloses withheld information at a slower pace, then the disclosures after the cutoff may also be negative. This narrows down the differences among disclosures when they are assigned to match different extents of a CEO's intention to sell. In return, it yields a coefficient with a smaller magnitude. As the coverage period extends, like 15 days in the case of (5,10) and (10,5), or 20 days in the case of (10,10), this misclassification problem gets ameliorated, thus producing coefficients

[31] I also redo the same set of tests for a 5-business-day disclosure window ($K = 5$). The results are summarized in Table 12 of Appendix A.3.

[32] I also tried ($L = 10, K = 20$), which lengthens the coverage to about one and a half months after a vesting date. The size of its coefficient rises by only 0.8 from 5 of ($L = 10, K = 10$), so it seems unnecessary to further extend this coverage. Overall, the flow of negative information lasts for one month or so after vesting dates.

of $\hat{I}_{Sale}$ with a larger magnitude.

For $L = 0$, the absolute value of $\hat{I}_{Sale}$'s coefficient in the case of (0,5) is around 4, and that of (0,10) is around 5, as the latter covers a longer period. When compared to other lags, (0,5) and (0,10) generate larger coefficients of $\hat{I}_{Sale}$ in magnitude due to their smaller coefficients of $\hat{Pr}\left(I_{Sale} = 1\right)$ in the first-stage regressions. Focus on $\hat{Pr}\left(I_{Sale} = 1\right)$'s coefficients in columns 4 of Table 5 and Table 12, those of $L = 5$ and $L = 10$ are quite close, given the same value of K (e.g., 0.293 for $L = 5$ and 0.286 for $L = 10$ in Table 5 with $K = 10$; 0.370 for $L = 5$ and 0.356 for $L = 10$ in Table 12 with $K = 5$). Therefore, the instruments developed from these two lags are comparably effective in predicting a CEO's intention to sell. $L = 0$ is an exception, as its coefficient of $\hat{Pr}\left(I_{Sale} = 1\right)$ almost halves (e.g., 0.177 in Table 5 with $K = 10$; 0.209 in Table 12 with $K = 5$). Since $\hat{I}_{Sale}$'s coefficient can be decomposed to $\hat{I}_{Sale} = \beta_{\frac{DiscConLeading}{\hat{Pr}(I_{Sale}=1)}} \cdot \left(\beta_{\frac{I_{Sale}}{\hat{Pr}(I_{Sale}=1)}}\right)^{-1}$, a weaker instrument mechanically makes it larger.

In summary, a CEO times firm disclosures contingent on the information disclosed. She decelerates the disclosures of negative information, whereas does not accelerate those of positive information. When the CEO's intention to sell rises due to her escalated concern of under-diversification, she tends to withhold negative information in advance. Together with the time limit imposed on the release of material information, this justifies why negative news anomalously gathers afterwards. On the other hand, the prominent positive tone of pre-sale disclosures does not result from her manipulation, because the disclosures preceding a CEO's exogenously strengthened intention to sell are not reported in a heightened positive tone. The CEO does not accelerate positive information, as she may not have any truthful positive news to speed up its disclosure. Moreover, there appears no reason for a CEO to withhold and then pile positive news closely before her stock sales, as positive information drives up the stock price permanently. A longer time for the market to digest positive news may even help her achieve a higher sale price.

As demonstrated in the "Introduction" part, I focus on mandatory disclosures because a CEO's ability to generate positive information (e.g. modify the content or wording of disclosures) is constrained in this setting. The absence of a significantly positive causal effect of a CEO's sale intention on pre-sale disclosures provides support for my assumption. First, a CEO may employ content manipulation by fabricating good news before her stock sales. This strategy turns out to be invalid. However, not all information disclosed through Form 8-Ks falls into mandated reporting. A CEO may disclose additional material information based on her judgment.[33] It seems that the CEOs in my sample do not use this strategy. Disclosures through Form 8-Ks, when compared to other voluntary channels, are truthful and costly to report. These may place barricades for a CEO to take advantage of this discretion. Even if the information is authentic, a CEO may modify the wording of its disclosure (i.e., making neutral information sound positive and positive information sound more positive by avoiding negative words). The setting of mandatory disclosures also limits her ability to exploit this discretionary space. Ideally, a publicly traded firm must file Form 8-K disclosures whenever material events occur within four business days. To meet this tight deadline, the firm is likely to use established templates, so I doubt a CEO's influence on the word choice when she tries to tailor it to her occasional personal needs.

[33]It is basically impossible for a CEO to generate a positive event or eliminate a negative event that drops into the "material event" category defined in Form 8-Ks. The events such as the entry into or termination of a material definitive agreement, the creation of a direct financial obligation, and material impairments are beyond a CEO's control. She cannot make one happen or hinder the other from happening to accommodate her personal needs. See "Final Rule: Additional Form 8-K Disclosure Requirements and Acceleration of Filing Date" for more details of the material events defined in Form 8-K: https://www.sec.gov/rules/final/33-8400.htm. Despite this limitation, a CEO may still originate less material information. This is also an area at her discretion.

6 Chapter 3 Manipulation from urgency to sell

In this chapter, I investigate how disclosures differ when they are exposed to a CEO's urgency to sell by connecting her stock sales with the options that are close to their deadlines. An option has a predetermined expiration date. In reference to the one-year threshold in Malmendier and Tate (2005), I define an "expiring option" as one with less than one year remaining life.[34] Its tighter deadline fuels a CEO's urgency to sell and limits her flexibility to time her sales based on disclosures. The CEO is more incentivized to manipulate information in this case because she has less chance of getting desirable information by just waiting.

Since an expiration date is determined on its option grant date, a CEO may adopt the timing strategy comparable to the case of a vesting date. A CEO knows when her options will vest and thus can forecast her higher propensity to sell subsequent to vesting dates. This entices the CEO to withhold negative information beforehand. Likewise, if a CEO holds expiring options, she knows the options will expire within one year and therefore can foresee her higher propensity to sell from now on until these predetermined deadlines. This enables the CEO to better prepare and withhold negative information in advance.

Although some previous studies examine a firm's disclosures around a CEO's option exercises, in this paper I assume the CEO's manipulation is mostly motivated by her sale decisions rather than exercise decisions and focus on the relation between firm disclosures and her stock sales, with sales split into multiple groups based on the different extents of urgency from option expiration.

Figure 7 provides some evidence in support of my argument. It plots the distribution of a CEO's option exercises by how soon she would also sell stocks after her exercises. It shows that over 80% of CEOs' option exercises happen on the same day with their stock sales, so it is not surprising to see a similar information pattern of the disclosures around their option

[34]Exercises and expirations of expiring options are not rare among CEOs based on the one-year threshold. As shown in Figure 19 of Appendix A.4, over two-thirds of the CEOs in the sample hold some options until the last year before their expiration dates.

Figure 7: Distribution of Option Exercises Given the Distances to Their Closest Stock Sales

This graph shows the distribution of a CEO's option exercises, with the sample categorized by an exercise's distance from its closest sale date of the CEO on or after the exercise date. The sample is first divided by the length of remaining life when the option is exercised: Exer_SH (Exer_LH) includes all the options that are exercised more (less) than 1 year before expiration. Each group is then categorized into 4 subgroups by distance: "0", "1-5", "6-10", "10+". The y-axis reports the fraction of each subgroup in the Exer_SH or Exer_LH. For example, the subgroup of "0" of Exer_SH means I focus on a CEO's exercises of options that have more than one year remaining life, count the number of this type of exercises that coincide with the CEO's stock sales and compute this number as a percentage of the total number of option exercises in Exer_SH. The distribution covers all the firms that are in the intersection of disclosure samples (SEC Analytics), sale samples, and option exercise samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018.

exercises.[35] Moreover, if a CEO decides to hold the stock after exercising the option, she has no incentive to manipulate information right away, because the profitable pattern cannot be locked in unless she cashes out. The CEO would rather wait until she makes a sale in the future. This coincides with Carpenter and Remmers (2001) and Aboody et al. (2008), who find that the stock price does not drop immediately after an option exercise.

[35]Exer_LH, with LH standing for long-holder, represents the option exercises that have a less-than-one-year remaining life. These options are exercised with less autonomy, because a CEO has to face a tighter deadline. For example, if the stock price is on a rising trend while the option is going to expire tomorrow, the CEO may choose to exercise the option and hold the share until this trend ends. This may explain its higher fraction of distance "10+" in its sample, comparing to Exer_SH (short-holder).

It is worth attention that some options may expire deeply out of money. In this paper, I define "deeply out-of-money" options as those with $\frac{S}{K} - 1 \leq -0.3$, where S is the spot price and K is the strike price.[36] Deeply out-of-money options may not well identify a CEO's urgency to sell, as there is little chance for her to manually push up the stock price above its strike price. Therefore, I remove these options from my sample.

6.1 Firm disclosures when sale intention overlaps with urgency

To begin with, I first identify when a CEO exercises expiring options or whether her options expire out of money. This specifies the dates before which the CEO holds expiring options and experiences urgency to sell. When a CEO's intention to sell overlaps with her urgency to sell, the CEO is more prone to disclosing positive information and withholding negative information before her sales, so I am looking for the signs of manipulation in the "overlapping" period.

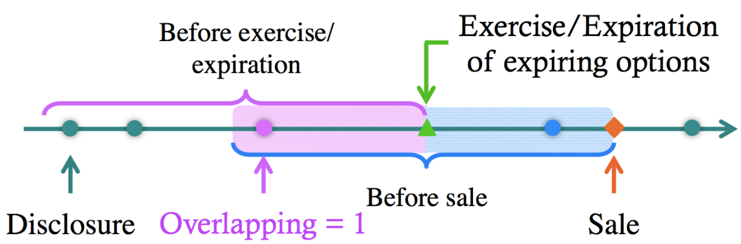
The definition of "overlapping" in this paper is defined as follows. First, let d_{Sale} denote a CEO's stock sale date and $d_{Exercise/Expiration}$ denote her exercise or expiration date of an expiring option. A pre-sale window is the 10-business-day period before a CEO's stock sale, $[d_{Sale} - 10, d_{Sale} - 1]$, and a post-sale window is the 10-business-day period after the sale, $[d_{Sale} + 1, d_{Sale} + 10]$. Likewise, a pre-exercise window is the 10-business-day period before her exercise or expiration of an expiring option, $\left[d_{Exercise/Expiration} - 10, d_{Exercise/Expiration} - 1\right]$, and a post-exercise window is the 10-business-day period after the exercise or expiration, $\left[d_{Exercise/Expiration} + 1, d_{Exercise/Expiration} + 10\right]$. Then, I define "overlapping" as the case when the disclosure date, ϕ, falls in an interval that overlaps either (i) the pre-sale and the pre-exercise windows,

$$\phi \in \left[d_{Exercise/Expiration} - 10, d_{Exercise/Expiration} - 1\right] \cap \left[d_{Sale} - 10, d_{Sale} - 1\right], \qquad (15)$$

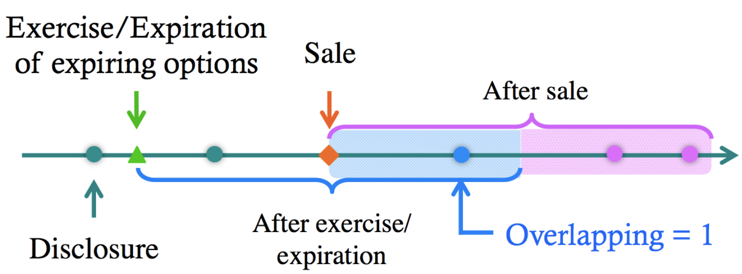
[36] I have tried this threshold from -0.1 to -0.5, and the results remain the same.

Figure 8: Classification of the Disclosures by Before, After, and Overlapping Indicators

Timeline 1: A disclosure with the indicator of Before$\times$Overlapping $= 1$



Timeline 2: A disclosure with the indicator of After$\times$Overlapping $= 1$



or (ii) the post-sale and the post-exercise windows,

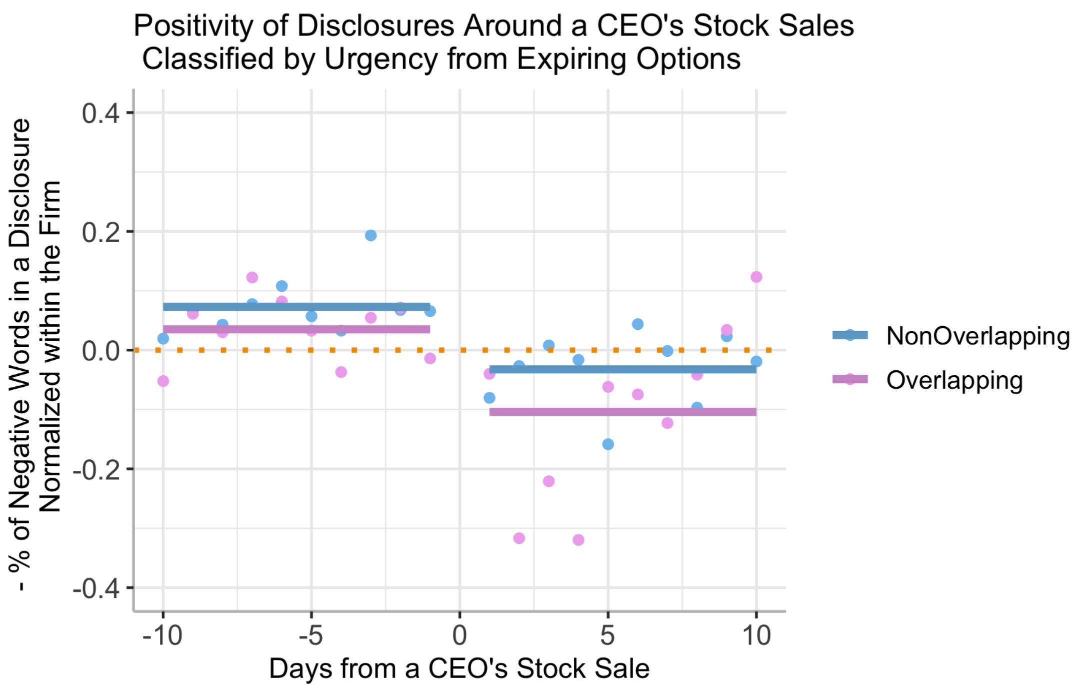
$$\phi \in \left[d_{Exercise/Expiration} + 1, d_{Exercise/Expiration} + 10\right] \cap \left[d_{Sale} + 1, d_{Sale} + 10\right]. \qquad (16)$$

For example, as illustrated in Timeline 1 of Figure 8, There are two disclosures filed in the pre-sale window, but only the earlier (left) one drops in the intersection of the pre-sale and pre-exercise windows and is classified as "overlapping". The later (right) one is a pre-sale disclosure classified as "non-overlapping". Similarly, Timeline 2 of Figure 8 shows an example that three disclosures are filed in the post-sale windows. The earliest (leftmost) one is classified as "overlapping" while the rest two are classified as "non-overlapping".

Next, I repeat the event study as in the last chapter, which draws the mean positivity of the disclosures around a CEO's stock sales. The only difference is that I classify the disclosures into two mutually exclusive groups – overlapping and non-overlapping – as defined above.

Figure 9: Mean Positivity of the Disclosures Classified by Urgency Around Stock Sales

This figure shows a plot of $DiscCon\,(k) - k$, the mean DiscCon score of 8-K disclosures that are released k business days away from their CEOs' closest stock sale dates. Before the mean calculation, the disclosures are divided into two mutually exclusive groups — overlapping and non-overlapping. Define a pre-sale (post-sale) window as the 10-business-day period before (after) a CEO's stock sale and a pre-exercise (post-exercise) window as the 10-business-day period before (after) her exercise or expiration of an expiring option. An expiring option refers to an option with less than one year remaining life. A disclosure is denoted as "overlapping" if it is filed either in the overlapping interval of pre-sale and pre-exercise windows or in that of post-sale and post-exercise windows. The option expirations that expire deeply out of money are removed from the sample. Each disclosure's DiscCon score is constructed as $DiscCon_{Graph} \equiv -Neg_{Norm}$. Neg_{Norm} is the percentage of negative words in this disclosure, normalized within its firm. The orange dotted line denotes the average DiscCon of each firm and the whole sample. A positive (negative) DiscCon signals a more positive (negative) tone in the disclosure as compared to the tones in other disclosures of its firm. It implies positive (negative) information in this disclosure. The solid line on the left (right) of $k = 0$ shows the average level of the DiscCon scores covering all the disclosures within the event window $k \in [-10, -1]$ ($k \in [1, 10]$) business days from their designated sales. The mean is cross-sectionally weighted. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics), sale samples, and option exercise samples (Thomson Reuter Insiders Data) from 2008 to 2018. The option expiration samples are inferred from Thomson Reuter Insiders and Execucomp. See Figure 20 in Appendix A.4, which shows the disclosure pattern following a 5-business-day window.



In Figure 9, it is not surprising to find that both the overlapping and non-overlapping groups replicate the upshift (downshift) in the mean positivity of the disclosures before (after) a CEO's stock sales. Rather, the main point of this graph is to show the differences in disclosures when the CEO is impelled by urgency to sell. Indeed, the negative tone of post-sale disclosures intensifies further in the "overlapping" group, as compared to the "non-overlapping" group, although the differences in the pre-sale disclosures are not obvious. Therefore, I examine whether the two groups are adequately different from each other by a regression test.

6.2 Regression analysis: Evidence of manipulation in disclosures

The regression is formulated as follows (ϕ denotes the filing date of a disclosure in the sample):

$$\begin{aligned} DiscCon_{i\phi} \sim & \alpha + \beta \cdot After_{i\phi} \times Overlapping_{i\phi} + \omega \cdot After_{i\phi} \\ & + \gamma \cdot Before_{i\phi} \times Overlapping_{i\phi} + \nu \cdot Before_{i\phi} \\ & + \delta_1 \cdot AGM_{Before,i\phi} + \delta_2 \cdot AGM_{After,i\phi} \\ & + \eta_1 \cdot lnAsset_{i\phi} + \eta_2 \cdot ROA_{i\phi} + \eta_3 \cdot TobinQ_{i\phi} \\ & + \eta_4 \cdot lnSale_{i\phi} + \eta_5 \cdot SaleGwth_{i\phi} \\ & + CEOFE_{i\phi} + FirmFE_i + Year \times Month_\phi + \epsilon_{i\phi}, \end{aligned} \tag{17}$$

where $DiscCon_{i\phi}$ is the disclosure score that quantifies the information disclosed by firm i on date ϕ. The dependent variable is defined as $DiscCon_{i\phi} \equiv -ln\left(\%Neg_{i\phi} + 1\right)$, and $\%Neg_{i\phi}$ denotes the percentage of negative words in this disclosure. The date control of $AGM_{i\phi,Before}$ ($AGM_{i\phi,After}$) indicate whether the filing date ϕ drops into the 10-business-day window before (after) firm i's annual general meeting.

$Before_{i\phi}$ and $After_{i\phi}$ are dummy variables that indicate a disclosure's position relative to its CEO's closest stock sale date. $Before_{i\phi} = 1$ if the filing date $\phi \in [d_{Sale} - 10, d_{Sale} - 1]$ and $After_{i\phi} = 1$ if the filing date $\phi \in [d_{Sale} + 1, d_{Sale} + 10]$.[37] The disclosures with more than one label (i.e., $Before_{i\phi} + After_{i\phi} = 2$) are removed from the sample. In other words, every observation satisfies $(Before_{i\phi}, After_{i\phi}) \in \{(0,1), (1,0), (0,0)\}$, and a disclosure filed closely

[37] I redo the same test as a robustness check based on a 5-business-day window. See Table 13 in Appendix A.4.

around a sale has $Before_{i\phi}+After_{i\phi}=1$. $Overlapping_{i\phi}$ is a dummy variable that indicates whether a disclosure falls in the overlapping interval. That is, $Before_{i\phi}\times Overlapping_{i\phi}=1$ if a pre-sale disclosure also drops in the pre-exercise window, as expressed in equation 15. The left dot within the pre-sale window on Timeline 1 of Figure 8 exemplifies a disclosure with $Before_{i\phi}\times Overlapping_{i\phi}=1$. Similarly, $After_{i\phi}\times Overlapping_{i\phi}=1$ if a post-sale disclosure also drop in the post-exercise window, as expressed in equation 16. The leftmost dot within the post-sale window on Timeline 2 of Figure 8 represents a disclosure with $After_{i\phi}\times Overlapping_{i\phi}=1$.[38]

The primary concern in this test is the potential selection bias problem, as a CEO who persistently holds an option until it becomes expiring may represent some unique firm features. For example, a firm led by an overconfident CEO may brings forth more negative information disproportionally. The fixed effects of firms and CEOs and the controls of firm characteristics in the regression should mitigate this concern. With these factors controlled, my focus is to examine whether firm disclosures differ when the same CEO has urgency to sell, on the condition that the firm is characterized by a similar set of performance metrics. My interest lies in the coefficient, β, of $After\times Overlapping$ (γ, of $Before\times Overlapping$), which measures the differences between the post-sale (pre-sale) disclosures of the "overlapping" and "non-overlapping" groups. $\beta\equiv\beta_2-\beta_1$ ($\gamma\equiv\gamma_2-\gamma_1$) tests the null hypothesis that the two groups disclose comparable information after (before) a CEO's stock sales.[39]

[38] With the help of $Before$ and $After$, the $Overlapping$ indicator segments the disclosures around a CEO's stock sales into four subgroups: before sale but not before exercise and expiration, before sale and before exercise and expiration, after sale but not after exercise and expiration, and after sale and after exercise and expiration. Together with the disclosures not close to any sale, they make up my full disclosure sample.

[39] When $Before+After\in\{0,1\}$, the regression covers all the available disclosures in the sample. The baseline disclosures (with $After=Before=Overalpping=0$) are those filed not around any sale, which take up to 85% of the entire sample. $After\times Overlapping$ and $After\times(1-Overlapping)$ ($Before\times Overlapping$ and $Before\times(1-Overlapping)$) split the disclosures after (before) sales into two mutually exclusive subgroups as to whether they are also filed after (before) any exercise or expiration of expiring options. The classificaton is exactly the same as how the disclosures around sales are partitioned into the "overlapping" and the "non-overlapping" groups in Figure 9. $After\times Overlapping$ and $After\times(1-Overlapping)$ ($Before\times Overlapping$ and $Before\times(1-Overlapping)$) account for 1% and 4.5% (2% and 7.5%) of the entire sample respectively. When $Before+After=1$, the regression covers only the disclosures around sales. The baseline disclosures ($After=Overlapping=0$) change to $Before\times(1-Overlapping)$, which represents the "non-overlapping" disclosures before sales.

$$
\begin{aligned}
DiscCon \sim \alpha &+ \beta_1 \cdot After \times (1 - Overlapping) + \beta_2 \cdot After \times Overlapping \\
&+ \gamma_1 \cdot Before \times (1 - Overlapping) + \gamma_2 \cdot Before \times Overlapping + ... \\
&= \underbrace{(\beta_2 - \beta_1)}_{\equiv \beta} \cdot After \times Overlapping + \beta_1 \cdot After \\
&+ \underbrace{(\gamma_2 - \gamma_1)}_{\equiv \gamma} \cdot Before \times Overlapping + \gamma_1 \cdot Before + \alpha + ...,
\end{aligned} \tag{18}
$$

When Before+After=1:

$$
\begin{aligned}
DiscCon \sim \beta \cdot After \times Overlapping &+ \beta_1 \cdot After \\
&+ \gamma \cdot Before \times Overlapping + \gamma_1 \cdot (1 - After) + \alpha + ... \\
&= \beta \cdot After \times Overlapping + (\beta_1 - \gamma_1) \cdot After \\
&+ \gamma \cdot Before \times Overlapping + \alpha + \gamma_1 + ...
\end{aligned} \tag{19}
$$

Columns 1 and 3 of Table 6 confirm that the interaction term $After \times Overlapping$ has a significantly negative coefficient. This verifies the downshift in the positivity of post-sale disclosures from the "non-overlapping" to the "overlapping" group in Figure 9. Therefore, the negative tone of post-sale disclosures does intensify when its CEO has urgency to sell. Compared to column 2, the confidence level of $After$ in column 3 drops to only 90% when $After \times Overlapping$ is added into the regression, suggesting that the pronounced negative tone of post-sale disclosures primarily stems from the "overlapping" group. Since a CEO knows she will probably sell after exercising expiring options, she may better prepare for these stock sales and withhold negative information till after the sales. Contrary to my expectation, however, the coefficients of $Before \times Overlapping$ in columns 1 and 3 are not positive, so the positive tone of pre-sale disclosures does not intensify, and a CEO does not disclose more positive information in advance though motivated by urgency to sell. This agrees with the asymmetry discovered in the causal effect test and also corroborates my

Table 6: Variation in Disclosures when Intention to Sell Overlaps with Urgency to Sell

This table provides the results of the regressions that examine whether a disclosure around a CEO's stock sale differs when the CEO has urgency to sell. The dependent variable is the DiscCon score of each disclosure, which is quantified as $DiscCon^{Y=DiscCon}_{Regression} \equiv -ln\,(\%Neg + 1)$. $\%Neg$ represents the percentage of negative words in this disclosure. Define a pre-sale (post-sale) window as the 10-business-day period before (after) a CEO's stock sale and a pre-exercise (post-exercise) window as the 10-business-day period before (after) her exercise or expiration of an expiring option. An expiring option refers to an option with less than one year remaining life. The dummy variable $Before = 1$ ($After = 1$) if the disclosure is released in the pre-sale (post-sale) window. The observations with conflicting classifications (i.e., $Before + After = 2$) are removed from the sample. Column 1 focuses on the disclosures around sales, while columns 2 and 3 cover all the disclosures in the sample. The dummy variable *Overlapping* = 1 if a disclosure is filed either in the overlapping interval of pre-sale and pre-exercise windows or in that of post-sale and post-exercise windows. T-statistics are reported in parentheses, with their standard errors adjusted in a two-way clustering at both the 4-digit SIC industry code and $Year \times Month$ levels. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics), sale samples and option exercise samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018. The option expiration samples are inferred from Thomson Reuter Insiders Data and Execucomp. Table 13 in Appendix A.4 provides the results of the same test based on a 5-business-day window.

Sample:	Before+After = 1	Before+After ∈ {0,1}	
	(1)	(2)	(3)
Before		0.035***	0.038***
		(6.04)	(6.24)
After	-0.047***	-0.016***	-0.011*
	(-5.10)	(-2.66)	(-1.76)
Before× *Overlapping*	-0.021*		-0.015
	(-1.73)		(-1.35)
After× *Overlapping*	-0.028**		-0.021**
	(-2.39)		(-2.06)
lnAsset	0.020	0.012	0.012
	(0.82)	(0.88)	(0.88)
ROA	-0.160	0.440***	0.440***
	(-0.53)	(4.04)	(4.03)
TobinQ	0.010*	0.006	0.005
	(1.81)	(1.43)	(1.37)
lnSale	0.030	0.015	0.015
	(1.28)	(1.06)	(1.07)
SaleGwth	-0.051**	-0.007	-0.007
	(-2.19)	(-0.59)	(-0.59)
AGM_{Before}	-0.007	0.008	0.008
	(-0.35)	(0.57)	(0.57)
AGM_{After}	-0.059***	-0.027***	-0.027***
	(-3.58)	(-2.71)	(-2.71)
Obs	11,654	75,968	75,968
Adj.R^2	0.26	0.23	0.23
Firm, CEO, Year×Month	Y	Y	Y

*,**, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

argument that a CEO's ability to accelerate or generate positive news is mostly muted in the setting of mandatory disclosures.

In addition, the coefficient of $Before \times Overlapping$ is slightly negative in column 1, in which case I narrow my focus to the disclosures around a CEO's stock sales. $Before \times Overlapping$ and $Before \times (1 - Overlapping)$ partition the disclosures before her sales into two groups. The latter consists of all the pre-sale disclosures that are not followed by any exercise and expiration of expiring options. Stock sales not associated with any expiring options probably originate from its CEO's timing of sales, so it is likely to find positive information before these endogenous sales. Conversely, a CEO's urgency to sell due to expiring options limits her flexibility to time sales, then it is less likely to find positive information before the stock sales that happen together with exercises or expirations of expiring options. As a result, the disclosures in the $Before \times Overlapping$ group present a less positive tone when benchmarked against the disclosures in the $Before \times (1 - Overlapping)$ group.

The findings in this section supplement the evidence of a CEO's manipulation in the timing of disclosures for her stock sales. If this manipulation did not exist, the CEO would take information as given and time her sale decisions based on it. Under such circumstances, when she perceives forthcoming negative information, her optimal decision is always to sell before its disclosure. Whether or not the CEO holds expiring options does not matter, and there should be similar disclosure patterns for the "overlapping" and "non-overlapping" groups around her stock sales. As I verify the differences between the disclosures of the two groups, manipulation exists in firm disclosures. Furthermore, it is timing manipulation rather than content or wording manipulation. A CEO would otherwise disclose more positive information before her sales instead of disclosing more negative information after her sales.

7 Conclusion

In this paper, I investigate whether a CEO takes advantage of the timing of firm disclosures. I find evidence in support of a CEO's timing manipulation that the CEO withholds negative information before her stock sales, so as to cash out at a higher price. I identify two scenarios in which a CEO tends to apply this timing strategy. First, a CEO's under-diversification concern due to the newly vested options signals an exogenous shock to her sale decision. Her strengthened intention to sell is followed by disclosures with a heightened negative tone, so the CEO consciously withholds negative information before an intended sale. Second, when a CEO faces urgency to sell due to the tighter deadline of expiring options, she is more incentivized to manipulate information. This variation parallels the incremental difference in disclosures, as the negative tone of post-sale disclosures intensifies further, suggesting that the CEO tends to withhold more negative information when confronted with urgency.

Interestingly, despite the relation that a CEO discloses more positive information before her stock sales, her enhanced sale intention does not demonstrate any significant causal role accounting for the positive tone of pre-sale disclosures. These results do not conflict, as the "timing of sales given a fixed schedule of disclosures" and the "timing of disclosures given a fixed schedule of sales" can co-exist. A vesting date is a predetermined date. An expiration date of an expiring option limits a CEO's flexibility to time her stock sales based on information, and therefore resembles a predetermined date. Under these two circumstances, the CEO's sale decisions are foreseeable, and she can withhold negative information till after the sales. On the other hand, the CEO can still watch for positive information and cash out after its release. As a consequence, a CEO's stock sales can be decomposed into the endogenous sales that contribute to the positive tone of pre-sale disclosures and the exogenous sales that contribute to the negative tone of post-sale disclosures.

This paper adds new ingredients to the literature concerning CEO opportunism: a CEO switches to a passive disclosure strategy by preventing the stock price from falling before her stock sales, as her ability to accelerate or generate positive information is mostly constrained in the setting of mandatory disclosures. This complements previous studies that look for a CEO's more aggressive strategy of pushing up the stock price and generally overlook the passive side. Moreover, this paper provides some implication for the current regulations that strive for accurate and timely disclosures: the "accuracy" part has somehow come true, since a CEO does not disclose more positive information in advance of her exogenous need for sale. This indicates the efficacy of the SEC's stringent monitoring in curbing a CEO's misleading and fraudulent disclosures; however, the "timeliness" part calls for further attention. The current requirement of a four-day deadline may need clearer guidelines, in order to make it more implementable. So long as a CEO still has the discretion to claim when information arrives, the timing of its disclosure can be manipulated to achieve her personal gains.

A Appendices

A.1 Profitability of timing manipulation

Thus far, I demonstrate how a CEO intentionally times firm disclosures for her own benefits. This is basically built upon a presumption that the withheld information elicits negative responses in the market, such that she seizes a higher stock price when cashing out. In Chapter 1, I already have shown the significantly negative correlation between a disclosure's percentage of negative words and its subsequent stock return. I may conjecture that the stock price tends to fall after a CEO discloses her withheld information, as it is narrated by more negative words. In the following test, I attempt to establish a more direct relation that links the disclosures and stock performance specifically around a CEO's stock sales to justify the above-mentioned timing strategy.

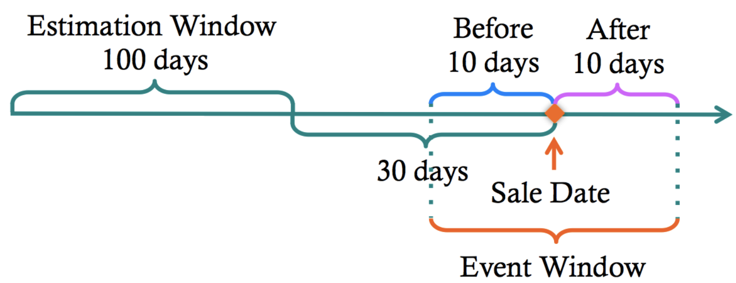
A.1.1 Computation of the CARs around a CEO's stock sales

I compute the cumulative abnormal returns (CARs) around a CEO's stock sales mainly in reference to Schultz (2003), Dahlquist and Jong (2008), and Karniouchina, Moore, and Cooney (2009). Roughly speaking, an abnormal return is the deviation from its counterfactual case, in which a stock sale did not take place. It is defined as the difference between an actual return and a predicted return, with the latter approximated from the returns earlier enough than the sale date. It is assumed that the predicted return implied from these returns are not influenced by its CEO's stock sales. In this paper, the predicted returns are based on the Fame-French 4-factor (FF4) model, with the parameters adjusted by the Dimson method. More details are presented below.

An abnormal return of firm i on a trading day d, which is within the event window of its CEO's stock sale date δ, is defined as follows:

$$AR_{i,d} = r_{i,d} - \hat{r}_{i,d}, \tag{20}$$

Figure 10: Timeline of Event and Estimation Windows

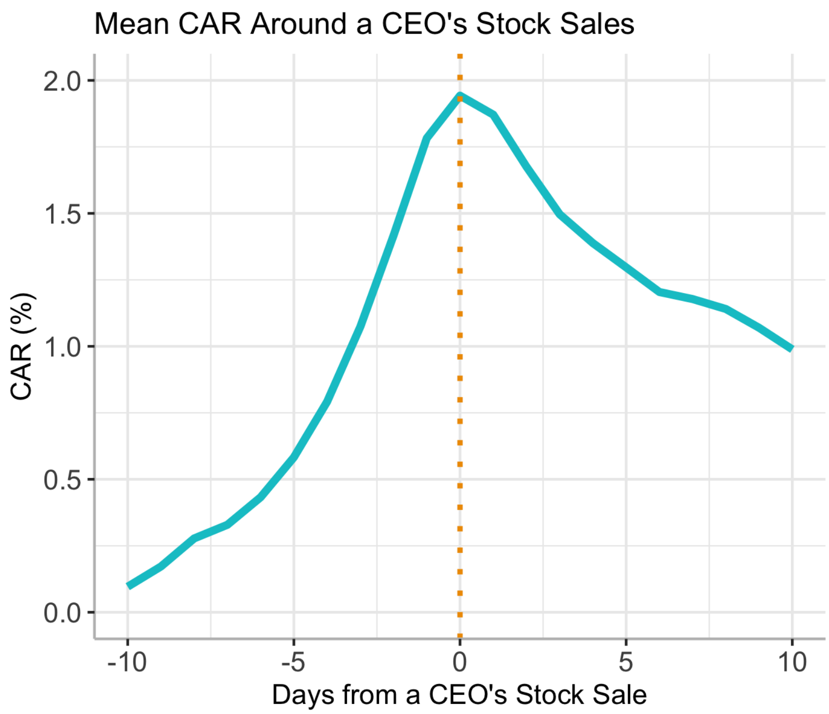


where $r_{i,d}$ is the actual daily return and $\hat{r}_{i,d}$ is the predicted daily return from the estimation window, as demonstrated in Figure 10. To be more specific, starting from a sale date δ, an event window covers the pre-sale and post-sale periods. In an event study, it is assumed that the stock return on a trading day $d \in [\delta - 10, \delta + 10]$ is affected by the event and therefore deviates from its "normal" level. $\hat{r}_{i,d}$ is designed to approximate this "normal" level, which firm i would otherwise have on date d without the event. Its estimation of the parameters $\{\alpha, \beta_{Mkt}, \beta_{SMB}, \beta_{HML}, \beta_{UMD}\}$ is based on the FF4 model and covers the daily returns of a 100-calendar-day window of $[\delta - 130, \delta - 31]$. The parameters have available values only if the regression sample has ≥ 30 data points, with Dimson adjustment to address the potential problem of estimation bias if the number of sample points is too limited.

Figure 11 displays how the stock return changes, as measured by its deviation from the counterfactual case, in a cumulative way within the event window of its CEO's sale. The CARs in Figure 11 are derived in the following order: (1) given one firm i and its CEO's sale date δ, $AR_{i\delta}(k)$ is the abnormal return k trading days away from δ (2) $AAR(k)$ is the average abnormal return k trading days away from a sale date, across all the firms and sale dates. Considering the potential problem of the cross-sectional dependence, AAR is cross-sectionally weighted. (3) $CAR(k) = \sum_{\kappa=-10}^{k} AAR(\kappa)$. It presents a salient upward and then downward trend of the CARs around a CEO's stock sales. The monotonically decreasing (increasing) trend of this curve manifests a series of consistently negative (positive) abnormal returns after (before) her sales. Its turning point at $k = 0$ indicates that the abnormal return

Figure 11: Mean CAR Around a CEO's Stock Sales

In this graph, I plot $CAR(k) - k$, the CAR covering -10 to k trading days relative to a CEO's stock sale. Let $AR_{i\delta}(k)$ denote the abnormal return of firm i k trading days away from its CEO's sale date δ, then $AAR(k)$, which stands for "average abnormal return," is the mean of all $AR(k)$ across firms and sale dates given the same value of k. $CAR(k)$ cumulates AAR from -10 up to k. The abnormal return, AR, is based on a Fama-French four-factor model, and AAR is a cross-sectionally weighted average. The sample ranges from 2008 to 2018.



reverses its sign exactly in line with the CEO's personal interest: she holds the stock until the last moment of a positive abnormal return, garners profits at the maximum point, and withdraws timely before its abnormal return drops into the negative territory.

Similarly, Table 7 provides the results of an examination of whether the CARs before and after a CEO's sale are significantly different from the null hypothesis 0. Slightly different from the procedure above, the CARs in Table 7 are computed in the following order: (1) given firm i and its CEO's sale date δ, $CAR_{Before,i\delta}$ and $CAR_{After,i\delta}$ respectively cumulate the abnormal returns of K-trading-day windows $[\delta - K, \delta - 1]$ and $[\delta + 1, \delta + K]$. I compute each CAR by first averaging the available abnormal returns and then rescaling it to the K-trading-day length. Here I choose $K = 10$ to be consistent with the length of the disclosure window I

Table 7: Summary Statistics of the CARs Around a CEO's Stock Sales

In this table, I report the mean and t-statistics of CARs around a CEO's stock sales. CAR_{Before} (CAR_{After}) cumulates the abnormal returns covering a 10-trading-day window of $[\delta - 10, \delta - 1]$ ($[\delta + 1, \delta + 10]$), given a sale date δ. The mean CARs are both equally weighted and cross-sectionally weighted. Each abnormal return is based on a Fama-French four-factor model. The sample period is from 2008 to 2018.

	Equally weighted		Cross-sectionally weighted	
	Before	After	Before	After
CAR (%)	2.028***	-1.087***	1.789***	-0.950***
	31.73	-19.20	18.09	-10.07
Obs	14,443	14,441	2,512	2,520

study in the main body of my paper. I can also imply a similar result in the case of a 5-trading-day window from Figure 11. (2) The set $\{CAR_{Before,id} \cdot I_{id}, CAR_{After,id} \cdot I_{id}\}_{i=1,d=1}^{i=N,d=D}$ represents all the available CAR_{Before} and CAR_{After} in the sample. I_{id} indicates if the CEO of firm i does have a sale on date d. Only those with $I_{id} = 1$ have an available value of $CAR_{Before,id}$ and $CAR_{After,id}$, and are kept in this set. (3) The equally weighted CAR is calculated as follows:

$$CAR_{EW} = \frac{\sum_{d=1}^{D} \sum_{i=1}^{N} CAR_{id} \cdot I_{id}}{\sum_{d=1}^{D} \sum_{i=1}^{N} I_{id}}. \tag{21}$$

This weighting scheme simply takes an average of all accessible observations. (4) The cross-sectionally weighted CAR, on the other hand, corrects for the cross-sectional dependence, because firms may co-move as a result of some common market condition on the same day:

$$CAR_{CW} = \frac{\sum_{d=1}^{D} I_{N_d>0} \left(\frac{1}{N_d} \sum_{i}^{N} CAR_{id} \cdot I_{id} \right)}{\sum_{d=1}^{D} I_{N_d>0}}, \tag{22}$$

where $N_d = \sum_{i}^{N} I_{id}$ and $I_{N_d>0} = 1$ only if there is at least one firm, whose CEO sells on date d. As is reported in Table 7, the CAR after (before) a sale is significantly negative (positive), even after the correction for the cross-sectional dependence among firms.

A.1.2 Incremental CAR around stock sales when firm discloses information

Nonetheless, a negative post-sale CAR is not sufficient to draw a compelling conclusion that a CEO profits from the timing strategy, as her sale transaction may depress the stock price directly. Since the adoption of Section 403 of SOX, outside investors can track insider transactions on a timely basis. Many studies also find that insiders' trading activities are informative, and the subsequent market reaction can be transaction-driven (Lorie and Niederhoffer, 1968; Givoly and Palmon, 1985; Seyhun, 1986, 1988, 1992b; Lakonishok and Lee, 2001). Once the market imitates a CEO's sale, the stock price will fall, regardless of the disclosures. For this reason, the price drop after a CEO's stock sale can be decomposed into the part reacting to the sale transaction itself and the rest reflecting the information disclosed after the sale.

To segregate the price drop that relates to post-sale disclosures, I develop a benchmark, $CAR_{After,NoFile}$, which denotes the CARs after the stock sales that are not followed by any disclosure. It captures the transaction-driven part of a price drop when the market observes CEOs selling stocks. Correspondingly, $CAR_{After,File}$ denotes the CARs after the stock sales that are followed by disclosures, so the central question is whether the extra post-sale disclosures in $CAR_{After,File}$ may account for its difference from $CAR_{After,NoFile}$. This necessitates adding the DiscCon measure into my regression (δ denotes a CEO's stock sale date and X∈{Before, After}):

$$\begin{aligned} CAR_{i\delta}^{X} \sim\ & \alpha + \beta \cdot After_{i\delta}^{X} + \gamma \cdot After_{i\delta}^{X} \times File_{i\delta}^{X} \\ & + \lambda \cdot File_{i\delta}^{X} + \omega \cdot File_{i\delta}^{X} \times DiscCon_{i\delta}^{X} \\ & + \eta_1 \cdot SUE_{i\delta} + \eta_2 \cdot Cvrg_{i\delta} \\ & + \eta_3 \cdot lnMakcap_{i\delta} + \eta_4 \cdot lnBM_{i\delta} \\ & + \eta_5 \cdot lnTurnover_{i\delta} + \eta_6 \cdot lnIlliquidity_{i\delta} \\ & + FirmFE_i + Year \times Month_{\delta} + \epsilon_{i\delta}, \end{aligned} \tag{23}$$

where $CAR_{i\delta}^{X}$ is the CAR either before or after its CEO's stock sale date δ. $CAR_{i\delta}^{After}$ ($CAR_{i\delta}^{Before}$) cumulates the abnormal returns of firm i within a 10-trading-day window of $[\delta + 1, \delta + 10]$ ($[\delta - 10, \delta - 1]$)[40] and is rescaled to 100%. $After_{i\delta}^{X}$ is a dummy variable that indicates whether $CAR_{i\delta}^{X}$ is from the "pre-sale" or "post-sale" period, with $After^{After} = 1$ and $After^{Before} = 0$. $DiscCon_{i\delta}^{X}$ is the mean DiscCon score averaging the disclosures within a specified window before or after the sale date δ. I stick to the 10-business-day window in alignment with the length I used in previous tests. Starting from one disclosure filed on date ϕ, as explicated in Subsubsection 4.1.1, if the DiscCon measure is placed on the right-hand side of the regression, it is quantified as $DiscCon_{i\phi} \equiv -ln\left(|Neg_{PastNorm,i\phi}| + 1\right) \cdot Sign\left(Neg_{PastNorm,i\phi}\right)$. $Neg_{PastNorm,i\phi}$ denotes the percentage of negative words in this disclosure, normalized by a past rolling benchmark. $DiscCon_{i\delta}^{X}$ can be expressed as follows:

$$
\begin{aligned}
DiscCon_{i\delta}^{After} &\equiv \frac{\sum_{\phi=\delta+1}^{\delta+10} DiscCon_{i\phi} I_{i\phi}}{\sum_{\phi=\delta+1}^{\delta+10} I_{i\phi}} \\
DiscCon_{i\delta}^{Before} &\equiv \frac{\sum_{\phi=\delta-10}^{\delta-1} DiscCon_{i\phi} I_{i\phi}}{\sum_{\phi=\delta-10}^{\delta-1} I_{i\phi}},
\end{aligned}
\tag{24}
$$

with $I_{i\phi} = 1$ if firm i files a disclosure on date ϕ.[41] $File_{i\delta}^{X}$ is a dummy variable coupled with $DiscCon_{i\delta}^{X}$. Since firms do not file Form 8-Ks daily, not every stock sale is preceded or followed by disclosures. $File_{i\delta}^{After}$ ($File_{i\delta}^{Before}$) equals 1 only if $DiscCon_{i\delta}^{After}$ ($DiscCon_{i\delta}^{Before}$) has an available value. $File = 1$ makes up to 35% of the entire sample.

I follow Loughran and McDonald (2011) and Tetlock et al. (2008) to formulate my regression and add some commonly used firm-level controls to it. $lnTurnover$ and $lnIlliquidity$ are quarterly updated and intended to capture a firm's liquidity. Stock turnover is the percentage of shares outstanding that are traded in the most recent quarter. Illiquidity, as defined in Amihud (2002), measures the average level of price impact per dollar of daily

[40] The parameters for calculating abnormal returns are based on a Fama-French four-factor model, with Dimson adjustment. The estimation covers the daily returns of a 100-calendar-day window $[\delta - 130, \delta - 31]$, and has available values only if the regression sample has ≥ 30 data points.

[41] I redo the same test in a 5-day window. See Table 10 in the following appendix section.

volume over the most recent quarter. Both liquidity controls are log transformed to mitigate the potential bias concern inherent in firm size, as in light of Brennan, Huh, and Subrahmanyam (2013). Analyst coverage, $Cvrg$, is also quarterly updated and is developed from the number of earnings forecasts listed on IBES Summary. A firm with a higher analyst coverage usually implies a higher exposure to the media and public attention, then a lower chance of mispricing.

I remove the $FF\alpha$ control in Tetlock et al. (2008). $FF\alpha$ is the intercept term from the set of estimated parameters of a Fama-French model (e.g., α, β_{exMkt}, β_{SMB}, β_{HML} in a three-factor model). When CAR is the dependent variable, $FF\alpha$ is mechanically correlated with it because of its definition:

$$\begin{aligned} AR &\equiv r - \left[r_f + \hat{\alpha} + \hat{\beta}_{exMkt}\left(r_m - r_f\right) + \hat{\beta}_{SMB}SMB + \hat{\beta}_{HML}HML \right] \\ &= r_{risk-adjusted} - \hat{\alpha} \end{aligned} \tag{25}$$

Since CAR cumulates the abnormal returns over some period, it is the sum of risk-adjusted returns minus multiple $FF\alpha$. If this control is introduced into the regression, my dependent variable actually changes to risk-adjusted returns, away from my target – abnormal returns. In an event study setup, an abnormal return measures the change in return from its counterfactual case where the event did not happen. However, if the dependent variable changes to a risk-adjusted return, which includes $FF\alpha$, I then test one independent variable's correlation with the part of return that is orthogonal to the risk factors. This deviates from my initial objective of studying the effect of an event.

The pivotal variable in Table 8 is $File \times DiscCon$, whose coefficient illustrates how the stock market reacts in connection with the disclosures around a CEO's stock sales. To better interpret the regression results and link them to my target difference term, $CAR_{After,File} - CAR_{After,NoFile}$, I first derive the expressions of $CAR_{After,File}$, $CAR_{After,NoFile}$, $CAR_{Before,File}$, and $CAR_{Before,NoFile}$ on the basis of equation 23. For example, $CAR_{After,File}$ is the case where $After = File = 1$, then $CAR_{After,File} = \beta + \gamma + \lambda + \omega DiscCon^{After} + ...$, whereas

Table 8: Relation Between CARs and Disclosures Around a CEO's Stock Sales

In this table, I present the results of a regression that examines the relation between the CARs and the disclosures around a CEO's stock sales. $X \in$ {Before,After} indicates whether the dependent variable, CAR, cumulates the abnormal returns before or after a sale. Given a sale date δ, $CAR_{i\delta}^{After}$ ($CAR_{i\delta}^{Before}$) covers a 10-trading-day window of $[\delta+1, \delta+10]$ ($[\delta-10, \delta-1]$) and is rescaled to 100%. The abnormal returns are approximated in the Fama-French four-factor model from the daily returns covering $[\delta-130, \delta-31]$. $After^{After} = 1$ and $After^{Before} = 0$. $DiscCon_{i\delta}^{After}$ ($DiscCon_{i\delta}^{Before}$) is the mean DiscCon score of all the disclosures within a 10-business-day window of $[\delta+1, \delta+10]$ ($[\delta-10, \delta-1]$). The DiscCon of a disclosure filed on date ϕ is quantified as $DiscCon_{i\phi} \equiv -ln\left(|Neg_{PastNorm,i\phi}|+1\right) \cdot Sign\left(Neg_{PastNorm,i\phi}\right)$, with $Neg_{PastNorm}$ equal to the percentage of negative words in this disclosure, normalized by a past rolling benchmark. $File^{Before}$ ($File^{After}$) $= 1$ only if $DiscCon^{Before}$ ($DiscCon^{After}$) has an available value. T-statistics are reported in parentheses, with their standard errors adjusted in a two-way clustering at both the 4-digit SIC industry code and $Year \times Month$ levels. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics) and sale samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018. I redo the same test in a 5-day window. See Table 10 in the following appendix section.

	DV: %CAR
After	-2.379***
	-14.25
After×File	-1.026***
	-5.36
File	1.008***
	5.86
File×DiscCon	0.300***
	2.87
lnMakcap	-2.406***
	-10.42
lnBM	0.381**
	2.58
lnTurnover	-0.460**
	-2.22
lnIlliquidity	-2.404***
	-4.06
Cvrg	0.298
	1.12
SUE	0.079***
	4.37
Obs	22,661
adj.R^2	0.10
Firm	Y
Year×Month	Y

*,**, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Variations in CARs Related to Disclosures Around a CEO's Stock Sales

This table shows how $CAR_{After,File}$, $CAR_{After,NoFile}$, $CAR_{Before,File}$, and $CAR_{Before,NoFile}$ are connected together. $CAR_{After,File}$ ($CAR_{Before,File}$) denotes the post-sale (pre-sale) CARs that are coupled with at least one disclosure and $CAR_{After,NoFile}$ ($CAR_{Before,NoFile}$) denotes the post-sale (pre-sale) CARs that are not coupled with any disclosure. (1)-(4) number the changes from one CAR group to the other, which are expressed by the coefficients of equation 23. The last two rows report the means and residual standard deviations of $DiscCon^{After}$ and $DiscCon^{Before}$. $DiscCon^{After}$ ($DiscCon^{Before}$) is the mean disclosure content score that covers all the disclosures within a 10-business-day window after (before) a CEO's stock sales. $DiscCon$ of one disclosure is defined as $DiscCon_{i\phi} \equiv -ln\left(|Neg_{PastNorm,i\phi}|+1\right) \cdot Sign\left(Neg_{PastNorm,i\phi}\right)$. $Neg_{PastNorm,i\phi}$ denotes the percentage of negative words in this disclosure, normalized by a past rolling benchmark.

$$CAR^X \sim \beta After^X + \gamma After^X \times File^X + \lambda File^X + \omega File^X \times DiscCon^X + ...$$

$$\begin{array}{ccc}
CAR_{Before,NoFile} & \overset{(1)}{\Longrightarrow} & CAR_{After,NoFile} \\
\Downarrow_{(2)} & & \Downarrow_{(3)} \\
CAR_{Before,File} & \overset{(4)}{\Longrightarrow} & CAR_{After,File}
\end{array}$$

(1)$CAR_{After,NoFile} - CAR_{Before,NoFile} = \beta = -2.38\%$

(2)$CAR_{Before,File} - CAR_{Before,NoFile} = \lambda + \omega DiscCon^{Before} = 1.01\% + 0.3 \cdot DiscCon^{Before}$

(3)$CAR_{After,File} - CAR_{After,NoFile} = \gamma + \lambda + \omega DiscCon^{After} = -0.02\% + 0.3 \cdot DiscCon^{After}$

(4)$CAR_{After,File} - CAR_{Before,File} = \beta + \gamma + \omega \Delta DiscCon = -3.41\% + 0.3 \cdot \Delta DiscCon$

$\Delta DiscCon \equiv DiscCon^{After} - DiscCon^{Before}$

Mean (Residual standard deviation) of $DiscCon^X$

$DiscCon^{Before}$	0.09 (0.66)
$DiscCon^{After}$	-0.06 (0.76)

$CAR_{After,NoFile} = \beta + ...$ as its $File = 0$. See Table 9 for the summary of these difference terms.

Particularly, in row (3) of Table 9, $CAR_{After,File} - CAR_{After,NoFile}$ is positively correlated with $DiscCon^{After}$, which averages the DiscCon scores of all the disclosures that closely follow the sales of $CAR_{After,File}$. Therefore, the variation in $CAR_{After,File}$ from its benchmark, $CAR_{After,NoFile}$, moves in parallel with the extra information disclosed after the sales. On average, $DiscCon^{After}$ is around -0.06 in the sample, so the post-sale disclosures generally convey a negative tone and deliver negative information. This is equivalent to a drop of 3.6 bps in $CAR_{After,File}$ as compared to $CAR_{After,NoFile}$. The sale sample in this test covers all stock sales. If a sale is triggered by its CEO's exogenously enhanced intention to sell (e.g., diversification need after option vesting dates and urgency to sell before option expiration dates), the sale is more likely to be followed by disclosures with a heightened negative tone, as a CEO tends to withhold negative information in preparation for this type of sale. One standard deviation decrease in $DiscCon^{After}$ means a decrease of 22.8 bps in the post-sale CAR of a 10-trading-day length. This equals an annualized CAR of -5.75 pps.

Similarly, to translate the coefficient of $\hat{I}_{Sale}$, -5.092 in Column 5 of Table 4, into some return, I first find out the relation between a disclosure's log transformed percentage of negative words and its associated CAR. That is, when the information positivity of a disclosure is defined in the same way as that in the 2SLS regression, one unit decrease in the information positivity is associated with a decrease of 0.248 pps in the 2-trading-day CAR.[42] One standard deviation enhancement in a CEO's intention to sell leads to a drop in the information positivity of subsequent disclosures, which predicts a CAR of -2.90 bps over a 2-trading-day period.[43] This says a CEO would otherwise give up an annualized CAR of 3.66 pps if she disclosed negative information as it occurred before her stock sales. The magnitude of this change seems smaller when compared to 5.75 pps above, because $DiscCon^{After}$ collects the disclosures after actual sales and is more likely to capture negative information withheld by CEOs. On the contrary, the causal effect test simulates a CEO's stock sales. A vesting date predicts her stronger intention to sell, but it is possible that there is no actual sale following her enhanced sale intention. As shown in Table 1 and Figure 4, the number of vesting dates in the sample is much higher than that of stock sales, and only about one tenth of vesting dates are closely followed by actual sales.[44] This makes the variation of a CEO's intention

[42] The dependent variable in the 2SLS regression of Table 4 does not require normalization. Its DiscCon measure is quantified as $DiscCon_{i\phi} \equiv -ln\,(\%Neg_{i\phi} + 1)$, and therefore, I need to know the average CAR in relation to a measure defined in this way. The regression is similar to my validation test in Appendix 4.2.1, except for one difference: it is formatted as "$CAR_{i,\phi\sim\phi+1}(\%) \sim \alpha + \beta \cdot DiscCon_{i\phi} + ...$", by replacing $Negative_{i\phi}$ and $Positive_{i\phi}$ in equation 3 with $DiscCon_{i\phi} \equiv -ln\,(\%Neg_{i\phi} + 1)$. This regression covers all 8-K disclosures. $\%Neg_{i\phi}$ denotes the percentage of negative words in the disclosure filed by firm i on date ϕ. It tests how the CAR on and closely after a disclosure is connected with the disclosure's positivity. The disclosures in my sample are mandated, reporting material information, and accessible to all investors. The market responds to this class of disclosures promptly, so I focus on a 2-trading-day CAR that cumulates the abnormal returns on and one day after the dates of disclosures.

[43] Following equations 14, $CAR(\%) \sim \beta \cdot [-ln\,(\%Neg + 1)] = -\beta \cdot ln\left(e^{-\Delta\iota} - 1 + 1\right) = \beta\Delta\iota$. Change in CAR(%) with $\iota = 0.023$, $\Delta = -5.092$, and $\beta = 0.248$ is $0.248 \cdot -5.092 \cdot 0.023 = -2.90‱$.

[44] Panel A of Table 1 shows that my sample contains 43,940 option vesting dates and only 28,164 stock sale dates. Figure 4 plots the distribution of vesting dates according to their distances from the closest sale

to sell, as implied by vesting dates, less likely to capture actual sales and their subsequent negative information, therefore lowering the magnitude of the change.

dates. The vesting dates that are followed by stock sales within a 10-trading-day window account for 12% of the entire sample. Up to 83% of the vesting dates in the sample have no subsequent stock sales within a 20-trading-day window (one calendar month).

A.1.3 Appendix: CARs and DiscCons around stock sales (5-day window)

Table 10: Relation Between CARs and Disclosures Around Stock Sales (5-day window)

In this table, I present the results of a regression that examines the relation between the CARs and the disclosures around a CEO's stock sales. $X \in$ {Before,After} indicates whether the dependent variable, CAR, cumulates the abnormal returns before or after a sale. Given a sale date δ, $CAR_{i\delta}^{After}$ ($CAR_{i\delta}^{Before}$) covers a 5-trading-day window of $[\delta+1, \delta+5]$ ($[\delta-5, \delta-1]$) and is rescaled to 100%. The abnormal returns are approximated in the Fama-French four-factor model from the daily returns covering $[\delta-130, \delta-31]$. $After^{After}=1$ and $After^{Before}=0$. $DiscCon_{i\delta}^{After}$ ($DiscCon_{i\delta}^{Before}$) is the mean DiscCon score of all the disclosures within a 5-business-day window of $[\delta+1, \delta+5]$ ($[\delta-5, \delta-1]$). The DiscCon of a disclosure filed on date ϕ is quantified as $DiscCon_{i\phi} \equiv -ln\left(|Neg_{PastNorm,i\phi}|+1\right) \cdot Sign\left(Neg_{PastNorm,i\phi}\right)$, with $Neg_{PastNorm}$ equal to the percentage of negative words in this disclosure, normalized by a past rolling benchmark. $File^{Before}$ ($File^{After}$) $=1$ only if $DiscCon^{Before}$ ($DiscCon^{After}$) has an available value. T-statistics are reported in parentheses, with their standard errors adjusted in a two-way clustering at both the 4-digit SIC industry code and $Year \times Month$ levels. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics) and sale samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018.

	DV: %CAR
After	-1.539***
	(-14.60)
After×File	-1.141***
	(-7.27)
File	1.198***
	(10.33)
File×DiscCon	0.283**
	(2.52)
lnMakcap	-1.219***
	(-7.35)
lnBM	0.282***
	(3.18)
lnTurnover	-0.286**
	(-2.19)
lnIlliquidity	-1.363***
	(-3.86)
Cvrg	0.141
	(0.87)
SUE	0.052***
	(5.07)
Obs	25,725
adj.R^2	0.08
Firm	Y
Year×Month	Y

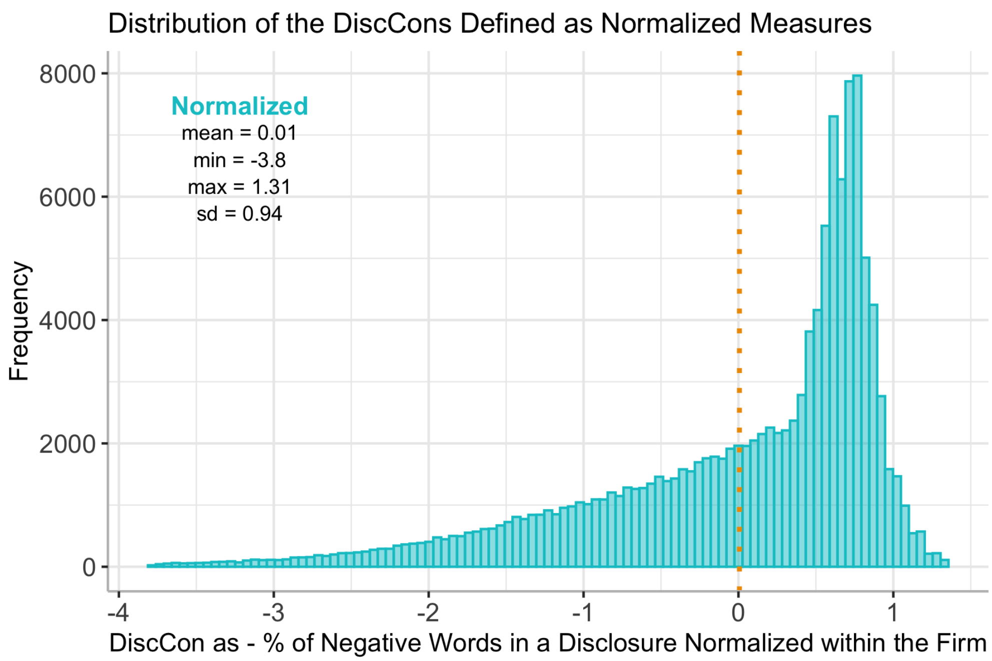
*,**, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

A.2 Distributions of DiscCons defined in alternative ways

A.2.1 DiscCon quantified as $-Neg_{Norm}$

Figure 12: Distribution of the DiscCons Defined as Normalized Measures

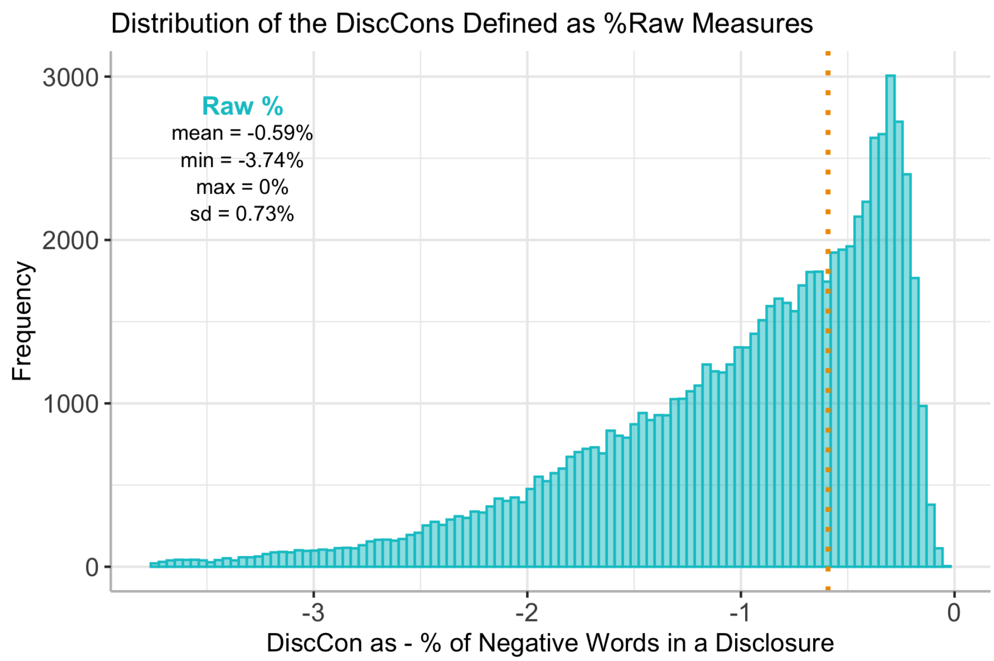
In this figure, I report the summary statistics and the distribution of DiscCon measures defined as: $DiscCon \equiv -Neg_{Norm}$. Neg_{Norm} is the percentage of negative words in a disclosure normalized by its firm's level. The firm-specific mean and standard deviation for normalization are derived from all the available points of this firm. The orange dotted line denotes the overall mean of this normalized DiscCon measure covering all the disclosures in the sample. The distribution includes all the Form 8-K disclosures of the firms that are in the intersection of disclosure samples (SEC Analytics) and sale samples (Thomson Reuter Insiders), ranging from 2008 to 2018.



A.2.2 DiscCon quantified as $-\%Neg$

Figure 13: Distribution of the DiscCons Defined as Raw%

In this figure, I report the summary statistics and the distribution of the DiscCon measures defined as: $DiscCon \equiv -\%Neg$. $\%Neg$ is the percentage of negative words in a disclosure. The orange dotted line denotes the overall mean of this raw percentage DiscCon measure covering all the disclosures in the sample. Points of 0% DiscCon are removed from the graph, to make the y-axis scale more comparable. The scale of 0% DiscCon is more than 10 times greater than the maximum scale of other values. The distribution includes all the Form 8-K disclosures of the firms that are in the intersection of disclosure samples (SEC Analytics) and sale samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018.



A.3 Manipulation from diversification needs

A.3.1 Firm disclosures around stock sales (5-day window)

Figure 14: Mean Positivity of the Disclosures Around Stock Sales (5-day window)

In this figure, I plot $DiscCon\,(k) - k$, the mean DiscCon score of 8-K disclosures that are released k business days away from their closest sale dates. Each disclosure's positivity, DiscCon, is constructed as $DiscCon_{Graph} \equiv -Neg_{Norm}$. Neg_{Norm} is the percentage of negative words in a disclosure normalized within its firm. The orange dotted line denotes the average DiscCon of each firm as well as the whole sample. A positive (negative) DiscCon signals a more positive (negative) tone in the disclosure as compared to the tones in other disclosures of its firm. It implies positive (negative) information in this disclosure. The solid line on the left (right) of $k = 0$ denotes the average level of the DiscCon scores covering all the disclosures within the event window $k \in [-5, -1]$ ($k \in [1, 5]$) business days from their designated sales. The mean is cross-sectionally weighted. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics) and sale samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018.

A.3.2 Regression analysis: Correlation between disclosures and stock sales

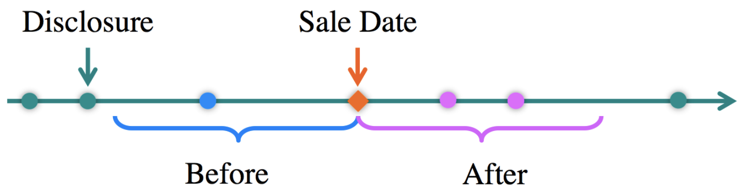
I formulate another event study to verify that the upward and downward shifts in the information content of the disclosures around a CEO's stock sales are significant. I start from a disclosure and then check if it happens around its CEO's sale date. If so, the disclosure will be allocated a dummy variable indicating either pre- or post-sale. The objective is to ascertain the change in the information content when a disclosure is released closely around a sale. The regression is designed as follows (ϕ denotes the filing date of a disclosure in the sample):

$$\begin{aligned} DiscCon_{i\phi} \sim & \alpha + \beta \cdot Before_{i\phi} + \gamma \cdot After_{i\phi} \\ & + \delta_1 \cdot AGM_{Before,i\phi} + \delta_2 \cdot AGM_{After,i\phi} \\ & + \eta_1 \cdot lnAsset_{i\phi} + \eta_2 \cdot ROA_{i\phi} + \eta_3 \cdot TobinQ_{i\phi} \\ & + \eta_4 \cdot lnSale_{i\phi} + \eta_5 \cdot SaleGwth_{i\phi} \\ & + CEOFE_{i\phi} + FirmFE_i + Year \times Month_\phi + \epsilon_{i\phi} \end{aligned} \tag{26}$$

where $DiscCon_{i\phi}$ is the disclosure content score of a Form 8-K disclosure by firm i on date ϕ. Let $\%Neg$ denote the percentage of negative words in this disclosure. The DiscCon measure on the left-hand side of a regression is a dependent variable, and is defined as $DiscCon^{Y=DiscCon}_{Regression} \equiv -ln\,(\%Neg + 1)$.

$Before_{i\phi}$ and $After_{i\phi}$ are dummy variables that indicate a disclosure's position relative to its closest sale date. For example, let the round dots on the timeline in Figure 15 represent the casual arrival of material information. Given a sale date (orange square), I can specify the K-business-day event windows before and after this sale. Let $K \in \{5, 10\}$. If a disclosure drops into the "before" ("after") window, then it is labeled as "pre-sale" ("post-sale") and $Before = 1$ ($After = 1$). d_{Sale} denotes firm i's closest sale date to the filing date ϕ. $Before_{i\phi} = 1$ if the date $\phi \in [d_{Sale} - K, d_{Sale} - 1]$, and $After_{i\phi} = 1$ if the date $\phi \in [d_{Sale} + 1, d_{Sale} + K]$. The disclosures with more than one label are removed from the sample. In other words, every observation satisfies $(Before_{i\phi}, After_{i\phi}) \in \{\{0,1\}, \{1,0\}, \{0,0\}\}$. If a disclosure has

Figure 15: Classification of 8-K Disclosures in Relation to a CEO's Stock Sales



$Before_{i\phi} + After_{i\phi} = 1$, it happens closely around a CEO's stock sale. Any disclosure in the sample has $Before_{i\phi} + After_{i\phi} \in \{0, 1\}$. Date controls of $AGM_{i\phi,Before}$ and $AGM_{i\phi,After}$ indicate whether the filing date ϕ drops into the K-business-day window before or after firm i's annual general meeting.

Columns (1) and (3) of Table 11 show the results of the regression only on the disclosures that are close to its CEO's stock sales. The disclosures are labeled as either "pre-sale" or "post-sale," such that $Before + After = 1$ for every observation in this regression. As reported in these columns, the variable $After$ has a significantly negative coefficient, indicating a prominent drop in the information content if a disclosure is released after a sale, when compared to the one before a sale. The results of whether this drop can be decomposed into the "before" and "after" parts are given in columns (2) and (4). The opposite signs of the coefficients of the $Before$ and $After$ variables show that the information content goes in inverse directions, regarding if this disclosure is released before or after a CEO's sale. In general, a disclosure before (after) a sale imparts more positive (negative) information than its non-before (non-after) counterpart does. The variation in content before and after a sale contributes to the drop in the coefficients in columns (1) and (3).

Table 11: Change in Disclosure Positivity Around a CEO's Stock Sales

This table provides the results of an examination of whether the positivity of a disclosure changes when it is close to a CEO's stock sale. The dependent variable is the DiscCon score of a disclosure. DiscCon, the disclosure content measure, is quantified as $DiscCon^{Y=DiscCon}_{Regression} \equiv -ln\left(\%Neg + 1\right)$, with $\%Neg$ denoting the percentage of negative words in this disclosure. The dummy variable $Before = 1$ ($After = 1$) if the disclosure is released within a K-business-day window before (after) its CEO's sale, with $K = \{5, 10\}$. The observations with conflicting classifications (e.g., $Before + After = 2$) are removed from the sample. Columns (1) and (3) show the results of the selected samples with $Before + After = 1$, that focus only on the disclosures around sales. Columns (2) and (4), denoted by $Before + After \in \{0, 1\}$, cover all the disclosures in the sample, irrespective of whether they are around their CEOs' stock sales or not. T-statistics are reported in parentheses, with their standard errors adjusted in a two-way clustering at both the 4-digit SIC industry code and $Year \times Month$ levels. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics) and sale samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018.

Window:	K = 5		K = 10	
Sample: Before+After	= 1	∈ {0,1}	= 1	∈ {0,1}
	(1)	(2)	(3)	(4)
Before		0.033***		0.036***
		(4.90)		(6.55)
After	-0.047***	-0.021***	-0.049***	-0.016***
	(-4.49)	(-3.00)	(-5.59)	(-2.63)
lnAsset	-0.005	0.021*	0.031	0.016
	(-0.16)	(1.66)	(1.52)	(1.34)
ROA	0.374	0.424***	-0.132	0.414***
	(1.47)	(3.86)	(-0.49)	(4.08)
TobinQ	0.005	0.007	0.012*	0.005
	(0.44)	(1.51)	(1.90)	(1.41)
lnSale	0.059**	0.015	0.019	0.011
	(2.05)	(1.28)	(1.26)	(1.05)
SaleGwth	-0.055*	-0.016	-0.039*	-0.010
	(-1.74)	(-1.23)	(-1.85)	(-0.91)
AGM_{Before}	-0.031	0.006	-0.008	0.008
	(-0.93)	(0.39)	(-0.40)	(0.63)
AGM_{After}	-0.070***	-0.022*	-0.058***	-0.025***
	(-3.43)	(-1.80)	(-3.90)	(-2.61)
Obs	7,990	76,512	13,517	90,357
adj.R^2	0.26	0.23	0.26	0.23
Firm	Y	Y	Y	Y
CEO	Y	Y	Y	Y
Year×Month	Y	Y	Y	Y

*,**, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

A.3.3 Timing of a CEO's option vesting

Figure 16: Seasonality of Option Vesting Compared to that of Some Important Firm Dates

The following graph investigates the seasonality of a CEO's option vesting, in comparison to that of some important firm events, e.g., 10-Ks, 10-Qs, and annual general meetings (AGMs). It draws out how often a CEO's option vesting as well as the aforementioned firm events takes place in each month throughout a year. The sample of each type of firm dates is classified into 12 subgroups by the month in which this event occurs and the bar for each specific month represents the proportion of the sample that occurs in this month. For every subgroup denoted by month, from the left to the right, the bars respectively report the percentages from 10-K, 10-Q, AGM, and its CEO's option vesting samples. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics), sale samples, and option grant samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018.

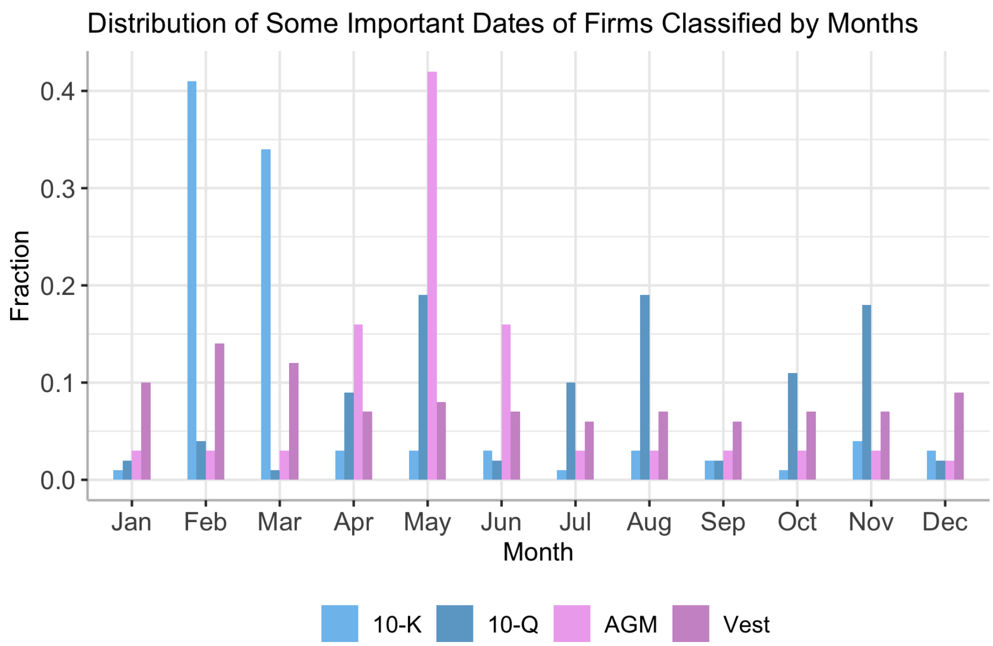


Figure 16 gives a general overview of how often a CEO's option vesting takes place in each month throughout a year, in comparison to some other important firm events, such as 10-Ks, 10-Qs, and AGMs. This is to check whether a CEO's option vesting dates coincide with the firm events that tend to release material information. If that is the case, then we may foresee the information pattern around a CEO's option vesting dates and the exclusion restriction assumption of my instrument fails. From the graph above, we can observe the seasonality of 10-Ks, 10-Qs, and AGMs. Most firms file their financial reports in February or March and arrange their annual meetings in April, May, or June. They generally report their quarterly earnings in April or May, July or August, and October or November. Unlike these events, their CEOs' option vesting dates distribute quite evenly in every month. In general, a CEO's option vesting shows no clear sign that it follows the seasonality as unveiled in a firm's 10-Ks, 10-Qs, and AGMs.

Figure 17: Distribution of Option Vesting Dates Given the Distances to Their Closest Firm Events

This graph plots the distribution of a CEO's option vesting dates according to how far away they are from some important firm events (e.g. 10-Ks, 10-Qs, and AGMs) that are closest to them. The "fraction" on the y-axis displays the percentage of the entire option vesting sample that is within some specific range around some specific event. The x-axis shows the subgroups that are classified by the number of days from a CEO's option vesting dates to their closest 10-Ks, 10-Qs, and AGMs. For example, the bar of "10-K" with a distance "0" reports the fraction of options that vest together with their firms' 10-K fillings. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics), sale samples, and option grant samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018.

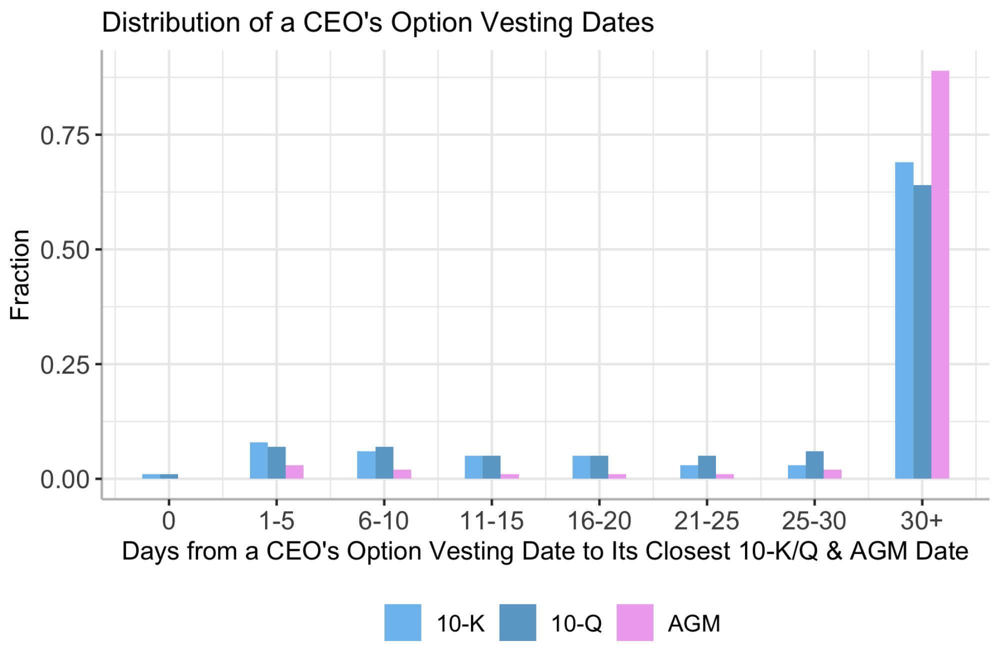
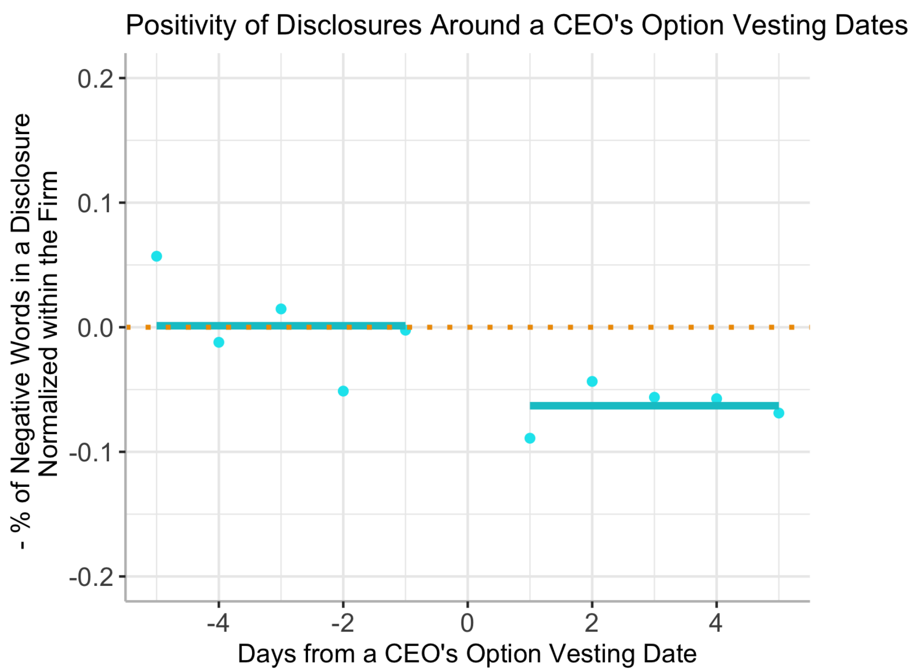


Figure 17 displays how a CEO's option vesting is scheduled relative to its closest 10-K, 10-Q, and AGM. Take the example of "10-K", I first locate the closest 10-K filing for each option vesting date, and then plot the distribution of vesting dates given the distances to their closest 10-Ks. The bar of "10-K" with a distance "0" represents the fraction of options that vest together with their firms' 10-K filings. Similarly, the bar in the "1-5" category represents the fraction of options that vest within the 5-day range around their firms' 10-K filings. Supplemental to Figure 16, this graph particularly compares the timing of a CEO's option vesting with that of the informative events within her firm. Most options vest at least one month apart from 10-Ks, 10-Qs, and AGMs. A CEO's option vesting does not coincide with these firm events. Therefore, option vesting dates are some exogenously determined dates that are independent of the firm's information and can be used to identify some exogenous change in a CEO's intention to sell.

A.3.4 Firm disclosures around vesting dates (5-day window)

Figure 18: Mean Positivity of the Disclosures Around Option Vesting Dates (5-day window)

In this figure, I plot $DiscCon\,(k) - k$, the mean DiscCon score of 8-K disclosures that are released k business days away from their CEO's option vesting dates. Each disclosure's content score, DiscCon, is constructed as $DiscCon_{Graph} \equiv -Neg_{Norm}$. Neg_{Norm} is the percentage of negative words in a disclosure normalized within its firm. The orange dotted line denotes the average DiscCon of each firm as well as the whole sample. A positive (negative) DiscCon signals a more positive (negative) tone in the disclosure as compared to the tones in other disclosures of its firm. It implies positive (negative) information in this disclosure. The solid line on the left (right) of $k = 0$ shows the average level of the content scores covering all the disclosures within the event window $k \in [-5, -1]$ ($k \in [1, 5]$) business days from their closest vesting dates. The mean is cross-sectionally weighted. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics), sale samples, and option grant samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018.



A.3.5 Instruments established from different lags (5-day window)

Table 12: Instruments from Different Lags After Option Vesting Dates (5-day window)

This table provides the results of the 2SLS regressions that rely on the instruments from different lag lengths, $L = \{0, 5, 10\}$ trading days, after an option vesting date. $I_{Vest,id} = 1$ if a CEO has an executive option turning exercisable during $[d - L, d]$ period. $I_{Sale,id} = 1$ if the CEO sells stock shares on date d. The instrument $\hat{Pr}(I_{Sale,id} = 1)$, the fitted probability of $I_{Sale,id} = 1$ from $I_{Vest,id}$, is generated by a probit model. Its relation with $I_{Vest,id}$ is reported in column 1. $DiscCon_{id}^{Trailing}$ ($DiscCon_{id}^{Leading}$) is a daily moving-average disclosure measure, defined as the mean DiscCon score of all the disclosures within a 5-business-day window before (after) date d, with each disclosure's DiscCon quantified as $-ln(\%Neg + 1)$. Columns 2 and 4 report the results of the first-stage regressions to validate the vesting-implied instrument, given the limited samples of $DiscCon_{id}^{Trailing}$ and $DiscCon_{id}^{Leading}$. Columns 3 and 5 report the second-stage regression results. T-statistics are reported in parentheses, with their standard errors adjusted in a two-way clustering at both the 4-digit SIC industry code and $Year \times Month$ levels. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics), sale samples, and option grant samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018. *,**, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

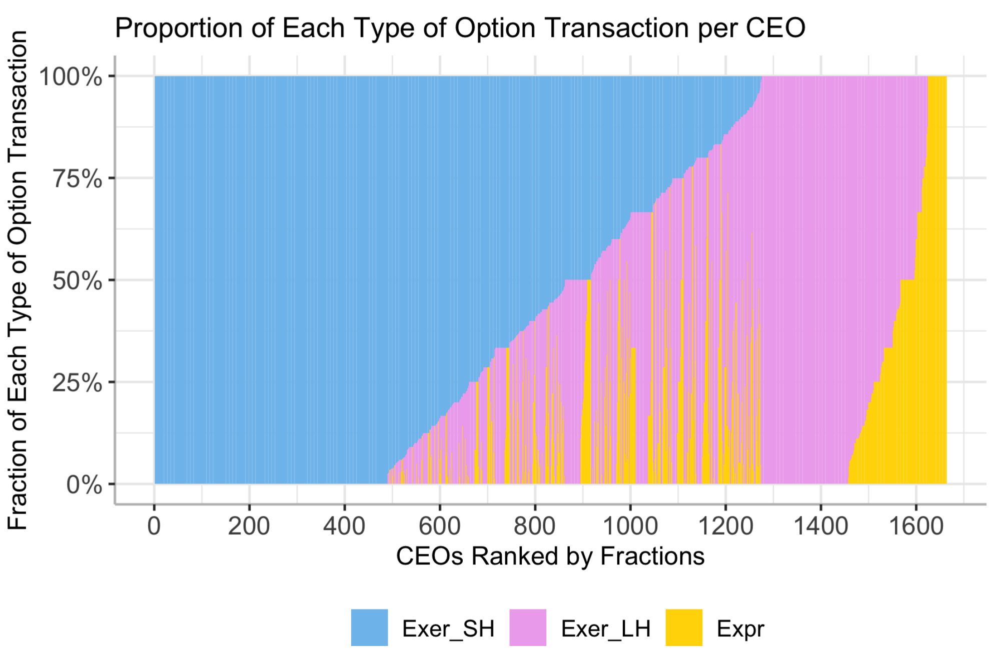
Regression:		Instrument	2SLS			
Sample:		Full	Trailing		Leading	
DV:		$Pr(I_{Sale} = 1)$	I_{Sale}	$DiscCon^{Trailing}$	I_{Sale}	$DiscCon^{Leading}$
Lag:		(1)	(2)	(3)	(4)	(5)
	I_{Vest}	0.372***				
		(21.71)				
L = 0	$\hat{Pr}(I_{Sale} = 1)$		0.391**		0.209**	
			(2.41)		(2.39)	
	$\hat{I}_{Sale}$			-0.944		-4.050**
				(-0.98)		(-1.99)
	F-Test		11.17		13.28	
	I_{Vest}	0.314***				
		(38.90)				
L = 5	$\hat{Pr}(I_{Sale} = 1)$		0.362***		0.370***	
			(3.84)		(3.98)	
	$\hat{I}_{Sale}$			-0.397		-1.801*
				(-0.53)		(-1.92)
	F-Test		11.18		13.32	
	I_{Vest}	0.284***				
		(41.61)				
L = 10	$\hat{Pr}(I_{Sale} = 1)$		0.258***		0.356***	
			(2.99)		(4.63)	
	$\hat{I}_{Sale}$			-1.669		-3.469***
				(-1.29)		(-2.85)
	F-Test		11.16		13.32	
Obs		1,970,785	413,845	413,845	413,166	413,166
Firm, CEO, time		N	Y	Y	Y	Y

A.4 Manipulation from urgency to sell

A.4.1 Is holding an executive option till the last year before its expiration common among CEOs?

Figure 19: Proportion of Each Type of Option Transaction per CEO

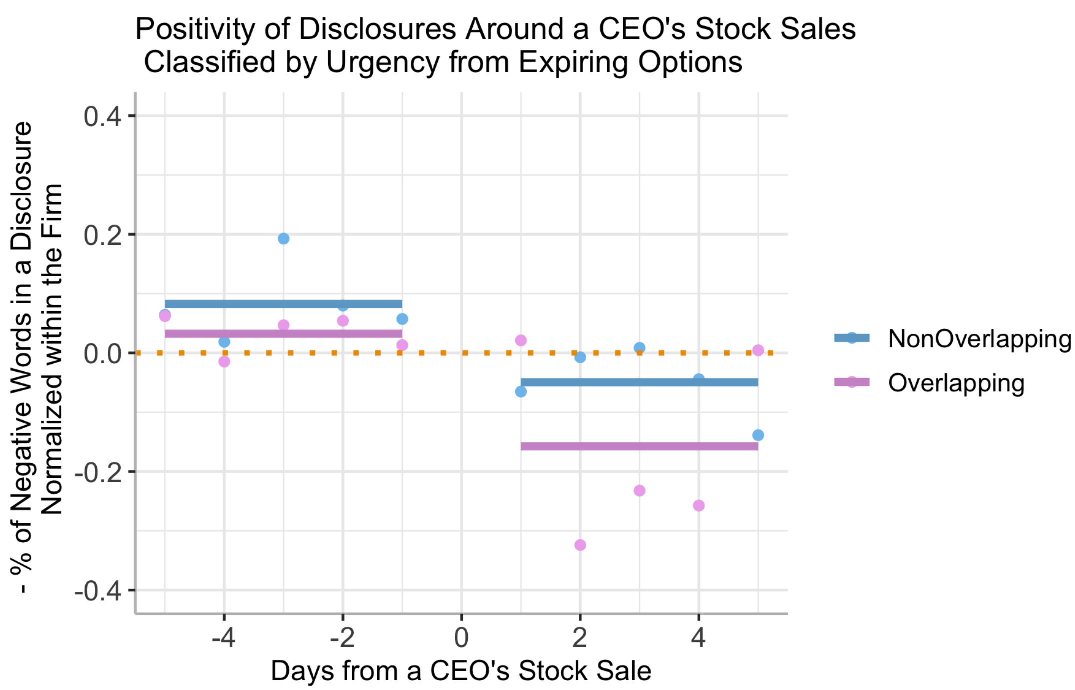
This graph shows the proportion bars for all the CEOs in the sample, with each bar specifying the fraction of each type of option transaction given one CEO. Exer_SH (Exer_LH) denotes the option exercises that occur more (less) than one year before expiration, and Expr denotes the expirations of the options that are not exercised throughout their life. The proportion bars are ranked by %Exer_SH, then %Exer_LH, and finally %Expr. For example, the leftmost bar means this CEO always exercises her executive options more than one year before their expiration dates, while the rightmost bar says this CEO always holds her options till they expire. The plot covers the CEOs of all the firms that are in the intersection of disclosure samples (SEC Analytics), sale samples, and option exercise samples (Thomson Reuter Insiders Data), from 2008 to 2018. The option expiration samples are inferred from Thomson Reuter Insiders and Execucomp.



A.4.2 Disclosures when sale intention overlaps with urgency (5-day window)

Figure 20: Mean Positivity of Disclosures Classified by Urgency Around Stock Sales (5-day window)

This figure shows a plot of $DiscCon\,(k) - k$, the mean DiscCon score of 8-K disclosures that are released k business days away from their CEOs' closest stock sale dates. Before the mean calculation, the disclosures are divided into two mutually exclusive groups — overlapping and non-overlapping. Define a pre-sale (post-sale) window as the 5-business-day period before (after) a CEO's stock sale and a pre-exercise (post-exercise) window as the 5-business-day period before (after) her exercise or expiration of an expiring option. An expiring option refers to an option with less than one year remaining life. A disclosure is denoted as "overlapping" if it is filed either in the overlapping interval of pre-sale and pre-exercise windows or in that of post-sale and post-exercise windows. The option expirations that expire deeply out of money are removed from the sample. Each disclosure's DiscCon score is constructed as $DiscCon_{Graph} \equiv -Neg_{Norm}$. Neg_{Norm} is the percentage of negative words in this disclosure, normalized within its firm. The orange dotted line denotes the average DiscCon of each firm and the whole sample. A positive (negative) DiscCon signals a more positive (negative) tone in the disclosure as compared to the tones in other disclosures of its firm. It implies positive (negative) information in this disclosure. The solid line on the left (right) of $k = 0$ shows the average level of the DiscCon scores covering all the disclosures within the event window $k \in [-5 - 1]$ ($k \in [1, 5]$) business days from their designated sales. The mean is cross-sectionally weighted. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics), sale samples, and option exercise samples (Thomson Reuter Insiders Data) from 2008 to 2018. The option expiration samples are inferred from Thomson Reuter Insiders and Execucomp.



A.4.3 Regression analysis: Evidence of manipulation (5-day window)

Table 13: Variation in Disclosures During the Overlapping Periods (5-day window)

This table provides the results of the regressions that examine whether a disclosure around a CEO's stock sale differs when the CEO has urgency to sell. The dependent variable is the DiscCon score of each disclosure, which is quantified as $DiscCon_{Regression}^{Y=DiscCon} \equiv -ln\left(\%Neg+1\right)$. $\%Neg$ represents the percentage of negative words in this disclosure. Define a pre-sale (post-sale) window as the 5-business-day period before (after) a CEO's stock sale and a pre-exercise (post-exercise) window as the 5-business-day period before (after) her exercise or expiration of an expiring option. An expiring option refers to an option with less than one year remaining life. The dummy variable $Before = 1$ ($After = 1$) if the disclosure is released in the pre-sale (post-sale) window. The observations with conflicting classifications (i.e., $Before + After = 2$) are removed from the sample. Column 1 focuses on the disclosures around sales, while columns 2 and 3 cover all the disclosures in the sample. The dummy variable $Overlapping = 1$ if a disclosure is filed either in the overlapping interval of pre-sale and pre-exercise windows or in that of post-sale and post-exercise windows. T-statistics are reported in parentheses, with their standard errors adjusted in a two-way clustering at both the 4-digit SIC industry code and $Year \times Month$ levels. The test covers all the firms that are in the intersection of disclosure samples (SEC Analytics), sale samples and option exercise samples (Thomson Reuter Insiders Data), ranging from 2008 to 2018. The option expiration samples are inferred from Thomson Reuter Insiders Data and Execucomp. *,**, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Sample:	Before+After = 1	Before+After ∈ (0,1)	
	(1)	(2)	(3)
Before		0.031***	0.034***
		4.45	4.82
After	-0.036***	-0.017**	-0.010
	-3.00	-2.35	-1.30
Before× *Overlapping*	-0.022		-0.017
	-1.59		-1.57
After× *Overlapping*	-0.046***		-0.032**
	-2.67		-2.11
lnAsset	-0.016	0.017	0.017
	-0.45	1.11	1.11
ROA	0.291	0.476***	0.474***
	1.04	4.10	4.08
TobinQ	0.004	0.007	0.007
	0.35	1.56	1.53
lnSale	0.082**	0.021	0.021
	2.15	1.35	1.36
SaleGwth	-0.064*	-0.019	-0.019
	-1.71	-1.22	-1.22
AGM_{Before}	-0.024	0.007	0.008
	-0.70	0.47	0.48
AGM_{After}	-0.068***	-0.022*	-0.022*
	-3.10	-1.85	-1.85
Obs	6,930	65,189	65,189
adj.R^2	0.26	0.23	0.23
Firm, CEO, Year×Month	Y	Y	Y

A.5 Variable definitions

A.5.1 Establishment of DiscCon and its associated applications

Disclosure-related notations

$\%Neg$	Raw percentage of negative words in an 8-K disclosure
Neg_{Norm}	$\%Neg$ normalized by its time-invariant firm-level benchmark; the benchmark is established from all available disclosures of the disclosure's firm
$Neg_{PastNorm}$	$\%Neg$ normalized by a time-varying, past rolling-basis benchmark; the benchmark is built upon all available disclosures of the disclosure's firm over one calendar year before the disclosure is filed; a disclosure filed more recently has a higher weight in the benchmark
$Pos_{PastNorm}$	$\%Pos$, the raw percentage of positive words in an 8-K disclosure, normalized by a time-varying rolling-basis benchmark

Definition of DiscCon	Application of the DiscCon measure
※ Time-invariant, firm-level benchmark:	
$-Neg_{Norm}$	Figure 3, Figure 5, Figure 9, Figure 14, Figure 18, Figure 20
$-ln\left(\%Neg+1\right)$	Table 4, Table 5 , Table 6, Table 11, Table 12, Table 13, columns 1 & 3 of Table 10
※ Time-varying, past rolling benchmark:	
$-ln\left(\lvert Neg_{PastNorm}\rvert+1\right)\cdot Sign\left(Neg_{PastNorm}\right)$	Table 8, columns 2 & 4 of Table 10
$ln\left(\lvert Neg_{PastNorm}\rvert+1\right)\cdot Sign\left(Neg_{PastNorm}\right)$ & $ln\left(\lvert Pos_{PastNorm}\rvert+1\right)\cdot Sign\left(Pos_{PastNorm}\right)$	Table 2, Table 3

A.5.2 Regression controls and tails

Variable	Definition	Filtering
$lnAsset$	$Asset_{i,d}$ is the total asset in quarter $Q_d - 1$.	1% left tail
$lnMakcap$	$Makcap_{i,d}$= #Shares $Outstanding_{i,Q_d-1}$ $\times$ $Price_{i,Q_d-1}$.	1% left tail
$TobinQ$	$TobinQ_{i,d}$= Market value of $assets_{i,Q_d-1}$/ Book value of $assets_{i,Q_d-1}$: Market value of $assets_{i,Q_d-1}$ = Total $assets_{i,Q_d-1}$ + $Makcap_{i,Q_d-1}$ - Common $equity_{i,Q_d-1}$; Book value of $asset_{i,Q_d-1}$ = Total $assets_{i,Q_d-1}$.	0.5% both tails
$lnBM$	$BM_{i,d}$= (Total $asset_{i,Q_d-1}$ - Total $liability_{i,Q_d-1}$) / $Makcap_{i,Q_d-1}$.	0.5% both tails
$lnSale$	$Sale_{i,d}$ is the total revenue in quarter $Q_d - 1$.	1% left tail
$SaleGwth$	$SaleGwth_{i,d}$= $ln\left(\left|\left(Sale_{Q_{i,d}-1} - Sale_{i,Q_d-2}\right)/Sale_{i,Q_d-2}\right| + 1\right)$ $\times$ sign($Sale_{i,Q_d-1} - Sale_{i,Q_d-2}$) on account of negative revenue.	0.5% both tails
AGM_X	$AGM_{Before,id} = 1$ ($AGM_{After,id} = 1$) if the date d drops into the 10-business day window before (after) the firm i's annual general meeting dates.	
SUE	Standardized Unanticipated Earnings SUE_{id} = (Actual EPS_{i,Q_d-1} - μ_{EPS,i,Q_d-1}) / σ_{EPS,i,Q_d-1}, where μ and σ are the mean and standard deviation of analyst forecasts on the earnings of the quarter $Q_d - 1$.	0.5% both tails
$PastReturn$	$PastReturn_{id}$ is the one-year holding period return covering the daily returns of $[m_d - 12, m_d - 1]$. m_d denotes date d's month.	0.5% both tails
$idioVol$	$idioVol_{id} = \sigma(\epsilon_{i\tau})$ is the standard deviation of the residuals $\epsilon_{i\tau}$, with $\tau \in [m_d - 4, m_d - 1]$ and $\epsilon_{i\tau} = R^e_{i\tau} - \tilde{R}^e_{i\tau}$. $\tilde{R}^e_{i\tau}$ is the excess return predicted from a risk factor model, given that the parameters are estimated from the daily returns of $[m_d - 4, m_d - 1]$ and adjusted by Dimson method.	1% right tail
$lnTurnover$	$Turnover_{i,d}$ = #Shares $Traded_{i,Q_d-1}$ / #Shares $Outstanding_{i,Q_d-1}$.	1% left tail
$lnIlliquidity$	$Illiquidity_{i,d} = \frac{1}{D_{i,Q_d-1}} \sum_{t \in Q_d-1} \left(\lvert R_{i,t}\rvert / \$Volume_{i,t}\right)$. D_{i,Q_d-1} is firm i's total number of trading days in the quarter $Q_d - 1$ and $R_{i,t}$ is daily stock return without dividends.	1% right tail
$Cvrg$	$Cvrg_{i,d} = ln\left(1 + \#_{forecasts,i,Q_d-1}\right)$, where $\#_{forecast,i,Q_d-1}$ is the number of EPS forecasts on IBES in the quarter $Q_d - 1$.	

Firm fundamentals of date d is matched with its most recent, available quarterly data of $Q_d - 1$. Q_d is the quarter of date d, and we do not have the data of Q_d until the end of it.

Variable	Definition	Filtering
$FF\alpha_{i,\delta-130\sim\delta-31}$	$FF\alpha_{i,\delta-130\sim\delta-31}$ is the intercept α from a risk factor model. Given a sale date δ, the parameter estimation covers the daily returns of a 100-calendar-day window $[\delta-130, \delta-31]$with Dimson adjustment and keeps in the sample only if the covered window has $\geq$30 data points.	0.5% both tails
$FF\alpha_{i,m_d-4\sim m_d-1}$	$FF\alpha_{i,m_d-4,m_d-1}$ is the intercept α from a risk factor model, based on which I compute the risk-adjusted return for month m_d. The parameter estimation covers the daily returns of a 4-calendar-month window $[m_d-4, m_d-1]$ with Dimson adjustment and keeps in the sample only if the covered window have $\geq$30 data points.	0.5% both tails

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