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ESSAYS ON CORPORATE DISCLOSURE,
GOVERNANCE, AND CAPITAL MARKETS

BY
ZHAO WANG

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY
IN
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UNIVERSITY OF RHODE ISLAND

2019

DOCTOR OF PHILOSOPHY DISSERTATION
OF
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2019

ABSTRACT

The purpose of this dissertation is to investigate the managerial behaviors and their impacts. In the first manuscript, we examine the relationship between managerial equity incentives and two anomalies: net share issuance anomaly and asset growth anomaly. In the presence of asymmetric information, managerial equity incentives mitigate the managers' empire-building motives while increasing their market timing motives. If the market underreacts to these motives, the negative return predicting effects (anomalies) of net share issuance and asset growth would be stronger, respectively, among stocks with higher and lower managerial equity incentives. Our evidence strongly supports this prediction. A hybrid strategy, which exploits the two anomalies in different groups of stocks screened by managerial equity incentives, earns significant alphas beyond transaction costs, even after controlling for the investment and profitability factors that are known to attenuate the two anomalies.

The second manuscript explores the predictability of market risk disclosure for stock price crash risk. The uncertainty surrounding a firm's exposure to a market risk factor may induce a negative skewness in its equity returns (crash risk). If so, an informative market risk disclosure can mitigate crash risk by reducing the factor exposure uncertainty. Motivated by this theoretical prediction, we posit a negative relationship between the level of narrative market risk disclosures (in Item 7A of Form 10K) and crash risk. Using Latent Dirichlet Allocation (LDA), we cluster the textual information in Item 7A into eight latent topics. Narratives of two of these topics, both related to risk exposures of input costs and/or output prices, are negatively associated with crash risk. The remaining six narratives, related to interest rate and foreign

exchange rate exposures, do not convey significant information about crash risk. This evidence contributes to the on-going regulatory discussion on the value of narrative market risk disclosures (in Item 7A) and demonstrates the usefulness of LDA in analyzing unstructured textual information in narrative disclosures.

The third manuscript examines an external power, institutional ownership, on discretionary behavior (market risk disclosure). By exploring why firms voluntarily provide more informative market risk disclosures, we document that institutional ownership plays an important role in enhancing readability and consistency. We find that investors' short-term investment horizon is positively related to the readability of market risk disclosure, and investors' independence is positively associated with both readability and consistency. Our additional analyses indicate that institutional investors' information needs drive the improvement in the readability of market risk disclosure and that their monitoring effects heighten the consistency of market risk disclosure.

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PREFACE

Manuscript format is in use.

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Manuscript 1

Net Share Issuance and Asset Growth Anomalies:

Effects of Managerial Incentives

by

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**Net Share Issuance and Asset Growth Anomalies:
Effects of Managerial Incentives**

Abstract

In the presence of asymmetric information, managerial equity incentives mitigate the managers' empire-building motives while increasing their market timing motives. If the market underreacts to these motives, the negative return predicting effects (anomalies) of net share issuance and asset growth would be stronger, respectively, among stocks with higher and lower managerial equity incentives. Our evidence strongly supports this prediction. A hybrid strategy, which exploits the two anomalies in different groups of stocks screened by managerial equity incentives, earns significant alphas beyond transaction costs, even after controlling for the investment and profitability factors that are known to attenuate the two anomalies.

It has been widely documented that firms that are aggressive in raising external capital and making capital investments tend to underperform their peers in the stock market. In particular, two simple measures of equity financing and corporate investments, “net share issuance” (total issuance less total repurchase) and “total asset growth,” exhibit negative and significant cross-sectional correlations with subsequent stock returns, beyond the effects of the market beta, size, book-to-market (B/M), and return momentum. These significant correlations are often referred to as the net share issuance (NSI) anomaly and the asset growth (AG) anomaly.¹

We are particularly interested in the return predictability of NSI and AG because these signals reflect the firm managers’ endogenous decisions to raise/retire equity capital and to make capital investments. These decisions depend on the managers’ incentives. A natural and interesting question, which has been rarely discussed in the literature, would be how managerial incentives affect the cross-sectional predictability of stock returns. This study undertakes this question with a focus on the NSI and AG anomalies, and shows that managerial incentives do exert significant effects on the return predictability of the NSI and AG signals. To our knowledge, this is one of the first studies that investigate the effects of managerial incentives on the cross-sectional

¹ For the NSI anomaly, please see Fama and French (2008) and Pontiff and Woodgate (2008). For the AG anomaly, please see Cooper, Gulen, and Schill (2008). Unlike many other anomalies documented in the literature, the AG and NSI anomalies are not driven by small stocks that are difficult to trade (Hou, Xue, and Zhang, 2017). Portfolio strategies that are designed to capture these anomalies require relatively low turnovers. It is interesting to examine the NSI and AG anomalies further as transaction costs do not wash away these anomalies completely (Novy-Marx and Velikov, 2016). Moreover, both anomalies are present not only in the US market but also in many developed markets outside the US (e.g., McLean, Pontiff, and Watanabe 2009; Watanabe, Xu, Yao, and Yu 2013) with some exceptions (e.g., Titman, Wei, and Xie, 2009). Fama and French (2008) consider log growth in the ratio of assets per split-adjusted share, which effectively measures the difference between the AG and NSI signals. Lipson Mortal, and Schill (2011) report that, by subtracting the NSI effect, the per-share measure of AG tends to dampen the AG anomaly. This study focuses on the total asset growth signal of Cooper, Gulen, and Schill (2008) for the AG anomaly.

predictability of stock returns, with special attention to the NSI and AG anomalies.

Specifically, we demonstrate that the NSI anomaly is significant only among the firms with high managerial equity incentives, while the AG anomaly is significant only among those with low managerial equity incentives.² These results yield intuitive and straightforward interpretations. On the one hand, in the presence of asymmetric information, firm managers generally have tendencies to engage in agency spending such as empire-building (Jensen, 1986). They may derive personal benefits from expanding their empire. Evaluating different explanations of the AG anomaly, Chan, Karceski, Lakonishok, and Sougiannis (2008) provide evidence that suggests that managers' empire-building incentives drive them to expand assets beyond the firm's economically optimal scale leading to low future returns. However, if the managers have higher equity exposure, their incentives to engage in empire-building is diminished as they are personally exposed to its value-destroying effects. As such, by aligning the managers' incentives to shareholder values, managerial equity incentives can help curtail such agency problems (e.g., Jensen and Murphy, 1990; Core and Guay, 1999; Kim and Purnanandam, 2014).

On the other hand, managerial equity incentives may also motivate the managers to engage in market timing activities. When the managers have better information about the firms' intrinsic values than the market, they have incentives to issue shares when

² Here high (or low) managerial equity incentives mean high (or low) sensitivities of the top managers' wealth to stock price changes. According to Edmans, Gabaix, and Jenter (2017), stock grants and options on company shares account for 50% to 60% of CEO and other top executives' compensation at US public firms in the period between 2000 and 2015. This study measures the total portfolio delta of the top five executives (TPD5) for each firm following Brisker, Autore, Colak, and Peterson (2014). Higher delta can motivate the managers to work harder or more effectively because they share gains and losses with the shareholders.

equity is overvalued and to repurchase shares when equity is undervalued. This benefits existing shareholders, although subsequent equity returns are lower (higher) following issuances (repurchases). In a recent study, Goto, Kalesnik, de Kok, and Kose (2018) observe a significant NSI anomaly only among firms that timed their equity financing activities successfully in the previous year, i.e., those that experienced share price gains (declines) following their share repurchase (issuance) activities in the preceding year. Their evidence suggests the significance of the managers' market timing motives behind the net share issuance anomaly.

And managers with high equity incentives have motives to issue overvalued equity when they can invest the proceeds in profitable opportunities. Undue use of the proceeds (such as overinvestments) would result in equity dilutions that hurt existing shareholders and the managers themselves. Consequently, when they have higher equity exposures they should have stronger incentives to redistribute wealth from new (or past) shareholders to existing/current shareholders by issuing overvalued equity and repurchasing undervalued equity (e.g., Myers and Majluf, 1984; Datta, Iskandar-Datta, and Raman, 2005; Brisker, Autore, Colak, and Peterson, 2014).

In both cases, asymmetric information makes it difficult for investors to fully incorporate the implications of the managers' empire-building and/or market-timing motives.³ Consequently, if the market's underreaction to market timing activities of some firm managers drives the NSI anomaly (e.g., Baker and Wurgler, 2002; Pontiff and Woodgate, 2008), high managerial equity incentives would intensify the NSI

³ Zhang (2006) argues that, if investors underreact to public information, they underreact even more in cases of greater information asymmetry/uncertainty. Consistent with this notion, both AG and NSI anomalies are stronger among firms with large idiosyncratic volatility than among others. See Lipson, Mortal, and Schill (2011) for the AG anomaly and Larrain and Varas (2013) for the NSI anomaly.

anomaly. In contrast, if the market's underreaction to empire-building activities of some entrenched managers drives the AG anomaly (e.g., Titman, Wei, and Xie, 2004; Cooper, Gulen, and Schill, 2008; Lipson, Mortal, and Schill, 2011), high managerial equity incentives should weaken the AG anomaly. Our evidence is fully consistent with these straightforward interpretations.

Taken together, seeing through the lens of managerial incentives, the market's underreaction to the implications of the managers' empire-building and/or market-timing motives appear to be an important determinant of the NSI and AG anomalies. Managerial equity incentives tend to mitigate the managers' empire-building motives but promote their market-timing motives. As such, the NSI anomaly is more pronounced among firms with high managerial equity incentives than others, while the AG anomaly is stronger among firms with low managerial equity incentives.

The asset pricing literature suggests that the NSI and AG anomalies are driven by the same economic force as the profitability and investment factors tend to subsume the two anomalies (e.g. Fama and French, 2015, 2016; Hou, Xue, and Zhang, 2015, 2017). Our findings, however, suggest that the two anomalies may be closely tied to two managerial incentives: market timing motives (to benefit existing shareholders) and empire-building motives (for the managers' personal benefits). The two effects appear to be different as the NSI anomaly and AG anomaly are concentrated in firms with high and low managerial equity incentives, respectively. Indeed, the hedge portfolio for exploiting the NSI anomaly among high managerial equity incentive firms is only moderately correlated with the hedge portfolio for exploiting the AG anomaly among low managerial equity incentive firms, which implies the benefit of diversification.

One of the practical implications of the evidence is that a “hybrid” strategy, which uses the NSI signal for firms with high managerial equity incentives but uses the AG signal for firms with low managerial equity incentives, should provide a sensible and viable stock selection strategy. This strategy provides an efficient way to exploit information in the NSI and AG signals that may have been overlooked by the market. We examine the profitability of this strategy carefully by explicitly accounting for the effects of transaction costs. In particular, we implement the Bayesian/Gibbs sampler-based transaction cost estimates for individual stocks following Hasbrouck (2009) that are used by Novy-Marx and Velikov (2016).

Main Results and Their Practical Implications

This study measures managerial equity incentives at the firm level by calculating the sensitivity of the top 5 executives’ wealth (based on ownership of stock, options, and restricted shares) to a 1% change in stock price (total portfolio delta of the top 5 executives or “TPD5”), following Datta, Iskandar-Datta, and Raman (2005) and Brisker, Autore, Colak, and Peterson (2014).⁴

To examine the effects of TPD5 on the NSI anomaly, we cross-sort stocks independently by NSI and TPD5. We then examine the return performance of the “Low

⁴ TPD5 captures dollar changes in the top 5 managers’ total portfolio values. We sort firms on TPD5 in each cross-section rather than on the ratio of TPD5 to the total portfolio value of the managers. This follows a natural intuition that managerial equity incentives are directly related to dollar sensitivities of the managers’ wealth. The ratio measure is more common in the literature because TPD5 tends to exhibit an extreme positive skewness and a strong correlation with firm size. The extreme skewness is not a concern because we use TPD5 only to sort firms into tercile groups. Our subsequent analyses will also explicitly control for size effects. Empirically, sorting by TPD5 and sorting by the ratio of TPD5 to the total portfolio value produce very similar results for the AG anomaly. However, sorting by TPD5 produces a much clearer difference in the NSI anomaly between the Top TPD5 tercile and the Bottom TPD5 tercile than sorting by the ratio of TPD5 to total portfolio value, conforming to our intuition that the TPD5 is more closely related to the managers’ market timing incentives than the ratio is.

NSI – High NSI” long-short “hedge” portfolio in the full sample and in subsample groups sorted by TPD5. We repeat this exercise for the AG anomaly by examining the return performance of the “Low AG – High AG” hedge portfolio in the full sample and in subsamples sorted by TPD5. All portfolios in this study are value-weighted (i.e., weighted by individual firms’ market capitalizations) and formed/ rebalanced once a year at the end of June. We examine portfolio returns in the ExecuComp universe, which includes stocks in the S&P 1500 index, from July 1993 to June 2017.⁵

With this setup, this study makes a few empirical contributions that should be of interest to investment professionals, especially to those who are interested in active equity portfolio selection. First, our evidence clearly speaks to the substantial effects of managerial incentives on the NSI and AG anomalies, offering novel insights into the cause and interpretation of the two anomalies. The evidence should enhance the investor confidence in the sensibility and efficacy of investment strategies that utilize the NSI and AG signals.

Second, this study suggests how investors can sharpen the NSI and AG signals by conditioning on TPD5. For example, a “Low NSI – High NSI” hedge portfolio earns a significant CAPM alpha of 8.65% per year ($t=4.15$; $IR=0.85$) and a 3-factor alpha of 7.38% per year ($t=3.82$; $IR=0.78$) in the full sample.⁶ However, the NSI hedge portfolios do not earn significant alphas in the Mid- and Bottom-tercile groups of TPD5. We can

⁵ More precisely, ExecuComp has started covering the S&P 1500 universe in 1994. The coverage in 1992-1993 was mostly for S&P 500 firms. However, excluding returns between July 1993 and June 1995 has virtually no effects on the findings we report below.

⁶ In this study, the information ratio (IR) is the annualized ratio of alpha to residual return volatility as in Grinold and Kahn (1999). Some readers may prefer the “appraisal ratio” terminology for this definition of IR. A rule of thumb would be that only the top 25% of active equity portfolio management strategies would attain an IR of 0.5 or above (e.g., Grinold and Kahn, 1999, p.114).

earn a significant CAPM alpha of 9.43% per year ($t=4.10$; $IR=0.84$) and a 3-factor alpha of 8.26% per year ($t=3.78$; $IR=0.77$) on the NSI hedge portfolio only when we focus on the top tercile of TPD5. Similarly, a “Low AG – High AG” hedge portfolio earns an annualized CAPM alpha of 8.09% per year ($t=2.87$; $IR=0.59$) and a 3-factor alpha of 5.93% ($t=2.42$; $IR=0.49$) in the full sample. However, by focusing on the bottom tercile of TPD5, we can substantially increase the CAPM alpha and the 3-factor alpha of the AG hedge portfolio to 11.36% and 10.14% per year ($t=3.42$ and 3.08 ; $IR=0.69$ and 0.63), respectively. Interestingly, the “Low AG – High AG” hedge portfolio earns a significant annualized alpha of 7.56% ($t=2.43$; $IR=0.50$) even after controlling for the Fama and French’s (2015) factors that include the CMA factor based on asset growth. Annualized alphas of these enhanced hedge portfolios (with appropriate conditioning on TPD5) far exceed the estimated annual portfolio rebalancing costs (based on the Bayesian/Gibbs sampler measure of Hasbrouck, 2009) of 0.76% for the “Low NSI – High NSI” hedge portfolio in the Top TPD5 tercile group and of 1.16% for the “Low AG – High AG” hedge portfolio in the Bottom TPD5 tercile group.

Third, this study provides an answer to an ongoing debate whether NSI provides incremental return predictability beyond AG and profitability (e.g., Hou, Xue, and Zhang, 2015, 2017; Fama and French, 2016). Some researchers and practitioners suspect that NSI becomes redundant as a return predictor once we control for the effects of AG and profitability. Firms issue equities when cash outlays required for capital investments and/or acquisitions exceed the available internal funds they can generate from business operations. Thus NSI may not convey incremental information about future stock returns once the benchmark factor model includes an investment (based on

AG) factor and a profitability factor (e.g., Hou, Xue, and Zhang, 2015; Fama and French, 2015). The 5-factor benchmark, that includes investment and profitability factors, indeed attenuates the return predictability of the NSI signal in the full sample. Nevertheless, when we focus on stocks in the top tercile of TPD5, the 5-factor alpha of a "Low NSI - High NSI" hedge portfolio earns a 5-factor alpha of 4.12% per year ($t=1.96$; $IR=0.40$), suggesting that the NSI signal conveys incremental return predictability among stocks with high TPD5s, even in the presence of the investment and profitability factors.

Based on these findings and implications, a practical investment strategy would combine the following two hedge portfolios of stocks screened by TPD5:

- a "Low NSI – High NSI" hedge portfolio of stocks in the Top tercile of TPD5, and
- a "Low AG – High AG" hedge portfolio of stocks in the Bottom tercile of TPD5.

In addition to generating significant and positive alphas, returns on these two hedge portfolios, formed with different stocks in different TPD5 tercile groups, exhibit a low correlation of 0.13. Consequently, a combined portfolio of the two hedge portfolios should achieve a risk reduction through diversification as well. By combining the two hedge portfolios with equal weights, the NSI-AG “hybrid” strategy (with TPD5 screening) would attain a CAPM alpha of 10.39% per year ($t=4.80$; $IR=0.98$), 3-factor alpha of 9.19% per year ($t=4.51$; $IR=0.92$) and a 5-factor alpha of 5.83% per year ($t=3.20$; $IR=0.65$). The annual portfolio turnover ratio for the hybrid strategy (with TPD5 screening) is 153.2%. Using the Bayesian/Gibbs sampler-based effective spreads

of individual stocks (Hasbrouck, 2000; Novy-Marx and Velikov, 2016), we estimate the average 2-way portfolio rebalancing cost to be 0.96% per year. After subtracting transaction costs, the 5-factor alpha of this hybrid strategy after transaction costs would still remain significant at 4.87% per year ($t=2.69$; $IR=0.55$).

The evidence clearly indicates that the NSI and AG signals complement each other in enhancing the cross-sectional predictability of stock returns while attaining diversification benefits, especially when they are formed by different groups of stocks screened by TPD5. A “hybrid” strategy that selects High TPD5 stocks for the NSI hedge portfolio and selects Low TPD5 stocks for the AG hedge portfolio, would provide a sensible and viable stock selection strategy that should be of practical value for active equity portfolio management. We also show that the TPD5-screened “NSI-AG Hybrid” hedge portfolio strategy has exhibited moderate systematic risk exposures over time and moderate downside (left-tail) risk

Data and Methodology

Key Variables

Our data sources include CRSP, Compustat, and ExecuComp. Our annual samples from Compustat and ExecuComp start in 1993 and end in the fiscal year 2016. Our sample universe consists of firms in the ExecuComp which includes firms in the S&P 1500 index plus firms that were once part of the index plus firms removed from the index that are still trading. The S&P 1500 index consists of the largest 500 stocks by market capitalization, the mid-cap 400, and the small-cap 600. Foerster, Tsagarelis, and Wang (2017) also use the S&P 1500 universe to ensure that their investment

strategies would be investable and relevant to practitioners. We collect monthly CRSP data through June 2017. Following Fama and French (2008), we exclude financial firms (SIC codes between 6000 and 6999) and firms with negative book equity values.

Net share issuance (NSI) is based on the number of shares outstanding adjusted for splits and other events such as stock dividends (Pontiff and Woodgate, 2008; Fama and French, 2008). We define NSI as the annual growth rate in a firm's split-adjusted number of equity shares:

$$NSI_{t-1} = \ln(Adj.Shares_{t-1}) - \ln(Adj.Shares_{t-2}),$$

where *Adj.Shares* is the split-adjusted number of shares, which is the number of shares outstanding adjusted for distribution events such as stock splits and stock dividends. *Adj.Shares_{t-1}* is the adjusted number of shares outstanding at the end of the fiscal year ending in the calendar year t-1. We then use *NSI_{t-1}* to construct portfolios at the end of June in the calendar year t.⁷

Total asset growth (AG) is measured similarly as the annual difference in natural logarithms of total assets (Compustat item 6) at the fiscal year ending in the calendar year t-1 and total assets at the fiscal year ending in the calendar year t-2. We then use this AG to construct portfolios at the end of June in the year t.

⁷ Fama and French (2008) and Pontiff and Woodgate (2008) motivate NSI as a cross-sectional return predictor to get around econometric concerns associated with long-run event studies (e.g., Brav, Geczy, and Gompers, 2000; Mitchell and Stafford, 2000; Schulz, 2003). A few earlier influential studies that use long-run event studies include Loughran and Ritter (1995, 1997), Spiess and Affleck-Graves (1995), Loughran and Vijh (1997), and Baker and Wurgler (2000) for the long-run underperformance following seasoned equity offerings and share-based acquisitions; and Ikenberry, Lakonishok, and Vermaelen (1995, 2000) for the long-run outperformance following share repurchases. Alternatives to NSI include Bradshaw, Richardson, and Sloan's (2006) net external financing signal from accounting statements and Daniel and Titman's (2006) composite equity issuance signal which measures the difference between the log cumulative growth of market capitalization and the log cumulative total return on the company's stock. This study focuses on the NSI signal as a direct measure of net share issuances.

TPD5 is the weighted average of “deltas” for the top five executives (e.g., Brisker, Autore, Colak, and Peterson, 2014).⁸ “Delta” here is the sensitivity of the manager’s wealth to stock price, estimated as the expected change in the dollar value of the manager’s entire portfolio of unrestricted stocks, restricted stocks and options from a 1% change in stock price (e.g., Core and Guay, 1999, 2002; Coles, Daniel, and Naveen, 2014). In calculating the weighted average of deltas, we assign a weight to each executive based on her/his total compensation for each year, following the approach used by Brisker, Autore, Colak, and Peterson (2014).

Portfolio Sorts

In each year, we form portfolios sorted by AG and NSI. Following Fama and French (2008) we examine positives and negatives of AG and NSI separately by allocating negative values of these variables to two groups using the median of negative values of the variable for the all-but-micro universe as the breakpoint, and by allocating positive values to five groups using quintile breakpoints for positive values of the variables for all-but-micro.⁹ Since a few firms have no net share issuances, the sorts for NSI have an additional cell for zeros. We also sort stocks independently into tercile groups (Top, Mid, Bottom) based on TPD5. We consider the full sample and the Top-, Mid-, and Bottom-TPD5 tercile subsamples, i.e., 4 sample groups in total.

⁸ The ExecuComp database provides compensation data for the top 5 highest compensated officers for each firm. An alternative would be to focus on the equity compensation “delta” of the CEO only. Our results remain almost identical when we use the CEO delta instead of TPD5. However, Armstrong, Larcker, Ormazabal, and Taylor (2013) argue that focusing on the incentives of the top management team would be more sensible than focusing on CEO incentives that may be confounded by the CEO’s individual-specific characteristics.

⁹ Following Fama and French (2008), we define micro-cap stocks as those which market capitalizations below the 20th NYSE percentile. All-but-micro universe includes all stocks other than micro-cap stocks.

Table 1 summarizes the average number of stocks per period in each portfolio between 1992 and 2016. The average number of firms per year in the whole sample is 1,760.9 for NSI and 1,726.9 for AG. Our portfolios consist of stocks that are included in the S&P 1500 index and stocks that were included in the index in the past (the ExecuComp universe). They are not populated by micro-cap stocks that are difficult to trade. Each portfolio corresponding to each cell is value-weighted, that is, weighted by each firm's market capitalization. We exclude portfolios corresponding to the cells with NSI=0, due to the small number of stocks in these cells (60.3 firms on average before sorting by TPD5). We, therefore, consider 28 portfolios corresponding to 2 negatives and 5 positives times 4 TPD5 groups (full sample and 3 tercile groups). All portfolios are value-weighted and rebalanced annually at the end of each June.

In the sample, we observe some relations in the number of firms between the signals (NSI and AG) and TPD5. For example, in the Low-Negative and High-Positive extreme groups of NSI, we tend to see more firms in the Top TPD5 tercile than in other tercile groups. In the middle groups of NSI, we tend to see more firms in the Bottom TPD5 tercile. We also observe the smaller number of stocks in the Low-Negative AG and the Top TPD5 cell and in the High-Positive AG and the Bottom TPD5 cell.

[Insert Table 1 here]

To examine how NSI and AG signals are associated with predictive variations in abnormal (benchmark-adjusted) stock returns, we take two approaches. In the first approach, we define and calculate Size-B/M adjusted abnormal return of each of the 28 value-weighted portfolios following Fama and French (2008). To implement this, we calculate Size-B/M adjusted abnormal return of each stock as the difference between

the stock's raw return and the return on its corresponding Size- and B/M-based matching portfolio as in Fama and French (2008). The Size-B/M matching portfolios are 25 value-weighted portfolios, which are constructed at the end of each June based on the interactions of five portfolios formed on size and five portfolios formed on B/M (Fama and French, 1993).¹⁰ For each of the 28 portfolios, we then calculate the time-series averages of Size-B/M adjusted abnormal returns as in Fama and French (2008).

Our second approach utilizes time-series regressions on the CAPM and 3-, 4-, and 5-factor benchmark models of Fama and French (1993, 2015) and Carhart (1997). In particular, we focus on the significance of the differences between “Low Negative” portfolio returns and “High Positive” portfolio returns. Specifically, we consider the “Low Negative minus High Positive” long-short hedge portfolios formed on NSI and AG in each (sub)sample. We call the hedge portfolios the “Low NSI – High NSI” hedge portfolio and the “Low AG – High AG” hedge portfolio. We then estimate “alphas” (average abnormal returns) of these hedge portfolios against the CAPM and against the 3-, 4-, and 5-factor benchmark models, which we obtain as intercepts from time-series regressions of hedge portfolio returns on the benchmark factors. Each time series regression uses 288 monthly portfolio returns and factors from July 1993 to June 2017. The CAPM uses the market excess return (Mkt-Rf) as the sole factor. The 3-factor model (Fama and French, 1993) adds the size (SMB), and B/M (HML) factors in addition to the market factor (Mkt-Rf). The 4-factor model (Carhart, 1997) adds the momentum factor (MOM) to the 3-factor model. The 5-factor model (Fama and French, 2015) replaces the momentum factor in the 4-factor model with the investment (CMA)

¹⁰ We obtain the breakpoints and value-weighted returns of the 25 Size-B/M matching portfolios from Kenneth French's website.

and profitability (RMW) factors. The investment (CMA) factor in the 5-factor model is based on joint sorts by AG and size. It is, therefore, a tall order to generate significant alphas against the 5-factor model using AG and/or NSI signals.

We note that the popular benchmark factors, such as SMB, HML, MOM, RMW, and CMA, do not account for transaction costs. The majority of existing empirical studies on the NSI and AG anomalies report alphas without accounting for the effects of transaction costs. To facilitate comparison with the existing literature, we first report alphas before transaction costs. We then devote a separate section to discuss the effects of portfolio rebalancing costs.

Empirical Results

Summary Statistics

Table 2 provides the pooled summary statistics of our main variables for the full sample and the three tercile subsamples by TPD5. Firms with high managerial equity incentives (TPD5) tend to have higher market capitalizations and lower B/M ratios.

The pooled mean and median of NSI are 7.1% and 0.7% respectively in the full sample. Pooled medians do not vary much across TPD5 tercile groups, but pooled means tend to be higher for the Top TPD5 tercile subsample than for the other tercile subsamples. This suggests that a few firms with high TPD5s engage in large stock issues, creating more positively skewed distribution of NSI within the Top TPD5 tercile subsample than in other tercile subsamples.

The pooled mean and median of AG are 16.2% and 7.1% respectively in the full sample. Both the mean and median tend to be higher among firms in the Top TPD5

tercile subsample than among those in other tercile subsamples. This may suggest that firms with high TPD5s are more active in investing in growth opportunities than other firms. Alternatively, firms with large growth opportunities may provide their managers with higher equity-based compensations.

The pooled mean and median of TPD5 are \$2.12 million and \$428 thousand. The distribution of TPD5 is extremely skewed to the right, as a small number of firms have very large TPD5s.

[Insert Table 2 here]

Size-B/M Adjusted Abnormal Returns of Portfolios Sorted on NSI and AG

Since firms with high TPD5s tend to have larger Size and lower B/M ratios than others, it is useful to control for the effects of Size and B/M in comparing return performances across different groups sorted by TPD5. We thus follow Fama and French (2008) in calculating the Size-B/M adjusted abnormal returns on the portfolios sorted on NSI and AG. We plot average Size-B/M adjusted abnormal returns in **Figure 1** for portfolios sorted on NSI in Panel A for portfolios sorted on AG in Panel B. Both figures plot average monthly Size-B/M adjusted abnormal returns for the seven portfolios sorted on NSI or AG in the Full sample and in the three tercile subsamples sorted by TPD5.

When we look closely at the return performances of the 28 portfolios in Panel A, the low returns of the Highest NSI portfolio clearly stand out. In the full sample, the average monthly Size-B/M adjusted abnormal returns are positive for all portfolios except for the -0.287% return for the High Positive portfolio. That is, a large fraction of

the NSI anomaly is largely attributable to low subsequent returns of the firms that have engaged in large share issuances (e.g., seasoned equity offerings, share-based acquisitions, etc.), consistent with the finding of Fama and French (2005, 2008).

Turning to the effects of managerial equity incentives (TPD5), the return difference between the Low NSI portfolio and the High NSI portfolio varies greatly across different tercile subsamples sorted by TPD5. The difference in average Size-B/M adjusted abnormal returns between the Low NSI portfolio and the High NSI portfolio is significant in the Top TPD tercile subsample (0.626% per month; $t=3.41$). However, differences in abnormal returns are not reliably different from zero in the Mid- and Bottom-TPD5 tercile subsamples. Again, the large difference in Size-BM adjusted abnormal returns between the Low NSI portfolio and the High NSI portfolio in the Top TPD5 tercile is mostly attributable to the large negative abnormal return (-0.389% per month) of the firms that have engaged in large equity issuances. One interpretation would be that, when firm managers' compensations are aligned with the current shareholders' interests, the managers are likely to make large equity issuances (e.g., seasoned equity offerings, share-based acquisitions) when they deem their stock prices to be overvalued in the market.

As is the case with NSI, the Low (Negative) AG portfolios tend to have higher average Size-B/M adjusted abnormal returns than the High (Positive) AG portfolios in Panel B. In the full sample, the average monthly Size-B/M adjusted returns are 0.284% for the Low (Negative) AG portfolio and -0.157% for the High (Positive) AG portfolio.

The difference in Size-B/M adjusted abnormal returns between the low AG portfolio and the High AG portfolio appears to be driven by stocks in the Bottom TPD5

tercile group. We observe a larger difference in Size-B/M adjusted abnormal returns between the Low Negative AG portfolio (0.589% per month) and the low abnormal return of the High Positive AG portfolio (-0.355% per month). The difference (0.944% per month; $t=3.42$) is statistically significant among the firms with low managerial equity incentives (the Bottom TPD5 tercile group). Among the firms with low managerial equity incentives, large increases in total assets may signal large agency spending by the managers, while large decreases in total assets may signal reduced agency spending by the managers.

[Insert Figure 1 here]

Managerial Equity Incentives and the NSI/AG Anomalies

While Size-B/M adjusted abnormal returns are useful to separate the effects of Size and B/M from those of managerial equity incentives (TPD5), differences in Size-B/M adjusted abnormal returns between portfolios do not yield straightforward interpretation. We thus conduct long-short hedge portfolio analyses using raw portfolio returns, as opposed to the Size-B/M adjusted abnormal returns. We then regress these raw hedge portfolio returns against the market factor and other standard benchmark factors such as the SMB, HML, MOM, RMW, and CMA.

Table 3 summarizes return performances of the “Low NSI - High NSI” hedge portfolios and those of the “Low AG - High AG” hedge portfolios for each of the tercile groups sorted by TPD5.

The NSI Anomaly

In the full sample, the “Low NSI – High NSI” hedge portfolio earns an average return of 0.535% per month (6.42% per year; $t=2.88$; $IR=0.59$). The hedge portfolio also earns positive and significant alphas against the CAPM as well as the 3- and 4-factor models of 0.721% per month (8.65% per year; $t=4.15$; $IR=0.85$), 0.615% per month (7.38% per year; $t=3.82$; $IR=0.78$) and 0.523% per month (6.28% per year; $t=3.30$; $IR=0.67$) respectively. However, the alpha is smaller and insignificant once we add the profitability (RMW) and investment (CMA) factors (5-factors) in the regressions. The 5-factor alpha is smaller and insignificant at 0.242% per month (2.90% per year; $t=1.63$; $IR=0.33$).

Interestingly, we see large variations in alphas across different tercile groups of TPD5. Alphas of the hedge portfolios formed in the Mid- and Bottom-TPD5 tercile subsamples are not reliably different from zero. The hedge portfolio formed in the Top TPD5 tercile earns significant alphas against the CAPM alpha as well as the 3- and 4-factor models of 0.786% per month (9.43% per year; $t=4.10$; $IR=0.84$), 0.688% per month (8.25% per year, $t=3.78$, $IR=0.77$) and 0.595% per month (7.13% per year; $t=3.29$, $IR=0.67$), respectively. Not surprisingly, at 0.343% per month (4.12% per year), the 5-factor alpha is lower than the 3-factor and 4-factor alphas in the Top TPD5 tercile. Nonetheless, it is still significant at $t=1.96$ and $IR=0.40$. The evidence indicates that the return predictability of the NSI signal arises mostly among firms with high managerial equity incentives, as measured by TPD5.

The AG Anomaly

Turning to the AG anomaly, the average difference in returns between the Low AG portfolio and the High AG portfolio is significant at 0.526% per month (6.31% per year; $t=2.20$; $IR=0.45$) in the full sample. After controlling for the market factor, 3-factors and 4-factors, the hedge portfolio earns alphas of 0.674% per month (8.09% per year; $t=2.87$; $IR=0.59$), 0.494% per month (5.93% per year, $t=2.42$, $IR=0.49$) and 0.401% per month (4.81% per year; $t=1.97$; $IR=0.40$) respectively. However, the alpha of the hedge portfolio becomes insignificant at 0.190% per month (2.28% per year; $t=1.03$; $IR=0.21$) against the 5-factor model. This would not be surprising because the CMA factor is based on cross-sorts by AG and firm size.

Turning to the effects of managerial equity incentives (TPD5), it is clear that the AG anomaly is significant only among firms with low TPD5s. Within the Bottom TPD5 tercile subsample, the “Low AG – High AG” hedge portfolio earns the CAPM alpha as well as the 3- and 4-factor alphas of 0.947% per month (11.36% per year; $t=3.38$; $IR=0.69$), 0.845% per month (10.14% per year; $t=3.08$; $IR=0.63$) and 0.806% per month (9.67% per year; $t=2.90$; $IR=0.59$), respectively. However, the 3- and 4-factor alphas are not significantly different from zero in the Mid- or the Top-TPD5 tercile subsamples. This indicates that the AG anomaly arises mostly among firms with low managerial equity incentives.

Interestingly, when we focus on the Bottom TPD5 tercile subsample, the 5-factor alpha of the “Low AG – High AG” hedge portfolio is quite significant at 0.630% per month (7.56% per year; $t=2.43$; $IR=0.50$). That is, the “Low AG – High AG” hedge

portfolio formed on stocks in the Bottom TPD5 subsample (low managerial equity incentives) generates a significant alpha even after controlling for the AG-based investment (CMA) factor. The CAPM alpha, the 3-, 4-, and 5-factor alphas of the Low AG – High AG hedge portfolio within the Bottom TPD5 tercile group are 11.36%, 10.14%, 9.67%, and 7.56% per year. That is, the return predictability of the AG signal is statistically significant and particularly salient among firms whose managerial incentives are not well aligned with the shareholders’ interests.

[Insert Table 3 here]

An “NSI-AG Hybrid” Strategy with TPD5 Screening

Our results suggest that the NSI signal provides a significant return prediction in the Top TPD5 tercile group of firms (with high managerial equity incentives), while the AG signal provides a significant return prediction in the Bottom TPD5 tercile group of firms (with low managerial equity incentives). It is then natural to consider a hybrid strategy that uses the NSI signal for stocks of firms with high managerial equity incentives and the AG signal for stocks of firms with low managerial equity incentives.

Moreover, the hybrid strategy may benefit from risk reduction through diversification. **Table 4** provides a correlation matrix between the “Low NSI - High NSI” hedge portfolio returns and the “Low AG - High AG” hedge portfolio returns in the full sample and in Top-, Mid-, and Bottom-TPD5 tercile subsamples. The “Low NSI - High NSI” hedge portfolio and the “Low AG - High AG” hedge portfolio formed in the full sample exhibit a return correlation of 0.478 during the sample period between July 1993 and June 2017. However, the “Low NSI - High NSI” hedge portfolio formed

by stocks in the Top-TPD5 tercile subsample and the “Low AG - High AG” hedge portfolio formed by stocks in the Bottom-TPD5 tercile subsample exhibit a much lower correlation at 0.133 during the sample period. Therefore, the scope for risk diversification can be quite large for combining the two hedge portfolios formed in different TPD5 tercile groups.

[Insert Table 4 here]

We thus consider a strategy that combines the following two long-short hedge portfolios with equal weights:

- a “Low NSI – High NSI” hedge portfolio of stocks in the Top tercile of TPD5, and
- a “Low AG – High AG” hedge portfolio of stocks in the Bottom tercile of TPD5.

We can view this “NSI-AG Hybrid” portfolio with TPD5 screening as a variant of the “conservative minus aggressive (CMA)” portfolio strategy that is conditioned on managerial equity incentives (as measured by TPD5).

To evaluate the value of TPD5 screening, we also consider another hybrid strategy that simply combines a “Low NSI – High NSI” hedge portfolio and a “Low AG – High AG” hedge portfolio in the full sample (with equal weights) without using the information in TPD5.

Table 5 summarizes time-series regressions of the two hybrid portfolio returns on the CAPM as well as the 3-, 4, and 5-factor benchmark models (Fama and French, 1993, 2015; Carhart, 1997). Both hybrid portfolios would generate highly significant alphas against the market factor and the 3-factor and 4-factor benchmark models. “The NSI-AG Hybrid” portfolio in the full sample (without TPD5 screening) would generate

CAPM alpha as well as 3- and 4-factor alphas of 0.698% per month (8.38% per year; $t=4.02$; $IR=0.82$), 0.554% per month (6.65% per year; $t=3.77$; $IR=0.77$) and 0.462% per month (5.54% per year; $t=3.20$; $IR=0.65$), respectively. However, with TPD5 screening, the hybrid portfolio's CAPM alpha and the 3- and 4-factor alphas are higher at 0.866% per month (10.39% per year; $t=4.80$; $IR=0.98$), 0.766% per month (9.19% per year; $t=4.51$; $IR=0.92$) and 0.700% per month (8.40% per year; $t=4.11$; $IR=0.84$), respectively.

Before controlling for the 5-factor model (including the CMA factor), both hybrid portfolios have negative exposures to the market factor and positive exposures to the HML (value) factor. Not surprisingly, however, both hybrid portfolios have significant loadings on the CMA factor. The inclusion of the CMA factor makes the portfolios' exposures to the market factor and the HML factor insignificant. The 5-factor model can explain the time series variations of the hybrid portfolio returns more than the 3-factor or 4-factor models, as shown by the large increases in the R-square coefficients. Without the TPD5 screening, the 5-factor model largely subsumes the alpha of the hybrid portfolio, as the 5-factor alpha drops to 0.216% per month (2.59% per year; $t=1.73$; $IR=0.35$) without the TPD5 screening.

However, by choosing different TPD5 tercile subsamples for the NSI and AG hedge portfolios, the "NSI-AG Hybrid" hedge portfolio would earn a 5-factor alpha of 0.486% per month (5.83% per year; $t=3.20$; $IR=0.65$). This illustrates the significant value provided by TPD5 screening. By focusing on NSI signals of stocks with high TPD5s (high managerial equity incentives) and on AG signals of stocks with low TPD5s (low managerial equity incentives), we can substantially improve the return performance of the hybrid portfolio. Interestingly, the TPD5-screened "NSI-AG

Hybrid” hedge portfolio has significant exposure (about one) to the CMA factor only in the 5-factor model. Still, the TPD5-screened “NSI-AG Hybrid” portfolio earns a significant alpha beyond the CMA and other factors in the 5-factor model.

[Insert Table 5 here]

Practical Considerations

Effects of Transaction Costs

Our evidence suggests that the NSI anomaly is mainly driven by stocks with high managerial equity incentives (Top TPD5 universe) and the AG anomaly is mainly driven by stocks with low managerial equity incentives (Bottom TPD5 universe). A TPD5-screened “NSI-AG Hybrid” portfolio strategy that combines the “Low NSI - High NSI” hedge portfolio in the Top TPD5 universe and the “Low AG - High AG” hedge portfolio in the Bottom TPD% universe would attain significant alphas against all popular benchmark factor models.

Like many existing studies on stock market anomalies, however, the evidence so far is based on paper-portfolio returns. As paper portfolios move to actual trading strategies, it becomes very important to account for the effects of transaction costs. As Novy-Marx and Velikov (2016) demonstrate, very few factors, constructed as long-short portfolios, with one-sided monthly turnover ratios exceeding 50% have any returns left after accounting for transaction costs. They further show that equally-weighted portfolios formed on factors, popular in the academic literature, become unprofitable after accounting for transaction costs. Hou, Xue, and Zhang (2017) document that the majority of documented anomalies are driven by micro-cap stocks that proliferate the extreme deciles, but these micro-cap stocks are very difficult and

costly to trade. Implicitly assuming short positions of any size and duration for these illiquid stocks also renders the analysis impractical and irrelevant. It is thus very important to examine the effects of transaction costs in discussing the practical implications of our evidence.

We note that our portfolio analyses presented above are relatively immune to these concerns because we focus on value-weighted portfolios formed in the ExecuComp universe. This universe consists of stocks that are (or were) part of the S&P 1500 index. Foerster, Tsagarelis, and Wang (2017, p.78) “chose the S&P 1500 to ensure that the stocks would be truly investable and that the tested investment strategies would be relevant to practitioners.” Nevertheless, it is important to account for the effects of transaction costs to make our analysis more relevant and interesting to practitioners.

To this end, we implement the Bayesian/Gibbs sampler based measure of transaction costs for all individual stocks in our universe (Hasbrouck 2009; Novy-Marx and Velikov 2016).¹¹ We are able to estimate transaction costs for all individual stocks in our sample universe. Let $tc_{j,t}$ be the estimated transaction cost (in %) of stock j at rebalancing time t . We then calculate the round-trip transaction cost of a long-short hedge portfolio as

$$Tcost_t = \sum_j (tc_{j,t} \times |w_{j,t} - w_{j,t-}|)$$

where $w_{j,t-}$ and $w_{j,t}$ are the weights of the j -th stock in the hedge portfolio before and after the portfolio rebalancing at t , respectively. $w_{j,t}$ (or $w_{j,t-}$) takes a positive value if the j -th stock is in the long leg (i.e., in the Low Negative cell in Table 1), a negative

¹¹ Hasbrouck (2009) uses a Bayesian/Gibbs sampler to construct a realistic transaction cost measure from daily stock returns, which has a correlation of 0.965 with the transaction level estimate. We greatly benefit from the SAS code provided by Joel Hasbrouck on his website. He also kindly answered our questions regarding the implementation of his transaction cost measures.

value if the stock is in the short leg (i.e., in the High Positive cell in Table 1), or a value of zero if the stock does not fall in either leg. Both the long leg and the short leg of the hedge portfolio are value-weighted at the time of rebalancing (at the end of June). Note that the standard turnover measure of a long-short hedge portfolio is given by $\frac{1}{2} \sum_j |w_{j,t} - w_{j,t-}|$ (e.g., Qian, Hua, and Sorensen 2007, p.236).

Table 6 reports average portfolio turnover ratios and average round-trip transaction costs for the “Low NSI - High NSI” hedge portfolios (formed in the Full sample, and in the Top TPD5 tercile subsample), for the “Low AG - High AG” hedge portfolios (formed in the Full sample and in the Bottom TPD5 tercile subsample), and for the “NSI-AG Hybrid” portfolios (in the Full sample and with TPD5 screening). Between June 1994 and June 2017, the average annual turnover ratios of the “Low NSI - High NSI” hedge portfolios are 149.1% (12.4% per month) in the Full sample and 153.1% (12.8% per month) in the Top TPD5 tercile subsample. The turnover ratios of the “Low AG - High AG” hedge portfolios are 163.2% (13.6% per month) in the Full sample and 154.0% (12.8% per month) in the Bottom TPD5 tercile subsample. The turnover ratios of the “NSI-AG Hybrid” portfolios are 145.3% (12.1% per month) in the Full sample (without the TPD5 screening) and 153.2% (12.8% per month) with the TPD5 screening.¹²

Average round-trip transaction costs for the “Low NSI - High NSI” hedge portfolio are 76.5 bps in the Full sample and 76.0 bps in the Top TPD5 subsample, and those for the “Low AG - High AG” hedge portfolio are 90.3 bps in the Full Sample and

¹² Novy-Marx and Velikov (2016) report monthly turnover ratios of 14.4% and 6.4%, respectively for NSI and AG value-weighted long-short portfolios using a larger sample universe and a longer period.

115.9 bps in the Bottom TPD5 subsample. Transaction costs tend to be larger in the Bottom TPD5 subsample because stocks in this subsample tend to be smaller, on average, than those in the Top- or Mid-TPD5 subsamples. Transaction costs for the “NSI-AG Hybrid” portfolios 77.6 bps in the Full sample and 95.7 bps with the TPD5 screening. Transaction costs per trade (one-way) are 24.8 bps for the “Low NSI - High NSI” hedge portfolio in the Top TPD5 tercile group, 37.6 bps for the “Low AG - High AG” hedge portfolio in the Bottom TPD5 tercile group, and 31.2 bps for the “NSI-AG Hybrid” portfolio with the TPD5 screening.

Transaction costs vary with market conditions. **Figure 2** plots transaction costs over time for the “Low NSI - High NSI” hedge portfolio in the Top TPD5 subsample and the “Low AG - High AG” hedge portfolio in the Bottom TPD5 subsample. While the latter strategy generally entails higher transaction costs than the former, there have been substantial time variations in the portfolio turnover costs. In particular, transaction costs are generally higher in stressed equity markets such as those in the early 2000s and those during the 2008-2009 crisis period.

[Insert Table 6 here]

[Insert Figure 2 here]

Table 7 reports alphas after transaction costs for the “Low NSI - High NSI” hedge portfolio, the “Low AG - High AG” hedge portfolio, and the “NSI-AG Hybrid” hedge portfolio. In the left panel, we consider the case in which we construct these portfolios in the full sample without using the information in TPD5 (managerial equity incentives). In the right panel, we consider the case in which we select subsamples by conditioning on TPD5. For example, the “Low NSI - High NSI” hedge portfolio focuses

on the subsample of firms in the Top TPD5 tercile group (with high managerial equity incentives), while the “Low AG - High AG” hedge portfolio focuses on the subsample of firms in the Bottom TPD5 tercile group (with low managerial equity incentives). The “NSI-AG Hybrid” hedge portfolio with TPD5 screening combines the two hedge portfolios screened by TPD5.

We subtract transaction costs from portfolio returns in every June and regress them on respective benchmark factors to obtain alphas as the intercept terms. The NSI anomaly generally survives the effects of transaction costs, but the 5-factor alpha is generally insignificant, consistent with the view that a profitability factor and an investment factor subsume the NSI anomaly (e.g., Hou, Xue, and Zhang, 2015; Fama and French, 2015).

The significance of the AG anomaly gets attenuated when we include transaction costs, which is consistent with what Novy-Marx and Velikov (2016) observe. However, we can resurrect the significant AG anomaly when we focus on the Bottom tercile of TPD5 (firms with low managerial equity incentives), even after accounting for the relatively large portfolio rebalancing costs (1.16% per year on average) associated with the “Low AG - High AG” hedge portfolio in that group.

The TPD5-screened “NSI-AG Hybrid” Portfolio strategy attains significant alphas against all benchmark factor models, including the 5-factor model. That is, by taking advantage of the NSI anomaly among stocks with high managerial equity incentives (TPD5s) and the AG anomaly among stocks with low managerial equity incentives (TPD5s), one can earn a significant alpha of 0.408% per month (4.90% per year; $t=2.69$; $IR=0.55$) after transaction costs even against the 5-factor model that

includes the CMA factor. This evidence clearly suggests the economic value of conditioning on managerial equity incentives in exploiting the NSI and AG anomalies.

[Insert Table 7 here]

Figure 3 plots log cumulative returns of the “NSI-AG Hybrid” portfolio strategy with TPD5 screening along with those of other portfolio strategies in excess of risk-free returns on the cash position. These cumulative returns account for portfolio rebalancing costs incurred at the end of each June. Panel A shows log cumulative returns on the two constituent portfolios of the TPD5-screened “NSI-AG Hybrid” portfolio strategy. We can see how the hybrid strategy blends the “Low AG - High AG” hedge portfolio of stocks in the Bottom TPD5 tercile (higher return and higher risk) and the “Low NSI - High NSI” hedge portfolio of stocks in the Top TPD5 tercile (lower return and lower risk) to derive diversification benefits from the low correlation of the two hedge portfolios. We can also see that the TPD5-screened hybrid strategy has generated superior returns quite consistently over time. There are three periods in which the strategy underperformed for a half year or longer, one between July 2005 and July 2006, one between February 2007 and September 2007, and the other between June 2014 and September 2015. Other than these periods, the “NSI-AG Hybrid” portfolio strategy with TPD5 screening has generated positive consistent return performance. This illustrates that, when combined with the information about managerial equity incentives in TPD5, NSI and AG still are viable and consistent cross-sectional predictors of stock returns.

Panel B compares the performance of the TPD5-screened “NSI-AG Hybrid” portfolio strategy with those of the “Low NSI - High NSI” and “Low AG - High AG” hedge portfolios formed in the Full sample and the Hybrid NSI-AG Hybrid portfolio

formed in the Full sample without using the information in TPD5. As we can see, the TPD5-screened “NSI-AG Hybrid” portfolio strategy has outperformed other strategies that employ the NSI and AG signals in the full sample. By focusing on stocks with high TPD5s (high managerial equity incentives) for the NSI signal and those with low TPD5s (low managerial equity incentives) for the AG signal, one can substantially improve the cross-sectional return predictability of stock returns while benefiting from risk reduction through diversification. Gains from utilizing the information in managerial equity incentives (TPD5) are substantial, even after accounting for transaction costs associated with the portfolio implementation.

[Insert Figure 3 here]

Downside Risk and Time-Varying Factor Exposures

A few factor investing strategies implemented with long-short hedge portfolios are often prone to large downside risk (e.g., Arnott, Harvey, Kalesnik, and Linnainmaa, 2019). Some strategies also exhibit high exposures to the market and other factor investing strategies, especially during the market downturn against the investors’ expectations for diversification. This section discusses the large downside (left-tail) risk and time-varying systematic risk exposures of the three hedge portfolio strategies of our interest: (1) the “Low NSI - High NSI” hedge portfolio formed in the Top TPD5 tercile group (with high managerial equity incentives), (2) the “Low AG - High AG” hedge portfolio formed in the Bottom TPD5 tercile group (with low managerial equity incentive), and (3) the TPD5-screened “NSI-AG Hybrid” hedge portfolio that combines (1) and (2).

Downside Risk

In **Table 8**, we examine each factor's (or hedge portfolio's) worst monthly returns during our sample period between July 1993 and June 2017. All factor (hedge portfolio) returns in the table have positive excess kurtosis, meaning that they contain some extreme return realizations compared to what normal distributions imply for the same standard deviations.

The market factor has the worst monthly return of -17.2% (in October 2008), which was 4.2 standard deviations away from its mean. The market factor exhibits a negative skewness (-0.73) in the distribution of returns. The momentum factor (MOM) and the profitability factor (RMW) are particularly prone to the large downside risk. MOM and RMW have the worst monthly returns of -34.4% (in April 2009) and -18.0% (in February 2002), respectively, which were 7.0 and 6.7 standard deviations away from their corresponding means. Both factors exhibit negative return skewness and high excess kurtosis, implying the presence of large left-tail risk.¹³ The CMA factor is less prone to the downside risk than the other factors as it exhibits a positive return skewness (0.67) and its worst monthly return (-6.9% in January 1999) was 3.4 standard deviations away from the mean.

As variants of the “Conservative Minus Aggressive” factor, our hedge portfolios formed on NSI and AG have positive return skewness, as is the case with the CMA factor. Here, our hedge portfolio returns account for transaction costs. The “Low NSI - High NSI” hedge portfolio in the Top TPD5 tercile group had a large negative return of

¹³ The large downside risk of the momentum factor, called the “momentum crash” has been documented by Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016).

-15.6% (in October 1999; 4.7 standard deviations away from the mean), The worst monthly return of the “Low AG - High AG” hedge portfolio formed in the Bottom TPD5 subsample is much smaller at -9.1% (in March 2015; only 2.1 standard deviations away from the mean). For the AG anomaly, focusing on the subsample of firms with low managerial equity incentives helps reduce the downside risk while increasing the Sharpe ratio.

The “NSI-AG Hybrid” hedge portfolio with TPD5 screening attains a high Sharpe ratio (0.78) while maintaining a positive return skewness (0.78) and containing the worst monthly return at a moderate level at -7.2% (in January 2001; 2.6 standard deviations away from the mean).

The evidence suggests that the hybrid strategy that jointly exploits (i) the NSI anomaly among the firms with high managerial equity incentives and (ii) the AG anomaly among the firms with low managerial incentives attains superior return performance without exposing the investors to large downside (left-tail) risk.

[Insert Table 8 here]

Time-Varying Factor Exposures

Figure 4 plots the three hedge portfolios’ exposures to the market factor (Panel A), the value (HML) factor (Panel B), and the momentum factor (Panel C). Each panel plots five-year factor exposures over time from June 1998 to June 2017. As firms with low (high) B/M ratios tend to be more aggressive (conservative) in raising capital and making capital investments, the NSI- and AG-based hedge portfolio strategies tend to exhibit high exposures to the value (HML) factor. Given that the value factor is

commonly used by factor investors, it is interesting to examine the exposure of our hedge portfolios to the value factor. Besides the value, another prominent factor that attracts factor investing strategies is the momentum factor (e.g., Asness, Moskowitz, and Pedersen, 2013). Exposures to the momentum factor are also interesting due to the large downside (left-tail) risk associated with the momentum factor.

Given the popularity of value- and momentum-based factor investing strategies, the three hedge portfolios proposed in this study may fail to provide diversification benefits if their exposures to the value and/or momentum factors increase unexpectedly during the market downturn. It is thus worthwhile to examine the time-variations in the exposures of the proposed hedge portfolio strategies (especially of the hybrid strategy) to the three factors.

Panel A shows that the NSI- and AG-based hedge portfolios had had negative market exposures before the mid-2000s. Their market exposures increase until August 2007, and then subsequently declined amid the global financial crisis. The AG-based hedge portfolio that aims to exploit the empire-building motive of managers with low managerial equity incentives (low TPD5s) exhibited a positive market exposure after the crisis. The NSI-based hedge portfolio that aims to exploit the market timing motive of managers with high managerial equity incentives (high TPD5s) exhibited a negative exposure during the same period. By offsetting the two beta exposures, the hybrid hedge portfolio has exhibited a more moderate and stable market beta exposure over the sample period.

Panel B shows that the three hedge portfolio strategies had positive exposures to the value (HML) factor before the mid-2000s. Their exposures to the value factor fell

sharply to almost zero (and even negative) before the global financial crisis, followed by an increase amid the crisis. After the crisis period, the AG-based hedge portfolio (in the Bottom TPD5 group) exhibit positive exposures to the value (HML) factor during the sample period. The positive exposure of the AG-based hedge portfolio to the HML factor is not surprising because the CMA factor (based on size and AG) has a high correlation (0.65) with the HML factor in the sample period. Interestingly, the NSI-based hedge portfolio (in the Top TPD5 group) had a higher (more positive) exposure to the HML factor than the AG-based one before the global financial crisis, but its value factor exposure has dropped substantially (even to negative) in the early 2010s. Again, the hybrid hedge portfolio has offset large variations in the value exposures of the two hedge portfolios, achieving a more moderate and stable value factor exposure.

Panel C plots the exposures of the three hedge portfolios to the momentum (MOM) factor. The NSI-based strategy, that aims to exploit the market timing motive of the managers with high managerial equity incentives tend to have higher momentum exposures than the AG-based strategy, that aims to exploit the empire building motive of the managers with low managerial equity incentives. Despite some variations over time, the three hedge portfolios' exposures to the momentum factor have been moderate.

While the NSI- and AG-based hedge portfolios have experienced some swings in their factor exposures, especially in their HML exposures, before and amid the global financial crisis, their market exposures dropped during the global financial crisis period. TPD5-screened "NSI-AG Hybrid" hedge portfolio has kept its factor exposures relatively moderate and stable by offsetting variations in the exposures of the NSI- and AG-based strategies. The force of diversification appears to have worked well for the

hybrid hedge portfolio strategy that exploits both the market-timing motives of the managers with high equity incentives and the empire-building motives of the managers with low equity incentives.

[Insert Figure 4 here]

Bottom Line

In the presence of asymmetric information between firm managers and investors, managerial equity incentives can mitigate the empire-building motives of the managers by aligning their interests with the shareholders' interests. While managerial equity incentives reduce agency conflicts between the managers and the shareholders, they may also create incentives for the managers to engage in market timing activities to benefit the existing/current shareholders by issuing overvalue equity and repurchasing undervalued equity.

To the extent that the market fails to incorporate the implications of the managers' empire building motives behind investments, the AG anomaly would arise. Similarly, if the market underreacts to the implications of the managers' market timing motives behind share issuances and/or repurchases, the NSI anomaly would ensue. Although the two anomalies are closely related to each other, we can use the information in equity-based managerial incentives to separate different sources of the NSI and AG anomalies.

Using TPD5 (total portfolio delta of the top 5 executives) to measure the degree of managerial equity incentives, we indeed find that the NSI anomaly is concentrated among firms with high equity-based managerial incentives. We also find that the AG

anomaly is concentrated among firms with low managerial equity incentives. By focusing on firms with high (or low) TPD5s, we can substantially enhance the NSI (or AG) anomaly. Although the Fama-French (2015) 5-factor model largely attenuates the NSI and AG anomalies in the full sample (without conditioning on managerial equity incentives), the NSI (or AG) signal would generate significant alphas when we focus on stocks with high (or low) TPD5s, even after controlling for the 5 factors that include the AG-based investment (CMA) factor.

The evidence suggests that the NSI and AG signals work in different groups of stocks. We consider a hybrid portfolio strategy that aims to exploit the NSI anomaly among stocks with high TPD5s (high managerial equity incentives) and the AG anomaly among those with low TPD5s (low managerial equity incentives). This hybrid strategy would earn significant alphas, consistently over time, even against the 5-factor model that has been shown to attenuate the NSI and AG anomalies.

In a recent study, Arnott, Harvey, Kalesnik, and Linnainmaa (2019) caution that many factor investing strategies motivated by academic studies may fall short of investor expectations. One of the main sources of exaggerated investor expectations is the unrealistic transaction cost assumptions used in existing studies. We address this concern by implementing realistic transaction cost measures and show that our evidence is robust to the effects of transaction costs. Other sources of exaggerated investor expectations are insufficient attention to the risk involved in factor investing strategies. Some factor investing strategies expose the investors to the large downside (left tail) risk and/or to increased systematic factor risk exposures (diminished diversification

benefits) during the market downturn. This study provides a careful assessment of the downside risk and time-varying factor risk exposures of the proposed hedge portfolios.

Finally, many factor investing strategies suffer from the data-mining bias and to the lack of economic foundations (e.g., Harvey, Liu, and Zhu, 2016; McLean and Pontiff, 2016). While it is difficult to eliminate these concerns completely, this study is based on a straightforward and intuitive economic rationale: While managers have incentives to issue (repurchase) equity when they believe it is overvalued (undervalued), their incentives to engage in such market timing activities increase when they themselves have high equity exposures. To the extent that the NSI anomaly is driven by the managers' market timing motives, we should expect a stronger NSI anomaly among firms whose managerial compensations have high equity exposures (TPD5s). Similarly, managers may also derive personal benefits from expanding their empire, but their incentives to engage in value-destroying empire-building activities diminish when they themselves have high equity exposures. To the extent that the AG anomaly reflects the market's underreaction to empire-building, we should observe a stronger AG anomaly among firms whose managerial compensations contain low equity exposures. Our empirical evidence provides strong support to these predictions.

This study is one of the first studies that demonstrate the significance of managerial equity incentives on the cross-sectional predictability of stock returns. We plan to extend the analysis to other measures of corporate governance (beyond managerial compensations) and to a larger set of return predicting signals in our follow-up studies.

References

- Armstrong, Christopher C., David F. Larcker, Gaizka Ormazabal, and Daniel J. Taylor. 2013. "The Relation between Equity Incentives and Misreporting: The Role of Risk-Taking Incentives." *Journal of Financial Economics*, vol. 109: 327-350.
- Arnott, Robert D., Campbell R. Harvey, Vitali Kalesnik, and Juhani T. Linnainmaa. 2019. "Alice's Adventures in Factorland: Three Blunders That Plague Factor Investing," SSRN Working Paper 3331680.
- Asness, Clifford S., Tobias J. Moskowitz, and Lasse Heje Pedersen. 2013. "Value and Momentum Everywhere." *Journal of Finance*, vol. 68 no. 3: 929-985.
- Baker, Malcom, and Jeffrey Wurgler. 2000. "The Equity Share in New Issues and Aggregate Stock Returns." *Journal of Finance*, vol. 55, no. 5 (October): 2219–2257.
- . 2002. "Market Timing and Capital Structure." *Journal of Finance*, vol. 57, no. 1 (February): 1–32.
- Barroso, Pedro, and Pedro Santa-Clara. 2015. "Momentum Has Its Moments." *Journal of Financial Economics*, vol. 116, no.1 (November): 111-120.
- Bradshaw, Mark T., Scott A. Richardson, and Richard G. Sloan. 2006. "The Relation between Corporate Financing Activities, Analysts' Forecasts and Stock Returns." *Journal of Accounting and Economics*, vol. 42, no. 1–2 (October): 53–85.
- Brav, Alon, Christopher Geczy, and Paul A. Gompers. 2000. "Is the Abnormal Return Following Equity Issuances Anomalous?" *Journal of Financial Economics*, vol. 56, no. 2 (May): 209–249.
- Brisker, Eric R., Don M. Autore, Gonul Colak, and David R. Peterson. 2014. "Executive Compensation Structure and the Motivations for Seasoned Equity Offerings." *Journal of Banking & Finance*, vol. 40 (March): 330–345.
- Carhart, Mark M. 1997. "On Persistence in Mutual Fund Performance." *Journal of Finance*, vol. 52, no. 1 (March): 57–82.
- Chan, Louis K. C., Jason Karceski, Josef Lakonishok, and Theodore Sougiannis 2008. "Balance sheet growth and the predictability of stock returns." Columbia Business School working paper.
- Cooper, Michael, Husein Gulen, and Michael J. Schill. 2008 "Asset Growth and the Cross-Section of Stock Returns," *Journal of Finance*, vol. 63, no. 4 (August): 1609-1651.

Coles, Jeffrey L., Naveen D. Daniel, and Laritha Naveen. 2014. "Co-opted Boards." *Review of Financial Studies*, vol. 27, no.6 (June): 1751-1796.

Core, John and Wayne Guay. 1999. "The Use of Equity Grants to Manage Optimal Equity Incentive Levels." *Journal of Accounting and Economics*, vol. 28, no. 2 (December): 151-184.

———. 2002. "Estimating the Value of Employee Stock Option Portfolios and Their Sensitivities to Price and Volatility." *Journal of Accounting Research*, vol. 40, no. 3 (June): 613-630.

Daniel, Kent, and Tobias Moskowitz. 2016. "Momentum Crashes." *Journal of Financial Economics*, vol. 122, no. 2 (November): 221-247.

Daniel, Kent, and Sheridan Titman. 2006. "Market Reactions to Tangible and Intangible Information." *Journal of Finance*, vol. 61, no. 4 (August): 1605–1643.

Datta, Sudip, Mai Iskandar-Datta, and Kartik Raman. 2005. "Executive Compensation Structure and Corporate Equity Financing Decisions." *Journal of Business*, vol. 78, no. 5 (September): 1859–1890.

Edmans, Alex, Xavier Gabaix, and Dirk Jenter. 2017. "Executive Compensation: A Survey of Theory and Evidence." NBER Working Papers 23596.

Fama, Eugene F., and Kenneth R. French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics*, vol. 33, no. 1 (February): 3-56.

———. 2005. "Financing Decisions: Who Issues Stock?" *Journal of Financial Economics*, vol. 76, no. 3 (June): 549–582.

———. 2008. "Dissecting Anomalies." *Journal of Finance*, vol. 63, no.4 (August): 1653–1678.

———. 2015. "A Five-Factor Asset Pricing Model." *Journal of Financial Economics*, vol. 116, no. 1 (April): 1–22.

———. 2016. "Dissecting Anomalies with a Five-Factor Model." *Review of Financial Studies*, vol. 29, no. 1 (January): 69-103.

Foerster, Stephen, John Tsagarelis, and Grant Wang. 2017. "Are Cash Flows Better Stock Return Predictors Than Profits?" *Financial Analysts Journal*, vol. 71, no. 1 (First quarter): 73-99.

Goto, Shingo, Vitali Kalesnik, Maarten de Kok, and Engin Kose. 2018. "Opportunistic Managers: Share-Price Timing Effects Are Larger Than You Think." Research Affiliates working paper.

- Grinold, Richard C. and Ronald N. Kahn. 1999. *Active Portfolio Management: A Quantitative Approach for Providing Superior Returns and Controlling Risk*, (Second Edition). McGraw-Hill.
- Harvey, Campbell, Yan Liu, and Heqing Zhu. 2016. "... and the Cross-Section of Expected Returns," *Review of Financial Studies*, vol. 29, no. 1 (January): 5-68.
- Hasbrouck, Joel. 2009. "Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data." *Journal of Finance*, vol. 64, no.3 (June): 1445-1477.
- Hou, Kewei, Chen Xue, and Lu Zhang. 2015. "Digesting Anomalies: An Investment Approach." *Review of Financial Studies*, vol. 28, no. 3 (March): 650–705.
- . 2017. "Replicating Anomalies." SSRN working paper 2961979.
- Ikenberry, David, Josef Lakonishok, and Theo Vermaelen. 1995. "Market Underreaction to Open Market Share Repurchases." *Journal of Financial Economics*, vol. 39, no. 2–3 (October/November): 181–208.
- . 2000. "Stock Repurchases in Canada: Performance and Strategic Trading." *Journal of Finance*, vol. 55, no. 5 (October): 2373–2397.
- Jensen, Michael C. 1986. "Agency Cost of Free Cash Flow, Corporate Finance, and Takeovers." *American Economic Review*, vol. 76, no. 2 (May): 323–329.
- Jensen, Michael C. and Kevin J. Murphy. 1990. "Performance Pay and Top-Management Incentives." *Journal of Political Economy*, vol. 98, no. 2 (April): 225-264.
- Kim, E. Han, and Amiyatosh Purnanandam. 2014. "Seasoned Equity Offerings, Corporate Governance, and Investments" *Review of Finance*, vol.18, no. 3 (July): 1023–1057.
- Larrain, Borja, and Felipe Varas. 2013. "Equity Issues and Return Volatility." *Review of Finance*, vol.17, no. 2 (April): 767–808.
- Lipson, Marc L., Sandra Mortal, and Michael J. Schill. 2011. "On the Scope and Drivers of the Asset Growth Effect." *Journal of Financial and Quantitative Analysis*, vol. 46, no. 6 (December): 1651-1682.
- Loughran, Tim, and Jay R. Ritter. 1995. "The New Issues Puzzle." *Journal of Finance*, vol. 50, no. 1 (March): 23–52.
- . 1997. "The Operating Performance of Firms Conducting Seasoned Equity Offerings." *Journal of Finance*, vol. 52, no. 5 (December): 1823–1850.

Loughran, Tim, and Anand M. Vijh. 1997. "Do Long-Term Shareholders Benefit from Corporate Acquisitions?" *Journal of Finance*, vol. 52, no. 5 (December): 1765–1790.

McLean, R. David, and Jeffrey Pontiff. 2016. "Does Academic Research Destroy Stock Return Predictability?" *Journal of Finance*, vol. 71, no. 1 (February): 5–32.

McLean, R. David, Jeffrey Pontiff, and Akiko Watanabe. 2009. "Share Issuance and Cross-Sectional Returns: International Evidence." *Journal of Financial Economics*, vol. 94, no. 1 (October): 1–17.

Mitchell, Mark L., and Erik Stafford. 2000. "Managerial Decisions and Long-Term Stock Price Performance." *Journal of Business*, vol. 73, no. 3 (July): 287–329.

Myers, Stewart C., and Nicholas S. Majluf. 1984. "Corporate Financing and Investment Decisions When Firms Have Information that Investors Do Not Have." *Journal of Financial Economics*, vol. 13, no. 2 (June): 187–221.

Novy-Marx, Robert, and Mihail Velikov. 2016. "A Taxonomy of Anomalies and Their Trading Costs," *Review of Financial Studies*, vol. 29, no. 1: 104–147.

Pontiff, Jeffrey, and Artemiza Woodgate. 2008. "Share Issuance and Cross-Sectional Returns." *Journal of Finance*, vol. 63, no. 2 (April): 921–945.

Qian, Edward E., Ronald H. Hua, and Eric H. Sorensen. 2007. *Quantitative Equity Portfolio Management: Modern Techniques and Applications*, Chapman & Hall/CRC.

Schultz, Paul. 2003. "Pseudo Market Timing and the Long-Run Underperformance of IPOs." *Journal of Finance*, vol. 58, no. 2 (April): 483–517.

Spiess, D. Katherine, and John Affleck-Graves. 1995. "Underperformance in Long-Run Stock Returns Following Seasoned Equity Offerings." *Journal of Financial Economics*, vol. 38, no. 3 (July): 243–267.

Titman, Sheridan, K.C. John Wei, and Feixue Xie. 2009. "Capital Investments and Stock Returns." *Journal of Financial and Quantitative Analysis*, vol. 39, no.4 (December): 677–700.

———. 2009. "Capital Investments and Stock Returns in Japan." *International Review of Finance*, vol. 9, no. 1–2 (March/June): 111–131.

Watanabe, Akiko, Yan Xu, Tong Yao, and Tong Yu. 2013. "The Asset Growth Effect: Insights from International Equity Markets." *Journal of Financial Economics*, vol. 108, no. 2 (May): 529–563.

Zhang, X. Frank. 2006. "Information Uncertainty and Stock Returns." *Journal of Finance*, vol. 61, no. 1 (February): 105–137.

Table 1. Average Number of Stocks (per Period) in Each Portfolio

	Negatives		Positives				
	Low	High	Low	2	3	4	High
<i>Sorting on NSI (average N=1,760.9)</i>							
All firms	236.0	283.1	231.9	285.1	255.8	193.7	215.1
Top TPD5	91.8	116.7	64.5	84.0	77.0	57.1	93.3
Mid TPD5	82.7	95.3	72.8	95.6	92.2	73.8	66.0
Bottom TPD5	61.5	71.1	94.6	105.5	86.5	62.7	55.7
<i>Sorting on AG (average N=1,726.9)</i>							
All firms	155.3	287.1	273.6	279.9	275.7	259.6	195.8
Top TPD5	28.3	81.0	86.5	102.8	108.0	103.2	80.0
Mid TPD5	42.1	98.2	91.3	96.2	94.9	93.9	66.8
Bottom TPD5	84.8	107.9	95.9	80.9	72.8	62.5	48.9

Notes: This table reports average numbers of stocks in each cell jointly sorted by NSI (or AG) and TPD5. Following Fama and French (2008) we treat positives and negatives of AG and NSI separately by allocating negative values of these variables to two groups using the median of negative values of the variable for the all-but-micro universe as the breakpoint, and by allocating positive values to five groups using quintile breakpoints for positive values of the variables for all-but-micro. Here, all-but-micro universe includes all stocks excluding micro-cap stocks, which are defined as stocks with market capitalizations below the 20th NYSE percentile. Since a few firms have no net share issuances, the sorts for NSI have an additional cell for zeros, though not shown in the table (only 60.3 firms per year on average before sorting by TPD5). Thus the table contains seven AG-sorted groups and eight NSI-sorted groups. We also sort stocks independently into tercile groups (Top, Mid, Bottom) based on TPD5. We consider the full sample and the Top-, Mid-, and Bottom-TPD5 tercile subsamples, i.e., 4 sample groups. Our sample universe is the ExecuComp universe that includes stocks that are (or were) included in the S&P 1500 index. Portfolios are formed annually every June from 1993 to 2016.

Table 2. Summary Statistics (FY 1992-2016)

		All Firms	TPD5 Tercile Groups		
			Top	Mid	Bottom
Market Capitalization (Size) (in \$ millions)	Mean	7,214.6	16,923.3	3,373.0	1,188.2
	St.Dev.	23,912.3	38,520.8	7,978.6	2,882.8
	5%	141.2	433.2	230.0	68.6
	Median	1,432.7	4,938.0	1,474.3	539.5
	95%	28,444.9	71,474.6	11,773.4	4,100.7
Book-to-Market Ratio (B/M)	Mean	0.622	0.447	0.581	0.844
	St.Dev.	0.691	0.380	0.449	1.010
	5%	0.120	0.092	0.136	0.171
	Median	0.495	0.370	0.487	0.673
	95%	1.429	1.039	1.292	1.940
Net Share Issuance (NSI)	Mean	0.071	0.102	0.065	0.044
	St.Dev.	0.237	0.27	0.211	0.223
	5%	-0.068	-0.068	-0.072	-0.064
	Median	0.007	0.006	0.008	0.007
	95%	0.674	0.713	0.564	0.409
Total Asset Growth (AG)	Mean	0.162	0.221	0.158	0.105
	St.Dev.	0.61	0.844	0.391	0.483
	5%	-0.155	-0.09	-0.122	-0.236
	Median	0.071	0.095	0.077	0.041
	95%	0.681	0.801	0.66	0.57
TPD5 (in \$000s)	Mean	2,124.4	5,706.0	467.1	116.8
	St.Dev.	28,172.0	48,241.5	219.9	84.7
	5%	24.1	575.8	162.5	0.0
	Median	428.0	1,707.0	429.0	105.2
	95%	5,031.5	12,305.5	886.2	272.5

Notes: This table provides summary statistics for the key variables used in in this study. Means, standard deviations, 5 percentile values, medians, and 95 percentile values are from the pooled sample covering fiscal years (FYs) from 1992 to 2016.

Table 3. Average Returns and “Alphas” of the “Low NSI – High NSI” and “Low AG – High AG” Hedge Portfolios

	“Low NSI - High NSI” Hedge Portfolio			“Low AG - High AG” Hedge Portfolio		
	Monthly (%)	t-stat	IR (p.a.)	Monthly (%)	t-stat	IR (p.a.)
All Firms						
Average Returns	0.535**	2.88	0.59	0.526*	2.20	0.45
CAPM Alpha	0.721**	4.15	0.85	0.674**	2.87	0.59
3-factor Alpha	0.615**	3.82	0.78	0.494*	2.42	0.49
4-factor Alpha	0.523**	3.30	0.67	0.401*	1.97	0.40
5-factor Alpha	0.242	1.63	0.33	0.190	1.03	0.21
Top TPD5 Tercile						
Average Returns	0.611**	3.04	0.62	0.387	1.35	0.28
CAPM Alpha	0.786**	4.10	0.84	0.562*	1.99	0.41
3-factor Alpha	0.688**	3.78	0.77	0.389	1.52	0.31
4-factor Alpha	0.595**	3.29	0.67	0.292	1.14	0.23
5-factor Alpha	0.343*	1.96	0.40	0.091	0.37	0.07
Mid TPD5 Tercile						
Average Returns	0.216	1.14	0.23	0.429	1.85	0.38
CAPM Alpha	0.332	1.79	0.37	0.439	1.85	0.38
3-factor Alpha	0.247	1.39	0.28	0.344	1.50	0.31
4-factor Alpha	0.179	1.01	0.21	0.274	1.19	0.24
5-factor Alpha	-0.106	-0.61	-0.13	0.198	0.91	0.19
Bottom TPD5 Tercile						
Average Returns	0.189	0.80	0.16	0.946**	3.42	0.70
CAPM Alpha	0.365	1.58	0.32	0.947**	3.38	0.69
3-factor Alpha	0.350	1.51	0.31	0.845**	3.08	0.63
4-factor Alpha	0.247	1.07	0.22	0.806**	2.90	0.59
5-factor Alpha	0.118	0.50	0.10	0.630*	2.43	0.50

Notes: This table reports average monthly returns and monthly “alphas” of the “Low NSI - High NSI” value-weighted long-short hedge portfolio and the “Low AG – High AG” value-weighted long-short hedge portfolio. “Alphas” are obtained as intercepts from time-series regressions of monthly hedge portfolio returns on the market (Mkt-Rf) factor (CAPM); Mkt-Rf, SMB, and HML factors (3-factor model); Mkt-Rf, SMB, HML, and MOM factors (4-factor model); and Mkt-Rf, SMB, HML, RMW, and CMA factors (5-factor model). We obtain these estimates in the four different samples: the full sample and the Top-, Mid-, and Bottom-TPD5 tercile subsamples. IR (p.a.) stands for the Information Ratio (per year), defined as the ratio of the annualized alpha to the annualized volatility of residual returns. The sample period runs from July 1993 to June 2017 (288 months). ** and * indicate the significance at the 1% and 5% levels, respectively.

Table 4. Return Correlations between the “Low NSI - High NSI” Hedge Portfolio Returns and the “Low AG - High AG” Hedge Portfolio Returns

	AG-Full	AG-Top TPD5	AG-Mid TPD5	AG-Bottom TPD5
NSI-Full	0.478	0.411	0.244	0.165
NSI-Top TPD5	0.427	0.362	0.227	0.133
NSI-Mid TPD5	0.375	0.324	0.323	0.167
NSI-Bottom TPD5	0.2	0.198	0.079	0.182

Notes: This table summarizes return correlations between “Low NSI - High NSI” value-weighted long-short hedge portfolios (formed in four different samples) and the “Low AG - High AG” value-weighted long-short hedge portfolios (formed in four different samples). The four samples are the full sample and three TPD5 tercile subsamples. Correlations are calculated from 288 monthly hedge portfolio returns from July 1993 to June 2017.

Table 5. Time-Series Regressions of the “NSI-AG Hybrid” Hedge Portfolio Returns against Benchmark Factors

	Intercept (monthly %) t-stat, SR/IR (p.a.)	Factor Loadings					Adj. R^2
		Mkt-Rf	SMB	HML	MOM or RMW	CMA	
<i>"NSI-AG Hybrid" Hedge Portfolio in the Full Sample (without TPD5 Screening)</i>							
Raw	0.531** 2.90, SR=0.59						-
CAPM	0.698** 4.02, IR=0.82	-0.257** -6.42					12.3%
3-factor	0.554** 3.77, IR=0.77	-0.212** -6.10	0.071 -1.49	0.520** 10.79			37.4%
4-factor	0.462** 3.20, IR=0.65	-0.163** -4.56	0.054 1.17	0.571** 11.84	0.131** 4.32		41.1%
5-factor	0.216 1.74, IR=0.25	-0.034 -1.01	0.085 1.96	0.049 0.88	0.223** 3.68	0.956** 12.14	59.1%
<i>"NSI-AG Hybrid" Hedge Portfolio with TPD5 Screening</i>							
Raw	0.778** 4.29, SR=0.88						-
CAPM	0.866** 4.80, IR=0.98	-0.136**					3.2%
3-factor	0.766** 4.51, IR=0.92	-0.113**	0.095	0.347**			14.6%
4-factor	0.700** 4.11, IR=0.84	-0.077	0.083	0.384**	0.094**		16.4%
5-factor	0.486** 3.2, IR=0.65	0.039	0.059	-0.102	0.082	1.002**	38.0%

Notes: This table reports time-series regressions of the “NSI-AG Hybrid” hedge portfolio returns against the benchmark factors. t-statistics are shown below coefficient estimates. SR and IR refer to the Sharpe ratio and Information Ratio, both per year, respectively. “MOM or RMW” indicates that table reports the coefficient on the MOM factor in the 4-factor model, and the coefficient on the RMW factor in the 5-factor model in that column. All constituent portfolios of the “NSI-AG Hybrid” portfolios are value-weighted and formed/ rebalanced at the end of each June. The sample period runs from July 1993 to June 2017 (288 months). ** and * indicate the significance at the 1% and 5% levels, respectively.

Table 6. Turnover and Rebalancing Costs for the Hedge Portfolios

	Turnover	Transaction Costs	
	per year	Annual Rebalancing	per trade
<i>(1) "Low NSI - High NSI" Hedge Portfolios</i>			
(1a) Full Sample	149.1%	0.765%	0.257%
(1b) Top TPD5	153.1%	0.760%	0.248%
<i>(2) "Low AG - High AG" Hedge Portfolios</i>			
(2a) Full Sample	163.2%	0.903%	0.277%
(2b) Bottom TPD5	154.0%	1.159%	0.376%
<i>(3) "NSI-AG Hybrid" Hedge Portfolios</i>			
(3a) Full Sample	145.3%	0.776%	0.267%
(3b) TPD5 Screened	153.2%	0.957%	0.312%

Notes: This table reports portfolio turnover ratios (per year) and estimated transaction costs (1) for the “Low NSI – High NSI” hedge portfolios formed (1a) in the Full sample and (1b) in the Top TPD5 tercile subsample; (2) for the “Low AG – High AG” hedge portfolios formed (2a) in the full sample and (2b) in the Bottom TPD5 tercile subsample; and (3) for the “NSI-AG Hybrid” hedge portfolio in the full sample (3a) that combines the hedge portfolios (1a) and (2a) with equal weights, and that with the TPD5 Screening (3b) that combines the two hedge portfolios (1b) and (2b) with equal weights. All constituent portfolios are value-weighted and rebalanced once a year at the end of each June. The definition and calculation of the turnover ratio for long-short hedge portfolios follow the conventional ones used in the practice of quantitative equity portfolio management (e.g., Qian, Hua, and Sorensen 2007, p.236). Annual rebalancing cost is the round-trip transaction costs (in %) incurred at the time of annual portfolio rebalancing. Per trade transaction cost is the average one-way trading cost implied by the rebalancing cost. Our transaction cost estimates are based on Bayesian/Gibbs sampler based transaction cost measures of individual stocks by Hasbrouck (2009).

Table 7. Return Performances of the Hedge Portfolios AFTER Transaction Costs

	Full Sample			Screened by TPD5		
	Monthly (%)	t-stat	IR (p.a.)	Monthly (%)	t-stat	IR (p.a.)
"Low NSI - High NSI"	<i>Full Sample</i>			<i>Top TPD5 Tercile</i>		
Average Returns	0.471*	2.52	0.51	0.547**	2.71	0.55
CAPM Alpha	0.656**	3.74	0.76	0.721**	3.74	0.76
3-factor Alpha	0.548**	3.38	0.69	0.621**	3.39	0.69
4-factor Alpha	0.462**	2.88	0.59	0.534**	2.93	0.60
5-factor Alpha	0.180	1.20	0.24	0.282	1.59	0.33
"Low AG - High AG"	<i>Full Sample</i>			<i>Bottom TPD5 Tercile</i>		
Average Returns	0.451	1.89	0.39	0.849**	3.07	0.63
CAPM Alpha	0.597*	2.54	0.52	0.847**	3.02	0.62
3-factor Alpha	0.415*	2.05	0.42	0.743**	2.71	0.55
4-factor Alpha	0.328	1.62	0.33	0.711*	2.56	0.52
5-factor Alpha	0.116	0.64	0.13	0.534*	2.07	0.42
"NSI-AG Hybrid"	<i>Full Sample</i>			<i>With TPD5 Screening</i>		
Average Returns	0.531**	2.90	0.59	0.699**	3.83	0.78
CAPM Alpha	0.698**	4.02	0.82	0.784**	4.32	0.88
3-factor Alpha	0.554**	3.77	0.77	0.683**	4.00	0.82
4-factor Alpha	0.462**	3.20	0.65	0.623**	3.63	0.74
5-factor Alpha	0.216	1.74	0.35	0.408**	2.69	0.55

Notes: This table reports average returns and “alphas” after transaction costs. We subtract rebalancing costs from monthly hedge portfolio returns in each June and use the hedge portfolio returns after transaction costs in time-series regressions against benchmark factors. The benchmark factors used in the 3-, 4-, and 5-factor models do not account for transaction costs. We use Hasbrouck’s (2009) Bayesian/Gibbs-sampler based transaction cost measures in calculating portfolio rebalancing costs. The sample period runs from July 1993 to June 2017 (288 months). ** and * indicate the significance at the 1% and 5% levels, respectively.

Table 8. Statistical Characteristics of Factor/Hedge Portfolio Returns

	Mean (%)	St.Dev.(%)	Sharpe R.	Skew.	Ex.Kurt.	Worst Monthly Returns	
	(monthly)	(monthly)	(p.a.)			in %	x S.D. away
<i>Benchmark Factors Before Transaction Costs</i>							
Mkt-Rf	0.649	4.29	0.52	-0.73	1.32	-17.2	-4.17
SMB	0.185	3.12	0.21	0.45	4.98	-14.9	-4.84
HML	0.194	3.06	0.22	0.17	2.59	-11.1	-3.69
MOM	0.407	5.01	0.28	-1.50	10.56	-34.4	-6.95
RMW	0.338	2.75	0.42	-0.43	9.39	-18.0	-6.66
CMA	0.247	2.10	0.41	0.67	2.56	-6.9	-3.39
<i>"Low NSI - High NSI" Hedge Portfolio after Transaction Costs</i>							
Full Sample	0.418	3.18	0.46	0.55	4.29	-12.6	-4.09
Top TPD5	0.547	3.43	0.55	0.25	3.69	-15.6	-4.71
<i>"Low AG - High AG" Hedge Portfolio after Transaction Costs</i>							
Full Sample	0.451	4.06	0.38	0.68	4.25	-17.9	-4.52
Bottom TPD5	0.849	4.70	0.63	0.74	1.78	-9.1	-2.13
<i>"NSI-AG Hybrid" Hedge Portfolios after Transaction Costs</i>							
Full Sample	0.466	3.12	0.52	0.82	6.29	-14.9	-4.93
TPD5-Screened	0.699	3.09	0.78	0.65	1.35	-7.2	-2.57

Notes: This table reports statistical characteristics of factor returns and the “Long NSI – High NSI,” “Long AG – High AG,” and “NSI-AG Hybrid” hedge portfolio returns. All hedge portfolio returns account for annual rebalancing costs in each June. Sharpe Ratio is annualized. Skew and Ex.Kurt mean the skewness and excess kurtosis. Non-zero values indicate deviations from the normal distributions (holding the standard deviations constant). The last two columns report the worst monthly returns during the sample period between July 1993 and June 2017. The last column indicates how many standard deviations away was the worst return from the mean. For example, the worst excess return of the market was -17.2%, which was the average return minus 17.8% which was 4.17 times the monthly standard deviation (4.29%) of the market return.

Figure 1. Size-B/M Adjusted Abnormal Returns

Panel A: Portfolios Sorted on NSI

Panel B: Portfolios Sorted on AG

Notes: This Figures plots average Size-B/M adjusted abnormal returns of portfolios formed on NSI (Panel A) and those sorted on AG (Panel B). Please see the notes to Table 1 for the portfolio sorts. In each panel is divided into four groups according to the samples: All portfolios are value-weighted and rebalanced annually at the end of June in each year. Each panel is divided into four groups according to different samples: The Full sample and the Top-, Mid-, and Bottom-TPD5 tercile subsamples. The numbers shown in the graphs are average monthly Size-B/M adjusted abnormal returns (in %) of the portfolios. To calculate Size-B/M adjusted abnormal returns, we allocate each individual stock to five size groups and

five B/M groups using NYSE breakpoints for quintiles (from Ken French's website) at the end of each June. Thus each stock is matched with one of the 25 (5x5) portfolios jointly sorted by Size and B/M. We then subtract the value weighted return of the matched portfolio (from Ken French's website) from each stock's raw return to calculate its Size-B/M adjusted abnormal return. The sample period runs from July 1993 to June 2017.

Figure 2. Portfolio Rebalancing Costs

Notes: This graph plots annual portfolio rebalancing costs year by year between 1994 and 2017. Portfolio rebalancing costs are based on round-trip transaction costs calculated from the Bayesian/Gibbs sampler based transaction cost estimates of Hasbrouck (2009). We consider three hedge portfolios of our main interest: (1) the “Low NSI – High NSI” value-weighted hedge portfolio of stocks in the Top TPD5 tercile group; (2) the “Low AG – High AG” value-weighted hedge portfolio of stocks in the Bottom TPD5 tercile group; and (3) the “NSI-AG Hybrid” hedge portfolio that combines the two with equal weights. All portfolios are rebalanced annually.

Figure 3. Log Cumulative Returns of the TPD5-Screened “NSI-AG Hybrid” Hedge Portfolio (After Transaction Costs)

Panel A: The TPD5-Screened “NSI-AG Hybrid” Hedge Portfolio and Its Two Constituents

Panel B: The “NSI-AG Hybrid” Hedge Portfolio With and Without TPD5 Screening

Notes: Each panel plots log cumulative returns on the TPD5 screened “NSI-AG Hybrid” hedge portfolio (the thick solid line) in comparison to those of other portfolios. Panel A plots the two constituent hedge portfolios: (1) The “Low NSI - High NSI” hedge portfolio of stocks in the Top TPD5 tercile (shown as “NSI (Top TPD5)”) and (2) The “Low AG - High AG” hedge portfolio of stocks in the Bottom TPD5

Tercile (shown as “AG (Bottom TPD5)”). Portfolios plotted in Panel B along with the TPD5 screened NSI-AG Hybrid hedge portfolio (the thick solid line) include the NSI-AG Hybrid portfolio strategy in the full sample (without TPD5 screening, shown as “Hybrid (Full Sample)”), and its two constituent portfolios: (1) The “Low NSI - High NSI” hedge portfolio in the full sample (shown as “NSI (Full Sample)”) and (2) The “Low AG - High AG” hedge portfolio in the full sample (shown as “AG (Full Sample)”). All constituent portfolios of stocks in the long legs and short legs are value-weighted, and formed/rebalanced at the end of each June. We subtract portfolio rebalancing costs from hedge portfolio returns in each June.

Figure 4. Time-Varying Factor Exposures

Panel A: Market Beta Exposures (Trailing 60 months)

Panel B: Value (HML) Factor Exposures (Trailing 60 months)

Panel C: Momentum (MOM) Factor Exposures (Trailing 60 months)

Notes: Each panel plots 5-year rolling estimates of three hedge portfolios' exposures to the market factor (Panel A), to the value (HML) factor (Panel B), and to the momentum (MOM) factor (Panel C) using univariate time-series regressions with rolling windows of 60 months. Each panel plots the time-varying exposures of the TPD5-screened NSI-AG Hybrid hedge portfolio (thick solid line) and those of its two constituent portfolios: the "Low NSI – High NSI" hedge portfolio formed by stocks in the Top TPD5 tercile subsample and the "Low AG – High AG" hedge portfolio formed by stocks in the Bottom TPD5 tercile subsample.

Manuscript 2

Market Risk Disclosure and Crash Risk: Evidence from Textual Analysis

by

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Market Risk Disclosure and Crash Risk: Evidence from Textual Analysis

Abstract

The uncertainty surrounding a firm's exposure to market risk factors may induce a negative skewness in its equity returns (crash risk). If so, a detailed market risk disclosure may mitigate crash risk by reducing the exposure uncertainty. Using Latent Dirichlet Allocation, we tease out eight latent topics in firms' market risk disclosures (Item 7A). Narratives of two of these topics, both related to input costs and/or output prices, are negatively associated with crash risk beyond other determinants. Some narrative market risk disclosures in Item 7A appear to provide useful information, despite the widely-held view that they convey only redundant information.

1. Introduction

The U.S. Securities Exchange Commission (SEC) issued Financial Reporting Release No. 48 (FRR 48) in 1997. FRR 48 mandates each firm to disclose, narratively, how it manages or hedges its market risk factors in Item 7A of Form 10-K filings.¹ These market risk factors include changes in market prices and rates for debt, equity, currency, commodity, and other traded instruments as well as their derivatives. While more than 20 years have passed since the release of FRR 48, the usefulness of narrative market risk disclosures (Item 7A) remains controversial.² There are widely-held perceptions that, while firms' narrative market risk disclosures may have the appearance of valid disclosures, in actuality many of them only provide routine, redundant, non-specific, and boilerplate information (e.g., Abraham and Shrieves, 2014; SEC, 2016).

To address the on-going discussion on the value of market risk disclosures, this study takes on the following questions. Does the narrative market risk disclosure (in Item 7A) provide useful information about the stock price crash risk, that is commonly measured as the negative skewness of the firm's equity returns? If so, what particular narrative topics discussed in Item 7A convey useful information about the negative return skewness? We tackle these questions by applying a text clustering algorithm to

¹ The disclosure requirements are described in Item 305 of Regulation S-K introduced under the Securities Exchange Act of 1933. Mandated market risk exposures prompt the firms to provide information about any market risk sensitive instruments that affect the firms' financial conditions, in conjunction with the quantitative disclosure of market risks of derivatives and hedging (SFAS No.133, No.161).

² The SEC (2016) is calling for further discussions on the usefulness of current market risk disclosures and on strategies to improve their informativeness. Mr. Wesley Bricker, the Chief Accountant at SEC, emphasized the importance of firm managers' attention and financial reporting oversight of firms' market risk disclosures in the 2018 Baruch College Financial Reporting Conference: "Working Together to Advance Financial Reporting" on May 3, 2018, in New York, NY. https://www.sec.gov/news/speech/speech-bricker-040318#_ftn9.

classify and quantify textual information in Item 7A. We focus on the relationship between narrative market risk disclosures and the conditional negative return skewness (stock price crash risk) because crash risk captures a dimension of downside risk or left tail risk that most market participants are concerned about.³

A significant challenge in analyzing the information content of Item 7A is the lack of compatibility in narrative market risk disclosures across firms (Hodder and McAnally, 2001). Each firm has a large discretion over how much and what sort of information it discloses in Item 7A. Some firms provide very detailed information about their risk exposures while other firms provide boilerplate information by merely restating disclosure requirements or summarizing their generic risk management policies in Item 7A.

To understand why some firms voluntarily provide more detailed risk disclosures in Item 7A than others, it is useful to take a step back and discuss why a firm would want to provide detailed disclosures voluntarily to the public, to begin with. An oft-cited motivation for voluntary disclosure is to lower the cost of capital by reducing the information uncertainty.⁴ In particular, voluntary disclosure helps reduce the asymmetric information between firm managers and outside investors and among different types of investors, which improves liquidity in a firm's stock and makes it

³ As Chen, Hong, and Stein (2001) note, the literature on stock price crash risk adopts a narrow and euphemistic definition of crash risk by associating it with negative skewness of the stock return distribution. We follow this tradition and use crash risk to mean the negative skewness of equity returns. Please see Habib, Hassan, and Jiang (2018) for a recent extensive review of the empirical literature on stock price crash risk. We are particularly interested in the cross-sectional relationship between risk disclosures in year T and the return skewness in T+1. We use the term “conditional skewness” (at T) to mean the skewness in T+1 that is explained by variables observed in T.

⁴ Arthur Levitt, the former chairman of SEC, argues that high-quality accounting standards are desired to lower the cost of capital (Levitt, 1998).

more attractive to investors (e.g., Diamond and Verrecchia, 1991; Healy, Hutton, and Palepu, 1999; Easley and O'Hara, 2004; Hughes, Liu, and Liu, 2007; Lambert, Leuz, and Verrecchia, 2007). In the context of the disclosure of risk factor exposures (as opposed to the disclosure of accounting items such as earnings and assets), the primary role of meaningful risk disclosure is to reduce the uncertainty about the risk (variance) of the firm's future cash flows. A recently proposed risk disclosure theory by Heinle and Smith (2017) implies that, by reducing the "variance uncertainty," a specific and detailed risk disclosure reduces the tail risk of the firm's future cash flows,⁵ and lowers the "variance uncertainty premium" in the firm's cost of capital.

An important source of the variance uncertainty, which investors cannot eliminate or avoid with the force of diversification, is the uncertainty surrounding the firm's exposures to market-wide (systematic) risk factors ("factor exposure uncertainty").⁶ As Heinle, Smith, and Verrecchia (2018) show, to the extent that the factor exposure uncertainty exacerbates the left-tail risk of the firm's future cash flows, the firm can lower the left-tail risk by providing informative risk disclosures. This theoretical implication motivates us to examine the empirical relationship between market risk disclosures and the stock price crash risk in this study. To our knowledge, this is the first study that investigates the empirical relationship between market risk disclosures (Item 7A) and stock price crash risk.

⁵ Recall that a student-t distribution with a low degree of freedom (very fat-tailed) is a mixture of normal distribution with uncertain (inverse gamma distributed) variances. Laplace and Logistic distributions, that are leptokurtic, are also examples of mixtures of normal distributions with uncertain variances (e.g., Andrews and Mallows, 1974).

⁶ In a recent study, Jin, Chen, and Yang (2019) investigates the impact of economic policy uncertainty on stock price crash risk in China. For example, they find that the relationship between economic policy uncertainty and stock price crash risk is pronounced among state-owned enterprises.

To analyze and compare the highly unstructured textual information in Item 7A across firms,⁷ we implement a Latent Dirichlet Allocation (LDA) model (Blei, Ng, and Jordan, 2003; Bao and Datta, 2014). LDA is a Bayesian text clustering algorithm that simultaneously uncovers and quantifies latent topics in text documents, without imposing a set of predefined keywords or topics. We apply an LDA model to narrative market risk disclosures (Item 7A) of U.S. public firms and tease out eight latent narrative topics.⁸ Each topic is associated with a group of firms that use similar vocabulary in discussing their risk exposures.

We find that two of these eight topics are significantly correlated with the conditional negative skewness of firm-specific equity returns even after controlling for industries and known-predictors of crash risk. The two informative topics are associated with the firms' risk exposures to commodity prices and raw material prices that affect their output prices and/or input costs. That is, firms that provide narratives of their exposures to commodity prices and raw material prices in Item 7A, no matter whether the exposures are large or small, tend to have lower conditional negative return skewness (stock price crash risk) than those that do not discuss these risk exposures, even after controlling for industry-specific effects.

By contrast, the remaining six topics, which are mainly related to interest rate and foreign exchange rate exposures, do not exhibit significant correlations with the

⁷ We focus on market risk disclosures in Item 7A, rather than the more general risk factor disclosure in Item 1A, because many of the "risk factors" discussed in Item 1A are firm-specific and mostly diversifiable. Our focus is on the role of risk disclosures in reducing the factor exposure uncertainty with respect to market-wide (systematic) risk factors.

⁸ As a clustering algorithm, LDA is similar to K-means clustering algorithm in that we need to specify the number of topics in advance. This study chooses eight topics but it would be interesting to examine how the number of topics affect the analysis. We leave this analysis for future follow-ups.

conditional skewness of firm-specific equity returns. Moreover, about a half of our sample firms choose to provide minimal market risk disclosures (with 100 words or less) in Item 7A. These firms generally have lower stock price crash risk than other firms. This evidence suggests that these firms may have no material exposures to market risk factors to begin with, and/or these firms may have little incentives to reduce the factor exposure uncertainty as the uncertainty induces positive (rather than negative) skewness in their equity returns. Put differently, firms that are not concerned about the effects of exposure uncertainty on crash risk tend to provide minimal market risk disclosures in Item 7A. However, among firms that are concerned about the effects of factor exposure uncertainty on crash risk, narrative disclosures of the risks associated with input costs and/or output prices help reduce the firms' exposure uncertainty and hence the conditional negative return skewness (stock price crash risk).

The rest of the paper is organized as follows. Section 2 provides the theoretical motivation for this study. Section 3 discusses the sample and our empirical methodology. Section 4 discusses our results. Section 5 discusses the implications of our findings and Section 6 concludes.

2. Market risk disclosures, factor exposure uncertainty and crash risk

2.1 Theoretical motivations

While theoretical discussions of disclosure decisions are traditionally concerned with accounting items (e.g., earnings, cash flows, sales, assets, etc.), a few recent studies discuss benefits and costs of providing risk disclosures to the public. Recent studies by Heinle and Smith (2017) and Heinle, Smith, and Verrecchia (2018) propose models in

which a firm's risk disclosure lowers the uncertainty surrounding the variance and factor exposures of its cash flows.⁹ Heinle, Smith, and Verrecchia (2018) show that factor exposure uncertainty introduces skewness and excess kurtosis (and all higher moments) in the conditional distribution of the firm's future cash flows. Mitigating the exposure uncertainty through risk disclosure may have positive or negative effects on the firm's equity value depending on whether the uncertainty induces positive skewness or negative skewness in the conditional cash flow distribution. When the factor exposure uncertainty induces the positive skewness, the firms would not have incentives to provide detailed risk disclosures to mitigate the uncertainty, as investors tend to favor positive skewness.¹⁰ When the factor exposure uncertainty induces the negative skewness, the firms may want to reduce the factor exposure uncertainty by providing detailed and specific market risk disclosures to mitigate the negative return skewness (stock price crash risk).¹¹

The factor exposure uncertainty also intensifies the "systematic skewness," or the co-skewness of a firm's equity return with systematic risk factors. Asset pricing theories suggest that the risk premium of a stock is negatively associated with the co-skewness of its return with systematic risk factors (e.g., Rubinstein, 1973; Friend and

⁹ In an earlier study, Jorgensen and Kirschenheiter (2003) propose a model in which firms with low cash flow variances disclose their risk exposures voluntarily while firms with high variances do not. Thus a voluntary risk disclosure itself signals a low variance of the firm's cash-flows and lowers the variance uncertainty in the meantime.

¹⁰ A behavioral explanation for investors' preference for positive skewness is that investors have inverse S-shaped utility functions (e.g., Barberis and Huang, 2008; Zhang 2013). Rational explanations of investors' preference for positive co-skewness, as we discuss below.

¹¹ In a recent study, Kim, Yeung, and Zhou (2019) show that stock price crash risk declines significantly for a firm that discloses "internal control weakness (ICW)" under Section 404 of the Sarbanes-Oxley Act, despite the disclosure itself signaling bad news. We can view that the disclosure of ICW reduces the uncertainty surrounding the quality of internal control over financial reporting.

Westerfield, 1980; Kraus and Litzenberger, 1976, 1983; Harvey and Siddique, 2000, Chung, Johnson, and Schill, 2006). For a firm with negative co-skewness, factor exposure uncertainty increases its cost of capital by intensifying the negative co-skewness¹². By reducing the factor exposure uncertainty, a detailed market risk disclosure may help lower the firm's cost of capital by lowering the degree of conditional negative co-skewness. By reducing the degree of conditional negative co-skewness, a detailed market risk disclosure also helps reduce the conditional negative skewness of firm-specific returns.

2.2. Practical perspectives

To further develop intuition about “factor exposure uncertainty,” let's consider an airline company as an example. The company's cash-flows are sensitive to fuel price fluctuations. If unhedged, a large increase in fuel prices raises the company's operating costs. The fuel price exposure of the company's cash flows, however, depends on the extent to which the company hedges the fuel price risk. If the company does not provide detailed information about the fuel price exposure, it implies a high exposure uncertainty and hence a large conditional negative return skewness when the negative exposure of its equity to the fuel price risk tends to increase in magnitude with fuel price increases.

Now suppose that the company voluntarily discloses its fuel price exposure. Consider two scenarios. In the first scenario, the company reports that its cash flows

¹² Ang, Chen, and Xing (2006) show that the effects of downside beta (asymmetric beta) is related but different from the effects of co-skewness. In our model, the asymmetric beta (as captured by the correlation between factor exposure and the factor itself) increases the co-skewness in the presence of factor exposure uncertainty. Please see Doan, Lin, and Chng (2014) for a recent empirical investigation in Australian stock markets.

have a large fuel price exposure and it does not hedge the fuel price risk. In the second scenario, the company reports that it does not have a large fuel price exposure as it has hedged most of the fuel price exposure with derivatives. These two scenarios have very different implications for the level of the fuel price exposure of its cash flows. However, both of these two disclosures have similar implications for the uncertainty surrounding the company's fuel price exposure. This is because both disclosures help reduce the exposure uncertainty, high or low, especially when the company provides detailed and specific information about the exposure. The presence of negations, such as the ones in “we do not have a large fuel price exposure,” “we do not hedge fuel price exposure,” etc. does not necessarily lower the informativeness of market risk disclosures. An informative market risk disclosure can lower the firm's factor exposure uncertainty regardless of the reported level of factor exposure.

In practice, most airline companies discuss their fuel price risk exposures, along with their interest rate risk and foreign currency risk exposures, in Item 7A. However, different airline companies discuss their market risk exposures differently. For example, Delta Airlines discusses its market risk disclosures with about 470 words in Item 7A (for 2017), among which 64 words are used to discuss its fuel price risk exposures. In contrast, Southwest Airlines' Item 7A is much lengthier with about 2,740 words, in which the company spends about 460 words to discuss how it uses derivatives to hedge fuel price risk. This does not necessarily imply that Southwest Airlines provide more informative risk disclosures than Delta Airlines. However, this simple comparison suggests that some companies provide more voluminous and extensive discussion of their market risk exposures than their industry peers.

2.3. Effects of factor exposure uncertainty on variance, skewness, and co-skewness

To clarify the intuition of the foregoing discussion about the relationship between factor exposure uncertainty and return skewness, let's consider a firm, indexed by i , whose benchmark-adjusted equity return $e_{i,t}$ takes the following form:

$$e_{i,t} = (\bar{\beta}_i + \tilde{\beta}_{i,t})f_t + \epsilon_{i,t}, \quad (1)$$

where f_t is a market risk factor with $f_t \sim N(0, \sigma_f^2)$, and $\epsilon_{i,t}$ is the firm's idiosyncratic return with $\epsilon_t \sim N(0, \sigma_\epsilon^2)$. The market risk factor may represent the interest rate risk, foreign exchange rate risk, stock price risk, commodity price risk, and so on. For simplicity, we focus on the case of a single market risk factor, f_t .

The true ex-ante exposure to the market risk factor, $(\bar{\beta}_i + \tilde{\beta}_{i,t})$, has two components: $\bar{\beta}_i$ denotes the estimated component of the factor exposure and $\tilde{\beta}_{i,t} \sim N(0, \sigma_\beta^2)$ represents the factor exposure uncertainty, where σ_β captures the degree of the factor exposure uncertainty. Detailed and specific risk disclosures should lower σ_β . In this example, the firm-specific return, after accounting for the estimated exposure to the market risk factor, is $e_{i,t} - \bar{\beta}_i f_t = \tilde{\beta}_{i,t} f_t + \epsilon_{i,t}$. Let us use $\eta_{i,t} = \tilde{\beta}_{i,t} f_t + \epsilon_{i,t}$ to denote the firm-specific return. Note that the firm specific return $\eta_{i,t}$ contains the effects of uncertain exposure to the systematic risk factor $\tilde{\beta}_{i,t} f_t$.

Assuming that the idiosyncratic return $\epsilon_{i,t}$ is uncorrelated with f_t and $\tilde{\beta}_{i,t}$ and letting $\rho_{\beta f} = \text{Corr}[\tilde{\beta}_{i,t}, f_t]$ denote the correlation between $\tilde{\beta}_{i,t}$ and f_t , we can simplify the variance of the firm-specific return as:

$$Var[\eta_{i,t}] = \sigma_\beta^2 \sigma_f^2 (1 + \rho_{\beta f}^2) + \sigma_\epsilon^2, \quad (2)$$

Equation (2) says that the firm-specific return variance $Var[\eta_{i,t}]$ increases with any elements of σ_β^2 , σ_f^2 , $\rho_{\beta f}^2$, and σ_ϵ^2 .

We can then express skewness of the firm-specific return, $Skew[\eta_{i,t}] = E[\eta_{i,t}^3] / E[\eta_{i,t}^2]^{\frac{3}{2}}$ as:

$$\begin{aligned} Skew[\eta_{i,t}] = & 3\rho_{\beta f} \times h(\sigma_\beta, \sigma_f, \rho_{\beta f}, \sigma_\epsilon) \\ & + 6\rho_{\beta f} \times h(\sigma_\beta, \sigma_f, \rho_{\beta f}, \sigma_\epsilon)^3 \end{aligned} \quad (3)$$

where $h(\sigma_\beta, \sigma_f, \rho_{\beta f}, \sigma_\epsilon) = 1 / \sqrt{1 + 2\rho_{\beta f}^2 + \frac{\sigma_\epsilon^2}{\sigma_\beta^2 \sigma_f^2}}$ is positive and increasing in the degree of factor exposure uncertainty σ_β . Equation (3) says that the sign of the skewness $Skew[\eta_{i,t}]$ depends on the correlation $\rho_{\beta f} = Corr[\tilde{\beta}_{i,t}, f_t]$. The degree of skewness increases with the factor exposure uncertainty (σ_β) and the factor risk (σ_f), and decreases with the idiosyncratic risk (σ_ϵ).

The asset pricing literature typically measures the co-skewness with a systematic factor f_t by $Coskew[\eta_{i,t}, f_t] = E[\eta_{i,t} f_t^2] / \sigma_f^3$. This co-skewness measures the degree of comovement between firm-specific returns ($\eta_{i,t}$) and factor variability (f_t^2). The sign of the factor does not matter for the co-skewness. The co-skewness measure simplifies to

$$Coskew[\eta_{i,t}, f_t] = 3\sigma_\beta \rho_{\beta f}. \quad (4)$$

Please see [Appendix A1](#) for the derivations of Equations (2), (3), and (4).

As Equations (3) and (4) show, the signs of $Skew[\eta_{i,t}]$ and $Coskew[\eta_{i,t}, f_t]$ agree with the sign of $\rho_{\beta f} = Corr[\tilde{\beta}_{i,t}, f_t]$. Under the assumption that $\tilde{\beta}_{i,t}$, f_t , and

$\epsilon_{i,t}$ are normally distributed (with zero skewness), the skewness of the firm specific return, $Skew[\eta_{i,t}]$ arises from the correlation between the factor exposure and the factor itself. Then, for a given level of $Corr[\tilde{\beta}_{i,t}, f_t]$, an increase in σ_β or σ_f tends to increase the degree of skewness, while an increase in σ_ϵ tend to decrease the degree of skewness. The degree of $Coskew[\eta_{i,t}, f_t]$ also increases with the factor exposure uncertainty σ_β .

For some firms, factor exposure is positively correlated with the market risk factor, i.e., $Corr[\tilde{\beta}_{i,t}, f_t] > 0$. This positive correlation implies that the exposure of the firm's equity returns to a market risk factor tends to increase (or decrease) with a favorable (or unfavorable) shock to the market risk factor. That is, favorable shocks to market risk factors have larger effects on the firm's equity than unfavorable shocks do, implying a convex relationship between the firm's equity return and the market risk factor. While quality risk disclosures can reduce the firm-specific variance by reducing σ_β , they also reduce positive skewness in returns, as $h(\sigma_\beta, \sigma_f, \rho_{\beta f}, \sigma_\epsilon)$ in Equation (3) increases with σ_β . By lowering the factor exposure uncertainty σ_β , detailed market risk disclosures should reduce the positive co-skewness, $Coskew[\eta_{i,t}, f_t] > 0$, when the factor exposure and the factor are positively correlated, i.e., $Corr[\tilde{\beta}_{i,t}, f_t] > 0$. Since risk-averse investors generally favor positive co-skewness, reducing the factor exposure uncertainty σ_β may not reduce the firm's cost of capital, even though it helps reduce the information asymmetry between firm managers and outside investors. Reducing the co-skewness may even increase the firm's cost of capital. As such, when $Corr[\tilde{\beta}_{i,t}, f_t] > 0$, firms would not have strong incentives to provide detailed market risk disclosures.

This implication is consistent with the theoretical prediction of Heinle, Smith, and Verrecchia, (2018).

For some other firms, factor exposure is negatively correlated with the market risk factor, i.e., $Corr[\tilde{\beta}_{i,t}, f_t] < 0$. That is, unfavorable shocks to market risk factors exert larger effects on the firm's equity values than favorable shocks do, implying a concave relationship between the firm's equity return and the factor. For these firms, detailed market risk disclosures can reduce not only the variance but also the negative skewness and negative co-skewness of firm-specific returns by slashing the factor exposure uncertainty, σ_{β} . These firms can benefit from providing detailed market risk disclosures as these disclosures may reduce their costs of capital. Meanwhile, detailed market risk disclosures also reduce the negative skewness of firm-specific returns, $-Skew[\eta_{i,t}]$, which is commonly used as an empirical measure of stock price crash risk in existing studies (e.g. Hutton, Marcus, and Tehranian, 2009; Callen and Fang, 2013; Chang, Chen, and Zolotoy, 2017).

Now, it is interesting to ask what determines the sign of $Corr[\tilde{\beta}_{i,t}, f_t]$. When the market risk factor f_t is the stock market return, several studies document an asymmetry between bull market betas and bear market betas (e.g., Ang and Chen, 2002; Ang, Chen, and Xing, 2006; Doan, Lin, and Chng, 2014). Empirically, bear market betas tend to be higher than bull market betas, suggesting negative correlations between beta exposures and the stock market return ($Corr[\tilde{\beta}_{i,t}, f_t] < 0$) for many stocks. However, asymmetric relationships between other market risk factors (e.g. interest rate risk exposure, foreign exchange rate risk, commodity price risk, etc.) and exposures to these factors may vary across firms.

One possible source of the negative correlation, $Corr[\tilde{\beta}_{i,t}, f_t] < 0$, which many studies on stock price crash risk advocate, is the tendency of firm managers to withhold unfavorable information from the public while releasing favorable information truthfully in a timely manner (e.g., Shin, 2003; Jin and Myers, 2006; Hutton, Marcus, and Tehranian, 2009; Kothari, Shu, and Wysocki, 2009). To illustrate the effects of this “behavior” on the correlation $Corr[\tilde{\beta}_{i,t}, f_t]$, let us consider an example of an airline company’s exposure to the fuel price risk. The company’s fuel price risk exposure is negative if the company does not fully hedge it, i.e., $\bar{\beta}_i < 0$, as unexpected surges in fuel prices increase the company’s operating costs. Without detailed disclosure of the exposure, outside investors do not have complete information about the company’s fuel risk exposure. Suppose that the market estimates that the company hedges its fuel price exposure partially. Then, let’s consider two polar cases.

First, suppose that the company does not hedge the fuel price risk at all. In this case, the managers may want to release the positive effects of fuel price declines right away, but they may want to withhold the disclosure of the negative cash flow effects of fuel price increases. When the unfavorable effects of fuel price surges accumulate and pass a threshold, the managers are unable to withhold them and release them at once, resulting in large drops in the firm’s equity value. Thus the magnitude of equity value declines associated with fuel price increases tends to be larger than that of equity price increases associated with fuel price drops. Consequently, the company’s fuel price risk exposure is more negative when the fuel price increases than when it declines, and hence $Corr[\tilde{\beta}_{i,t}, f_t] < 0$.

Second, suppose that the company hedges the fuel price risk fully in derivatives markets so that the company's fuel price exposure is zero. When the fuel price surges, the company gains on their hedging positions to offset increased operating costs, and the managers tend to release the information about their successful hedges in a timely manner. The company's equity price responds favorably, as the market anticipated partial hedges. However, when the fuel price drops, the company incurs losses in its hedging positions in derivatives contracts, but the managers may be reluctant to release information about the hedging losses immediately and delay the release of the information. Then they may be forced to report the accumulated hedging losses at once when the losses pass a threshold. This would disappoint investors as investors learn that the company does not benefit from the fuel price drops at all. In this case, the magnitude of the drop in the firm's equity value associated with fuel price drops is larger than that of the increase in the firm's equity value associated with fuel price increases, implying $Corr[\tilde{\beta}_{i,t}, f_t] < 0$.¹³

In either case – unhedged or hedged -- the correlation between the factor risk exposure and the factor itself tends to be negative when firm managers disclose favorable effects of market risk factors (e.g. fuel price risk) right away while dribbling out unfavorable effects slowly (e.g., Chen, Hong, and Stein, 2001). This bad news hoarding behavior tends to result in increased exposures of the firm's equity to

¹³ Another strand of the literature focuses on the asymmetric information content between positive news and negative news in the presence of bad news hoarding behavior of firm managers. Shin (2003) shows that, when a manager has the discretion to disclose or withhold news that is unverifiable, full disclosure is not supported in equilibrium, but a strategy that discloses all observed good news and withholds all bad news is, providing a rationale for bad news hoarding behavior. In his model, risk-averse investors require higher discount rates as they observe more negative information, leading to large reactions of stock prices to bad news than to positive news, thereby increasing the conditional negative return skewness (crash risk).

unfavorable factor shocks than to favorable shocks, i.e., $Corr[\tilde{\beta}_{i,t}, f_t] < 0$. For these firms, an increase in the factor exposure uncertainty (an increase in σ_β) exacerbates the conditional negative return skewness (stock price crash risk), but informative market risk disclosures may reduce the factor exposure uncertainty σ_β , which mitigates the negative return skewness. By reducing the factor risk exposure uncertainty, detailed market risk disclosures may also reduce investors' panics and sensitive trading behaviors in response to unfavorable shocks, thereby reducing stock price crash risk (e.g., Rajgopal, 1999; Linsmeier, Thornton, Venkatachalam, and Welker, 2002; Thornton and Welker, 2004).

3. Sample selection and research design

3.1 Data and sample

We source data from Form 10-Ks from the SEC EDGAR database, combined with data from CRSP and Compustat. We focus on the CRSP-Compustat-EDGAR merged sample of firm-years between 2002 and 2016 but excludes firms operating in the financial industry (SIC codes 6000-6999) and the public utility industry (SIC codes 4000-4999). We focus on the 2002-2016 period because the disclosure quality is not consistent before and after Sarbanes-Oxley Act of 2002, and EDGAR does not have sufficient Item 7A data before 2002. Moreover, explaining the stock price crash risk during the 2000-2001 Tech-Bubble Crash is beyond the scope of this study. After removing observations with missing dependent variables or control variables, our sample consists of 45,417 firm-year observations.

3.2 *Extracting latent topics in Item 7A with an LDA*

Textual information in narrative disclosures is highly unstructured. Same risk-related keywords may be discussed in completely different contexts by different companies. We thus employ an unsupervised topic model that does not pre-specify any keywords or classifications before parsing textual documents.¹⁴ In particular, we employ an LDA model (Blei, Ng, and Jordan, 2003) to uncover common latent topics in the textual information of narrative market risk disclosures in Item 7A. The traditional LDA model is a three-level hierarchical Bayesian model, which considers text documents as mixtures of topics composed of individual words with certain probabilities. Under the assumption that a firm's narrative disclosure is a finite mixture of topics each of which is a distribution over a fixed vocabulary of unspecified keywords, this statistical model allows us to cluster keywords with their probability and capture corresponding market risk exposures expressed in a descriptive format.

This paper utilizes Bao and Datta's (2014) sentence-based LDA model to extract these topics in Item 7A.¹⁵ We then classify and quantify each firm's narrative market disclosure by (i) Topic Assignments (i.e., which topics appear in the firm's Item 7A?) and (ii) Topic Proportions (i.e., what are the proportions of different topics discussed in the firm's Item 7A?). The key inferential problem for the sentence-based LDA model is computing the posterior distribution of the hidden variables θ (Topic Proportions) and

¹⁴ [Appendix A2](#) provides a review of prior studies that apply textual analyses to firms' risk disclosures.

¹⁵ The traditional LDA assumes that the order of words appeared in a document does not matter, and it also does not consider the sentence boundaries. However, Bao and Datta (2014) argue that each sentence is unlikely to cover multiple risks in risk disclosures. They assume words in the same sentence belong to the same topic.

z (Topic Assignments) given the model parameters and the observed documents w :

$$p(\theta, z | w, \alpha, \beta) = \frac{p(\theta, z, w | \alpha, \beta)}{p(w)} \quad (5)$$

In this study, we first program in Python to read all Item 7A disclosures in our sample. Second, we use Bao and Datta's (2014) sentence-based LDA algorithm analyze the words from the pooled text to identify eight topics that the words fit in. Our estimation of parameters and latent variables follow the Bayesian posterior mode estimation method described in Heinrich (2008) and Bao and Datta (2014). Third, we assign each sentence in every Item 7A to a topic and summarize most frequently used words in each topic. We then predict whether each topic appears and, if so, its proportion, in a specific disclosure based on the words mixture of the disclosure.

Panel A of [Table 9](#) exhibits keywords for each topic extracted by the LDA model. Different topics may share some keywords. For example, Topics 3, 4, and 8 share the following keywords in their vocabularies, $\{foreign, currency, exchange\}$, suggesting that they are related to foreign currency exposures. While these three topics are related to foreign currency exposures, they are used by different groups of firms in different contexts. To provide specific examples of narrative market risk disclosures of different topics, we read multiple documents that have very high proportion for one specific topic (greater than 95%) and very low proportion for other topics (less than 5%). Employing these documents allow us to tease out different topics behind the list of keywords. We provide topic by topic examples in Panel B of [Table 9](#).

< Insert Table 9 Here >

We characterize a firm's disclosure of each topic by two latent variables: (i)

Topic Assignment, z and (ii) Topic Proportion, θ . For Topic Assignments (z), we create dummy variables for the eight topics. If a firm-year discloses a particular topic, the topic assignment of the firm-year takes a value of 1 for the topic and 0 otherwise. We use A_TOPIC1 through A_TOPIC8 to refer to these dummy variables. Topic Proportion (θ) is the estimated proportion which each firm-year devotes to disclose a particular topic in Item 7A (P_TOPIC1 through P_TOPIC8). Each P_TOPIC ranges between 0 and 1. For example, if a firm-year devotes 50% of total sentences in discussing a particular topic, the firm-year takes a value of 0.5 for that P_TOPIC .

To run an LDA, we require each text document (Item 7A) to contain more than 100 words. However, the majority of firms have very short narrative market risk disclosures under Item 7A with only 100 words or less. While we are able to apply LDA to obtain topic allocations and topic proportions for 22,116 firm-years (48.7% of the sample), the other 23,301 firm-years (51.3% of the sample) have no topic allocations or topic proportions.

There are a few reasons why firms provide only very short narrative disclosures in Item 7A. Some of the 23,301 firm-years may not have any material market risk exposures to report in Item 7A. Others may choose to provide as little information as possible in mandatory market risk exposures in Item 7A. For example, firms have little incentives to provide detailed market risk disclosures when factor exposure uncertainty induces right tail risk (positive skewness) in their cash flows, i.e., when $Corr[\tilde{\beta}_{i,t}, f_t] > 0$. Thus firms that choose not to provide detailed disclosures are likely to have lower

negative return skewness.¹⁶

Since very short Item 7A's may provide additional information to our analysis, we retain 23,301 firm-years without Topic Assignments or Topic Proportions by replacing their missing values with zero. We then include a dummy variable to indicate these firms.¹⁷

3.3 Stock price crash risk

Following Chen, Hong, and Stein (2011] and numerous subsequent studies (e.g., Jin and Myers, 2006; Hutton, Marcus, and Tehranian, 2009; Callen and Fang, 2013; Chang, Chen, and Zolotoy, 2014), we measure crash risk by the negative coefficient of skewness of firm-specific daily returns (*NCSKEW*). *NCSKEW* is the relevant empirical measure of $-Skew[\eta_{i,t}]$. As we show in Equation (3), we predict a positive relationship between the magnitude of *NCSKEW* and the factor exposure uncertainty. Informative risk disclosures should then be negatively associated with *NCSKEW*.

We calculate *NCSKEW* for firm i over fiscal year T as follows:

$$NCSKEW_{i,T} = - \left[n(n-1)^{\frac{3}{2}} \sum R_{i,t}^3 \right] / \left[(n-1)(n-2) \left(\sum R_{i,t}^2 \right)^{\frac{3}{2}} \right] \quad (6)$$

¹⁶ There are also firms that discuss their market risk disclosures in other sections of 10-K filings and keep the Item 7A minimal. Distinguishing among these possibilities is interesting but difficult, and we leave it for future work.

¹⁷ The situation here is similar to a case in which we examine the information content of R&D expenses. As Koh and Reeb (2015) report, some firms leave R&D expenses blank in their financial statements even when they actively engage in patent activities. Koh and Reeb (2015) suggest that replacing missing R&Ds with zero and adding a dummy variable to indicate blank R&D firms would be more appropriate than excluding the blank R&D firms altogether.

where n is the number of daily returns in fiscal year T . The firm-specific daily return, $R_{i,t}$, which is defined as the natural logarithm of one plus the residual return. Here, the residual return $\varepsilon_{i,t}$ is from a market and industry index model to compute firm-specific daily returns, $R_{i,t} = \ln(1 + \varepsilon_{i,t})$, allowing for nonsynchronous trading (Dimson, 1979; Hutton, Marcus, and Tehranian, 2009; Chang, Chen, and Zolotoy, 2014):

$$r_{i,t} = a_i + b_{1,i}r_{m,t-1} + b_{2,i}r_{I,t-1} + b_{3,i}r_{m,t} + b_{4,i}r_{I,t} + b_{5,i}r_{m,t+1} + b_{6,i}r_{I,t+1} + \varepsilon_{i,t} \quad (7)$$

where $r_{i,t}$ is the stock return on firm i for day t , $r_{m,t}$ is the market return for day t that is measured by the return on the CRSP value-weighted market index, and $r_{I,t}$ is the industry return for day t . Each industry return is based on the first two digits of SIC codes and value-weighted.

3.4 Regression model

We examine the impact of market risk exposures on stock price crash risk (negative return skewness) by estimating the following panel regression model employing one-year-ahead (fiscal year $T+1$) realization of negative return skewness (crash risk) as the dependent variable:

$$NCSKEW_{i,T+1} = \beta_0 + \beta_j TOPIC_{i,T}^j + MISS_{i,T} + \sum_K \gamma_K CONTROLS_{i,T}^K + YearFE + IndustryFE + \varepsilon_{i,T+1}, \quad (8)$$

for each topic $j=1, \dots, 8$, where $NCSKEW_{i,T+1}$ represents the negative skewness of firm-specific returns (crash risk). $TOPIC_j$ refers to each of our eight topics of market risk exposures (either A_TOPICs and P_TOPICs) extracted via LDA from Item 7A of 10-K

forms.

We focus on β_j ($j=1,\dots,8$) because it represents the effect of each topical disclosure (Topic Assignment or Topic Proportion) on the conditional negative return skewness (stock price crash risk). *MISS* is the indicator variable that takes a value of 1 when Item 7A contains no more than 100 words or 0 otherwise. *CONTROLS^K* summarizes the set of control variables, including the lagged dependent variable *NCSKEW_{i,T}*. *YearFE* and *IndustryFE* are year fixed effects and industry fixed effects, respectively.

We select our control variables based on prior research. Since an influential paper by Chen, Hong, and Stein (2001), a growing body of the literature examines the determinants of stock price crash risk. Chen, Hong, and Stein (2001) emphasize that increases in stock trading volume predict future crash risk as they capture differences in opinions and many bearish investors tend to get sidelined in the presence of short-sale constraints. They further suggest that managers tend to disclose good news right away while dribbling bad news out slowly. Many subsequent studies focus on the role of this bad news hoarding behavior by firm managers in driving stock price crash risk. Managers of opaque firms have more scope for hiding bad news from the market. Empirical evidence indicates that firms with high accruals tend to have higher future crash risk than those with low accruals (e.g., Jin and Myers, 2006; Hutton, Marcus, and Tehranian, 2009), and firms with more conservative accounting practices tend to have lower crash risk than others (Kim and Zhang, 2016). Callen and Fang (2013) also find

that firms in industries with high litigation-risk tend to have a low crash risk.¹⁸ From a different angle focusing on investors' skewness preference, Zhang (2013) argues that the book-to-market ratio and accounting profitability predict the skewness of stock returns.

Following these studies, we employ the following control variables in our regression analyses: stock return kurtosis (*KUR*), stock return volatility (*SIGMA*), cumulative returns (*CUM_RET*), book-to-market ratio (*BM*), book leverage ratio (*LEV*), return on equity (*ROE*), firm size (*LNSIZE*), stock turnover (*DTURNOVER*), and working-capital accruals (*ACCRUALS*). [Appendix A3](#) provides details of these variables. We follow existing studies in including the lagged *NCSKEW* to control for possible persistence in crash risk. We also control for Fama-French 48 industry membership dummies and year-fixed effects to control for industry-specific and year-specific variations in crash risk. We use standard errors clustered at the firm level for inferences.

4. Empirical results

4.1 Descriptive statistics

[Table 10](#) presents descriptive statistics for the variables used in our study. Among the eight latent topics extracted in our LDA procedure, Topic 4 and Topic 1 are the most commonly discussed in Item 7A. Around 43.9% and 43.0% of our firm-years

¹⁸ Chang, Chen, and Zolotoy (2017) document that high stock liquidity (as measured by a low effective spread) induces short-term pressure and increases managers' ex ante incentives to withhold bad news. As high liquidity also facilitates the exit of transient institutions, high liquidity can magnify the ex post stock price reactions to bad news releases, thereby increasing stock price crash risk.

discuss Topic 4 and Topic 1, respectively, in Item 7A of their 10-K filings (Table 01, Panel A). These correspond to about 90% of the 22,116 firm-years that provide Item 7As with more than 100 words in their narrative market risk disclosures. Disclosures of these two topics also have larger proportions than the other topics in Item 7A. Furthermore, proportions of Topic 1 have high correlations with those of the other topics, except Topics 2 and 7 (Table 10, Panel B). Proportions of Topic 4 also have high correlations with those of the other topics, except Topic 2. Thus Topics 1 and 4 appear to summarize commonly discussed topics in Item 7A.

In contrast, Topics 2 and 7 are the least commonly discussed topics of market risk exposures. Around 28.3% and 29.2% of our sample-years discuss these topics (Table 10, Panel A). These correspond to about 60% of the firms-years that provide Item 7As with more than 100 words. Proportions of these topics have low correlations with those of the other topics. These topics are associated with exposures that affect the firms' output prices and/or input costs. Topic 2 is related to “*commodity price risk and derivatives*,” and Topic 7 is associated with “*risks in product prices and materials costs*” that have significant effects on the firms' operating revenues and costs.

In Panel B, we can also see that the proportion of each topic tends to increase with the market capitalization (*LNSIZE*) and decrease with the book-to-market ratio (*BM*). That is, large growth firms tend to spend more than 100 words in Item 7A. These characteristics are also associated with future *NCSKEW*, though the correlation coefficients are not very large. Correlations between *NCSKEW* and our control variables are consistent with the prior literature.

< Insert Table 10 Here >

Table 11 reports relations between the disclosure of each topic and the control variables that are known to predict future stock price crash risk. Panel A reports Probit regressions of topic assignments and Panel B reports OLS regressions of topic proportions. After controlling for industry effects and year effects, the disclosure (assignment) of Topic 2, “*commodity price risk and derivatives*,” is positively associated with return on equity (*ROE*) and firm size (*LNSIZE*), and negatively associated with the stock return volatility (*SIGMA*), cumulative returns (*CUM_RET*), book-to-market ratio (*BM*), financial leverage (*LEV*), and accruals (*ACCRUALS*). These control “variables, except accruals (*ACCRUALS*), also predict the disclosure of Topic 7, “*risks in product prices and materials costs*.” Firms with low financial leverage (*LEV*) tend to disclose Topic 5, while firms with high financial leverage tend to disclose Topic 6 in Item 7A.

< Insert Table 11 Here >

4.2 Market risk disclosures and stock price crash risk

Table 12 reports the regression results for one-year ahead *NCSKEW* (Equation (8)). We first examine the relation between disclosures of eight latent topics and one-year ahead crash risk without controlling for other known predictors of future crash risk. In Table 12, we only include lagged dependent variable and dummies in the indicator of missing latent topics (*MISS*) as the control variable in addition to year- and industry-fixed effects. In all regressions, coefficients on *MISS* are negative and significant, consistent with the notion that firms with very short narrative market risk disclosures (in Item 7A) do not have material risk exposures to report or do not have incentives to provide detailed market risk disclosures. For example, when the factor exposure

uncertainty induces positively skewed cash flows, i.e., when $Corr[\tilde{\beta}_{i,t}, f_t] > 0$, the firm does not have a strong incentive to mitigate the factor exposure uncertainty, as a detailed market risk disclosure may reduce the positive skewness of its cash flows (Heinle, Smith, and Verrecchia, 2018).

In Panel A, we examine the coefficient on each topic assignment (A_TOPIC). We find that the coefficients on Topic 2 assignment (A_TOPIC2) (-0.048; $t=-2.16$) and Topic 7 assignment (A_TOPIC7) (-0.069; $t=-3.20$) are negative and statistically significant at the 5% and 1% levels, respectively. Coefficients on Topic 3 and Topic 5 assignments are positive and moderately significant at the 10% level. In Panel B, we repeat the same exercise using Topic Proportions (P_TOPICs) rather than Topic Assignments (A_TOPICs). Only the coefficient on Topic 7 proportion (P_TOPIC7) is reliably different from zero. It is negative (-0.239; $t=-3.42$) and significant at the 1% level.

These regression results suggest that disclosures of Topic 2 (*commodity price risk and derivatives*) and Topic 7 (*risks in product prices and materials costs*) are negatively and significantly correlated with conditional negative skewness (predicted crash risk). That is, firms that provide narratives of these topics tend to have lower stock price crash risk than those that do not discuss these topics. In contrast, disclosures of the other topics do not convey significant or consistent information about future crash risk. These topics are apparently related to disclosures of interest rate and foreign currency exchange rate exposures, though they are discussed in different contexts.

< Insert Table 12 Here >

To take a deeper look at the information content of these two topical risk

disclosures (Topics 2 and 7), we control for other variables that are known to predict future crash risk and tabulate regression results in [Table 13](#). In general, higher excess kurtosis (*KUR*) and recent specific stock returns (*CUM_RET*) are positively associated with future crash risk (*NCSKEW*). The recent volatility of specific stock returns (*SIGMA*), and the book-to-market ratio (*BM*) are negatively associated with future crash risk. Firms with large size (*LNSIZE*), large increases in trading volume (*DTURNOVER*), and large accruals (*ACCRUALS*) are positively and significantly correlated with future *NCSKEW*. These results are consistent with the findings of existing studies. We note that the low adjusted R^2 of these regressions. Even with the inclusion of these known predictors, the lagged *NCSKEW*, and industry dummies, their adjusted R^2 s of the regressions of *NCSKEW* are only around 3.6%, consistent with the difficulty of predicting the skewness of returns documented by Singleton and Wingender (1986) and corroborated by many subsequent studies (see the recent review by Habib, Hasan, and Jiang, 2018).

After controlling for these predictors of future crash risk, disclosures of Topic 2 (*commodity price risk and derivatives*) remain significant in predicting future crash risk negatively, no matter whether we use Topic 2 Assignment (*A_TOPIC2*) or Topic 2 Proportion (*P_TOPIC2*). Coefficients disclosures of Topic 7 (*risks in product prices and materials costs*) are negative but only moderately significant (at the 10% level). This exercise shows that disclosures of Topic 2 (*commodity price risk and derivatives*) provide significant and incremental information about the firms' future crash risk. The information revealed by disclosures of Topic 7 (*risks in product prices and materials costs*), on the other hand, appears to be partly reflected in recent characteristics of stock

returns (*KUR*, *SIGMA*, *CUM_RET*) and the book-to-market ratio (*BM*).

The coefficients on *MISS* are significantly and consistently negative, suggesting that firms that do not provide market risk disclosures may not have any material market risk disclosures to being with, and/or may not have incentives to reduce the exposure uncertainty as the uncertainty induces positive skewness in their equity returns (i.e., $Corr[\tilde{\beta}_{i,t}, f_t] > 0$).

A natural question is the economic significance of the negative correlations between the disclosures of Topic 2 and Topic 7 and conditional negative return skewness (*NSCKEW*). For example, the conditional negative return skewness of the firms that discuss Topic 2 or Topic 7 (*A_TOPIC2*=1 or *A_TOPIC7*=1) is lower than that of those that do not by about 0.052 or 0.039 after controlling for other predictors of crash risk. While this difference looks small relative to the magnitude of the ex post negative return skewness, the return skewness is very difficult to predict as indicated by the low adjusted R^2 of the regressions. In fact, the magnitude of the negative effects of the risk disclosures of Topic 2 and Topic 7 on the conditional negative return skewness is comparable to the effects of *DTURNOVER*, the variable Chen, Hong, and Stein (2001) focuses on. For example, increasing *DTURNOVER* by 1 standard deviation in our sample increases *NCSKEW* by 0.034. Increasing *BM* (e.g. Zhang, 2013) by 1 standard deviation decreases *NSCKEW* by 0.039. Given the prominence of these variables in explaining the conditional negative return skewness accepted in the literature, it would be safe to argue that disclosing Topic 2 and Topic 7 in Item 7A have economically meaningful effects on the conditional negative return skewness (crash risk).

< Insert Table 13 Here >

4.3 An alternative measure of stock price crash risk

Chen, Hong, and Stein (2001) consider down-to-up volatility (*DUVOL*) as an alternative measure of stock price crash risk. *DUVOL* is the natural logarithm of the ratio of the volatilities between negative returns and positive firm-specific daily returns:

$$\begin{aligned} DUVOL_{i,T} = & \log \left\{ (n_d - 1)^{-1} \sum_{Down} R_{i,t}^2 \right\} \\ & - \log \left\{ (n_u - 1)^{-1} \sum_{Up} R_{i,t}^2 \right\} \end{aligned} \quad (8)$$

where n_d is the number of down days over the fiscal year T and n_u is the number of up days over the fiscal year T . Like *NCSKEW*, a higher *DUVOL* indicates a more left-skewed distribution of stock returns. As a log ratio of two partial second moments, *DUVOL* is less likely to be affected by a small number of extremely returns than *NCSKEW* (e.g. Callen and Fang, 2013). Meanwhile, *DUVOL* may not necessarily fully represent the left-tail risk induced by factor exposure uncertainty. For example, *DUVOL* is not a direct empirical measure of $-Skew[\eta_{i,t}]$. Nevertheless, it would be worthwhile examining how narrative market risk disclosures are correlated with *DUVOL* in the following year. The pooled correlation between *NCSKEW* and *DUVOL* is 0.61.

We replace *NCSKEW* in Equation (8) with *DUVOL* and report the regression results in [Table 14](#) and [Table 15](#). Regressions reported in [Table 15](#) include the known predictors of crash risk as additional control variables while those in [Table 14](#) do not.

In Panel A of [Table 14](#), coefficients on Topic 2 and Topic 7 assignments are negative and significant at the 5% and 10% level, respectively. In Panel B, coefficients

on Topic 2 and Topic 7 proportions are negative and significant at the 10% and 5% level. Thus narrative disclosures of Topic 2 (*commodity price risk and derivatives*) and Topic 7 (*risks in product prices and material costs*), as measured by topic assignments and topic proportions, are negatively correlated with one-year ahead *DUVOL*, consistent with their negative correlations with one-year ahead *NCSKEW* in [Table 12](#).

< Insert Table 14 Here >

When we include the known predictors of crash risk ([Table 14](#)), recent return volatility (*SIGMA*) and the book-to-market ratio (*BM*) are negatively associated with subsequent *DUVOL*, while recent cumulative returns (*CUM_RET*) are positively associated with subsequent *DUVOL*, consistent with the predictions of these variables for subsequent *NCSKEW*. However, other firm characteristics, such as firm size (*LNSIZE*), profitability (*ROE*), financial leverage (*LEV*), accruals (*ACCRUALS*), and large increases in trading volume (*DTURNOVER*) do not exhibit significant correlations with subsequent *DUVOL* though they predict subsequent *NCSKEW*. These results are consistent with the earlier findings of Chen, Hong, and Stein (2001), Hutton, Marcus, Tehranian (2009), and Callen and Fang (2013), among others.

After controlling for these variables, Topic 2 assignment and proportion (*A_Topic2* and *P_Topic2*) are significantly and negatively correlated with subsequent *DUVOL*. Topic 7 assignment and proportion (*A_Topic7* and *P_Topic7*), on the other hand, are no longer significantly correlated with subsequent *DUVOL*.

Putting together, narrative disclosures of Topic 2 (*commodity price risk and derivatives*) and Topic 7 (*risks in product prices and materials costs*) are negatively associated with subsequent stock price crash risk, as measured by *NCSKEW* and

DUVOL. However, the evidence is generally stronger for *NCSKEW* than for *DUVOL*. The more moderate evidence for *DUVOL* than for *NSCKEW* is not surprising because *NCSKEW* is a direct empirical measure of $-Skew[\eta_{i,t}]$ while *DUVOL* is an indirect measure. While the degree of $-Skew[\eta_{i,t}]$ should depend on factor exposure uncertainty (Equation (3)) which the market risk disclosure can mitigate, *DUVOL* aims to provide a measure of the asymmetry of a return distribution.

< Insert Table 15 Here >

5. Concluding Remarks

While many market participants would agree on the importance of improving the quality of market risk disclosures, there have been on-going discussions on the informativeness of narrative market risk disclosures that are currently mandated by the SEC in Item 7A of Form 10K filings. There are widely-held perceptions that many narrative market risk disclosures provide only boilerplate information (e.g., Abraham and Shrieves, 2014; SEC 2016).

To contribute to the regulatory discussion, this study takes on a question if the textual information in a firm's narrative market risk disclosure in Item 7A provides useful information about the firm's stock price crash risk. While narrative market risk disclosures are notoriously difficult to compare across firms (Hodder and McAnally, 2001), an LDA model (Blei, Ng, and Jordan, 2003; Bao and Datta, 2014) proves useful to tease out a small number of latent narrative topics. LDA allows us to group firms by the narrative topics they disclose in Item 7A.

Using LDA, we find that the majority of the latent narrative topics extracted from Item 7A, mainly related to interest rate risk exposures and foreign exchange rate risk exposures, do not provide significant information about stock price crash risk. However, we are able to uncover two latent narrative topics that are negatively correlated with the negative conditional negative return skewness (stock price crash risk). The two topics, “*commodity price risk and derivatives*” and “*risks in product prices and materials costs*” are related to risk exposures in the firms’ input costs and/or output prices. In particular, disclosures of the former convey significant incremental information about the firms’ stock price crash risk even after we control for other known predictors of crash risk. Specifically, the firms that discuss these topics related to the risks in input costs and/or output prices tend to have lower stock price crash risk than those that do not provide narratives of these risk exposures. The evidence suggests that the narrative disclosures of these topics help reduce the uncertainty surrounding the risk exposures of the firms’ input costs and/or output prices. Firms that provide these narratives provide non-redundant and non-boilerplate information to the public in their narrative market risk disclosures (Item 7A).

Meanwhile, about a half of our sample firms provide very few narratives (with 100 words or less) in Item 7A. These firms generally have lower stock price crash risk. This evidence suggests that these firms may not have material exposures to market risk factors to begin with, and/or they may have no incentives to reduce factor exposure uncertainty, as the uncertainty induces positive, rather than negative, skewness in their equity returns. Market risk disclosures are not necessarily relevant for all firms, as some firms are not concerned about the effects of exposure uncertainty on crash risk.

To our knowledge, this is the first study that investigates the relationship between narrative market risk disclosures (mandated in Item 7A) and stock price crash risk. The paper's contributions are twofold. First, this paper's analysis provides a new angle to the role of market risk disclosures in reducing the factor exposure uncertainty and hence the conditional negative return skewness (stock price crash risk). It shows that some narrative disclosures, related to the firms' input costs and/or output prices, appear to convey significant information to help reduce the factor exposure uncertainty and hence crash risk, while other narratives do not. Meanwhile, firms that are not concerned about crash risk provide only minimal information in Item 7A. These findings contribute to the ongoing regulatory discussion over the value of mandatory narrative market risk disclosures in Item 7A (e.g. SEC 2016). Second, this study demonstrates that an LDA model is useful to classify, quantify, and compare unstructured narrative disclosures in Item 7A across firms, which can help improve the process of security analysis, valuation, and risk management for investors, regulators, and other market participants.

Appendices

A1: Derivations of equations (2), (3), and (4)

We consider the variance and skewness of firm-specific returns,

$\eta_{i,t} = \tilde{\beta}_{i,t}f_t + \varepsilon_t$, where $\tilde{\beta}_{i,t} \sim N(0, \sigma_{\beta}^2)$, $f_t \sim N(0, \sigma_f^2)$, and $\varepsilon_t \sim N(0, \sigma_{\varepsilon}^2)$. The idiosyncratic return ε_t is uncorrelated with $\tilde{\beta}_{i,t}$ and f_t . $\rho_{\beta f}$ denotes the correlation between $\tilde{\beta}_{i,t}$ and f_t . Then the second and third moments of the firm-specific return are

$$\begin{aligned} E[\eta_{i,t}^2] &= E[\tilde{\beta}_{i,t}^2 f_t^2] + 2E[\tilde{\beta}_{i,t} f_t \varepsilon_t] + E[\varepsilon_t^2], \\ E[\eta_{i,t}^3] &= E[\tilde{\beta}_{i,t}^3 f_t^3] + 3E[\tilde{\beta}_{i,t}^2 f_t^2 \varepsilon_t] + 3E[\tilde{\beta}_{i,t} f_t \varepsilon_t^2] + E[\varepsilon_t^3]. \end{aligned}$$

Given that $\tilde{\beta}_{i,t}$, f_t , and ε_t are Normal random variables with zero means, Isserlis' (1916, 1918) theorem implies that $E[\tilde{\beta}_{i,t} f_t \varepsilon_t] = 0$, $3E[\tilde{\beta}_{i,t}^2 f_t^2 \varepsilon_t] = 0$, $E[\varepsilon_t^3] = 0$, and

$$\begin{aligned} E[\tilde{\beta}_{i,t}^2 f_t^2] &= E[\tilde{\beta}_{i,t}^2]E[f_t^2] + 2E[\tilde{\beta}_{i,t} f_t]^2 \\ &= \sigma_{\beta}^2 \sigma_f^2 (1 + 2\rho_{\beta f}^2) \\ E[\tilde{\beta}_{i,t}^3 f_t^3] &= 9E[\tilde{\beta}_{i,t}^2]E[\tilde{\beta}_{i,t} f_t]E[f_t^2] + 6E[\tilde{\beta}_{i,t} f_t]^3 \\ &= 9\sigma_{\beta}^3 \sigma_f^3 \rho_{\beta f} + 6\sigma_{\beta}^3 \sigma_f^3 \rho_{\beta f}^3 \\ E[\tilde{\beta}_{i,t} f_t \varepsilon_t^2] &= \sigma_{\varepsilon}^2 E[\tilde{\beta}_{i,t} f_t] \\ &= \sigma_{\beta} \sigma_f \sigma_{\varepsilon}^2 \rho_{\beta f} \end{aligned}$$

It follows that the variance of the firm-specific return is

$$E[\eta_{i,t}^2] = \sigma_{\beta}^2 \sigma_f^2 + \sigma_{\varepsilon}^2 + 2\sigma_{\beta}^2 \sigma_f^2 \rho_{\beta f}^2, \text{ which provides Equation (2).}$$

The skewness of the firm-specific return, $Skew[\eta_{i,t}] = E[\eta_{i,t}^3] / E[\eta_{i,t}^2]^{\frac{3}{2}}$

(Equation (3)), is

$$\begin{aligned}
Skew[\eta_{i,t}] &= \frac{9\sigma_\beta^3\sigma_f^3\rho_{\beta f} + 6\sigma_\beta^3\sigma_f^3\rho_{\beta f}^3 + 3\sigma_\beta\sigma_f\rho_{\beta f}\sigma_\varepsilon^2}{E[\eta_{i,t}^2]^{\frac{3}{2}}} \\
&= \frac{6\sigma_\beta^3\sigma_f^3\rho_{\beta f} + 3\sigma_\beta\sigma_f\rho_{\beta f}E[\eta_{i,t}^2]}{E[\eta_{i,t}^2]^{\frac{3}{2}}} \\
&= 6\rho_{\beta f} \times h(\sigma_\beta, \sigma_f, \rho_{\beta f}, \sigma_\varepsilon)^3 + 3\rho_{\beta f} \times h(\sigma_\beta, \sigma_f, \rho_{\beta f}, \sigma_\varepsilon)
\end{aligned}$$

where $h(\sigma_\beta, \sigma_f, \rho_{\beta f}, \sigma_\varepsilon) = \frac{1}{\sqrt{1 + \frac{\sigma_\varepsilon^2}{\sigma_\beta^2\sigma_f^2} + 2\rho_{\beta f}^2}}$. Note that $h(\sigma_\beta, \sigma_f, \rho_{\beta f}, \sigma_\varepsilon) > 0$ and

$$\frac{\partial}{\partial \sigma_\beta} h(\sigma_\beta, \sigma_f, \rho_{\beta f}, \sigma_\varepsilon) > 0.$$

Using $E[\eta_{i,t}f_t^2] = 3\sigma_\beta\sigma_f^3\rho_{\beta f}$, we can simplify the co-skewness of the firm specific return with the factor (Equation (4)) as:

$$Coskew[\eta_{i,t}, f_t] = \frac{E[\eta_{i,t}f_t^2]}{\sigma_f^3} = 3\sigma_\beta\rho_{\beta f}.$$

A2: Prior applications of textual analyses to risk disclosures

An increasing number of studies apply language processing algorithms to analyze textual information in firms' risk disclosures. For example, Campbell *et al.* (2014) measure the informativeness of a firm's risk factor disclosure by counting the number of risk-related keywords in Item 1A of Form 10-K. Kravet and Musulu (2013) similarly measure the degree of risk exposures by counting the number of sentences with at least one predefined risk-related keywords, including *{can/cannot, could, may, might, risk*, uncertain*, likely to, subject to, potential*, vary*/varies, depend*, expos*, fluctuat*, possibl*, susceptible, affect, influenc*, and hedg*}*.

Hope, Hu, and Lu (2016) employ the Stanford Named Entity Recognition (NER) tool to extract specific entity names in Item 1A of Form 10-K. These specific entity

names include names of persons, locations, organizations, quantitative numbers in percentages, money values in dollars, times and dates. They then define the “specificity” of risk disclosures by counting the number of these specific entity names scaled by the total number of words in that section. They show that the stock market reacts more to the 10-K filings with higher “specificity.” Similarly, analysts’ reliability in assessing the firms’ fundamental risk tends to be higher for firms with more specific risk disclosures.

Instead of analyzing texts, Loughran and McDonald (2014) propose to use the “file size” of 10-K to proxy the readability of financial report. They argue that financial report users can effectively obtain more information from more readable financial reports than from less readable ones. Ertugrul *et al.* (2017) find that the readability measured by 10-K file size is negatively related to future stock price crash risk.

Item 1A discusses a wide range of risk-related topics including environmental risk, litigation risk, regulation risk, supply chain disruption risk, and so on. Due to the high dimensionality, many of the extracted latent topics do not yield straightforward interpretations, or they allow for multiple interpretations. This study employs the sentence-based LDA model of Bao and Datta (2014) by focusing on eight latent topics in Item 7A. By focusing on eight topics, we are able to provide intuitive interpretations of the latent topics, all of which are related to changes in market prices or rates and derivatives.

A3: Variables definition

A_TOPICs and P_TOPICs are Topic Assignments (z) and Topic Proportions (θ), respectively (see Equation (5)), for the eight latent topics extracted from an LDA

model. *NCSKEW* is the negative skewness of firm-specific stock returns, defined in Equation (6).

Our panel regressions (Equation (8)) also consider the following control variables. *MISS* is the indicator variable that takes the value of one for firms-years with very short market risk disclosures in Item 7A (with 100 words or less) and 0 otherwise. We calculate the return kurtosis (*KUR*), return volatility (*SIGMA*), and cumulative returns (*CUM_RET*) using firm-specific daily returns over the fiscal year and include them as control variables. *BM* is the log ratio of the book value of equity to the market value of equity, following Fama and French (2008). *LEV* is the book value of all liabilities divided by total assets at the end of the fiscal year. *ROE* is the income before extraordinary items divided by the book value of equity at the end of the fiscal year. *LNSIZE* is the natural logarithm of the market value of equity at the end of the fiscal year. *DTUROVER* is the difference between the average monthly share turnover over the fiscal year and that over the previous fiscal year, which is known to be a strong predictor of crash risk (e.g. Chen, Hong, and Stein, 2001). *ACCRUALS* is defined as the change in accounts receivable plus the change in inventory minus the change in accounts payable minus the change in taxes payable plus the change in other assets (Frankel and Sun, 2018). We winsorize each variable at 1% and 99%.

Reference

- Abraham, S., and P.J. Shrikes, 2014, Improving the Relevance of Risk Factor Disclosure in Corporate Annual Reports, *The British Accounting Review* 46(1), 91-107.
- Andrews, D.F., and C.L. Mallows, 1974, Scale Mixtures of Normal Distributions, *Journal of the Royal Statistical Society, Series B (Methodological)* 26, 99-102.
- Ang, A. and J. Chen, 2002, Asymmetric Correlations and Equity Returns, *Journal of Financial Economics* 63, 443-494.
- Ang, A., J. Chen, and Y. Xing, 2006, Downside Risk, *Review of Financial Studies* 19(4), 1191-1239.
- Bao, Y. and A. Datta, 2014, Simultaneously Discovering and Quantifying Risk Types from Textual Risk Disclosures, *Management Science* 60, 1371-1391.
- Barberis, N. and M. Huang, 2008, Stocks as Lotteries: The Implications of Probability Weighting for Security Prices, *American Economic Review* 98(5), 2066-2100.
- Blei, D.M., A.Y. Ng, and M.I. Jordan, 2003, Latent Dirichlet Allocation, *Journal of Machine Learning Research* 3 (January), 993-1022.
- Callen, J.L, and X. Fang, 2013, Institutional Investor Stability and Crash Risk: Monitoring versus Short-Termism?" *Journal of Banking & Finance* 37, 3047-3063.
- Campbell, J.L, H. Chen, D.S Dhaliwal, H.-M. Lu, and L.B Steele, 2014, The Information Content of Mandatory Risk Factor Disclosures in Corporate Filings, *Review of Accounting Studies* 19, 396-455.
- Chang, X., Y. Chen, and L. Zolotoy. 2017, Stock Liquidity and Stock Price Crash Risk, *Journal of Financial and Quantitative Analysis* 52(4), 1605-1637.
- Chen, J., H. Hong, and J.C. Stein, 2001, Forecasting Crashes: Trading Volume, Past Returns, and Conditional Skewness in Stock Prices, *Journal of Financial Economics* 61, 345-381.
- Chung, Y.P., H. Johnson, and M.J. Schill, 2006, Asset Pricing when Returns are Nonnormal: Fama-French Factors versus Higher-Order Systematic Comments, *Journal of Business* 79(2), 923-940.
- Diamond, D.W. and R.E. Verrecchia, 1991, Disclosure, Liquidity, and the Cost of Capital, *Journal of Finance* 66, 1325-1355.
- Dimson, E., 1979, Risk Measurement When Shares Are Subject to Infrequent Trading, *Journal of Financial Economics* 7, 197-227.
- Doan, M.P., C.T. Lin, M. Chng, 2014, Higher Moments and Beta Asymmetry: Evidence from Australia, *Accounting and Finance* 54, 779-807.
- Dyer, T., M. Lang, and L. Stice-Lawrence, 2017, The Evolution of 10-K Textual Disclosure: Evidence from Latent Dirichlet Allocation, *Journal of Accounting and Economics* 64, 221-245.

- Easley, D., and M. O'Hara, 2004, Information and the Cost of Capital, *Journal of Finance* 59, 1553–1583.
- Ertugrul, M., J. Lei, J. Qiu, and C. Wan, 2017, Annual Report Readability, Tone Ambiguity, and the Cost of Borrowing, *Journal of Financial and Quantitative Analysis* 52(2), 811–836.
- Fama, E.F, and K.R. French, 2008, Dissecting Anomalies, *Journal of Finance* 63, 1653–1678.
- Frankel, R., and Y. Sun, 2018, Predicting Accruals Based on Cash-Flow Properties, *The Accounting Review* 93, 165–186.
- Friend, I. and R. Westerfield, 1980, Co-Skewness and Capital Asset Pricing, *Journal of Finance* 35, 897-913.
- Habib, A., M.M. Hasan, and H. Jiang, 2018, Stock Price Crash Risk: Review of the Empirical Literature, *Accounting and Finance* 58, 211–251.
- Harvey, C.R. and A. Siddique, 2000, Conditional Skewness in Asset Pricing Tests, *Journal of Finance* 55, 1263-1295.
- Healy, P.M., A.P. Hutton, and K.G. Palepu, 1999, Stock Performance and Intermediation Changes Surrounding Sustained Increases in Disclosure, *Contemporary Accounting Research* 16(3), 485-520.
- Heinle, M.S, and K.C. Smith, 2017, A Theory of Risk Disclosure, *Review of Accounting Studies* 22, 1459–1491.
- Heinle, M.S, K.C. Smith, and R.E. Verrecchia, 2018, Risk-Factor Disclosure and Asset Prices, *The Accounting Review* 93, 191–208.
- Heinrich, G., 2008, Parameter Estimation for Text Analysis, Technical Note. vsonix GmbH + University of Leipzig, Germany.
- Hodder, L., and M.L. McNally, 2001, SEC Market-Risk Disclosures: Enhancing Comparability, *Financial Analysts Journal* 57, 62–78.
- Hope, O.K., D. Hu, and H. Lu, 2016, The Benefits of Specific Risk-Factor Disclosures, *Review of Accounting Studies* 21, 1005–1045.
- Hughes, J.S, J. Liu, and J. Liu, 2007, Information Asymmetry, Diversification, and Cost of Capital, *The Accounting Review* 82, 705–29.
- Hutton, A.P, A.J Marcus, and H. Tehranian, 2009, Opaque Financial Reports, R2, and Crash Risk, *Journal of Financial Economics* 94, 67–86.
- Isserlis, L., 1916, On Certain Probable Errors and Correlation Coefficients of Multiple Frequency Distributions with Skew Regression, *Biometrika* 11(3),185-190.
- Isserlis, L, 1918, On a Formula for the Product-Moment Coefficient of Any Order of a Normal Frequency Distribution in Any Number of Variables, *Biometrika* 12 (1/2),134-139.
- Jin, L. and S.C. Myers, 2006, R2 around the World: New Theory and New Tests, *Journal of Financial Economics* 79, 257–92.

- Jin, X., Z. Chen, and X. Yang, 2019, Economic Policy Uncertainty and Stock Price Crash Risk, *Accounting and Finance* 58, 1291-1318.
- Jorgensen, B.N., and M.T. Kirschenheiter, Discretionary Risk Disclosures, *The Accounting Review* 78, 449–69.
- Kim, J.-B., I. Yeung, and J. Zhou 2019, Stock Price Crash Risk and Internal Control Weakness: Presence vs. Disclosure Effect, *Accounting and Finance* forthcoming.
- Kim, J.-B. and L. Zhang, 2016. Accounting Conservatism and Stock Price Crash Risk: Firm - level Evidence, *Contemporary Accounting Research* 33(1), 412 – 441.
- Koh, P.-S., and D.M. Reeb, 2015, Missing R&D, *Journal of Accounting and Economics* 60, 73–94.
- Kothari, S.P, S. Shu, and P.D Wysocki, 2009, Do Managers Withhold Bad News?, *Journal of Accounting Research* 47, 241–76.
- Kraus, A., and R. Litzenberger, 1976, Skewness Preference and the Valuation of Risky Assets, *Journal of Finance* 31, 1085-1100.
- Kraus, A., and R. Litzenberger, 1983, On the Distributional Conditions for a Consumption-Oriented Three Moment CAPM, *Journal of Finance* 38, 1381-1391.
- Kravet, T. and V. Muslu, 2013, Textual Risk Disclosures and Investors' Risk Perceptions, *Review of Accounting Studies* 18, 1088-1122.
- Lambert, R., C. Leuz, and R.E. Verrecchia, 2007, Accounting Information, Disclosure, and the Cost of Capital,” *Journal of Accounting Research* 45 (May),385-420.
- Levitt, A., 1998, The Importance of High Quality Accounting Standards, *Accounting Horizons* 12, 79-82.
- Linsmeier, T.J, D.B. Thornton, M. Venkatachalam, and M. Welker, 2002, The Effect of Mandated Market Risk Disclosures on Trading Volume Sensitivity to Interest Rate, Exchange Rate, and Commodity Price Movements, *The Accounting Review* 77, 343–77.
- Loughran, T. and B. McDonald, 2014, Measuring Readability in Financial Disclosures, *Journal of Finance* 69(4), 1643–1671.
- Rajgopal, S., 1999, Early Evidence on the Informativeness of the SEC's Market Risk Disclosures: The Case of Commodity Price Risk Exposure of Oil and Gas Producers, *The Accounting Review* 74, 251–80.
- Rubinstein, M., 1973, The Fundamental Theorem of Parameter-Preference Security Valuation. *Journal of Financial and Quantitative Analysis* 8, 61–69.
- Securities and Exchange Commission (SEC), 2016, SEC Concept Release: Business and Financial Disclosure Required by Regulation S-K. Release Nos. 33-10064; 34-77599; File No. S7-06-16. Washington, DC.
- Shin, H.S., 2003, Disclosures and Asset Returns, *Econometrica* 71, 105–33.
- Singleton, J.C. and J. Wingender, 1986, Skewness Persistence in Common Stock Returns, *Journal of Financial and Quantitative Analysis* 21(3), 335-341.

- Thornton, D.B., and M. Welker, 2004, The Effect of Oil and Gas Producers' FRR No. 48 Disclosures on Investors' Risk Assessments, *Journal of Accounting, Auditing & Finance* 19, 85–114.
- Zhang, X.-J., 2013, Book-to-Market Ratio and Skewness of Stock Returns, *The Accounting Review* 88(6), 2213–2240.

Table 9. Latent Topics Extracted from Item 7A via LDA

<i>Panel A. Clustering of Keywords</i>	
Topics	Keywords
1	Interest, rates, market, value, fair, changes, increase, debt, risk, change, cash, approximately, million, decrease
2	Value, price(s), fair, market, risk, gas, derivative, natural, financial, contracts, oil, commodity, instruments, credit
3	Foreign, contracts, currency, instruments, derivative, financial, forward, exchange, use, hedge, rate, interest, enter, exposure, trading
4	Foreign, currency, exchange, changes, rate(s), interest, risk, market, financial, results, exposed, fluctuations, exposure, operations
5	Investment(s), cash, securities, market, financial, equivalents, credit, portfolio, rate, money, risk, marketable, debt, million
6	Rate(s), interest, million, debt, credit, outstanding, variable, fixed, swap, amount, borrowings, based, facility, revolving
7	Price(s), products, cost(s), market, raw, sales, certain, future, operating, significant, material(s), subject
8	Foreign, currency, million, exchange, net, denominated, dollar, income, value, currencies, losses, approximately, gains, sales, ended
<i>Panel B. Interpretations of the Topics Extracted by LDA: Topic by Topic Examples</i>	
Topics	Description
1	Topic 1 discusses whether and how changes in interest rates affect the fair value of firms' debt instruments and cash flows and tools that firms utilize to manage risks associated with fluctuations in interest rates.
2	Topic 2 discusses firms' exposure to commodity risk derived from price volatility for production in the oil markets. It also addresses what derivatives are used to hedge these commodity risks and whether the use of derivatives will limit firms' access to credit facilities.
3	Topic 3 discusses whether firms are exposed to foreign currency exchange and interest risks, what financial instruments are used to hedge these risks, and whether firms enter transactions for trading or speculative purpose.
4	Topic 4 discusses whether adverse changes in financial market prices or rates such as interest and foreign currency exchange risks will cause fluctuations in results of operations.
5	Topic 5 discusses the firms' holding of cash, cash equivalents, and marketable securities. It also addresses the extent to which firms invest excess cash and cash equivalent in money market account that invests in debt securities or short-term financial instruments so that firms can minimize the exposure due to adverse changes in interest rates.
6	Topic 6 discusses how firms' fixed- and variable- rate debt obligations and interest rate swap are impacted by interest risks and the detailed information regarding interest on borrowings under various credit facilities.
7	Topic 7 discusses firms' exposure to market risks derived from raw materials and how the fluctuations in the exchange rates of dominant currencies affect the cost of materials, sales, and future operating results.
8	Topic 8 discusses how the foreign currency exchange rates relative to the dominated currencies affect the sales and whether the comprehensive income/losses exposure to realized and unrealized foreign currency gains and losses is significant.

Table 10. Descriptive Statistics*Panel A. Summary statistic: Pooled Sample (N=45,417)*

VARIABLES	MEAN	STD	MIN	MEDIAN	MAX
<i>A_TOPIC1</i>	0.430	0.495	0	0	1
<i>A_TOPIC2</i>	0.283	0.450	0	0	1
<i>A_TOPIC3</i>	0.415	0.493	0	0	1
<i>A_TOPIC4</i>	0.439	0.496	0	0	1
<i>A_TOPIC5</i>	0.313	0.464	0	0	1
<i>A_TOPIC6</i>	0.367	0.482	0	0	1
<i>A_TOPIC7</i>	0.292	0.455	0	0	1
<i>A_TOPIC8</i>	0.394	0.489	0	0	1
<i>P_TOPIC1</i>	0.083	0.143	0	0	0.960
<i>P_TOPIC2</i>	0.040	0.121	0	0	0.980
<i>P_TOPIC3</i>	0.055	0.097	0	0	0.880
<i>P_TOPIC4</i>	0.084	0.137	0	0	0.940
<i>P_TOPIC5</i>	0.054	0.128	0	0	0.950
<i>P_TOPIC6</i>	0.067	0.139	0	0	0.990
<i>P_TOPIC7</i>	0.036	0.105	0	0	0.990
<i>P_TOPIC8</i>	0.066	0.126	0	0	0.970
<i>NCSKEW</i>	-0.021	1.413	-3.912	-0.125	4.513
<i>ROE</i>	-0.119	0.852	-5.966	0.064	5.615
<i>LEV</i>	0.180	0.182	0	0.140	0.950
<i>ACCRUALS</i>	0.006	0.088	-0.959	0.008	0.477
<i>BM</i>	-0.578	1.096	-3.253	-0.629	3.492
<i>DTURNOVER</i>	0.019	1.020	-3.224	0.004	3.133
<i>LNSIZE</i>	5.997	2.077	0.339	6.014	10.295
<i>KUR</i>	7.761	11.237	-0.149	3.818	65.049
<i>SIGMA</i>	0.034	0.019	0.006	0.029	0.122
<i>CUM_RET</i>	0.140	0.620	-0.840	0.052	2.714

Panel B. Pearson correlations: Pooled Sample (M=45,417)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) <i>P_TOPIC1</i>	1.00							
(2) <i>P_TOPIC2</i>	0.03	1.00						
(3) <i>P_TOPIC3</i>	0.23	0.13	1.00					
(4) <i>P_TOPIC4</i>	0.22	0.05	0.37	1.00				
(5) <i>P_TOPIC5</i>	0.34	-0.01	0.09	0.15	1.00			
(6) <i>P_TOPIC6</i>	0.23	0.07	0.23	0.17	-0.02	1.00		
(7) <i>P_TOPIC7</i>	0.04	0.13	0.11	0.12	0.00	0.08	1.00	
(8) <i>P_TOPIC8</i>	0.13	0.03	0.34	0.37	0.12	0.11	0.08	1.00

Notes: Please see [Appendix A3](#) for variable definitions. Each continuous variable is winsorized at 1% and 99%.

Table 11. Topic Assignments/Proportions and Firm Characteristics*Panel A. Topic assignments*

VARIABLES	A_TOPIC 1	A_TOPIC 2	A_TOPIC 3	A_TOPIC 4	A_TOPIC 5	A_TOPIC 6	A_TOPIC 7	A_TOPIC 8
KUR	-0.000 (-0.10)	-0.001 (-1.64)	0.000 (0.19)	-0.001 (-0.89)	0.000 (0.37)	0.000 (0.30)	-0.000 (-0.48)	0.000 (0.08)
SIGMA	-2.357*** (-4.48)	-1.919*** (-3.41)	-2.465*** (-4.64)	-2.431*** (-4.62)	-1.380** (-2.46)	-4.025*** (-7.46)	-1.616*** (-2.94)	-1.944*** (-3.64)
CUM_RET	-0.084*** (-6.99)	-0.065*** (-5.20)	-0.093*** (-7.79)	-0.078*** (-6.58)	-0.100*** (-7.93)	-0.050*** (-4.16)	-0.049*** (-4.01)	-0.089*** (-7.35)
BM	-0.204*** (-28.17)	-0.157*** (-20.74)	-0.190*** (-26.25)	-0.209*** (-28.88)	-0.225*** (-28.19)	-0.163*** (-22.52)	-0.192*** (-25.21)	-0.192*** (-26.14)
LEV	-0.176*** (-4.82)	-0.127*** (-3.32)	-0.216*** (-5.88)	-0.365*** (-9.95)	-1.159*** (-28.99)	0.440*** (11.98)	-0.401*** (-10.47)	-0.463*** (-12.40)
ROE	0.043*** (5.05)	0.027*** (3.06)	0.036*** (4.17)	0.040*** (4.75)	0.025*** (2.82)	0.055*** (6.30)	0.038*** (4.30)	0.036*** (4.15)
LNSIZE	0.085*** (19.94)	0.074*** (16.37)	0.102*** (23.74)	0.093*** (21.78)	0.066*** (14.47)	0.055*** (12.64)	0.027*** (6.14)	0.102*** (23.49)
DTURNOVER	0.004 (0.64)	0.011 (1.64)	0.005 (0.81)	0.006 (0.92)	-0.010 (-1.49)	0.020*** (3.05)	0.008 (1.22)	0.000 (0.01)
ACCRUALS	-0.020 (-0.26)	-0.189** (-2.41)	-0.094 (-1.27)	-0.078 (-1.06)	0.101 (1.31)	-0.070 (-0.92)	0.036 (0.47)	-0.063 (-0.85)
INDUSTRY FE	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
OBSERVATIONS	45,400	45,400	45,400	45,400	45,400	45,400	45,400	45,400
PSEUDO R ²	0.078	0.052	0.077	0.082	0.101	0.068	0.048	0.080

Panel B. Topic proportions

VARIABLES	P_TOPIC 1	P_TOPIC 2	P_TOPIC 3	P_TOPIC 4	P_TOPIC 5	P_TOPIC 6	P_TOPIC 7	P_TOPIC 8
KUR	0.000 (1.18)	-0.000*** (-3.79)	0.000 (1.26)	-0.000 (-1.34)	0.000 (1.04)	0.000 (0.86)	-0.000 (-1.17)	0.000 (1.12)
SIGMA	0.095 (1.53)	0.102* (1.90)	-0.005 (-0.11)	-0.061 (-1.03)	0.153** (2.44)	-0.340*** (-5.58)	0.087* (1.71)	-0.031 (-0.59)
CUM_RET	0.002** (2.00)	-0.002** (-2.09)	-0.002*** (-3.07)	0.001 (0.82)	-0.002** (-2.48)	0.004*** (4.37)	0.001 (1.33)	-0.002** (-2.28)
BM	-0.001 (-0.96)	0.002** (2.21)	0.001** (2.33)	-0.002** (-2.44)	-0.005*** (-5.61)	0.005*** (4.86)	-0.002** (-2.26)	0.002* (1.87)
LEV	0.004 (0.62)	0.011* (1.74)	0.004 (0.88)	-0.033*** (-5.66)	-0.090*** (-14.53)	0.134*** (16.19)	-0.012** (-1.99)	-0.019*** (-3.38)
ROE	0.000 (0.51)	-0.001 (-0.86)	-0.001** (-2.03)	-0.000 (-0.24)	-0.003*** (-3.71)	0.004*** (4.47)	0.001 (1.27)	0.000 (0.27)
LNSIZE	-0.003*** (-4.85)	0.006*** (6.01)	0.004*** (7.96)	-0.002*** (-3.44)	-0.001* (-1.72)	-0.004*** (-5.71)	-0.003*** (-4.68)	0.004*** (5.84)
DTURNOVER	-0.000 (-0.50)	0.001 (1.31)	-0.000 (-0.40)	0.000 (0.77)	-0.001*** (-2.87)	0.002*** (4.40)	-0.001 (-1.37)	-0.001 (-1.25)
ACCRUALS	0.016*** (2.65)	-0.019*** (-4.27)	-0.014*** (-3.77)	0.003 (0.58)	0.013** (2.36)	-0.006 (-1.00)	0.002 (0.44)	0.004 (0.76)
MISS	-0.170*** (-64.02)	-0.085*** (-29.62)	-0.110*** (-59.62)	-0.171*** (-69.70)	-0.111*** (-40.39)	-0.139*** (-49.86)	-0.078*** (-32.45)	-0.134*** (-52.67)
INDUSTRY FE	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
OBSERVATIONS	45,417	45,417	45,417	45,417	45,417	45,417	45,417	45,417
ADJ. R ²	0.383	0.205	0.368	0.413	0.283	0.318	0.182	0.341

Notes: This table reports relations between the disclosure of each topic and our control variables that are known to predict future crash risk. *A_TOPICS* are topic assignments, and *P_TOPICS* are topic proportions. Panel A reports the results of Probit regressions of topic assignments and Panel B reports results of OLS regressions of topic proportions. All regressions include Fama-French 48 industry

dummies and year fixed effects. MISS is the indicator variable that takes the value of one for firms-years without topics assignments or topic proportions due to very short market risk disclosures in Item 7A (with 100 words or less). t-statistics are reported in parentheses with robust standard errors clustered at the firm level. Continuous variables are winsorized at 1% and 99% level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 12. Latent Topics and One-Year Ahead Negative Return Skewness (NCSKEW)*Panel A. Lead NCSKEW on each topic assignment without control variables (N=40,184)*

VARIABLES	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8
<i>A_TOPIC</i>	0.003 (0.11)	-0.048** (-2.16)	0.055* (1.86)	-0.018 (-0.53)	0.037* (1.66)	0.036 (1.41)	-0.069*** (-3.20)	0.017 (0.62)
<i>NCSKEW</i>	0.039*** (6.36)	0.039*** (6.33)	0.039*** (6.36)	0.039*** (6.35)	0.039*** (6.36)	0.039*** (6.35)	0.039*** (6.31)	0.039*** (6.36)
<i>MISS</i>	-0.151*** (-4.71)	-0.183*** (-8.87)	-0.107*** (-3.66)	-0.170*** (-5.07)	-0.131*** (-6.42)	-0.127*** (-5.16)	-0.196*** (-9.69)	-0.140*** (-5.25)
INDUSTRY FE	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
ADJ. R ²	0.012	0.012	0.012	0.012	0.012	0.012	0.013	0.012

Panel B. Lead NCSKEW on each topic proportion without control variables (N=40,184)

VARIABLES	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8
<i>P_TOPIC</i>	0.070 (1.07)	-0.085 (-1.47)	0.070 (0.80)	0.071 (1.00)	0.065 (0.95)	-0.014 (-0.22)	-0.239*** (-3.42)	0.047 (0.64)
<i>NCSKEW</i>	0.039*** (6.36)	0.039*** (6.35)	0.039*** (6.35)	0.039*** (6.35)	0.039*** (6.36)	0.039*** (6.36)	0.039*** (6.32)	0.039*** (6.35)
<i>MISS</i>	- 0.142*** (-7.84)	-0.162*** (-9.79)	-0.146*** (-7.98)	- 0.142*** (-7.45)	-0.147*** (-8.96)	-0.156*** (-8.95)	-0.172*** (-10.67)	-0.148*** (-8.24)
INDUSTRY FE	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
ADJ. R ²	0.012	0.012	0.012	0.012	0.012	0.012	0.013	0.012

Notes: This table reports OLS regressions of one-year-ahead negative skewness of firm-specific returns (crash risk), *NCSKEW*. Please see [Appendix A2](#) for variable definitions. Panel A shows the relationship between Topic Assignments and one-year ahead crash risk. Panel B shows the relationship between Topic Proportions and one-year-ahead *NCSKEW*. All regressions include Fama-French 48 industry dummies and year fixed effects. *t*-statistics, based on robust standard errors clustered at the firm level are reported in parentheses below the coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 13. Latent Topics and One-Year Ahead Negative Return Skewness (*NCSKEW*) Controlling for Known Predictors of Crash Risk

Dependent Variable: One-Year Ahead NCSKEW (N=40,184)

VARIABLES	Topic 2		Topic 7	
	(1)	(2)	(3)	(4)
<i>A_TOPIC</i>	-0.052** (-2.35)		-0.039* (-1.78)	
<i>P_TOPIC</i>		-0.213*** (-3.58)		-0.133* (-1.90)
<i>NCSKEW</i>	0.045*** (7.02)	0.045*** (7.00)	0.045*** (7.05)	0.045*** (7.05)
<i>MISS</i>	-0.092*** (-4.48)	-0.079*** (-4.83)	-0.084*** (-4.17)	-0.071*** (-4.41)
<i>KUR</i>	0.002** (2.11)	0.002** (2.08)	0.002** (2.13)	0.002** (2.12)
<i>SIGMA</i>	-5.053*** (-8.66)	-5.032*** (-8.62)	-5.053*** (-8.65)	-5.040*** (-8.63)
<i>CUM_RET</i>	0.131*** (9.34)	0.130*** (9.31)	0.131*** (9.37)	0.131*** (9.37)
<i>BM</i>	-0.036*** (-4.98)	-0.035*** (-4.91)	-0.036*** (-5.03)	-0.036*** (-5.01)
<i>LEV</i>	-0.077* (-1.73)	-0.076* (-1.72)	-0.081* (-1.82)	-0.080* (-1.80)
<i>ROE</i>	0.014 (1.38)	0.014 (1.37)	0.015 (1.39)	0.015 (1.39)
<i>LNSIZE</i>	0.063*** (13.67)	0.064*** (13.89)	0.062*** (13.49)	0.062*** (13.54)
<i>DTURNOVER</i>	0.033*** (4.44)	0.033*** (4.46)	0.033*** (4.44)	0.033*** (4.42)
<i>ACCRUALS</i>	0.258*** (3.02)	0.256*** (3.01)	0.261*** (3.06)	0.260*** (3.05)
INDUSTRY FE	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES
ADJ. R ²	0.036	0.036	0.036	0.036

Notes: This table reports OLS regressions of one-year-ahead crash risk (negative return skewness), *NCSKEW*. We report results only for Topic 2 (Commodity Price Risk and Derivatives; columns (1), (2)) and Topic 7 (Risk in Product Prices and Materials Costs; columns (3), (4)). Columns (1) and (3) focus on the effects of Topic Assignments (*A_TOPIC*), while columns (2) and (4) focus on the effects of Topic Proportions (*P_TOPIC*). Please see [Appendix A3](#) for variable definitions. All regressions include Fama-French 48 industry dummies and year fixed effects. *t*-statistics, based on robust standard errors clustered at the firm level are reported in parentheses below the coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 14. Latent Topics and One-Year Ahead Down-to-Up Volatility (*DUVOL*)*Panel A. Lead DUVOL on each topic assignment without control variables (N=40,177)*

VARIABLES	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8
<i>A_TOPIC</i>	-0.003 (-0.36)	-0.016** (-2.46)	0.012 (1.42)	-0.006 (-0.58)	0.003 (0.46)	0.014* (1.91)	-0.011* (-1.75)	0.002 (0.20)
<i>DUVOL</i>	0.073*** (11.22)	0.073*** (11.20)	0.073*** (11.22)	0.073*** (11.22)	0.073*** (11.22)	0.073*** (11.21)	0.073*** (11.21)	0.073*** (11.22)
<i>MISS</i>	-0.031*** (-3.06)	-0.037*** (-4.72)	-0.018*** (-1.88)	-0.033*** (-3.06)	-0.026*** (-3.80)	-0.017*** (-1.89)	- 0.035*** (-4.34)	-0.027*** (-3.02)
INDUSTRY FE	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
ADJ. R ²	0.012	0.012	0.012	0.012	0.012	0.012	0.013	0.012

Panel B. Lead DUVOL on each topic proportion without control variables (N=40,177)

VARIABLES	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8
<i>P_TOPIC</i>	0.012 (0.64)	-0.034* (-1.81)	0.016 (0.62)	0.022 (1.09)	-0.001 (-0.06)	0.017 (0.94)	-0.050** (-2.38)	0.012 (0.59)
<i>DUVOL</i>	0.073*** (11.22)	0.073*** (11.20)	0.073*** (11.22)	0.073*** (11.22)	0.073*** (11.22)	0.073*** (11.21)	0.072*** (11.21)	0.073*** (11.22)
<i>MISS</i>	- 0.026*** (-3.75)	-0.031*** (-4.34)	-0.026*** (-3.57)	- 0.024*** (-3.43)	-0.028*** (-4.33)	-0.026*** (-3.53)	-0.032*** (-4.52)	-0.026*** (-3.78)
INDUSTRY FE	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
ADJ. R ²	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007

Notes: This table reports OLS regressions of one-year-ahead down-to-up volatility, *DUVOL*. Please see [Appendix A3](#) for variable definitions. Panel A shows the relationship between Topic Assignments and one-year ahead *DUVOL*. Panel B shows the relationship between Topic Proportions and one-year ahead *DUVOL*. All regressions include Fama-French 48 industry dummies and year fixed effects. *t*-statistics, based on robust standard errors clustered at the firm level are reported in parentheses below the coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 15. Latent Topics and One-Year Ahead Down-to-Up Volatility (*DUVOL*) Controlling for Known Predictors of Crash Risk

Dependent Variable: One-Year Ahead DUVOL (N=40,177)

VARIABLES	Topic 2		Topic 7	
	(1)	(2)	(3)	(4)
<i>A_TOPIC</i>	-0.016** (-2.55)		-0.007 (-1.08)	
<i>P_TOPIC</i>		-0.050** (-2.56)		-0.032 (-1.58)
<i>DUVOL</i>	0.071*** (10.39)	0.071*** (10.36)	0.071*** (10.40)	0.071*** (10.40)
<i>MISS</i>	-0.022*** (-3.04)	-0.017** (-2.54)	-0.017** (-2.35)	-0.015*** (-2.41)
<i>KUR</i>	0.001* (1.88)	0.001* (1.88)	0.001* (1.89)	0.001* (1.89)
<i>SIGMA</i>	-2.785*** (-6.72)	-2.781*** (-6.72)	-2.785*** (-6.72)	-2.782*** (-6.72)
<i>CUM_RET</i>	0.042*** (9.29)	0.042*** (9.28)	0.042*** (9.30)	0.042*** (9.30)
<i>BM</i>	-0.009** (-2.39)	-0.009** (-2.35)	-0.009** (-2.40)	-0.009** (-2.40)
<i>LEV</i>	-0.007 (-0.37)	-0.007 (-0.37)	-0.008 (-0.42)	-0.080 (-0.41)
<i>ROE</i>	0.008 (0.66)	0.008 (0.66)	0.008 (0.67)	0.008 (0.67)
<i>LNSIZE</i>	-0.001 (-0.63)	-0.001 (-0.49)	-0.001 (-0.70)	-0.001 (-0.69)
<i>DTURNOVER</i>	0.003 (1.16)	0.003 (1.16)	0.003 (1.15)	0.003 (1.14)
<i>ACCRUALS</i>	-0.064 (-0.68)	-0.064 (-0.68)	-0.063 (-0.67)	-0.064 (-0.67)
INDUSTRY FE	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES
ADJ. R ²	0.014	0.014	0.014	0.014

Notes: This table reports OLS regressions of one-year-ahead down-to-up volatility, *DUVOL*. We report results only for Topic 2 (Commodity Price Risk and Derivatives; columns (1), (2)) and Topic 7 (Risk in Product Prices and Materials Costs; columns (3), (4)). Columns (1) and (3) focus on the effects of Topic Assignments (*A_TOPIC*), while columns (2) and (4) focus on the effects of Topic Proportions (*P_TOPIC*). Please see [Appendix A3](#) for variable definitions. All regressions include Fama-French 48 industry dummies and year fixed effects. *t*-statistics, based on robust standard errors clustered at the firm level are reported in parentheses below the coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Manuscript 3

What Explains Variations in the Informativeness of Market Risk Disclosure?

Evidence from Institutional Ownership

by

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What Explains Variations in the Informativeness of Market Risk Disclosure?

Evidence from Institutional Ownership

Abstract

The usefulness of market risk disclosure (Item 7A) has received great attention in the last two decades, especially after the U.S. Securities and Exchange Commission (SEC) calling for further discussions on the usefulness of current market risk disclosure and on strategies to improve their informativeness. By exploring why firms voluntarily provide more informative market risk disclosures, we document that institutional ownership plays an important role in enhancing readability and consistency. We find that investors' short-term investment horizon is positively related to the readability of market risk disclosure, and investors' independence is positively associated with both readability and consistency. Our additional analyses indicate that institutional investors' information needs drive the improvement in the readability of market risk disclosure and that their monitoring effects heighten the consistency of market risk disclosure.

1. Introduction

Market risk exposures are widely used in modern asset pricing theory and risk management theory. To help market participants better assess firms' exposures to capital market risks¹, the U.S. Securities and Exchange Commission (SEC) mandated market risk disclosures by adding Item 7A, *Quantitative and Qualitative Disclosures about Market Risk*, to Form 10-K in 1997. Previous studies support the usefulness of market risk disclosures (e.g., Rajgopal, 1999; Linsmeier, Thornton, Venkatachalam, and Welker 2002; Thornton and Welker, 2004). In their market risk disclosures, firms are mandated to disclose their near-term² market risk exposures and how they manage these risks. However, current disclosure guidelines allow managerial discretion in determining disclosure formats and content of market risk disclosure, resulting in significant heterogeneity in the informativeness (e.g., Hodder, Koonce, and McAnally, 2001). Thus, understanding what affects managerial discretion in market risk disclosure practices might have broad implications for regulators, market participants, and capital markets.

Market risk disclosure reveals firms exposure to systematic risk from the capital market. Investors' wealth is largely driven by their portfolio firms' exposures to systematic risk, but these exposures are not common knowledge of investors. Heinle, Smith, and Verrecchia (2018) model shows that risk factor disclosure plays an important role when investors have imperfect knowledge about firms' exposures to systematic risk

¹ Market risks refer to risks arising from changes in interest rate, foreign currency exchange rates, commodity prices, equity prices, and other market changes that affect market risk sensitive instruments. Market Risk Disclosure FAQ - Sec.gov. <https://www.sec.gov/divisions/corpfin/guidance/derivfaq.htm>.

² The term "near term" means a period of time going forward up to one year from the date of the financial statements. See <https://www.law.cornell.edu/cfr/text/17/229.305>.

factors. Therefore, self-serving investors may have incentives to align market risk disclosure practices with their interest. In line with this argument, we examine the effects of investors on the information content of market risk disclosure. In particular, we study whether institutional ownership affects the textual characteristics of market risk disclosure and explore the mechanism behind it. We focus on institutional investors because they dominate the ownership structure of U.S. firms and influence a variety of corporate issues (e.g., Ball, 2001; Chemmanur, He, and Hu, 2009; Derrien, Kecskes, and Thesmar, 2013).

Firms have great flexibility in the wording used to discuss their market risk exposures and risk management. In a 2016 concept release, the SEC calls for more discussion on the usefulness of market risk disclosure. The SEC is interested in (1) improving the readability of market risk disclosures and, as a result, (2) allowing information users to constantly benefit from the information content of market risk disclosures. Our choice of two proxies for the informativeness of market risk disclosure, namely *readability and consistency*, is in line with the SECs' interest and we consider textual analysis as a proper way to compare the highly unstructured textual information in market risk disclosures.

Following Li (2008), we first employ *readability* measured by the Fog Index to capture how easily investors understand market risk disclosure. Highlighted by the SEC's Plain English Initiative of 1998 (SEC, 1998), lower readability of the disclosure could impede the flow of information. Then, we estimate the *consistency* of market risk disclosure using the similarity score (Brown and Tucker, 2010), which measures the degree to which the current market risk disclosure is textually similar to the preceding

one. However, greater disclosure consistency could be interpreted in two ways. On the one hand, greater consistency could be a signal of echoes of the past, which means that firms merely report redundant information, leading to an unhelpful disclosure in the longer term. On the other hand, greater consistency could reflect less uncertainty and greater managerial persistence (Bozanic and Thevenot, 2015).

We expect that the effects of different institutional investors on these two textual characteristics are not homogeneous. Previous studies, such as Callen and Fang (2013), conclude two opposite yet coexisting views on the impact of institutional investors: short-termism and monitoring. We continue this line of argument and distinguish institutional investors based on their investment horizons and independence. Next, we investigate the effects of investor horizon (independence) on readability and consistency, respectively.

We posit that investor horizon is associated with the readability of market risk disclosure. In practice, market risk exposures discussed in Item 7A are generally over a one-year period.³ Thus, market risk disclosure provides essential short-run information that drives short-term investors' decisions, but does not fully address long-term investors' concerns. Moreover, the information asymmetry between incumbent shareholders and potential investors leads to a reduction in price, and thereby short-term owners prefer more disclosures that will mitigate this information asymmetry (Cadman, Heinle, and Macciocchi, 2018). In order to inflate their own profit, short-term investors are more likely to pressure management to reduce information asymmetry on short-run

³ For example, Target Corporation reports, "Based on our balance sheet position at January 28, 2017, the **annualized** effect of a 0.5 percentage point decrease in interest rates would be to decrease earnings before income taxes by \$7 million." See Target's 2016 Annual Report at <https://corporate.target.com/annual-reports/2016/10-k/10-K-Part-II/Item-7A-Quantitative-and-Qualitative-Disclosures-A>.

market risk exposures. Based on the above argument, we predict that short-term institutional ownership is positively associated with the readability of market risk disclosure.

We further make two competing hypotheses on relationships between investor horizon and the consistency of market risk disclosure. If greater consistency represents redundant information, short-term institutional ownership should be negatively related to this feature because of short-term investors' demand for informative market risk disclosures. If the consistency is in line with the view of managerial persistence, there should exist a positive relationship between long-term institutional ownership and consistency. When long-term investors dominate the ownership, the firm is not necessarily to sacrifice long-term goals to respond to short-term concerns (e.g., Bushee, 1998; Cadman and Sunder, 2014), and thereby exhibits higher managerial persistence.

We also predict that firms with more independent investors improve the readability of market risk disclosure. Independent investors do not have the business connections with their investee firms that dependent investors possess. Prior literature suggests that independent investors demand more public information and monitor management more actively than dependent investors (e.g., Brickley, Lease, and Smith, 1988; Ramalingegowda and Yu, 2012; Sakaki, Jackson, and Jory, 2017). Thus, independent investors could pressure management to produce market risk disclosures with greater readability to reduce information asymmetry. In addition, independent investors could impede the consistency of market risk disclosure if this characteristic is associated with less informativeness, or they could be positively related to the consistency as they discipline managers to focus on maximizing the long-run firm value.

Our main results are consistent with predictions on the readability and some predictions on the consistency. We find that total institutional ownership is positively related to the readability and consistency. In addition, we find that firms with higher short-term or higher independent institutional ownership provide more readable market risk disclosure, and we observe an insignificant relationship between long-term institutional ownership and the readability of market risk disclosure. We also document a positive association between independent institutional ownership and the consistency of market risk disclosure. However, we do not find a robust relationship between consistency and both short-term and long-term ownership. These results are robust to alternative model specifications.

Our study makes several contributions. First, to the best of our knowledge, this is the first study that attempts to explain the institutional pressures/influences on managerial discretion in market risk disclosure. Despite the fact that understanding drivers of managerial discretion in market risk disclosure has broad implication for regulators and market participants, this issue receives limited attention from prior research. We identify institutional ownership as an important factor driving the differences in the information content of market risk disclosure. We reinforce the growing awareness among regulators and market participants that managerial discretion makes the information content of Item 7A susceptible to manipulation. We show that different types of existing institutional shareholders account for a significant variation in the informativeness of Item 7A.

Second, our findings, to a certain degree, address regulators' concerns. In a 2016 concept release, the SEC expressed interest in improving the usefulness of market risk

disclosure by making it more readable and comparable. Also, Wesley Bricker, the Chief Accountant of the SEC, encourages managers to be attentive in market risk disclosures.⁴ Our findings reveal that major investors' self-serving incentives, to a certain degree, explain the variation in market risk disclosure practice. Regulators can take our findings into consideration when revising disclosure requirement to improve the informativeness of market risk disclosure.

We also extend the literature on the relationship between institutional ownership and corporate disclosure. Our study provides a new scope to understand the effect of short-term investors on corporate disclosure. Different from Callen and Fang (2013) and Andreou, Antoniou, Horton, and Louca (2016), we find that short-term ownership alleviates information asymmetry. Their studies document that firm-specific stock price crash risk increases with short-term institutional ownership, suggesting short-term investors pressure managers to conceal negative information, which harms the information environment. However, our findings indicate that these negative effects of short-term investors on the information environment do not hold all the time. In our case, short-term investors reduce information asymmetry in the near future to meet their information needs.

The remainder of the paper is organized as follows. Section 2 reviews related literature and develops theoretical hypotheses. Section 3 discusses the construction of our sample. In Section 4, we present the main empirical results and robustness tests. Section 5 concludes the paper.

⁴ Remarks before the 2018 Baruch College Financial Reporting Conference: "Working Together to Advance Financial Reporting". See <https://www.sec.gov/news/speech/speech-bricker-040318>.

2. Literature and hypothesis development

2.1. Market risk disclosure – background and related research

In 1997, the SEC issued FRR No. 48, *Disclosure of Accounting Policies for Derivative Financial Instruments, and Derivative Commodity Instruments and Disclosure of Quantitative and Qualitative Information about Market Risk Inherent in Derivative Financial Instruments, Other Financial Instruments, and Derivative Commodity Instruments*, mandating registrants to disclose quantitative and qualitative information about their market risk exposures and how their risk exposures are managed (SEC 1997). The rule addresses risks arising from fluctuations in interest rates, foreign currency exchange rates, commodity prices, equity prices, and other market changes that affect market risk sensitive instruments.

A few studies investigate the impact of market risk disclosure and suggest that market risk disclosures convey useful information to investors. Earlier studies focus on the effect of the initial adoption of market risk disclosure. For example, Rajgopal (1999) and Thornton and Welker (2004) examine oil and gas producers' exposures to commodity price risk and show the adoption of market risk disclosure has an incremental power to explain stock return sensitivity to market risk factors. Linsmeier et al. (2002) find that trading volume sensitivity to changes in interest rates, foreign currency exchange rates, and energy prices significantly decreases after the initiation of Item 7A. Further, the adoption of market risk disclosure has an impact on the cost of capital (Guo, 2009).

Some recent studies consider the effect of the informativeness of market risk disclosure. In a theoretical setting, Heinle et al. (2018) investigate how investors react

to disclosures about risk exposures and provide implication for asset pricing. They assume that firms' exposures to systematic risk factors are unknown, and their model implies that market risk disclosures help reduce the uncertainty regarding the firm's cash flow volatility. Using evidence from textual analysis, Kohlbeck and Luo (2018) document that informative market risk disclosures help improve firm's stock liquidity level and reduce stock liquidity uncertainty. Goto, Luo, and Wang (2018) also document that specific topics of market risk disclosures predict future stock price crash risk.

Although market risk disclosure is mandatory to non-small reporting companies, the extent to which firms disclose market risk exposures and risk management varies across firms. The lack of details regarding the quantitative measure of market risks and the lack of discussion regarding risk management strategies may not help fulfill the objectives of FRR No.48 (Roulstone, 1999). Thus, firms' flexibility given by FRR No.48 could adversely affect information users' risk judgments (Hodder et al., 2001; Lin and Lin, 2017; Sribunnak and Wong, 2004). Though previous research investigates the impact of market risk disclosure, to the best of our knowledge, none of the existing literature examines what drives firms' discretion in market risk disclosure.

2.2. Institutional ownership

As one of the important market participants, institutional investors dominate the ownership of U.S. firms. A large body of research suggests that they have an influence on corporate policies (Derrien et al., 2013), corporate governance (Brickley et al., 1988; Chen, Harford, and Li, 2007; Gaspar, Massa, and Matos, 2005), market timing (Chemmanur et al., 2009), and accounting conservatism (Ball, 2001; Ramalingegowda

and Yu, 2012; Watts, 2003). Recent studies suggest that institutional ownership is significantly associated with the information environment of firms. For example, Boone and White (2015) document a causal effect of institutional ownership on management disclosure, analyst coverage, and stock liquidity. Peer effects literature also suggests that the increment in institutional ownership of a firm increases its competitors' likelihood and frequency to issue management forecasts (Lin, Mao, and Wang, 2018).

Following Bushee (1998), most of the studies interpret the impact of institutional ownership on corporate decisions from the view that institutional investors could act as "traders" or "owners." Trader effects refer to a scenario that institutional investors place excessive focus on short-term targets and do not efficiently discipline managers to maximize long-run value. Owner effects refer that institutional investors have incentives to monitor and discipline managers because they are sophisticated and have large equity holdings. Both of these two competing views could make sense given the different characteristics of institutional investors.

In line with the coexistence of trader effects and owner effects, one strand of literature focuses on the investment horizons of institutional investors. Institutional investors have different investment horizons because they have different maturities of liabilities or they have different investment strategies (Derrien et al., 2013). While short-term institutional investors can temporarily boost the stock price, they can also lead to excess stock price volatility and management myopia, which is detrimental to long-term firm value (Bolton, Scheinkman, and Xiong, 2006; Bushee, 1998). To cater to short-term institutional investors' interest in short-term cash flow, undervalued firms engage in less investment, less equity financing, and more dividend declaration (Derrien et al.,

2013). Conversely, long-term investors tend to monitor and discipline managers. Prior literature documents that long-term institutional investors enhance the value of acquisitions and post-merger performance, and reduce the cost of equity (Attig, Cleary, El Ghouli, and Guedhami, 2013; Chen et al., 2007; Gaspar et al., 2005).

Another strand of literature concentrates on the independence of institutional investors. Brickley et al. (1988) suggest that institutional investors who have potential business ties with their portfolio firms are less independent. As a result, they may not always act for maximizing shareholders' value. Meanwhile, the authors document that institutional investors with greater independence are more likely to monitor the management and oppose management actions if these actions are against their interests. Further, monitoring costs for independent institutions are less than those for dependent institutions. Chen et al. (2007) argue that independent institutional investors with longer horizon engage in fewer short-term tradings and exercise better monitoring through influencing management effort and gathering more information. Using international evidence, Ferreira and Matos (2008) also advocate that dependent institutional investors tend to be pressure-sensitive and support management actions.

2.3. Hypotheses development

Previous literature documents that market risk disclosures are informative to market participants (e.g., Linsmeier et al., 2002) and institutional investors' self-serving incentives motive them to influence firms' disclosure practices (e.g., Boone and White 2015). Moreover, different investment horizon and dependence of institutional ownership lead to their different incentives in influencing corporate disclosure. In this

hypotheses development section, we first discuss the association between institutional ownership horizon and characteristics of market risk disclosure. We then discuss the association between institutional ownership independence and characteristics of market risk disclosure.

2.3.1. Institutional ownership horizon and market risk disclosure

Brochet, Loumioti, and Serafeim (2015) suggest that disclosure horizon reflects the impact of investor horizons. Market risk disclosure in Item 7A focuses on near-term exposures and reduce short-term market risk uncertainty. Therefore, this information is more attractive to investors with a short-term focus. Long-term investors are relatively interested in long-term risk exposures and less depend on public information (Bushee and Noe, 2000; Porter, 1992;). Therefore, long-term investors may have fewer incentives to improve the information content of short-term disclosures. However, the widely-recognized monitoring role of long-term institutional investors may pressure managers to disclose in compliance with the “plain writing” initiative, which improves the readability of market risk disclosure. We conjecture that the effect of long-term ownership on readability reflects a trade-off between monitoring costs and information advantages.

We posit that short-term investors have incentives to affect the readability of market risk disclosure, and provide two reasons for this prediction. First, short-term institutional investors need to collect and process information in order to develop a good understanding of market risk exposures and further make better trading decisions. Less opaque and more understandable market risk disclosures reduce information processing cost of incumbent short-term institutional investors and provide a better chance of

market timing. Second, in the absence of less opaque and more understandable market risk disclosures, potential investors require a premium for the information asymmetry, which results in a reduction in price (Cadman et al., 2018). To maximize their profits from frequent tradings, short-term investors are likely to pressure managers to provide disclosures that are more readable. Managers may respond to this pressure because they fear that a disappointment will trigger large sellings, which result in a temporary undervaluation of the firm's stock price (Bushee, 1998). The above discussion leads to our first hypothesis:

Hypothesis 1: Short-term institutional ownership is positively associated with the readability of market risk disclosure.

In the introduction section, we have briefly discussed two views on the consistency of market risk disclosure. First, Abraham and Shrives (2014) suggest when the consequences of the incremental disclosures are unclear, risk-averse managers are unwilling to make changes to current disclosures. As such, market risk disclosures are textually similar over time just because management repeats disclosures from previous years. In the longer term, market risk disclosures will be overlooked as they are less informative. In order to obtain timely information, short-term investors have incentives to hinder repetitive market risk disclosures. Second, Bozanic and Thevenot (2015) document that the textual similarity of disclosures is associated with decreases in overall and common uncertainty of the information environment. This implies that managers are diligent and honest in their estimation. The view of managerial persistence suggests

that when the manager focuses on long-term goals, the firm engages in relatively stable operation, and thereby their risk exposures and risk management strategies are similar over time. Therefore, long-term investors tend to induce consistent disclosures. In contrast, it is difficult to predict the relationship between short-term investors and market risk disclosure consistency because their demands of greater information could result in consistent disclosures, but their short-term focuses could pressure managers to discuss more short-term issues. Based on the above discussion, we make the following hypotheses:

Hypothesis 2a: Short-term institutional ownership is negatively associated with the consistency of market risk disclosure.

Hypothesis 2b: Long-term institutional ownership is positively associated with the consistency of market risk disclosure.

2.3.2. Institutional ownership independence and market risk disclosure

The connection between investors and their portfolio firms determines their access to firms' private information. As having business ties with the firm, dependent investors are more likely to be knowledgeable about the decision-making process of management and form a clearer prospect of the firm's future performance. With the intent to exploit their information advantages, dependent investors have few incentives to pressure firms to provide better disclosures.

In contrast, independent investors have limited access to private information and heavily rely on firms' disclosure to advance their understanding. Previous studies

document at least two mechanisms that informative market risk disclosures may alleviate independent investors' information shortage stemmed from the lack of business relations. First, risks disclosed in Item 7A are essential information inputs of managerial decision-making and help account for firms' financing and investing activities, operating strategies, and variation in expected returns on bonds and stocks (e.g., Titman, 1992; Barry, Mann, and Mihov, 2008; Adler and Dumas, 1983; Chow, Lee, and Solt, 1997). Second, readers of market risk disclosures can access managerial risk preference and the effectiveness of risk management, as Item 7A discusses the strategy and outcome of risk management. Thus, an understandable market risk disclosure enables independent investors to interpret the information effectively. We state our Hypothesis 3 as follows:

Hypothesis 3: Independent institutional ownership is positively associated with the readability of market risk disclosure.

Independent investors are also expected to have an impact on the consistency of market risk disclosure. If the consistency represents that management providing redundant information, independent investors, as the demander of public information, are likely to impede textually-similar disclosures. Alternatively, the well-documented monitoring effects of independent investors discipline managers to be diligent and honest in their disclosure and focus on the long-run performance. Based on the view of managerial persistence, the monitoring effects could induce management to provide more consistent disclosures. This makes us predict that:

Hypothesis 4a: Independent institutional ownership is negatively associated with the consistency of market risk disclosure.

Hypothesis 4b: Independent institutional ownership is positively associated with the consistency of market risk disclosure.

3. Research Design

3.1. Sample selection

Our sample of market risk disclosures is extracted from Item 7A of 10-K filings. We obtain 10-K filings from the SEC's EDGAR filings database for fiscal years from 2003 to 2016. We exclude small reporting companies because they are not mandated to disclose market risk exposures and may have negligible institutional ownership, as Gompers and Metrick (2001) show that firm size is positively related to institutional ownership.⁵ We also exclude firms in utility and financial service industries (SIC of 4000-4999 and 6000-6999) because they are highly regulated and have different reporting practice. These exclusions result in a sample contains 43,416 firm-year observations. Then, we remove 2,376 10-K filings whose Item 7A has 100 words or less. Such market risk disclosures cannot provide sufficient information for textual analyses and imply that market risk exposures are immaterial. To measure consistency, we require that firms in our sample have at least two-consecutive-year Item 7A disclosures. This step reduces our sample by 862 observations. Financial data are from the

⁵ Smaller reporting companies are not required to disclose market risk exposures. A smaller reporting company is currently defined as a company that has a public float of less than \$75 million in common equity as of the last business day of its most recently completed second fiscal quarter, or if a public float of zero, has less than \$50 million in annual revenues as of its most recently completed fiscal year end.

COMPUSTAT database, and stock prices and returns are from the CRSP. We calculate institutional ownership based on the Thomson Reuters Institutional Holdings database (13F). Our final sample consists of 17,726 firm-year observations.

3.2. Measures of institutional ownership

We define institutional ownership as, for each publicly traded firm, the ratio of shares held by institutional investors to the number of shares outstanding (Gompers and Metrick, 2001; Asquith, Pathak, and Ritter, 2005), and the annual institutional ownership is the mean of quarterly ownerships.

Our measure of investor horizon is based on Derrien et al. (2013). We define institutional investors' horizon as their portfolio turnover, and we compute the turnover as follows. First, we compute the fraction of a stock i held by an institutional investor j that is sold in three years. Zero is assigned to this stock turnover if investor j is a net buyer of this stock during the three-year period. Second, we calculate investor j 's portfolio turnover at time t as the weighted average of all turnovers of stocks in the portfolio. The weight of each stock is the weight at time $t-3$ (i.e., three years ago). As we use quarterly data, the annual institutional investors' horizon is the average of quarterly horizons. According to the time-series means and medians of investor horizons, we consider 25% as the cutoff to divide investors into two groups. Institutional investors with a portfolio turnover of 25% or less are considered as long-term investors (Harford, Jenter, and Li, 2011). Consistent with Derrien et al. (2013), we find the distribution of the cutoff is stable over time, and investor horizons are persistent. Thus, institutional investors are either long-term investors or short-term investors.

The independence of institutional investors is based on their potential business connections with investee firms (Brickley et al., 1988; Ramalingegowda and Yu, 2012; Sakaki et al., 2017). We define investors with the 13F type code of 3 (investment companies and their managers), 4 (investment advisors), or 5 (pension funds, university endowments, and foundations) as independent investors, and investors with the 13F type code of 1 (banks) or 2 (insurance companies) are dependent investors.

Prior literature indicates that institutional ownership could be determined by some firm-specific characteristics. We address this concern by using residual ownership rather than raw ownership. Following Ramalingegowda and Yu (2012), we define the residual ownership as the residuals from the following regression (Gompers and Metrick, 2001):

$$\begin{aligned} IO_t = & \beta_0 + \beta_1 BM_{t-1} + \beta_2 SIZE_t + \beta_3 VOLATILITY_{t-2,t} + \beta_4 TURNOVER_{-3} \\ & + \beta_5 PRICE_t + \beta_6 SP500_t + \beta_7 MOMENTUM_{-2,0} \\ & + \beta_8 MOMENTUM_{-12,-3} + \beta_9 AGE_t + \beta_{10} YIELD_{t-1} + \varepsilon_t, \end{aligned} \quad (1)$$

where IO_t represents institutional ownership at the end of year t . BM_{t-1} represents book to market ratio at the end of year $t-1$. $SIZE_t$ is estimated as the natural logarithm of the market value of equity at the end of year t . $VOLATILITY_{t-2,t}$ represents the standard deviation of monthly returns over the previous two years. $TURNOVER_{-3}$ represents monthly volume adjusted by the number of shares outstanding, measured for three months prior to the end of year t . $PRICE_t$ is estimated as the natural logarithm of share price measured at the end of year t . $SP500_t$ is a dummy variable that is equal to 1 if the firm is included in the S&P 500 index the end of year t , and 0 otherwise. $MOMENTUM_{-2,0}$ is firm's three-month gross return prior to the end of year t . $MOMENTUM_{-12,3}$ is firm's nine-month gross return ending three months prior to the end of year t . AGE_t is

estimated as the natural logarithm of the number of years a firm is listed on CRSP. $YIELD_{t-1}$ is the dividend adjusted by market value at the end of year $t-1$. The firm subscript is omitted for brevity. Appendix A discusses the details of estimating residual institutional ownership.

3.3. *The information content of disclosures*

In line with the SECs' interest in (1) improving the readability of market risk disclosures and (2) allowing information users to constantly benefit from the information content of market risk disclosures (SEC), we adopt two textual measures, namely readability and consistency, to capture the characteristics of market risk disclosure. The first characteristic, readability, is measured by the Fog Index (Li, 2008)⁶. The Fog Index (*FogIndex*) captures two aspects of readability: average sentence length and the fraction of complex words. Higher Fog Index suggests lower readability. A more readable document is likely to reduce investors' uncertainty. Based on this argument, prior studies document that more readable information is associated with better information environment (e.g., Li 2008; Biddle, Hilary, and Verdi, 2009; Leheavy, Li, and Merkley, 2011; Bozanic and Thevenot, 2015). Also, the readability of firm filings is used to gauge compliance with the SEC's plain writing initiative. Therefore, a market risk disclosure with higher readability is expected to increase investors' understanding of information.

⁶ Loughran and McDonald (2014) report that 10-K document file size is a simple readability measure that outperforms the Fog Index and avoids the measurement error caused by parsing document. However, their study is based on the entire 10-K file rather than a section of the 10-K file. This file size measure may not be applicable to Item 7A because we need to parse the filing in order to extract Item 7A. Also, we notice that Item 7A file size is very small. Thus, this measure may not capture sufficient variations in the readability of market risk disclosure. Therefore, we continue to use the Fog Index as the measure of readability.

The second characteristic is the consistency between market risk disclosures in the current year and previous year. We use the similarity score (Bozanic and Thevenot, 2015) to measure the consistency of market risk disclosure. First, we calculate the frequency of a word in a document and normalize the frequency based on the document size because the frequency of a word is likely to be higher in a large document. In the first step, all words are considered equally important. Second, we weight down (up) the effects of more (less) frequently occurred words and calculate the inverse document frequency. Third, we take the product of normalized word frequency from the first step and the inverse document frequency from the second steps. Finally, we derive a vector for each document using the numbers from the third step. The cosine of the vectors of pairwise documents is the similarity score (*SimScore*). *SimScore* is between 0 and 1, and 1 indicates two disclosures are identical.

4. Empirical analyses

4.1. Descriptive Statistics

Table 16 presents the descriptive statistics of the variables used in our analyses. The average *FogIndex* and average *SimScore* for our sample are 9.632 and 0.8163, respectively. *FogIndex* of Item 7A is much lower than that of full 10-K filings documented in prior research (e.g., Lehavy et al., 2011), suggesting that Item 7A, on average, is more readable than the full 10-K filing. The average total, long-term, short-term, independent, and dependent residual ownership estimated based on Equation (1) are 14.59%, 6.52%, 6.09%, 17.14%, and -2.46%, respectively. The average long-term independent, short-term independent, long-term dependent, and short-term dependent

residual ownership are 7.55%, 8.1%, -0.99%, and -1.94%, respectively.

<Insert Table 16 >

Table 17 reports the Pearson Correlation between variables. All types of institutional ownership are negatively associated with *FogIndex*. Total, short-term, independent, and short-term independent ownership are positively related to *SimScore*. Long-term, dependent, long-term independent, long-term dependent, and short-term dependent institutional ownership are negatively related to *SimScore*. However, correlations reported in Table 17 should be interpreted with caution because they could be driven by the highly positive correlations between different types of institutional institutions.

<Insert Table 17>

4.2. Baseline model results

We investigate the impact of existing institutional ownership on the one-year-ahead readability and the consistency of market risk disclosure. We measure the disclosure variables in year t and regress them on residual ownership in year $t-1$ and firm-specific control variables. Our baseline OLS regression model is in the following general form:

$$DISCLOSURE_{i,t} = \beta_0 + \beta_1 \widehat{IO}_{i,t-1} + \beta_2 CONTROL + \beta_3 YEAR_t + \beta_4 INDUSTRY_i + \varepsilon_{i,t}, (2)$$

In this model, $Disclosure_{i,t}$ is the textual characteristics of Item 7A (i.e., readability and consistency). Our key independent variable of interest is $\widehat{IO}_{i,t-1}$, which represents different types of residual ownership. *CONTROL* stands for a set of control variables that are motivated from prior literature on the determinants of corporate

disclosure, and detailed variable definitions are presented in Appendix B. All control variables except *AGE*, *ITEM1A*, and *E-INDEX* are lagged by one year. This practice aims to minimize the endogeneity concern of the joint determination of disclosures and institutional ownership. Year fixed effects are controlled to account for the common macroeconomic environment, and industry fixed effects are controlled at Fama-French 48 industry categories to account for all time-invariant industry-level factors that could jointly determine both institutional ownership and the characteristics of market risk disclosure. Standard errors clustered at the firm level. We winsorize all continuous variables at 1% and 99% of their distribution to minimize the effects of outliers.

Besides OLS results, we report the Fama-MacBeth regression results as robust checks. Petersen (2009) suggest that the Fama-MacBeth approach, comparing with the OLS, produces unbiased standard errors and correctly sized confidence intervals when the residuals of a given year are potentially correlated across firms. We employ the Fama-MacBeth approach to address the concern that some unobservable underlying factors could affect cross-sectional residuals. Therefore, we report the results of two specifications for each dependent variable.

4.2.1. Institutional ownership and characteristics of market risk disclosures

We first examine the impact of institutional ownership on market risk disclosure without considering investor horizon and independence. Table 18 presents the impact of total institutional ownership on market risk disclosure characteristics. In Columns (1) and (2), we regress the readability measured by the Fog Index (*FogIndex*) on total institutional ownership (*rTOTAL*) and control variables. The OLS result shows that the

coefficient on *rTOTAL* is -0.479 and statistically significant at the 5% level. The Fama-MacBeth result exhibits a consistent result that the coefficient on *rTOTAL* is -0.5675 and statistically significant at the 1% level. Consistent with recent studies, such as Bonne and White (2015), our results indicate that institutional ownership improves the readability of market risk disclosure, thereby lowering information asymmetry.

In Column (3) and (4), we regress the consistency measured by the similarity score (*SimScore*) on total institutional ownership (*rTOTAL*) and control variables. Both the OLS result and the Fama-MacBeth result suggest that total institutional ownership is significantly positively related to *SimScore* with coefficients of 0.0258 and 0.0371, respectively. Our results indicate that firms with more existing institutional investors tend to provide a consistent (textually similar) market risk disclosure in the next year.

<Insert Table 18>

Turning to control variables, we find that larger firms with more business segments tend to provide less-readable market risk disclosures. This may reflect that the discussion on market risk exposures and risk management is associated with the complexity of the business. Inspired by Li (2010), we include an indicator variable for litigation risk. The regression results show firms in high litigation risk industries provide less-readable market risk disclosures, implying that these firms are more likely to use jargon and complex sentences to reduce litigation risk. We also observe that older firms, paying-dividend firms, and firms with higher book-to-market ratio disclose less-readable information in Item 7A. In addition, we control for an indicator variable for the post-Item 1A period.⁷ This variable reflects more attention of the regulator on risk

⁷ The SEC added Item 1A Risk Factor to Form 10-K in 2005. Therefore, the post-Item 1A period in this paper refers to 2006 to 2016.

disclosure. Our results show that this indicator variable is significantly positively related to the readability of market risk disclosure, suggesting that firms provide market risk disclosures with greater readability when they are restricted to more risk-disclosure requirements from the regulator.

For the consistency of market risk disclosure, both the OLS results and the Fama-MacBeth results indicate that firms will provide textually similar market risk disclosures when they have higher book-to-market ratio, more foreign segments, and higher litigation risk. After the initiation of Item 1A, firms are more likely to provide consistent market risk disclosures.

4.2.2. Investor horizon and characteristics of market risk disclosures

In this subsection, we investigate whether investor horizon affects the information content of market risk disclosure. We first examine the relationship between institutional ownership with different investment horizon and the one-year-ahead readability of market risk disclosure. We argue that short-term institutional investors are significant for improving the readability of market risk disclosure, whereas long-term institutional investors are less likely to affect this short-run-focused disclosure.

To test our predictions, we estimate Eq. (2) and include both short-term ownership and long-term ownership in the regressions simultaneously. Column (1) and (2) of Table 19 report our results. We find that short-term institutional ownership enhances the readability of market risk disclosure. The estimated coefficients from the OLS regression and the Fama-MacBeth regression are negative and significant,

indicating a consistently positive relationship between short-term institutional ownership and readability. Our results are also economically significant. Brochet et al. (2015) suggest that investors' horizon can affect disclosure horizon. In our case, short-term investors' information needs, to some extent, improve the information environment of their investee firms.

Long-term ownership is not significantly related to the readability of market risk disclosure. This finding implies that monitoring costs outweigh the benefits that long-term investors could obtain from a more readable market risk disclosure. In summary, the findings are consistent with our Hypothesis 1.

Next, we argue that investor horizon could affect the consistency of market risk disclosure. However, the mixed interpretations of consistency lead to mixed predictions on which type of investors are related to this characteristic. We posit that short-term investors enhance consistency if this is a signal of redundant information, and long-term investors boost consistency if this is a signal of managerial persistence.

Column (3) and (4) of Table 19 show the results. We find short-term institutional ownership is insignificantly associated with the consistency of market risk disclosure. Long-term institutional ownership is significantly positively related to consistency when we use the Fama-MacBeth approach to estimate Eq. (2). However, this relationship is not robust for the OLS estimation. These inconsistent findings may suggest the consideration of monitoring costs.

<Insert Table 19>

Overall, the findings are more likely to support Hypothesis 2b rather than Hypothesis 2a, indicating that the consistency of market risk disclosure is more likely

to signal managerial persistence rather than redundant information.

4.2.3. Investor independence and characteristics of market risk disclosures

In this subsection, we focus on the effect of investor independence on textual characteristics of market risk disclosure. Our partition of investor independence is based on the business connection between institutional investors and their investee firms. Following prior literature (e.g., Ramalingegowda and Yu, 2012; Sakaki et al., 2017), we consider institutional investors who are banks or insurance firms as dependent investors and others as independent investors. Our Hypothesis 3 predicts that independent institutional ownership is positively related to the readability of market risk disclosure.

Column (1) and (2) of Table 20 reports the results of estimating Eq. (2) whose key explanatory variables are both independent and dependent institutional ownership. Both the OLS and the Fama-MacBeth regression results suggest a significantly negative association between independent institutional ownership and the Fog Index. These findings support our hypothesis, indicating that independent investors more depend on public information relative to dependent investors. This is consistent with the argument that independent investors have limited access to private information. Since extensive literature, such as Chen et al. (2007), shows that independent institutional investors are more active in monitoring, one could argue that their positive effect on readability is due to monitoring effect. We show that this argument is less likely to explain our findings by conducting additional analyses in Section 4.4.

<Insert Table 20>

We next test whether investor independence is related to the consistency of

market risk disclosure. Our prediction on the relationship between independence and consistency is still based on the interpretation of the consistency of market risk disclosure. When consistency indicates that managers provide boilerplate information, independent investors' information needs lead to a negative association between their ownership and the consistency of market risk disclosure. In contrast, when consistency represents greater focuses on long-run value maximization, independent investors heighten governance, leading to a positive relationship between their ownership and consistency.

We test our predictions in Column (3) and (4) of Table 20. We find a significantly positive relationship between independent institutional ownership and the consistency of market risk disclosure. This relationship holds for both regression specifications. Thus, these findings are consistent with our Hypothesis 4b, suggesting that it is more likely to interpret the consistency of market risk disclosure as a signal of managerial persistence rather than providing redundant information.

4.3. Discussion on causality

Our main results are based on residual institutional ownership rather than raw institutional ownership. The residual ownership approach help mitigate an endogeneity concern that institutional ownership is determined by firm characteristics. In this section, we further address two causality concerns, reverse causality and simultaneity. We argue that reverse causality is less plausible because we focus on the impact of incumbent institutional investors rather than the change in the ownership. Existing residual ownership is relatively exogenous to one-year-ahead market risk disclosure because

incumbent ownership is less likely to be determined by the future discretionary characteristics. Hence, we do not need an external shock, such as the Russell 1000/2000 reconstitution in previous studies (e.g., Boone and White, 2015) to alleviate the reverse causality concern.

Further, the residual ownership may still consist some unknown factors that drive institutional ownership and textual characteristics simultaneously. However, this possibility is less likely to affect our results. We find that Gompers-Metrick (2001) determinants explain almost half of the variations in institutional ownership. Prior research, such as Ramalingegowda and Yu (2012), adds other factors to this model, but add little explanatory power. In addition, the R^2 s of our models are less than 0.12, implying that unobserved managerial discretion could account for a large portion of the variations in dependent variables. Therefore, it could be hard to find a factor(s) that can significantly drive both existing residual ownership and textual characteristics of market risk disclosure.

4.4. Additional tests

4.4.1. Joint effects of investor horizon and independence

As the effect of institutional ownership on the consistency could be interpreted by both information needs and monitoring effects, we provide a further analysis of the joint effects of investor horizon and independence to explore potential mechanism behind it. We sort all institutional investors into four categories: long-term independent investors, long-term dependent investors, short-term independent investors, and short-term dependent investors. Among these four groups of investors, we specifically focus

on two groups: long-term independent investors and short-term independent investors. Chen et al. (2007) suggest that long-term independent investors have the strongest incentives to monitor managers. Thus, their effects are more likely to reflect monitoring effects. Similarly, short-term independent investors have the strongest information needs, and their influence mostly stems from their information demands.

<Insert Table 21>

We present our findings in Table 21. Column (1) and (2) show that short-term institutional ownership is significantly negatively related to the Fog Index, but long-term independent institutional ownership does not have a consistently significant effect on the readability of market risk disclosure. These findings imply that information needs are more likely to drive the improvement of the readability of market risk disclosure. In addition, the monitoring effects are less influential on readability.

In Column (3) and (4), we find that long-term independent institutional ownership is the only group that significantly affect the consistency of market risk disclosure. Thus, our results suggest that consistency, in our case, is mostly driven by monitoring effects, and thereby reflects managerial consistency as we expect in Hypothesis 4b.

Incorporating our findings, we argue that information needs drive the improvement in the readability of market risk disclosure and that monitoring effects heighten the consistency of market risk disclosure.

4.4.2. The impact of firms' overall information environment

Since market risk disclosure is a part of corporate disclosures, the

informativeness of market risk disclosures *per se* could be consistent with the overall information environment of the firm. To address this issue, we control for the overall information quality in our regressions. Our proxy for the overall information quality is the accrual quality developed by Dechow and Dichev (2002) and modified by McNichols (2002). Unlike the modified Jones Model (1991), this measure focuses on short-term working accruals and captures the extent to which accruals map into cash flows. We estimate a cross-sectional regression as demonstrated by Equation (3) by year for each industry to obtain residuals, which represent accrual estimation errors. We then calculate the standard deviation of residuals over the previous four years. Lower standard deviation represents higher accruals quality.

$$WC_CHANGE_{i,t} = \beta_0 + \beta_1 CFO_{i,t-1} + \beta_2 CFO_{i,t} + \beta_3 CFO_{i,t+1} + \beta_4 \Delta SALES_{i,t} + \beta_5 PPE_{i,t} + \varepsilon_{i,t}, \quad (3)$$

Variables in Equation (3) are defined as follows. $WC_CHANGE_{i,t}$ represents the change in working capital, including the sum of the increase in accounts receivable, the increase in the inventory, the decrease in accounts payable, the decrease in accrued tax, the increase in other assets, and the decrease in other liabilities, all scaled by average total assets. $CFO_{i,t-1}$, $CFO_{i,t}$ and $CFO_{i,t+1}$ stand for cash flow from operating activities in year $t-1$, t , and $t+1$, respectively. $\Delta SALES_{i,t}$ is the change in sales, scaled by total assets at the beginning of fiscal year t . $PPE_{i,t}$ represents the gross value of property, plants, and equipment, scaled by total assets at the beginning of fiscal year t .

Table 22 presents the regression estimates. After controlling for accrual quality, the impacts of institutional ownership on the characteristics of market risk disclosure still hold and are consistent with the baseline model results. We also observe that higher

accrual quality is associated with higher readability and higher consistency of market risk disclosures.

<Insert Table 22>

5. Conclusion

Market risk disclosures provide market participants useful information and the SEC is interested in improving the informativeness of market risk disclosure (SEC, 2016). In order to improve the quality of market risk disclosure, it is important to understand factors that cause managerial discretion in market risk disclosure. This study investigates the relationship between institutional ownership and information quality of market risk disclosure. Using textual analysis and residual institutional ownership, we find that institutional ownership enhances the readability and consistency of market disclosure. In addition, we find that short-term institutional ownership is significantly positively related to readability and independent institutional ownership is significantly positively associated with both readability and consistency. Our additional analyses indicate that information needs drive the improvement of the readability of market risk disclosure, and monitoring effects drive the enhancement of the consistency of market risk disclosure. Our results still hold when we consider the overall information environment of firms. Taken together, these results also suggest the consistency of market risk disclosure is a signal of managerial persistence and good governance.

Our study makes several contributions. First, we identify institutional ownership as an important factor driving the variations in the information content of market risk disclosure. Second, we address regulators' concern on improving the usefulness of

market risk disclosure. In addition, we provide a new scope to understand the effect of short-term investors on corporate disclosure. In the case of market risk disclosure, short-term ownership improves the informativeness of market risk disclosure, and thereby lower information asymmetry.

Reference

- Abraham, S., Shrives, P. J., 2014. Improving the relevance of risk factor disclosure in corporate annual reports. *The British Accounting Review*, 46(1), 91-107.
- Adler, M., Dumas, B., 1983. International portfolio choice and corporation finance: A synthesis. *The Journal of Finance*, 38(3), 925-984.
- Andreou, P. C., Antoniou, C., Horton, J., Louca, C., 2016. Corporate governance and firm-specific stock price crashes. *European Financial Management*, 22(5), 916-956.
- Asquith, P., Pathak, P. A., Ritter, J. R., 2005. Short interest, institutional ownership, and stock returns. *Journal of Financial Economics*, 78(2), 243-276.
- Attig, N., Cleary, S., El Ghouli, S., Guedhami, O., 2013. Institutional investment horizons and the cost of equity capital. *Financial Management*, 42(2), 441-477.
- Ball, R., 2001. Infrastructure requirements for an economically efficient system of public financial reporting and disclosure. *Brookings-Wharton papers on financial services*, 2001(1), 127-169.
- Barry, C. B., Mann, S. C., Mihov, V. T., Rodriguez, M., 2008. Corporate debt issuance and the historical level of interest rates. *Financial Management*, 37(3), 413-430.
- Bebchuk, L., Cohen, A., Ferrell, A., 2009. What matters in corporate governance?. *The Review of Financial Studies*, 22(2), 783-827.
- Biddle, G. C., Hilary, G., Verdi, R. S., 2009. How does financial reporting quality relate to investment efficiency?. *Journal of Accounting and Economics*, 48(2-3), 112-131.
- Bolton, P., Scheinkman, J., Xiong, W., 2006. Executive compensation and short-termist behavior in speculative markets. *The Review of Economic Studies*, 73(3), 577-610.
- Boone, A. L., White, J. T., 2015. The effect of institutional ownership on firm transparency and information production. *Journal of Financial Economics*, 117(3), 508-533.
- Bourveau, T., Schoenfeld, J., 2017. Shareholder activism and voluntary disclosure. *Review of Accounting Studies*, 22(3), 1307-1339.
- Bozanic, Z., Thevenot, M., 2015. Qualitative disclosure and changes in Sell-Side financial analysts' information environment. *Contemporary Accounting Research*, 32(4), 1595-1616.

- Brickley, J. A., Lease, R. C., Smith Jr, C. W., 1988. Ownership structure and voting on antitakeover amendments. *Journal of Financial Economics*, 20, 267-291.
- Brochet, F., Loumiot, M., Serafeim, G., 2015. Speaking of the short-term: Disclosure horizon and managerial myopia. *Review of Accounting Studies*, 20(3), 1122-1163.
- Brown, S. V., Tucker, J. W., 2010. Large-sample evidence on firms' year-over-year MD&A modifications. *Journal of Accounting Research*, 49(2), 309-346.
- Bushee, B. J., 1998. The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review*, 73(3) 305-333.
- Bushee, B. J., Noe, C. F., 2000. Corporate disclosure practices, institutional investors, and stock return volatility. *Journal of Accounting Research*, 38, 171-202.
- Cadman, B. D., Heinle, M. S., Macciocchi, D., 2018. Investor Horizon and Disclosure Policies. *SSRN Working Paper*.
- Cadman, B., Sunder, J., 2014. Investor horizon and CEO horizon incentives. *The Accounting Review*, 89(4), 1299-1328.
- Callen, J. L., Fang, X., 2013. Institutional investor stability and crash risk: Monitoring versus short-termism?. *Journal of Banking & Finance*, 37(8), 3047-3063.
- Chemmanur, T. J., He, S., Hu, G., 2009. The role of institutional investors in seasoned equity offerings. *Journal of Financial Economics*, 94(3), 384-411.
- Chen, X., Harford, J., Li, K., 2007. Monitoring: Which institutions matter?. *Journal of Financial Economics*, 86(2), 279-305.
- Chow, E. H., Lee, W. Y., Solt, M. E., 1997. The exchange-rate risk exposure of asset returns. *Journal of Business*, 105-123.
- Dechow, P. M., Dichev, I. D., 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review*, 77(s-1), 35-59.
- Derrien, F., Kecskés, A., Thesmar, D., 2013. Investor horizons and corporate policies. *Journal of Financial and Quantitative Analysis*, 48(6), 1755-1780.
- Fama, E. F., MacBeth, J. D., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3), 607-636.

- Ferreira, M. A., Matos, P., 2008. The colors of investors' money: The role of institutional investors around the world. *Journal of Financial Economics*, 88(3), 499-533.
- Gaspar, J. M., Massa, M., Matos, P., 2005. Shareholder investment horizons and the market for corporate control. *Journal of Financial Economics*, 76(1), 135-165.
- Gompers, P. A., Metrick, A., 2001. Institutional investors and equity prices. *The Quarterly Journal of Economics*, 116(1), 229-259.
- Goto, S., Luo, X., Wang, Z., 2018. Market Risk Disclosures and Stock Price Crash Risk. *Working Paper*.
- Guo, H. T., 2009. Quantitative Market Risk Disclosure, Bond Default Risk and the Cost of Debt: Why Value at Risk?. *Advances in Quantitative Analysis of Finance and Accounting*, (7), 175-214.
- Harford, J., Jenter, D., Li, K., 2011. Institutional cross-holdings and their effect on acquisition decisions. *Journal of Financial Economics*, 99(1), 27-39.
- Heinle, M. S., Smith, K. C., Verrecchia, R. E., 2018. Risk-Factor Disclosure and Asset Prices. *The Accounting Review*, 93(2), 191-208.
- Hodder, L., Koonce, L., McAnally, M. L., 2001. SEC market risk disclosures: Implications for judgment and decision making. *Accounting Horizons*, 15(1), 49-70.
- Jones, J. J., 1991. Earnings management during import relief investigations. *Journal of Accounting Research*, 29(2), 193-228.
- Kohlbeck, M., Luo, X., 2018. The association of the relative informativeness of market risk disclosures with stock liquidity. *Working Paper*.
- Lehavy, R., Li, F., Merkley, K., 2011. The effect of annual report readability on analyst following and the properties of their earnings forecasts. *The Accounting Review*, 86(3), 1087-1115.
- Li, F., 2008. Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics*, 45(2-3), 221-247.
- Li, X., 2010. The impacts of product market competition on the quantity and quality of voluntary disclosures. *Review of Accounting Studies*, 15(3), 663-711.
- Lin, B. X., Lin, C. M., 2017. SEC FRR No. 48 and analyst forecast accuracy. *Applied Economics Letters*, 24(6), 427-432.

- Lin, Y., Mao, Y., Wang, Z., 2017. Institutional Ownership, Peer Pressure and Voluntary Disclosures. *The Accounting Review*, 93(4), 283-308.
- Linsmeier, T. J., Thornton, D. B., Venkatachalam, M., Welker, M., 2002. The effect of mandated market risk disclosures on trading volume sensitivity to interest rate, exchange rate, and commodity price movements. *The Accounting Review*, 77(2), 343-377.
- Loughran, T., McDonald, B., 2014. Measuring readability in financial disclosures. *The Journal of Finance*, 69(4), 1643-1671.
- McNichols, M. F., 2002. Discussion of The Quality Earnings of Accruals and Earnings: The of Role of Estimation Errors, *The Accounting Review*, 77 (s-1), 61–69.
- Petersen, M. A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, 22(1), 435-480.
- Porter, M. E., 1992. Capital disadvantage: America's failing capital investment system. *Harvard Business Review*, 70(5), 65-82.
- Rajgopal, S., 1999. Early evidence on the informativeness of the SEC's market risk disclosures: The case of commodity price risk exposure of oil and gas producers. *The Accounting Review*, 74(3), 251-280.
- Ramalingegowda, S., Yu, Y., 2012. Institutional ownership and conservatism. *Journal of Accounting and Economics*, 53(1-2), 98-114.
- Roulstone, D. T., 1999. Effect of SEC financial reporting release No. 48 on derivative and market risk disclosures. *Accounting Horizons*, 13(4), 343-363.
- Sakaki, H., Jackson, D., Jory, S., 2017. Institutional ownership stability and real earnings management. *Review of Quantitative Finance and Accounting*, 49(1), 227-244.
- Securities and Exchange Commission (SEC), 1997. *Disclosure of Accounting Policies for Derivative Financial Instruments, and Derivative Commodity Instruments and Disclosure of Quantitative and Qualitative Information about Market Risk Inherent in Derivative Financial Instruments, Other Financial Instruments, and Derivative Commodity Instruments*. Release Nos. 33–7386; 34–38223; IC-22487; FR 48; International Series No.1047; File No. 27-35-95. Washington, D.C.: SEC.
- Securities and Exchange Commission (SEC), 1998. A Plain English Handbook: How to create clear SEC disclosure documents. Washington, D.C.: SEC.
- Securities and Exchange Commission (SEC), 2016. SEC Concept Release: *Business*

and Financial Disclosure Required by Regulation S-K. Release Nos. 33-10064; 34-77599; File No. S7-06-16. Washington, DC.: SEC.

Sribunnak, V., Wong, M. H., 2004. Foreign exchange sensitivity-analysis disclosures and market-based risk measures. *Working Paper*.

Titman, S., 1992. Interest rate swaps and corporate financing choices. *The Journal of Finance*, 47(4), 1503-1516.

Thornton, D. B., Welker, M., 2004. The effect of oil and gas producers' FRR No. 48 disclosures on investors' risk assessments. *Journal of Accounting, Auditing & Finance*, 19(1), 85-114.

Watts, R. L., 2003. Conservatism in accounting part I: Explanations and implications. *Accounting Horizons*, 17(3), 207-221.

Appendix A. Estimation of residual ownership by different types of institution

We estimate Equation (1) for each type of institutional ownership using the Fama-MacBeth regression. Theoretically, the residual ownership is related to raw institutional ownership, but is not related to firm-specific characteristics. Including the residual ownership in our main regressions alleviate the concern that some significant economic determinants of institutional ownership also explain the characteristics of market risk disclosure. Table A1 reports the results of the Fama-MacBeth regressions. We regress different types of institutional ownership on ten Gompers-Metrick (2001) determinants. Our results are consistent with prior research. We find that all types of institutional investors tend to invest more in larger, less volatile, and liquid firms, and they are not momentum investors. We also find differences across these institutional investors. For instance, long-term institutions and dependent institutions are more likely to invest in mature firms with the higher dividend yield, but short-term institutions and independent institutions tend to invest in younger firms with lower dividend yield.

<Insert Table A1>

We extract regression residuals as our residual ownership measures and denote them as $rTOTAL$, $rLONG$, $rSHORT$, $rIND$, $rDEP$, $rLONGIND$, $rLONGDEP$, $rSHORTIND$, and $rSHORTDEP$ for our nine categories of raw institutional ownership, respectively.

Table A1. Annual Fama-MacBeth regressions of institutional ownership on Gompers-Metrick (2001) determinants

	Horizon			Independence			Horizon×Independence		
	TOTAL _t	LONG _t	SHORT _t	IND _t	DEP _t	LONGIND _t	SHORTIND _t	LONGDEP _t	SHORTDEP _t
BM _{t-1}	0.0011 (0.850)	0.0034*** (4.014)	-0.0022* (-1.860)	0.0004 (0.284)	0.0006 (1.459)	0.0031*** (3.588)	-0.0022* (-1.793)	0.0006*** (4.534)	-0.0001 (-0.166)
SIZE _t	0.0682*** (24.102)	0.0293*** (15.743)	0.0395*** (22.375)	0.0498*** (13.591)	0.0165*** (20.703)	0.0181*** (8.614)	0.0309*** (14.367)	0.0092*** (25.151)	0.0058*** (5.990)
VOLATILITY _{t-2,t}	-0.2828*** (-7.432)	-0.1393*** (-7.642)	-0.1630*** (-4.957)	-0.2159*** (-7.679)	-0.0778*** (-4.868)	-0.1158*** (-7.079)	-0.1161*** (-5.868)	-0.0325*** (-8.101)	-0.0568*** (-3.479)
TURNOVER ₋₃	0.0020*** (7.551)	0.0005*** (5.849)	0.0016*** (7.143)	0.0020*** (8.384)	0.0000 (0.163)	0.0005*** (6.697)	0.0016*** (7.950)	-0.0000 (-0.325)	-0.0000 (-0.008)
PRICE _t	0.0463*** (15.711)	0.0229*** (14.187)	0.0269*** (17.770)	0.0431*** (18.057)	0.0057*** (9.359)	0.0208*** (17.305)	0.0256*** (20.950)	0.0038*** (10.780)	0.0039*** (6.421)
SP500 _t	-0.0792*** (-4.119)	-0.0275*** (-2.927)	-0.0516*** (-4.438)	-0.0989*** (-5.886)	0.0210*** (7.272)	-0.0420*** (-5.346)	-0.0570*** (-5.695)	0.0169*** (8.789)	0.0077*** (3.493)
MOMENTUM _{-2,0}	-0.0547*** (-8.882)	-0.0286*** (-8.596)	-0.0288*** (-8.693)	-0.0449*** (-8.060)	-0.0107*** (-9.927)	-0.0218*** (-7.298)	-0.0249*** (-8.122)	-0.0069*** (-10.482)	-0.0041*** (-4.384)
MOMENTUM _{-12,-3}	-0.0344*** (-9.202)	-0.0210*** (-8.505)	-0.0150*** (-8.109)	-0.0278*** (-7.659)	-0.0065*** (-10.248)	-0.0171*** (-7.421)	-0.0123*** (-7.423)	-0.0043*** (-12.509)	-0.0025*** (-3.500)
AGE _t	0.0002 (0.081)	0.0168*** (14.929)	-0.0156*** (-6.606)	-0.0067*** (-2.995)	0.0065*** (7.261)	0.0099*** (12.003)	-0.0162*** (-7.004)	0.0066*** (13.026)	0.0004 (0.789)
YIELD _{t-1}	-0.1168** (-2.175)	0.0500* (1.800)	-0.1694*** (-4.505)	-0.2096*** (-4.381)	0.0855*** (3.266)	-0.0144 (-0.805)	-0.2046*** (-5.375)	0.0607*** (3.342)	0.0291** (2.164)
CONSTANT	-0.0286*** (-3.142)	-0.0303*** (-6.481)	0.0076 (1.149)	0.0104 (1.210)	-0.0319*** (-9.030)	0.0040 (0.827)	0.0178*** (2.850)	-0.0251*** (-12.554)	0.0018 (0.888)
N	110,758	104,274	108,199	108,141	106,613	99,617	106,180	99,747	93,235
Adj. R ²	0.571	0.472	0.469	0.482	0.463	0.329	0.412	0.428	0.18

This table reports the results of the Fama-MacBeth regression of different types of institutional ownership on ten Gompers-Metrick (2001) determinants. Following Ramalingegowda and Yu (2012), we mitigate the endogeneity concern use residuals of these regressions to construct the measure of residual ownership and omit firm subscripts i for brevity. TOTAL_t is the total institutional ownership at the end of year t . LONG_t and SHORT_t represent the ownership by long-term and short-term institutional investors, respectively, at the end of year t . IND_t and DEP_t represent the ownership by independent and dependent institutional investors, respectively, at the end of year t . LONGIND_t, LONGDEP_t, SHORTDEP_t represent the ownership by long-term independent institutional investors, short-term independent institutional investors, long-term dependent institutional investors, and short-term dependent institutional investors at the end of year t , respectively. BM_{t-1} is book to market ratio at the end of year $t-1$. SIZE_t is the natural logarithm of market value of equity at the end of year t . VOLATILITY_{t-2,t} is the standard deviation of monthly returns over the previous two years. TURNOVER₋₃ is the monthly volume adjusted by the number of shares outstanding, measured for three months prior to the end of year t . PRICE_t is the natural logarithm of share price measured at the end of year t . SP500_t is a dummy variable that is equal to 1 if the firm is included in the S&P 500 index the end of year t , and 0 otherwise. MOMENTUM_{-2,0} is firm's three-month gross return prior to the end of year t . MOMENTUM_{-12,-3} is firm's nine-month gross return ending three months prior to the end of year t . AGE_t is the natural logarithm of the number of years a firm is listed on CRSP. YIELD_{t-1} is the dividend adjusted by market value at the end of year $t-1$. We report t -statistic in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Appendix B. Control variable description

Variable name	Description
SIZE	The natural logarithm of market value of equity in year $t-1$.
BM	Book to market ratio of the firm in year $t-1$.
LEV	Leverage ratio calculated as book value of debt to book value of assets in year $t-1$.
FOREIGNSALE	The number of foreign sales adjusted by total sales in year $t-1$.
FOREIGNSEG	The number of foreign segments in year $t-1$.
BUSSEG	The number of business segments in year $t-1$.
COVERAGE	The number of unique analysts providing annual forecasts in year $t-1$.
STDRET	The standard deviation of daily stock returns of the firm over year $t-1$.
LITRISK	A dummy variable that equals to one if the firm is in SIC industries 2833-3836, 3507-3577, 3600-3674, 5200-5961, or 7370-7374, which are industries with high litigation risk, and zero otherwise.
DIV	A dummy variable that equals to one if the firm pays dividends in year $t-1$, and zero otherwise.
HASD	A dummy variable that equals to one if the firm uses derivative instruments in year $t-1$, and zero otherwise.
TOBINQ	Market value of assets (book value of assets plus market value of common stock less book value of common stock and balance sheet deferred taxes) divided by book value of assets.
AGE	The natural logarithm of the number of years a firm is listed on CRSP, measured in year t .
ITEM1A	A dummy variable measured in year t . that equals to one if the firm-year is between 2006 and 2016, and zero otherwise.
E-INDEX	The entrenchment index from Bebchuk, Cohen, and Ferrell (2009), measured in year t .

This table provides definitions of the independent variables controlled in the empirical analysis.

Table 16. Descriptive statistics

	N	Mean	Std Dev	P25	Median	P75
<i>FogIndex_t</i>	17,726	9.6320	1.5817	8.4000	9.6000	10.4000
<i>SimScore_t</i>	17,726	0.8163	0.2055	0.7684	0.8909	0.9501
<i>rTOTAL_{t-1}</i>	17,726	0.1459	0.2067	0.0039	0.1569	0.2966
<i>rLONG_{t-1}</i>	17,726	0.0652	0.1227	-0.0236	0.0537	0.1468
<i>rSHORT_{t-1}</i>	17,726	0.0609	0.1370	-0.0386	0.0584	0.1548
<i>rIND_{t-1}</i>	17,726	0.1714	0.1877	0.0405	0.1860	0.3104
<i>rDEP_{t-1}</i>	17,726	-0.0246	0.0430	-0.0527	-0.0304	-0.0018
<i>rLONGIND_{t-1}</i>	17,726	0.0755	0.1100	-0.0055	0.0644	0.1458
<i>rSHORTIND_{t-1}</i>	17,726	0.0810	0.1306	-0.0156	0.0801	0.1726
<i>rLONGDEP_{t-1}</i>	17,726	-0.0099	0.0275	-0.0282	-0.0141	0.0035
<i>rSHORTDEP_{t-1}</i>	17,726	-0.0194	0.0268	-0.0363	-0.0244	-0.0090
<i>SIZE_{t-1}</i>	17,726	6.4312	1.7263	5.2669	6.3713	7.5390
<i>BM_{t-1}</i>	17,726	0.3029	0.5377	0.0885	0.2536	0.4932
<i>LEV_{t-1}</i>	17,726	0.3963	1.1115	0.0020	0.1158	0.3652
<i>FOREIGNSALE_{t-1}</i>	17,726	0.0131	0.0504	0.0000	0.0000	0.0169
<i>FOREIGNSEG_{t-1}</i>	17,726	4.8231	6.6551	0.0000	3.0000	7.0000
<i>BUSSEG_{t-1}</i>	17,726	5.9467	4.7673	3.0000	3.0000	9.0000
<i>COVERAGE_{t-1}</i>	17,726	6.1778	8.8005	0.0000	2.0000	9.0000
<i>STDRET_{t-1}</i>	17,726	0.0287	0.0156	0.0181	0.0250	0.0351
<i>LITRISK_{t-1}</i>	17,726	0.3961	0.4891	0.0000	0.0000	1.0000
<i>DIV_{t-1}</i>	17,726	0.3693	0.4826	0.0000	0.0000	1.0000
<i>HASD_{t-1}</i>	17,726	0.3375	0.4729	0.0000	0.0000	1.0000
<i>TOBINQ_{t-1}</i>	17,726	2.1208	1.6541	1.1798	1.6010	2.4307
<i>AGE_t</i>	17,726	5.0604	0.8992	4.5433	5.1475	5.6630
<i>ITEM1A_t</i>	17,726	0.7566	0.4292	1.0000	1.0000	1.0000
<i>E-INDEX_t</i>	17,726	1.5788	1.9620	0.0000	0.0000	3.0000

This table reports descriptive statistics for the sample. There are 17,726 firm-year observations. Control variable definitions are in Appendix B.

Table 17. Pearson correlations

Panel A: Dependent variables and key explanatory variables										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>FogIndex_t</i> (1)										
<i>SimScore_t</i> (2)	0.0402**									
<i>rTOTAL_{t-1}</i> (3)	-0.0861**	0.0279**								
<i>rLONG_{t-1}</i> (4)	-0.0614**	-0.0319**	0.7586**							
<i>rSHORT_{t-1}</i> (5)	-0.0750**	0.0654**	0.8106**	0.2395**						
<i>rIND_{t-1}</i> (6)	-0.0776**	0.0451**	0.9778**	0.7197**	0.8094**					
<i>rDEP_{t-1}</i> (7)	-0.0671**	-0.0607**	0.4911**	0.4724**	0.3286**	0.3038**				
<i>rLONGIND_{t-1}</i> (8)	-0.0520**	-0.0196**	0.7341**	0.9737**	0.2229**	0.7293**	0.3192**			
<i>rSHORTIND_{t-1}</i> (9)	-0.0677**	0.0762**	0.7799**	0.2081**	0.9785**	0.8116**	0.1815**	0.1983**		
<i>rLONGDEP_{t-1}</i> (10)	-0.0623**	-0.0672**	0.4417**	0.5371**	0.1929**	0.2986**	0.7947**	0.3392**	0.1535**	
<i>rSHORTDEP_{t-1}</i> (11)	-0.0475**	-0.0330**	0.3438**	0.2067**	0.3402**	0.1941**	0.7695**	0.1711**	0.1450**	0.2392**
Panel B: Control variables										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>SIZE_{t-1}</i>	0.0609**	0.0767**	0.0034	-0.0713**	0.0315**	0.0790**	-0.3028**	-0.0229**	0.1067**	-0.2023**
<i>BM_{t-1}</i>	0.0275**	0.0140	0.0301**	0.0887**	-0.0243**	0.0029	0.1218**	0.0730**	-0.0513**	0.0882**
<i>LEV_{t-1}</i>	0.0001	-0.0225**	0.0722**	0.0762**	0.0452**	0.0528**	0.1018**	0.0664**	0.0259**	0.0706**
<i>FOREIGNSALE_{t-1}</i>	0.0170**	0.0292**	-0.0391**	-0.0601**	-0.0150**	-0.0127	-0.1253**	-0.0390**	0.0087	-0.1060**
<i>FOREIGNSEG_{t-1}</i>	-0.0296**	0.0413**	0.0214**	0.0071	0.0212**	0.0366**	-0.0460**	0.0203**	0.0318**	-0.0412**
<i>BUSSEG_{t-1}</i>	0.0636**	0.0093	-0.0071	0.0088	-0.0273**	-0.0033	-0.0201**	0.0152**	-0.0216**	-0.0212**
<i>COVERAGE_{t-1}</i>	0.0562**	0.0410**	0.0117	-0.0482**	0.0425**	0.0495**	-0.1426**	-0.0271**	0.0855**	-0.0831**
<i>STDRET_{t-1}</i>	-0.0127	-0.1021**	-0.0612**	0.0069	-0.0641**	-0.1188**	0.2361**	-0.0299**	-0.1189**	0.1672**
<i>LITRISK_{t-1}</i>	-0.0071	-0.0019	-0.0342**	-0.0533**	0.0056	-0.0345**	0.0028	-0.0569**	0.0058	0.0208**
<i>DIV_{t-1}</i>	0.0945**	0.0318**	-0.1085**	-0.0479**	-0.1378**	-0.0882**	-0.1379**	-0.0303**	-0.1126**	-0.1006**
<i>HASD_{t-1}</i>	0.0468**	0.0447**	0.0239**	-0.0109	0.0289**	0.0504**	-0.1033**	0.0091	0.0544**	-0.0782**
<i>TOBINO_{t-1}</i>	0.0178**	0.0146	0.1613**	-0.2026**	-0.0624**	-0.1362**	-0.1648**	-0.1884**	-0.0380**	-0.1316**
<i>AGE_t</i>	0.0718**	0.0503**	-0.0473**	-0.0410**	-0.0478**	-0.0202**	-0.1346**	-0.0118	-0.0247**	-0.1405**
<i>ITEMIA_t</i>	-0.0017	0.2200**	0.1415**	-0.1039**	0.2888**	0.1924**	-0.1582**	-0.0484**	0.3028**	-0.2624**
<i>E-INDEXT_t</i>	0.0181**	0.0817**	0.1916**	0.1450**	0.1357**	0.2147**	-0.0121	0.1442**	0.1746**	0.0838**

This table reports the Pearson correlation coefficients of the variables in Eq. 2. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. All control variables are defined in Appendix B.

Table 18. Institutional ownership and market risk disclosure

	Dependent variable: <i>FogIndex</i>		Dependent variable: <i>SimScore</i>	
	(1) OLS	(2) FM	(3) OLS	(4) FM
<i>rTOTAL_{t-1}</i>	-0.4790** (-2.381)	-0.5675*** (-4.499)	0.0258** (2.329)	0.0371*** (3.669)
<i>SIZE_{t-1}</i>	0.1258*** (3.114)	0.1472*** (7.758)	0.0032 (1.532)	-0.0014 (-0.610)
<i>BM_{t-1}</i>	0.1493** (2.184)	0.2192*** (4.622)	0.0193*** (4.581)	0.0171*** (3.548)
<i>LEV_{t-1}</i>	-0.0388 (-1.053)	-0.0376* (-1.892)	0.0012 (0.667)	-0.0038** (-2.383)
<i>FOREIGNSALE_{t-1}</i>	0.4019 (0.666)	1.7477 (1.355)	-0.0228 (-0.621)	-0.0438 (-0.830)
<i>FOREIGNSEG_{t-1}</i>	-0.0056 (-0.782)	-0.0086** (-2.634)	0.0008** (2.184)	0.0014*** (4.681)
<i>BUSSEG_{t-1}</i>	0.0196* (1.823)	0.0194*** (6.679)	0.0001 (0.138)	0.0006 (1.491)
<i>COVERAGE_{t-1}</i>	0.0064 (1.169)	0.0024 (0.650)	0.0002 (0.795)	0.0001 (0.268)
<i>STDRET_{t-1}</i>	4.3841* (1.762)	5.3438** (2.533)	-0.3012 (-1.499)	-0.7696*** (-4.007)
<i>LITRISK_{t-1}</i>	0.3074** (2.449)	0.1335*** (3.195)	0.0179** (2.266)	0.0112** (2.967)
<i>DIV_{t-1}</i>	0.2445*** (3.251)	0.2678*** (8.002)	0.0062 (1.307)	0.0054 (1.682)
<i>HASD_{t-1}</i>	0.1191 (1.554)	0.2393** (2.908)	-0.0039 (-0.861)	-0.0015 (-0.419)
<i>TOBINQ_{t-1}</i>	0.0015 (0.059)	-0.0212 (-1.600)	-0.0004 (-0.250)	0.0022 (1.510)
<i>AGE_t</i>	0.1709*** (2.790)	0.1756*** (5.862)	-0.0077** (-2.343)	-0.0106 (-1.408)
<i>ITEMIA_t</i>	-0.4282** (-2.268)		0.2844*** (12.931)	
<i>E-INDEX_t</i>	-0.0346 (-1.503)	-0.0321** (-2.276)	0.0019 (1.584)	0.0046 (1.305)
<i>CONSTANT</i>	7.9585*** (10.665)	7.8931*** (43.461)	0.5180*** (9.772)	0.8387*** (30.335)
Year FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
N	17,726	17,726	17,726	17,726
Adj. R ²	0.053	0.045	0.111	0.024

This table reports the effects of institutional ownership on textual characteristics of market risk disclosure. Our results of the OLS regression and the Fama-MacBeth regression are reported. In Column (1) and (2), dependent variable is the readability of market risk disclosure, which is measured by the Fog Index in year t . In Column (3) and (4), dependent variable is the consistency of market risk disclosure, which is measured by the similarity score in year t . Our independent variable of interest is $rTOTAL_{t-1}$, which represent the residual ownership of institutional investors at the end of year $t-1$. The sample comprises 17,726 firm-years from 2002 to 2016. We report t-statistic in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Other control variables are defined in Appendix B.

Table 19. Investor horizon and market risk disclosure

	Dependent variable: <i>FogIndex</i>		Dependent variable: <i>SimScore</i>	
	(1) OLS	(2) FM	(3) OLS	(4) FM
<i>rLONG_{t-1}</i>	-0.3439 (-1.275)	-0.3651 (-1.719)	0.0299 (1.642)	0.0620*** (3.851)
<i>rSHORT_{t-1}</i>	-0.6021** (-2.201)	-0.7360*** (-10.237)	0.0211 (1.363)	0.0152 (1.071)
<i>SIZE_{t-1}</i>	0.1218*** (2.995)	0.1427*** (7.466)	0.0031 (1.502)	-0.0017 (-0.588)
<i>BM_{t-1}</i>	0.1477** (2.144)	0.2183*** (4.620)	0.0188*** (4.472)	0.0154** (2.942)
<i>LEV_{t-1}</i>	-0.0426 (-1.153)	-0.0438** (-2.167)	0.0013 (0.747)	-0.0040** (-2.476)
<i>FOREIGNSALE_{t-1}</i>	0.4302 (0.712)	1.7458 (1.382)	-0.0227 (-0.620)	-0.0480 (-0.895)
<i>FOREIGNSEG_{t-1}</i>	-0.0056 (-0.788)	-0.0088** (-2.582)	0.0008** (2.148)	0.0014*** (4.668)
<i>BUSSEG_{t-1}</i>	0.0196* (1.826)	0.0195*** (6.626)	0.0001 (0.117)	0.0007 (1.344)
<i>COVERAGE_{t-1}</i>	0.0067 (1.211)	0.0026 (0.675)	0.0002 (0.818)	0.0001 (0.589)
<i>STDRET_{t-1}</i>	4.8175* (1.932)	5.6678** (2.668)	-0.3215 (-1.599)	-0.7754*** (-4.039)
<i>LITRISK_{t-1}</i>	0.3049** (2.416)	0.1317*** (3.303)	0.0184** (2.332)	0.0105** (2.781)
<i>DIV_{t-1}</i>	0.2439*** (3.218)	0.2659*** (7.518)	0.0062 (1.288)	0.0042 (1.376)
<i>HASD_{t-1}</i>	0.1220 (1.589)	0.2421** (2.895)	-0.0038 (-0.848)	-0.0013 (-0.353)
<i>TOBINQ_{t-1}</i>	0.0018 (0.072)	-0.0207 (-1.527)	-0.0004 (-0.249)	0.0022 (1.545)
<i>AGE_t</i>	0.1715*** (2.795)	0.1767*** (5.800)	-0.0077** (-2.341)	-0.0102 (-1.404)
<i>ITEMIA_t</i>	-0.3933** (-2.033)		0.2810*** (12.661)	
<i>E-INDEX_t</i>	-0.0353 (-1.532)	-0.0333** (-2.390)	0.0019 (1.544)	0.0044 (1.243)
<i>CONSTANT</i>	7.9385*** (10.645)	7.8893*** (42.186)	0.5232*** (9.865)	0.8395*** (29.502)
Year FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
N	17,726	17,726	17,726	17,726
Adj. R ²	0.053	0.046	0.110	0.025

This table reports the effects of institutional ownership of investors with different horizon on textual characteristics of market risk disclosure. Our results of the OLS regression and the Fama-MacBeth regression are reported. In Column (1) and (2), dependent variable is the readability of market risk disclosure, which is measured by the Fog Index in year t . In Column (3) and (4), dependent variable is the consistency of market risk disclosure, which is measured by the similarity score in year t . Our independent variables of interest are $rLONG_{t-1}$, and $rSHORT_{t-1}$, which represent the residual ownership of long-term institutional investors and short-term institutional investors at the end of year $t-1$, respectively. The sample comprises 17,726 firm-years from 2002 to 2016. We report t-statistic in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Other control variables are defined in Appendix B.

Table 20. Investor independence and market risk disclosure

	Dependent variable: <i>FogIndex</i>		Dependent variable: <i>SimScore</i>	
	(1) OLS	(2) FM	(3) OLS	(4) FM
<i>rIND_{t-1}</i>	-0.5394** (-2.276)	-0.6596*** (-5.923)	0.0277** (2.189)	0.0328** (2.370)
<i>rDEP_{t-1}</i>	-0.0207 (-0.023)	0.4004 (0.490)	-0.0120 (-0.225)	0.0718 (0.803)
<i>SIZE_{t-1}</i>	0.1315*** (3.260)	0.1541*** (8.102)	0.0025 (1.210)	-0.0016 (-0.722)
<i>BM_{t-1}</i>	0.1578** (2.303)	0.2270*** (4.916)	0.0188*** (4.442)	0.0163** (2.786)
<i>LEV_{t-1}</i>	-0.0383 (-1.041)	-0.0360 (-1.638)	0.0014 (0.792)	-0.0031* (-1.989)
<i>FOREIGNSALE_{t-1}</i>	0.4013 (0.667)	1.6942 (1.362)	-0.0230 (-0.625)	-0.0482 (-0.901)
<i>FOREIGNSEG_{t-1}</i>	-0.0057 (-0.789)	-0.0088** (-2.584)	0.0008** (2.162)	0.0015*** (4.630)
<i>BUSSEG_{t-1}</i>	0.0194* (1.795)	0.0189*** (5.901)	0.0001 (0.152)	0.0007 (1.478)
<i>COVERAGE_{t-1}</i>	0.0061 (1.114)	0.0024 (0.672)	0.0002 (0.813)	0.0001 (0.445)
<i>STDRET_{t-1}</i>	4.0705 (1.587)	4.9728** (2.312)	-0.3419* (-1.688)	-0.8100*** (-4.059)
<i>LITRISK_{t-1}</i>	0.3144** (2.495)	0.1406*** (3.379)	0.0181** (2.294)	0.0116*** (3.103)
<i>DIV_{t-1}</i>	0.2442*** (3.243)	0.2663*** (7.887)	0.0063 (1.309)	0.0049 (1.727)
<i>HASD_{t-1}</i>	0.1198 (1.558)	0.2388** (2.964)	-0.0036 (-0.809)	-0.0020 (-0.544)
<i>TOBINQ_{t-1}</i>	0.0011 (0.042)	-0.0193 (-1.416)	-0.0004 (-0.261)	0.0023 (1.480)
<i>AGE_t</i>	0.1698*** (2.759)	0.1780*** (6.257)	-0.0077** (-2.348)	-0.0100 (-1.447)
<i>ITEMIA_t</i>	-0.4552** (-2.422)		0.2830*** (12.654)	
<i>E-INDEX_t</i>	-0.0358 (-1.603)	-0.0337** (-2.404)	0.0021* (1.697)	0.0046 (1.358)
<i>CONSTANT</i>	7.9921*** (10.717)	7.8881*** (44.516)	0.5213*** (9.822)	0.8386*** (33.361)
Year FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
N	17,726	17,726	17,726	17,726
Adj. R ²	0.053	0.047	0.111	0.026

This table reports the effects of institutional ownership of investors with different independence on textual characteristics of market risk disclosure. Our results of the OLS regression and the Fama-MacBeth regression are reported. In Column (1) and (2), dependent variable is the readability of market risk disclosure, which is measured by the Fog Index in year t . In Column (3) and (4), dependent variable is the consistency of market risk disclosure, which is measured by the similarity score in year t . Our independent variables of interest are $rIND_{t-1}$, and $rDEP_{t-1}$, which represent the residual ownership of independent institutional investors and dependent institutional investors at the end of year $t-1$, respectively. The sample comprises 17,726 firm-years from 2002 to 2016. We report t-statistic in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Other control variables are defined in Appendix B.

Table 21. The joint impact of horizon and independence on market risk disclosure

	Dependent variable: <i>FogIndex</i>		Dependent variable: <i>SimScore</i>	
	(1) OLS	(2) FM	(3) OLS	(4) FM
<i>rLONGIND_{t-1}</i>	-0.4601 (-1.440)	-0.5816** (-2.913)	0.0399* (1.954)	0.0717*** (4.177)
<i>rSHORTIND_{t-1}</i>	-0.6524** (-2.103)	-0.8061*** (-12.117)	0.0148 (0.891)	0.0030 (0.160)
<i>rLONGDEP_{t-1}</i>	0.5336 (0.410)	2.0824* (1.786)	-0.0998 (-1.134)	-0.0062 (-0.064)
<i>rSHORTDEP_{t-1}</i>	-0.3572 (-0.306)	-1.3447 (-1.249)	0.0648 (0.788)	0.2003 (0.999)
<i>SIZE_{t-1}</i>	0.1268*** (2.989)	0.1467*** (9.812)	0.0017 (0.811)	-0.0009 (-0.399)
<i>BM_{t-1}</i>	0.1406** (1.973)	0.2347*** (3.683)	0.0172*** (4.054)	0.0123* (1.952)
<i>LEV_{t-1}</i>	-0.0550 (-1.381)	-0.0427* (-1.856)	0.0004 (0.242)	-0.0045** (-2.470)
<i>FOREIGNSALE_{t-1}</i>	0.4214 (0.695)	1.8822 (1.374)	-0.0202 (-0.545)	-0.0354 (-0.644)
<i>FOREIGNSEG_{t-1}</i>	-0.0056 (-0.787)	-0.0092** (-2.196)	0.0007** (1.983)	0.0014*** (4.697)
<i>BUSSEG_{t-1}</i>	0.0186* (1.694)	0.0183*** (5.350)	0.0001 (0.313)	0.0006* (1.787)
<i>COVERAGE_{t-1}</i>	0.0064 (1.147)	0.0025 (0.646)	0.0003 (0.955)	0.0002 (0.836)
<i>STDRET_{t-1}</i>	4.2461 (1.529)	5.6970** (2.291)	-0.3050 (-1.476)	-0.7219*** (-3.101)
<i>LITRISK_{t-1}</i>	0.3362** (2.574)	0.1319*** (4.352)	0.0175** (2.208)	0.0084* (2.000)
<i>DIV_{t-1}</i>	0.2530*** (3.243)	0.2688*** (6.783)	0.0060 (1.243)	0.0054 (1.650)
<i>HASD_{t-1}</i>	0.1253 (1.616)	0.2532** (2.957)	-0.0036 (-0.807)	-0.0026 (-0.680)
<i>TOBINQ_{t-1}</i>	-0.0099 (-0.415)	-0.0213 (-1.522)	-0.0005 (-0.327)	0.0019 (1.459)
<i>AGE_t</i>	0.1727*** (2.747)	0.1874*** (6.279)	-0.0074** (-2.254)	-0.0112 (-1.328)
<i>ITEMIA_t</i>	-0.4565** (-2.203)		0.3009*** (12.175)	
<i>E-INDEX_t</i>	-0.0378* (-1.672)	-0.0393** (-2.898)	0.0023* (1.836)	0.0045 (1.355)
<i>CONSTANT</i>	8.1446*** (10.721)	7.8584*** (41.127)	0.5064*** (9.097)	0.8440*** (29.677)
Year FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
N	17,726	17,726	17,726	17,726
Adj. R ²	0.053	0.047	0.111	0.026

This table reports the results of the OLS regression and the Fama-MacBeth regression. In Column (1) and (2), dependent variable is the readability of market risk disclosure, which is measured by the Fog Index in year t . In Column (3) and (4), dependent variable is the consistency of market risk disclosure, which is measured by the similarity score in year t . Our independent variables of interest are $rLONGIND_{t-1}$, $rSHORTIND_{t-1}$, $rLONGDEP_{t-1}$, $rSHORTDEP_{t-1}$, which represent the residual ownership of long-term independent institutional investors, short-term independent institutional investors, long-term dependent institutional investors, and short-term dependent institutional investors at the end of year $t-1$, respectively. The sample comprises 17,726 firm-years from 2002 to 2016. We report t-statistic in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Other control variables are defined in Appendix B.

Table 22. The impact of firms' overall information environment on market risk disclosures

	(1)	(2)	(3)	(4)
Panel A: Dependent variable is FogIndex				
<i>rTOTAL_{t-1}</i>	-0.5199*** (-4.102)			
<i>rLONG_{t-1}</i>		-0.2893 (-1.504)		
<i>rSHORT_{t-1}</i>		-0.3799** (-2.138)		
<i>rIND_{t-1}</i>			-0.4482*** (-3.137)	
<i>rDEP_{t-1}</i>			-0.9177 (-1.590)	
<i>rLONGIND_{t-1}</i>				-0.3764* (-1.747)
<i>rSHORTIND_{t-1}</i>				-0.4924*** (-2.579)
<i>rLONGDEP_{t-1}</i>				-0.9658 (-1.154)
<i>rSHORTDEP_{t-1}</i>				-0.6108 (-0.689)
<i>WAccrual_{t-1}</i>	0.4580** (2.332)	0.4854** (2.282)	0.4760** (2.422)	0.5123** (2.465)
Year fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
N	17,128	17,128	17,128	17,128
Adj. R ²	0.052	0.047	0.050	0.056
Panel B: Dependent variable is SimScore				
<i>rTOTAL_{t-1}</i>	0.0256** (2.298)			
<i>rLONG_{t-1}</i>		0.0292 (1.604)		
<i>rSHORT_{t-1}</i>		0.0205 (1.324)		
<i>rIND_{t-1}</i>			0.0263** (2.097)	
<i>rDEP_{t-1}</i>			-0.0043 (-0.082)	
<i>rLONGIND_{t-1}</i>				0.0378* (1.866)
<i>rSHORTIND_{t-1}</i>				0.0130 (0.790)
<i>rLONGDEP_{t-1}</i>				-0.0859 (-0.994)
<i>rSHORTDEP_{t-1}</i>				0.0699 (0.887)
<i>WAccrual_{t-1}</i>	-0.0496** (-2.321)	-0.0487** (-2.275)	-0.0522** (-2.428)	-0.0465** (-2.186)
Year fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
N	17,128	17,128	17,128	17,128
Adj. R ²	0.111	0.110	0.111	0.108

This table reports the results of the fixed effects regressions of disclosure features on institutional ownership with considering the impact of firms' overall information environment. The sample comprises 17,128 firm-years from 2002 to 2016. In Panel A, the dependent variable is the readability of market risk disclosure, which is measured by the Fog Index. In panel B, the dependent variable is the consistency of market risk disclosure, which is measured by similarity score. We report t-statistic in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Other control variables are defined in Appendix B.