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Migration Fear and Stock Price Crash Risk

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Abstract: We examine whether migration fear increases future stock price crash risk. We find that a 10 percentage point increase in the migration fear index increases the future stock price crash risk by 17 to 19 percentage points. Our results hold after controlling for macroeconomic conditions, including economic policy uncertainty, and using instrumental variables to address endogeneity issues. The impact of migration fear on crash risk is larger for firms with greater asymmetric information and firms with weaker monitoring mechanisms. We conclude that migration fear can significantly change risk tolerance in financial markets and affect stock price crash risk.

Keywords: Migration fear, Asymmetric information, Stock price crash risk

JEL Classifications: G10, G41

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1 Introduction

Migration is a complex issue that generates strong opinions and emotions, and few policy debates are as hotly contested by politicians as the immigration debate. In December 2018, political disagreements in the United States about immigration led to a 35-day government shutdown – the longest ever in US history.[2] Recently, the US Supreme Court upheld the controversial pandemic-era migration policy implemented by the Trump administration, known as Title 42, that allows for the expulsion of migrants at the US-Mexico border to prevent the spread of COVID-19.[3] Similarly, Allen (2016) published a report warning that migration-related fears could lead to the collapse of the European Union within the next decade. The report informed that rising anti-immigrant sentiment across the continent had the potential for increased political instability and economic challenges. While risk and uncertainty are intrinsically related to the fear of immigration, there is surprisingly little research that explicitly engages with the notions of migration fear and whether it has the potential to make markets extremely fragile. We address this important issue in this paper.

Our study examines whether migration fear affects the stock price crash risk (hereafter crash risk) of a firm. Crash risk has come under the spotlight after the 2008 financial crisis. Both institutional and individual investors care about crash risk because a sudden drastic decline in stock prices can impose significant losses on their portfolios. We focus on the firm-specific crash risk that captures the left tail risk of stock returns. It refers to the likelihood of a sudden, drastic decline in stock prices and is an important characteristic of the distribution of stock returns.

Theoretically, crash risk arises when bad news that has been hoarded deliberately by managers accumulates beyond a critical threshold and suddenly becomes publicly available to investors leading to a large negative outlier in the distribution of returns. Many studies have identified firms' internal characteristics, such as financial reporting and corporate dis-

[2]https://www.aljazeera.com/news/2019/1/25/us-govt-shutdown-how-long-who-is-affected-why-did-it-begin

[3]https://www.wsj.com/articles/what-is-title-42-border-rules-migration-11649118539

closures (Hutton, Marcus and Tehranian, 2009; Jin and Myers, 2006; Kim, Li and Zhang, 2011*b*), managerial characteristics and managerial incentives (Al Mamun, Balachandran and Duong, 2020; Andreou, Louca and Petrou, 2017; Kim, Li and Zhang, 2011*a*) and internal corporate governance mechanisms (Andreou, Antoniou, Horton and Louca, 2016; Ben-Nasr and Ghouma, 2018; Hu, Li, Taboada and Zhang, 2020; Kim, Li and Li, 2014) as factors affecting crash risk. Few other studies have highlighted external factors to the firm like analyst coverage and optimism (Kim, Lu and Yu, 2019), religion (Callen and Fang, 2015), social trust (Li, Wang and Wang, 2017) and media sentiment (An, Chen, Naiker and Wang, 2020) as other informal institutional mechanisms that affect crash risk. A handful of recent studies take a macro policy perspective and show that economy-wide factors such as economic policy uncertainty (Jin, Chen and Yang, 2019; Jing, Lu, Zhao and Zhou, 2023) and geopolitical risk (Xu, He, Zhou, Ding and Chen, 2023) can also act as catalysts for crash risk. Our study extends this strand of literature by examining whether migration fear affects a firm's crash risk.

We conjecture that migration fear may affect stock price crashes through the primary mechanism of information asymmetry and investors' heterogeneous beliefs. First, firms with asymmetric information are more likely to have strong motivations for withholding negative news, especially during a volatile macroeconomic environment characterized by heightened migration fear (Jin and Myers, 2006). As fear increases, it becomes difficult for investors to access comprehensive information, inducing information asymmetry, which may help managers to conceal bad news. Increased fear and uncertainty are followed by high fluctuation in companies' earnings and cash flows, providing greater incentives for managers to distort financial information to alleviate short-term performance pressures or smooth earnings.[4] Furthermore, fear of migration can contribute to increased market volatility. It can influence investor confidence, impacting stock prices and valuations. Increased migration fear can lead to disagreement among investors regarding stock prices, leading to negative opinions being

[4]Kothari, Shu and Wysocki (2009) find that managers strategically engage in this behavior, as bad news could adversely affect their professional career opportunities, compensation, and reputations.

hidden. Due to short-sales limitations in the market, bearish investors do not initially participate, and their information remains undisclosed in prices. If preceding bullish investors exit the market, the initially bearish traders may become marginal "support buyers", revealing more about their signals. Consequently, an increase in migration fear can contribute to an elevated risk of stock price crashes, as the accumulation of negative information eventually surfaces and triggers a sudden downturn (Habib, Hasan and Jiang, 2018; Hong and Stein, 2003).

We adopt Baker, Bloom and Davis (2015) Migration Fear Index to examine the impact of migration fear on stock price crash risk. To construct the index, they count the number of newspaper articles with at least one term from each of the 'Migration (M)' and 'Fear (F)' term sets, and then divide by the total count of newspaper articles in the same calendar quarter and country.[5] We use the Migration Fear Index to estimate the effect of migration fear on future stock price crash risk with respect to U.S. firms. Besides controlling for the classic predictors of stock price crash risk from the literature (share turnover, market-to-book ratio, return on assets, size, leverage, returns, kurtosis of returns, and standard deviation of returns), we also include several macroeconomic proxies (unemployment rate and inflation) to control for the uncertainty arising from business cycles.[6] Additionally, to ensure that the effect we estimate can be attributed to migration fear and not to some other policy uncertainty, we control for the general level of economic uncertainty like VIX, index for global economic movements, and economic policy uncertainty (EPU) index in the economy.

In our study, we find evidence of a persistent positive relationship between migration fear and future stock price crash risk. In our preferred specification, we estimate that a 10% increase in the migration fear index is associated with an average increase in future stock price crash risk by approximately 17%-19% relative to the average crash risk in the sample. This is a sizable effect, considering that the migration fear index increased by nearly 70%

[5] The terms in the Migration (M) set includes "border control", Schengen, "open borders", migrant, migration, asylum, refugee, immigrant, immigration, assimilation, "human trafficking", and the terms in the Fear (F) set includes anxiety, panic, bomb, fear, crime, terror, worry, concern, violent.

[6] For reference, see Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry (2018).

during our sample period (see Figure 1). We document evidence that the positive effect of migration fear on future crash risk primarily works through the information asymmetry channel. From an investor's point of view, migration fear may lead to negative sentiments, forcing them to seek private information. As investors collect private information about the firm value before trading, this asymmetry of information decreases liquidity (e.g. widens bid-ask spreads) in the pricing process (Nagar, Schoenfeld and Wellman, 2019). We consider stock liquidity as a proxy for asymmetric information. We find that the positive effect of migration fear is more pronounced in firms with higher illiquidity. These findings provide insights grounded in agency theory, elucidating the positive connection between migration fear and future crash risk.

In addition, our investigation delves into the potential mediation effect of the severity of a firm's agency conflicts on the positive relationship between migration fear and future stock price crashes. The severity of asymmetric information assists the opportunistic managerial behavior of hoarding bad news, thereby leading to future stock price crashes. Empirical evidence suggests that firms with weaker external monitoring mechanisms are more susceptible to crash risk (Callen and Fang, 2013). Consequently, we anticipate that the association between migration fear and future crash risk is more pronounced for firms with weaker external monitoring mechanisms and firms exhibiting greater risk-taking tendencies. To highlight external monitoring mechanisms, we investigate two types of firms - regulated firms and firms undertaking and reporting their environmental, social, and governance (ESG) activities. We find that the positive effect of migration fear is lower in regulated firms compared to unregulated firms, and in firms with higher ESG scores compared to their peers. The results possibly indicate that executives in these firms are more transparent in the information they disclose about their firms; hence the appetite or scope for bad news hoarding is relatively low, and the probability of crash risk is lower. We also find that firms exhibiting positive managerial sentiment, and riskier firms, proxied by their cash flow volatility, are more susceptible to future crash risk in an environment of migration fear.

Our findings hold up to a battery of robustness tests. First, to alleviate potential endogeneity concerns, we show that our results remain robust in an IV specification in which a measure of average migration fear indices in three large European countries (France, Germany and the U.K.) for the same time period is used as an instrument for U.S. migration fear index. Second, we consider a first-differenced regression specification to control for "measurement error" issues. In addition, we show that our results are robust when we use alternative definitions of migration fear.

Our paper contributes to the literature in several ways. First, to our knowledge, this is the first study to assess the relation between migration fear and future stock price crash risk. By focusing on a unique perspective, higher moments of the stock return distribution, this study provides new evidence concerning the economic consequences of migration fear. In particular, our findings identify significant costs that migration fear brings to firms and their shareholders. The fact that crash risk is significantly higher following an increase in migration fear implies that a sizeable cohort of investors is indeed affected by this fear sentiment. Our empirical evidence is useful for understanding the role that migration fear plays in influencing both corporate behavior and investor welfare. Second, our results contribute to the stream of research that examines the determinants of future stock price crash risk. We provide evidence of the asymmetric information channel of how migration fear can affect stock crash risk. In particular, we demonstrate that the effect of migration fear is stronger in firms with higher illiquidity. Such firms avert timely disclosure of bad news, and can expose firms to higher crash risk (Chang, Chen and Zolotoy, 2017). Finally, we find that the effect is stronger among regulated firms, firms with weak corporate social responsibility, firms with a positive managerial sentiment, and less risky firms. Such firms have a poor standard of transparency and engage in more bad news hoarding.

This paper proceeds as follows. Section 2 develops the hypotheses for the empirical tests. Section 3 introduces the sample and variables used in the paper. Section 4 discusses the empirical methodology and results, and section 5 concludes the paper.

2 Literature Review and Hypothesis Development

Heightened fear and uncertainty in the macroeconomic environment inevitably impact firms' performance and profitability (Binz, 2022; Tzomakas, Anastasiou, Katsafados and Krokida, 2023). Numerous studies employing various measures of fear and uncertainty have consistently shown their substantial impact on corporate operations and performance, especially in the face of adverse shocks. Managers tend to respond to elevated fear and uncertainty by implementing strategic adjustments, such as reducing capital investments both at the firm and industry levels (Gulen and Ion, 2016), scaling back merger and acquisition activities (Bonaime, Gulen and Ion, 2018; Nguyen and Phan, 2017), and restraining other business investments and innovation (Lou, Chen, Yin, Zhang and Yu, 2022; Xu, 2020). These findings highlight the significant role that fear and uncertainty play in shaping managerial decisions and corporate behaviors.

The literature examining the link between the fear of immigration and financial markets is sparse. Fraser and Ungor (2019) find that the impact of migration fear and uncertainty has a negative influence on economic activity such as industrial production and unemployment rates. Czudaj (2018) and Ordu-Akkaya (2018) examine the volatility transmission between migration fear indices to the stock market indices and argue that a part of the volatility of equity markets can be explained by the migration fear sentiments of investors. Kamışlı (2019) reports that the stock market indices of different sectors such as financial, healthcare, and technology in Germany, France, and the United Kingdom are cointegrated with the migration fear indices of their own countries. Bai, Kerr, Wan and Yorulmaz (2023) investigate the role of migration fear on minority crowd-funding success and find that minorities are 2.4% less likely to achieve their crowd-funding goals than white creators during periods of low migration fear, but this shortfall triples during periods with the highest fear level. While these papers investigate the effect of migration fear and its impact on financial activities, none of these studies explicitly explore the impact on the stock price crash risk.

Our study examines whether migration fear affects a firm's stock price crash risk. The crash risk of a firm in the face of increased migration fear is influenced by a combination of external market conditions and internal firm-specific factors. Investigating the underlying mechanism, we hypothesize that the influence of migration fear on future crash risk is related to information asymmetry and investors' heterogeneous beliefs. Migration fear can lead to liquidity concerns in financial markets. Investor sentiment plays a crucial role. If a firm is perceived as being well-prepared for external risks and communicates effectively with investors, it may experience a more favorable response during challenging times. On the other hand, if investors become hesitant to trade, liquidity can dry up, exacerbating price movements.

Agency theory suggests that price crash risk arises due to the information asymmetry between managers of a firm and external stakeholders. Kothari et al. (2009) argue that in the conventional setting, high information asymmetry can encourage managers to disclose all types of news to avoid potential market penalties from investors. However, regarding the selective disclosure of bad news and good news, the impact of information asymmetry becomes less evident. We argue that increased information asymmetry creates opportunities for managers to withhold bad news. Firms with asymmetric information tend to have larger incentives to hoard bad news due to the volatility of the external macroeconomic environment with greater uncertainty (Jin and Myers, 2006). Periods of increased fear could add to the information asymmetry, which increases manager's ability to manipulate earnings (Nagar et al., 2019).

One challenge with pursuing this line of inquiry is that we do not directly observe informational asymmetry between managers and external stakeholders. Moreover, it is difficult to identify a single variable that captures information asymmetry. We consider stock liquidity as a proxy for information asymmetry. Stock liquidity can provide some insights into information dissemination in the market and prior literature has found that firms with severe information asymmetry have poor stock liquidity (Attig, Fong, Gadhoum and Lang, 2006;

Brockman and Chung, 2003; Wang and Zhang, 2015). The authors argue that increased informed trading in a firm's stock enhances its stock liquidity. If investor trading is collectively informed, we expect that trading would lead to an improvement in stock liquidity. This leads to our main hypothesis:

Hypothesis: *Migration fear has a positive effect on stock price crash risk, and the effect is stronger for firms with higher information asymmetry.*

Furthermore, in section 9, we provide additional discussion on factors that can enhance or attenuate the effect of migration fear and crash risk.

3 Sample, Variable Measurement, and Descriptive Statistics

3.1 Measures of Firm-Specific Stock Price Crash Risk

We use multiple data sources to obtain the U.S. corporations data from 2000q1 to 2019q4. We do not include data after 2019q4 to purge any effect of the pandemic and provide a robust foundation for understanding the effect of migration fear on future crash risk. To construct the stock price crash risk measures we obtain weekly price data from the Center for Research in Security Prices (CRSP). The quarterly firm-level financial information data is taken from the Compustat database. We exclude observations with less than 26 weeks of stock return data, as well as observations with missing values necessary to construct the crash risk variables and control variables. Depending on our crash risk variables, our main specifications have either 269,784 (9,851 unique firms) or 269,935 (9,170 unique firms) firm-quarter observations.

Following the literature, we define stock price crashes as large negative firm-specific return outliers. To measure the stock price crash risk, first, we compute residual stock returns by estimating firm-specific weekly returns for each firm in each quarter using the following expanded index model:

$$r_{i,w} = \beta_0 + \beta_1 r_{m,w-1} + \beta_2 r_{FF_{In},w-1} + \beta_3 r_{m,w} + \beta_4 r_{FF_{In},w} + \beta_5 r_{m,w+1} + \beta_6 r_{FF_{In},w+1} + \epsilon_{i,w}, \quad (1)$$

where $r_{i,w}$ is the return on stock i in week w, $r_{m,w}$ is the CRSP value-weighted market index return in week w, and $r_{FF_{In},w}$ is the Fama and French value-weighted industry index in week w, and $\epsilon_{i,w}$ is the error term. To allow for nonsynchronous trading, our model in Equation (1) includes the lead and lag market and industry index returns (Dimson, 1979).

The residuals from equation (1) are the firm-specific weekly returns. Chen, Hong and Stein (2001) and Hutton et al. (2009) suggest using the natural log of 1 plus the residual term from Equation (1) since they are highly skewed. Following them, we calculate the firm-specific weekly returns, denoted by $WR_{i,w}$, as the natural log of 1 plus the residual term from equation (1), i.e. $WR_{i,w}{=}ln(1+\epsilon_{i,w})$.

Next, employing the firm-specific weekly return, we measure two stock price crash risk variables constructed by Chen et al. (2001).[7]

The first measure is the negative conditional return skewness ($NCSKEW$) for each firm-quarter, and is calculated by dividing the negative value of the third moment of firm-specific weekly returns ($WR_{i,w}$) over the standard deviation of firm-specific weekly returns raised to the third power as follow:

$$NCSKEW_{i,Q} = -\frac{\left(n(n-1)^{\frac{3}{2}} \sum WR_{i,w}^3\right)}{\left((n-1)(n-2)\left(\sum WR_{i,w}^2\right)^{\frac{3}{2}}\right)}, \quad (2)$$

where $WR_{i,w}$ is a firm-specific weekly return, and n is the number of trading days for firm i in quarter Q. Because of the negative sign, $NCSKEW$ increases as the return distribution becomes more negatively skewed. Therefore, a higher value of $NCSKEW$ implies a more left-skewed return distribution, and higher crash risk.

[7] These two measures are widely used in the literature, for example Callen and Fang (2015); Hu et al. (2020); Kim et al. (2014); Wen, Xu, Ouyang and Kou (2019).

The second measure is the "down-to-up volatility", denoted by $DUVOL$. This measure records asymmetric volatilities between positive and negative firm-specific weekly returns. To construct the $DUVOL$ measure of crash risk, we first calculate the quarterly mean of a firm's specific weekly return, then for each firm in a given quarter we separate weekly returns below the annual mean "down weeks" and above the annual mean "up weeks". Then we find the standard deviation of up and down weeks sub-samples separately and calculate the $DUVOL$ as follows:

$$DUVOL_{i,Q} = \log \left[\frac{(n_u - 1) \sum_{down} WR_{i,t}^2}{(n_d - 1) \sum_{up} WR_{i,w}^2} \right], \tag{3}$$

where n_u and n_d are the number of up and down weeks over quarter Q. The higher the $DUVOL_{i,Q}$, the higher the crash risk.

3.2 Migration Fear Index

We measure migration fear using an aggregate index developed by Baker et al. (2015). The data is publicly available at quarterly frequency for U.S.[8] This index is a textual-based analysis calculated using the methodology of Baker, Bloom and Davis (2016). The authors use the scaled frequency of articles in eight leading U.S. newspapers containing the following two term sets. The first set is *"Migration (M)"* and includes, *{"border control", Schengen, "open borders'", migrant, migration, asylum, refugee, immigrant, immigration, assimilation, "human trafficking"}*. The second set is *"Fear (F)*" and includes, *{"anxiety, panic, bomb, fear, crime, terror, worry, concern, violent"}*. Baker et al. (2015) count the number of newspaper articles with at least one term from each of the *"Migration (M)"* and *"Fear (F)"* term sets, and then divide by the total count of newspaper articles (in the same calendar quarter and country).

[8]Migration fear data is available at http://www.policyuncertainty.com/immigration*fear.html*.

3.3 Control Variables

Our set of firm-level control variables, consistent with prior literature (Chen et al., 2001; Jin and Myers, 2006), includes the following: $DTURN$, denoting the change in the average quarterly share turnover from the previous quarter, where share turnover is calculated as the quarterly share trading volume divided by the average number of shares outstanding during the specified year-quarter period; $RETURN$, representing the average of firm-specific weekly returns over the specified year-quarter period, multiplied by 100; MTB, the quarterly ratio of the market value of equity plus total liabilities over book value of equity plus total liabilities; ROA, the quarterly ratio of operating income before depreciation to total assets; $SIZE$, the logarithm of a firm's total assets in the specified year-quarter period; LEV, the quarterly ratio of total liabilities to total assets; $KURT$, the kurtosis of firm-specific weekly returns during the specified year-quarter period; and $SIGMA$, the standard deviation of firm-specific weekly returns over the same year-quarter period.

We also include other macroeconomic variables to control for the general economic environment. VIX is defined as the Chicago Board Options Exchange's CBOE Volatility Index; LEI is defined as the Leading Economic Index representing the global economic movements developed by the University of Michigan; $UNEMPLOY$ is the unemployment rate defined as the total unemployment as a percentage of the total labor force; $INFLATION$ is defined as the inflation rate of the U.S. economy; and EPU is the Baker et al. (2016) quarterly three component economic policy uncertainty index. The Appendix summarizes the definitions of the variables used in this study and the data sources.

3.4 Descriptive statistics

Figures 2 and 3 provide scatter plots to visually explore the relation between migration fear and $NCSKEW$ and $DUVOL$, respectively. The graphs suggest a positive association between these variables. In Table 1, we present the Pearson (pairwise) correlation matrix for the key variables of interest in our study. Our future stock price crash risk measures,

$NCSKEW$ and $DUVOL$ are both significantly and positively correlated with one another. Although these measures are constructed differently from firm-specific weekly returns, they seem to be picking up much of the same information. The correlation coefficient between $NCSKEW$ and $DUVOL$ is 0.95, which is comparable to that reported earlier in the literature.[9] The migration fear variable ($MFEAR$) is significantly and positively correlated with $DUVOL$ at the 1% level and positively correlated with $NCSKEW$. The univariate results are consistent with our expectation that firms located in areas with higher migration risk display higher levels of future stock price crash risk.

In Table 2, we present the summary statistics (mean, standard deviation, quartiles, minimum and maximum value) for the key variables. The mean values of stock price crash risk measures $NCSKEW$ and $DUVOL$ are 0.055 and 0.060, respectively. The mean value and standard deviation of $MFEAR$ are 4.66 and 0.356, respectively. Overall, the mean values and standard deviations of $NCSKEW$ and $DUVOL$ are very similar to the ones reported in the earlier literature.

[Insert Tables 1 and 2 about here]

3.5 Methodology

To test the relationship between migration fear and future stock price crash risk, we employ the following baseline regression model:

$$CRASH\_RISK_{i,T+1} = \alpha_i + \beta_1 MFEAR_T + \sum_n \beta_n X^n_{i,T} + \sum_m \beta_m Z^m_T + \epsilon_{i,T} \tag{4}$$

where $CRASH\_RISK_{i,T+1}$ is one of the two crash risk measures constructed in Section 3.1 and $MFEAR_T$ is the natural logarithm of the measure of migration fear explained in Section 3.2. The X term contains a set of firm-specific control variables and the Z term controls for the economy-wide macroeconomic factors explained in Section 3.3. Here, i indexes firms,

[9]For example, see Callen and Fang (2015).

and T indexes calendar quarters. The α_i's are the firm fixed effects. We include cluster robust standard errors at the firm level to control for firm heterogeneity, serial correlations and heteroskedasticity in the error term $\epsilon_{i,T}$. Our focus is on the effect of $MFEAR_T$ on $CRASH\_RISK_{i,T+1}$, that is, on the coefficient β_1.

4 Empirical Results

4.1 Main Results

We begin our empirical analysis by estimating the effect of migration fear on firm-specific crash risk. Table 3 shows the results of our regression analysis of equation 4, where we measure future firm-specific crash risk by $NCSKEW_{T+1}$ in columns 1 to 3 and $DUVOL_{T+1}$ in columns 4 to 6 respectively. Columns (1) and (4) measure the effect of $MFEAR$ on $CRASH\_RISK$ without any control variables and columns (2) and (5) include additional firm-specific control variables. Finally, our preferred specifications are columns (3) and (6) that include both firm-specific and additional macroeconomic controls, including a control for economic policy uncertainty. Across all the models in Panel A, the estimated coefficient of $MFEAR$ is positive and statistically significant at less than 1% level. For our preferred specifications in columns (3) and (6), the t-statistics are 11.57 and 12.08, respectively. The results indicate that migration risk is positively associated with future stock price crash risk, consistent with the main hypothesis of our study.

To further examine the economic significance of the results, Panel B of Table 3 calculates the marginal effect for our preferred specification in columns (3) and (6). For a 10 percentage point increase in $MFEAR_T$ from its mean of 4.66, $NCSKEW_{T+1}$ and $DUVOL_{T+1}$ increase by 16.8% and 18.9%, respectively.[10] Given that our sample mean of the crash variables are 0.055 and 0.060 for $NCSKEW_{T+1}$ and $DUVOL_{T+1}$ respectively, the marginal effect of

[10]Predicted $NCSKEW_{T+1}$ and $DUVOL_{T+1}$ evaluated at the mean of $MFEAR_T$ are equal to 0.0548 and 0.0597, respectively, and at the mean plus a 10 percentage point increase in $MFEAR_T$ are equal to 0.0648 and 0.0719, respectively.

migration fear on crash risk is not only statistically significant, but also economically meaningful. In comparison, the estimated impact of a 10 percentage point increase in migration fear from its mean value on firm-specific crash risk is similar in economic significance to the impact of $SIZE$ on crash risk (18.2% for $NCSKEW_{T+1}$ and 18.3% for $DUVOL_{T+1}$) and $LEVERAGE$ on crash risk (20.0% for $NCSKEW_{T+1}$ and 20.0% for $DUVOL_{T+1}$).

The results for control variables are largely consistent with the prior literature. Specifically, the coefficients on $DTURN_T$, $RETURN_T$, MTB_T, $SIZE_T$ and $SIGMA_T$ are positive and significant at the 1% level across all six specifications. In addition, we observe negative and significant coefficients at the 1% level on ROA_T and LEV_T. Furthermore, to control for contemporaneous macroeconomic factors, in columns (3) and (6), we include VIX_T, LEI_T, $UNEMPLOY_T$ and $INFLATION_T$. These macroeconomic controls are also found to be significant with correct signs in all specifications.

Using an index to measure economic policy uncertainty in China, Jin et al. (2019) find that economic policy uncertainty has a positive effect on stock price crash risk. Thus, we also include a control for economic policy uncertainty (EPU) in columns (3) and (6), along with other macroeconomic measures of uncertainty (VIX_T, LEI_T, $UNEMPLOY_T$ and $INFLATION_T$). Our results show that the estimated coefficient β_1 remains statistically significant and similar in sign and magnitude even after the inclusion of this variable. The fact that the explanatory power of the migration fear index is not absorbed by the economic policy uncertainty index or macroeconomic uncertainty is reassuring. The results indicate that the estimated effect of migration fear on crash risk is not picking up local or global economic uncertainty, or policy-related uncertainty.

[Insert Table 3 about here]

4.2 Migration Fear and Crash Risk: Differential Impact on Industries

We complement our previous analysis by investigating the migration fear sensitivity of firms that have greater exposure to migration-related risks. Several prominent studies have investigated survey data on voters and documented that fears about the negative consequences of immigration on wages and employment play a major role in generating anti-immigrant attitudes (Mayda, 2006; Scheve and Slaughter, 2001). We examine whether the relation between migration fear and crash risk is greater among firms in industries with a higher percentage of immigrant workers. We hypothesize that the effect of migration fear will be greater in firms belonging to these industries since these firms will be more sensitive to migration fear. Using data from Pew Research Center, we categorize firms in two groups: top U.S. industries by immigrant share of workers (computer and electronic products, food manufacturing, textile, apparel and leather manufacturing, and other not specified manufacturing), construction, and agriculture and extraction belong to group 1 and the rest in group 2.[11] We find that migration fear has a greater effect on crash risk for firms that belong to industries with a greater share of immigrant workers. The results presented in Table 4 suggest that the marginal effect between the two groups of industries is greater by 10.2 and 11.7 percentage points for $NCSKEW_{T+1}$ and $DUVOL_{T+1}$ respectively.

[Insert Table 4 about here]

4.3 Endogeneity Issues

Although migration fear is likely to be caused by external factors, endogeneity (especially, measurement error and reverse causality) could still be a concern. To address this issue, we follow an instrumental variable strategy. We use the average migration fear index scores of France, Germany and the United Kingdom over the same sample period as the instrumental

[11] See https://www.pewresearch.org/hispanic/2016/11/03/industries-of-unauthorized-immigrant-workers/.

variable.[12] Panel A of Table 5 presents the results of the first-stage regressions and Panel B report the results of the second-stage regressions. After controlling for simultaneity, we continue to find that migration fear has a positive and statistically significant effect on stock price crash risk. The diagnostic tests also provide validity of our regression results. The test of under-identification rejects the null hypothesis that our instrument is irrelevant. The Cragg–Donald Wald F-statistic (85,411) is far greater than the Stock and Yogo (2005) critical value (16.38) at the 10% maximal IV size, rejecting the null hypothesis that our instrument is weak.

[**Insert Table 5 about here**]

Next we consider a specification in first differences. This will allow us to eliminate any time-invariant effects specific to stock price crash risk. Table 6 presents the results for the two different measures of $CRASH\_RISK$. The estimation results confirm our earlier findings. In both models, we find that the change in migration fear has a positive and statistically significant effect on the change in future stock price crash risk (t-statistics = 12.08 and 19.33, respectively).

[**Insert Table 6 about here**]

Finally, as an additional robustness check, we provide a sub-sample analysis with periods of heightened migration fear. Our sub-sample include the periods 2001q3 and 2001q4 (September 11 attack), 2006q2 (Comprehensive Immigration Reform Act), 2015q3 and 2015q4 (European migrant crisis), 2016 and 2017 (Trump's reforming American Immigration for a Strong Economy Act). Such analysis with a shorter time period help us with better identification of the "exogenous" migration fear shocks and provide an additional test of endogeneity. The results, presented in Table 7, indicate that migration fear has a positive and significant effect on crash risk. Comparing the results to the full-sample in Table 3,

[12]The migration fear indices of these three countries were also developed by Baker et al. (2016) using the same textual-based methodology.

we find that migration fear has a stronger effect on crash risk during periods of increased migration fear.

[Insert Table 7 about here]

Taken together, the results for our endogeneity checks do not suggest any issue of omitted correlated variables. Reverse causality, that is, the change in the migration fear due to firm-specific crash risk, also seems unlikely. We are also unaware of any theory suggesting a reverse causation. Therefore, we treat migration fear as an exogenous shock to the firm. In addition, using current $MFEAR_i$ to predict $CRASH\_RISK_{i,T+1}$ in the main regression helps to alleviate any concern of reverse causality. Our endogeneity checks provide credibility that our findings reflect properties of migration fear and are not an artifact of the construction of the migration fear index.

4.4 Channel Testing: Is the impact of migration fear on crash risk stronger for firms with higher information asymmetry?

Our baseline results suggest that higher migration fear leads to higher crash risk. In the next part of our empirical analysis, we ask whether all stocks are equally affected by migration fear. We argue that this might not be the case due to the presence of asymmetric information.

Thus, we examine the relationship between migration fear and crash risk in the presence of asymmetric information. Increased fear and uncertainty is associated with crash risk through its impact on the manager's bad news hoarding behavior and investor's heterogeneous beliefs. Periods of increased risk and uncertainty add to the information asymmetry, which increases manager's ability to manipulate earnings (Nagar et al., 2019). Thus, under asymmetric information, investors' uncertainty about the firm's true value increases further. Hence, a bad news shock (migration fear) can increase information hoarding by managers and aggravate the crash risk in these firms.

We consider stock liquidity as a proxy for asymmetric information based on the earlier literature (Glosten and Milgrom, 1985; Kyle, 1985).[13] More recently, Beyer, Cohen, Lys and Walther (2010) and Das and Yaghoubi (2023) have shown that asymmetric information is negatively related to stock liquidity. The authors argue that the presence of information asymmetry between managers and investors creates an adverse selection problem that reduces market liquidity. An increase in migration fear increases uncertainty that can exacerbate the costs borne by the firm and its investors. This fear and uncertainty diminishes the ability of investors to extract accurate forward-looking information. To compensate, investors gather 'private signals' regarding firm prospects and investment opportunities. The relative precision of their own private signal leads to shocks that can be either positive or negative. This can lead to investor overconfidence arising from biased self-attribution, where such investors can erroneously consider other market participants' decisions to be less well-informed than theirs. Thus, if the shocks are sufficiently negative, this overconfidence can lead to illiquidity in the market. This scenario can lead to a reduction in trading volume and a widening of the bid-ask spread.

Some empirical papers have investigated the effect of stock liquidity on crash risk. Edmans (2009) argues that higher stock liquidity may result in monitoring of firm management by blockholders inducing lower information hoarding and crash risk. Similarly, Holden, Jacobsen and Subrahmanyam (2014) show higher stock liquidity enhances information production and informed trading, decreasing crash risk and Chang et al. (2017) present a competing viewpoint suggesting that stock liquidity can exacerbate crash risk.

Thus, we proxy asymmetric information with two commonly used measures of stock (il)liquidity. Our first measure of (il)liquidity is *Amihud*, which is constructed as follows:

$$Amihud_{i,t} = \frac{|r_{i,t}|}{P_{i,t} * Volume_{i,t}} \times 10^3, \tag{5}$$

[13]The authors use the bid-ask spread and Kyle's lambda (price impact) as measures of liquidity.

where $|r_{i,t}|$ is the return, $P_{i,t}$ is the closing price, and $Volume_{i,t}$ is the number of traded shares of stock i on day t. The quarterly measure of *Amihud* is constructed using the average of daily measures.

Our second measure is *Spread*, which is calculated as follows:

$$Spread_{i,t} = \frac{2 \times (Ask_{i,t} - Bid_{i,t})}{Ask_{i,t} + Bid_{i,t}} \times 10^2, \tag{6}$$

where $Ask_{i,t}$ and $Bid_{i,t}$ are the adjusted ask price and bid price of stock i on day t, respectively. We calculate a quarterly measure as the average of daily measures. Both *Amihud* and *Spread* measure the degree of stock illiquidity.

Table 8 presents these results. To allow for a more nuanced interpretation of the coefficients and to mitigate measurement problems, we do a sub-sample analysis. We split the sample based on the top and bottom 20% values of (il)liquidity measures and estimate each sub-sample separately. Columns (1) and (2) report the results for high and low values of $NCSKEW_{T+1}$, and Columns (3) and (4) for high and low values of $DUVOL_{T+1}$ respectively. Panels A and B report these results for *Amihud* and *Spread* respectively. Across all the specifications, we find that the positive effect of migration fear is more pronounced for firms with higher illiquidity. For a 10 percentage point increase in $MFEAR_T$ from its mean, the marginal effect in $NCSKEW_{T+1}$ is 50 percentage points greater for *Amihud* and 38 percentage points for *Spread*. Similarly, the marginal effect in $DUVOL_{T+1}$ is 44 percentage points greater for *Amihud* and 32 percentage points for *Spread*. Overall, these findings further confirm a positive and significant association between migration fear and crash risk that is stronger in the presence of asymmetric information.

[Insert Table 8 about here]

4.5 Mitigating factors on the relationship between migration fear and crash risk

We further investigate whether the positive effect of migration fear on future stock price crash risk exhibits heterogeneity in the cross-section of firms. We consider several external and internal governance variables that can act as mediating variables in attenuating the impact of migration fear on crash risk.

4.5.1 Effect of industry regulation on the relationship between migration fear and crash risk

Existing literature demonstrates that corporate governance mechanisms play an important role in reducing the level of information asymmetry between insiders and external stakeholders, which significantly decrease the likelihood of stock price collapse. We consider the regulatory status of firms as a proxy for the transparency of a specific firm. Previous investigations into the relation between financial reporting quality and stock price crash risk reveal that stocks are less likely to crash in industries with stricter accounting regulations and enforcement standards. Since regulations strengthen information disclosure and improve the effects of direct supervision and external auditors (Abedifar, Li, Johnson, Song and Xing, 2019; Kim and Zhang, 2016). Outside investors may have difficulty in accessing the full information of the firms in unregulated industries, resulting in potential future stock price crash risk. Similarly, DeFond, Hung, Li and Li (2015) delve into the impact of International Financial Reporting Standards (IFRS) adoption worldwide and discover that IFRS adoption leads to a decrease in stock price crash risk for non-financial firms, particularly in countries where IFRS adoption improves financial reporting quality, and Kubick and Lockhart (2016) documents that firms located closer to the Securities and Exchange Commission (SEC) exhibit smaller crash risks. This finding provides evidence that SEC oversight influences disclosure practices in a manner that mitigates crash risk.

Following Kothari et al. (2009), we create a dummy variable ($IND_{REGULATED}$) where we define regulated industries (non-financial institutions) as firms belonging to industries with Standard Industrial Classification (SIC) codes 4811–4899, 4922–4924, 4931, and 4941.

The results are reported in Panel A of Table 9. Consistent with our hypothesis, we find that the effect of migration fear on crash risk is positive and statistically significant for firms in unregulated industries, whereas the effect is insignificant for firms in regulated industries. On average, the marginal effect is 7.8 percentage points for $NCSKEW_{T+1}$ and 10.8 percentage points for $DUVOL_{T+1}$ respectively. Overall, the results support the notion that migration fear is greater among firms that belong to unregulated industries and have a lower transparency relative to firms in regulated industries. This transparency acts as an external monitoring mechanism and deters managers from withholding bad news from external stakeholders.

[Insert Table 9 about here]

4.5.2 Effect of CSR on the relationship between migration fear and crash risk

Another important aspect of a firm's commitment to a high standard of transparency is its engagement with corporate socially responsible (CSR) activities (Kim et al., 2014). By committing to voluntary disclosures of CSR activities is a mechanism to reduce information asymmetry. Previous studies present varying perspectives on the implications of CSR for managers' bad news-hoarding behavior and transparency in corporate financial reporting. Kim, Park and Wier (2012) discover that socially responsible firms also demonstrate responsible behavior in financial reporting, showing reduced evidence of earnings management. This suggests that firms committed to higher ethical standards have a positive impact on the quality of accounting information. Similarly, (Gelb and Strawser, 2001) find that firms engaged in socially responsible activities tend to provide more financial disclosure, indicating that increased transparency is perceived as part of their socially responsible behavior in the overall implementation of CSR practices. Thus, firms that prioritize a strong CSR culture and maintain high ethical standards in financial reporting are likely to display increased transparency and a reduced inclination to withhold negative news from investors.[14] As a result, we expect that these firms will be associated with a lower risk of stock price crashes. Therefore, we argue that the impact of migration fear on stock price crash risk is more prominent for firms with lower CSR activities.

CSR disclosures is also linked to the literature that focuses on how "internal social capital" of a firm influences its crash risk. Earlier work by Antoni and Sacconi (2011) suggests that a firm's Corporate Social Responsibility (CSR) activities are a good proxy for its social capital. From a shareholder perspective, if high social capital firms are perceived as more trustworthy, investors may place a valuation premium on these firms when overall trust in companies is low (see Guiso, Sapienza and Zingales (2008)), as in the 2008–2009 financial crisis. If firms are in a high social trust environment, executives are more trustworthy and honest in the information they disclose about their firms. Thus, bad news is hidden less and crash risk is lower.

To proxy for CSR activities, we use the ESG scores of a firm reported from Refinitiv DataStream. The ESG scores are designed to transparently and objectively measure a company's relative ESG performance, commitment and effectiveness across 10 main themes based on publicly reported data. These include Environmental: resource use, emissions, innovation; Social: work-force, human rights, community, product responsibility; and Governance: management, shareholders, CSR strategy. To compare the heterogeneous effect, we compare firms with CSR scores in the bottom 20% with the ones in the top 20% of the distribution.

Panel B of Table 9 presents these results. Consistent with our hypothesis, we find that the effect of migration fear on crash risk is larger in firms in the bottom 20% of the CSR score distribution. For a 10 percentage point increase in $MFEAR_T$, $NCSKEW_{T+1}$ increases by 23% and $DUVOL_{T+1}$ by 44%. In comparison, the marginal effects for $NCSKEW_{T+1}$ and

[14] However, managers may also use voluntary disclosures opportunistically to conceal bad news for an extended period. If managers engage in CSR to cover up bad news and divert shareholder scrutiny, CSR would be associated with higher crash risk. Empirical findings by Kim et al. (2014); Lee (2016) suggest that firms with better CSR disclosures have a lower crash risk.

$DUVOL_{T+1}$ increase by 44% $DUVOL_{T+1}$ by 3% and 6%, respectively. The marginal effects imply a substantial mitigating effect of migration fear on crash risk due to CSR activities.

4.5.3 Effect of managerial sentiment on the relationship between migration fear and crash risk

Perceptions of risk and sentiment can play a significant role in managerial decision-making. Moreover, it can increase the costs of searching for and processing information for the investors, exacerbating the 'asymmetric information' problem (Kahneman, 1973). Under such an environment, managers are under low pressure to hoard bad news from the investors. Thus, managers' incentives and abilities to withhold bad news are strengthened during periods of heightened risk and fear through a temporary loosening of monitoring constraints (Kempf, Manconi and Spalt, 2017). As a result, bad news accumulates leading to greater future crash risk.

We focus on firm-specific managerial sentiment that may reveal information about the future prospects of the firm, and thus exacerbate or attenuate the information asymmetry problem. Intuitively, investors may follow managers' sentiment in financial disclosures to gauge their sentiment. Any changes in sentiment are typically presumed to be reflected in investors' perceived expectations and risk appetite and thus reflect the true value of the firm value.[15] Easterwood, Paye and Xie (2021) argue that earnings conference calls provide information concerning the underlying asymmetries in future cash flow shocks that drives stock crash risk.

Previous studies have documented how external investors hold a crucial role in stock price crashes.[16] According to the "signaling hypothesis", managers can often use their tone

[15] Zhang and Zhang (2023) develop an asset pricing model with sentiment interactions between institutional and individual investors under the condition of information asymmetry and demonstrate that uninformed investors may mistake sentiment as information to make decisions, and when the sentiment is large enough, consequently the effect of truly private information on prices will be weakened.

[16] Chen et al. (2001) provide empirical evidence linking differences of opinion among investors to an increase in crash risk. Other studies by An and Zhang (2013) and Callen and Fang (2013) highlight the role of institutional investors in monitoring and reducing future stock price crash risk.

in earnings conference calls to signal their private information, thereby affecting stock crash risk (Loughran and McDonald, 2016). Given the spontaneous and interactive nature of earnings conference calls, one can easily detect managers' intention to mislead through the calls than through written documents or pre-rehearsed announcements (Hobson, Mayew and Venkatachalam, 2012; Larcker and Zakolyukina, 2012). In addition, Skinner (1997) and Druz, Petzev, Wagner and Zeckhauser (2020) argue that managers have incentives to disclose true information about political impact on firm's business, including costs of doing business, increased market competition and restrictions on business opportunities to lessen potential litigation costs associated with such calls. Thus, positive managerial sentiment is associated with lower future stock price crash risk.

To construct the measure of managerial sentiment, one can employ textual analysis to extract sentiment from mandated company disclosures. In a broader sense, textual analysis can pick up subtle cues in management's earnings conference calls and SEC filings to assess the quantity and quality of information in a collection of text, including both the intended message and any unintended revelations. Based on the work of Loughran and McDonald (2016), we categorize managerial sentiments based on their positive or negative sentiments. We conjecture that firms with positive managerial sentiments will have lesser incentives to hide information, and hence a lower probability of a crash risk.

In Panel C of Table 9, we find that the effect of migration fear on crash risk is much larger when the managerial sentiment is low. The observed difference, between higher and lower managerial sentiments, in marginal effects of one standard deviation increase in migration fear is greater by 14.2 and 14.7 percentage points for $NCSKEW_{T+1}$ and $DUVOL_{T+1}$ respectively. This result supports our conjecture migration fear will have a lower impact on crash risk when managerial sentiments are positive, as it indicates that the firm is unlikely to hide bad news.

4.5.4 Effect of cash flow volatility on the relationship between migration fear and crash risk

Recent literature has highlighted the negative impact of cash flow volatility on firms (Harris and Roark, 2019). Alnahedh, Bhagat and Obreja (2019) analyzed the S&P 500 index and concluded that cash flow volatility negatively affects corporate investment, leading to a decrease in corporate value. Given the impact of cash flow volatility on corporate investment and financing decisions, we further explore whether crash risk is more pronounced when firms have higher risk due to higher cash flow volatility.

Information asymmetry between managers and external investors may intensify the concealment of negative information as cash flow volatility rises. When cash flow volatility is high, management may perceive migration fear as a more uncertain external environment, potentially causing the accumulation of negative information. Furthermore, when cash flow volatility is high, it becomes challenging for market participants to comprehend the true firm performance, thus enabling managers to conceal bad news. Additionally, high cash flow volatility acts as an opacity that can shield insiders, allowing them to divert firm resources, particularly cash flows, for an extended period, leading to a significant drop in stock prices when this resource diversion is disclosed (Kim et al., 2011*a*). As this bad news accumulates over time and is suddenly revealed, it can trigger a stock price crash.

In this study, we utilize a Cash Flow Volatility calculated as the rolling standard deviation of quarterly cash flows divided by total assets, employing an 8-quarter window (Keefe and Yaghoubi, 2016).[17]

In Panel D, we find that the effect of migration fear on crash risk is much larger when cash flow volatility is high. The observed difference, between higher and lower cash flow volatility, in marginal effects of one standard deviation increase in migration fear is greater by 14.2 and 14.7 percentage points for $NCSKEW_{T+1}$ and $DUVOL_{T+1}$ respectively. This

[17] We also test using a 4-quarter window, and our results remain quantitatively unchanged.

result supports our conjecture migration fear will have a higher impact on crash risk when cash flow volatility is high, as it indicates that the firm is unlikely to hide bad news.

4.6 Additional Robustness Test

To examine the validity of our main result, we perform an additional robustness test. We consider an alternative definition of migration fear. We consider an indicator variable for refugees and internally displaced persons (IDPs), $REFUGEES$, as an alternative measure of migration risk. This variable measures the pressure upon states caused by the forced displacement of large communities as a result of social, political, environmental or other causes, measuring displacement within countries, as well as refugee flows into others.[18] We expect $REFUGEES$ to be highly correlated with our measure of migration fear.

These results reported in Table 10 confirm our earlier findings. In both models, we find that $REFUGEES$ has a positive and statistically significant effect on the change in future stock price crash risk (t-statistics = 12.08 and 19.33, respectively).

[Insert Table 10 about here]

5 Concluding remarks

Our primary focus is on the firm-specific stock price crash risk, which captures the potential for extreme negative outcomes in stock returns. The concept of tail risk, representing the third moment of stock returns, has gained significant attention since the 2008 financial crisis. Both institutional and individual investors are concerned about crash risk as a sudden and significant decline in stock prices can result in substantial losses within their investment portfolios.

[18] The indicator measures refugees by country of asylum, recognizing that population inflows can put additional pressure on public services, and can sometimes create broader humanitarian and security challenges for the receiving state, if that state does not have the absorption capacity and adequate resources. These measures are considered within the context of the state's population (per capita) and human development trajectory, and over time (year-on-year spikes), recognizing that some IDPs or refugees for example, may have been displaced for long periods of time.

Over the past two decades, economists' perceptions about immigration have shifted. Our study is the first to document the effect of migration fear on future stock price crash risk. We find robust evidence that migration fear is positively correlated with future stock price crash risk. This positive association is statistically and economically significant even after controlling for macroeconomic factors, economic policy uncertainty, the level of investor sentiment, investor attention and other factors known to affect stock price crash risk. To alleviate "endogeneity" concerns, we implement an IV strategy by using average migration fear scores for three different countries for the same time period as the instrumental variable. We also use a first-differenced regression specification to control for "measurement error" issues. We find that, on average, a 10 percentage point increase in migration fear leads to a 17 - 19 percentage point increase in future crash risk. These results are consistent with our conjecture that people's fear of the impact of migration on the economy and their financial well-being can lead to increased risk aversion and demand for a higher risk premium. This, in turn, can lead to a decrease in stock prices and an increase in stock price crash risk.

Our evidence further suggests that the positive relation between migration fear and crash risk travels through the asymmetric information channel. We proxy asymmetric information by stock liquidity and find that illiquid firms, as measured by *Amihud* and *Spread*, have a stronger propensity for future crash risk. We also investigate other firm-specific characteristics that can enhance or mitigate the effect of migration fear on crash risk. We find that firms in unregulated industries, with weak corporate social responsibility, and riskier firms, as measured by their cash flow volatility, have a greater probability of future crash risk. These findings enrich our understanding of the impact of migration fear on future stock price crash risk and shed light on how migration fear interacts with firm characteristics to influence heterogeneous effects.

While our study is novel in investigating the impact of migration fear on stock price crash risk, it has some limitations. The data on migration fear does not allow us to directly examine firm-specific-migration-fear related shocks. This is an area for future extension as richer data becomes available.

Our study complements the existing literature on the external determinants of future stock price crash risk. Overall, our findings suggest that migration fear has an important impact on investor welfare, manifested through future stock price crash risk.

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6 Figures and Tables

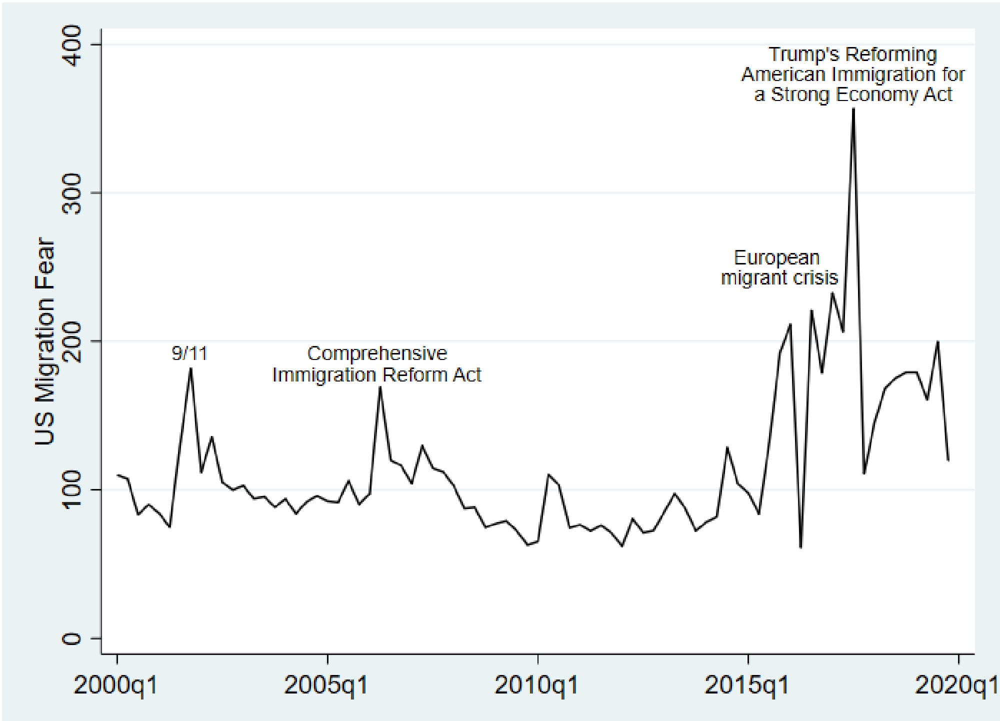

Figure 1: The U.S. migration fear index: 2000q1 – 2020q1.

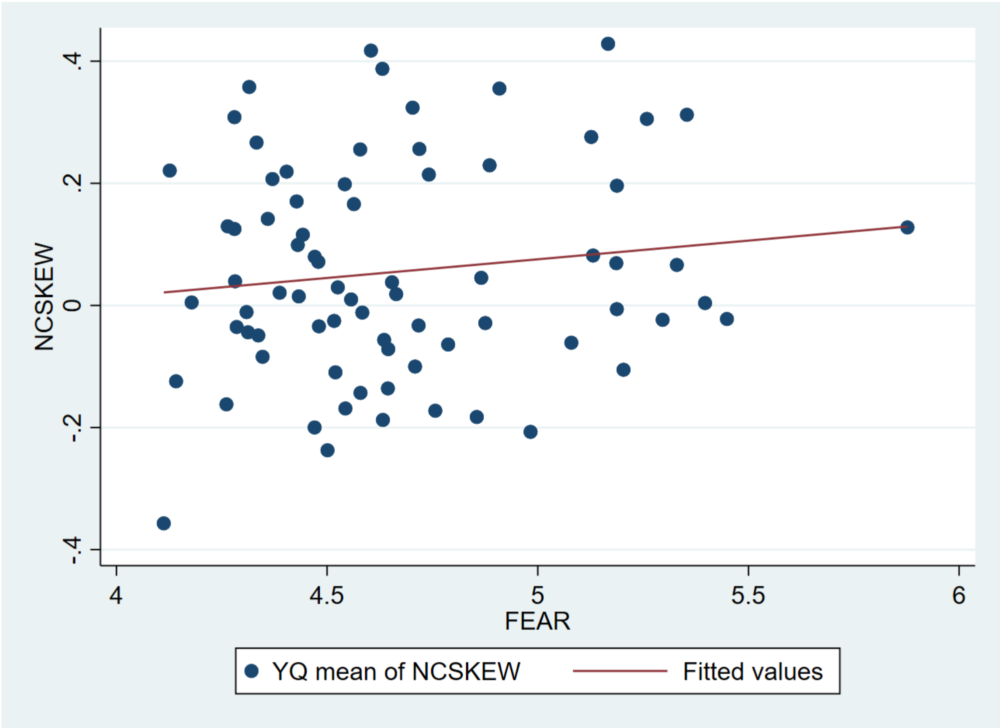

Figure 2: The figure depicts the correlation and trend between $MFEAR$ and $NCSKEW$.

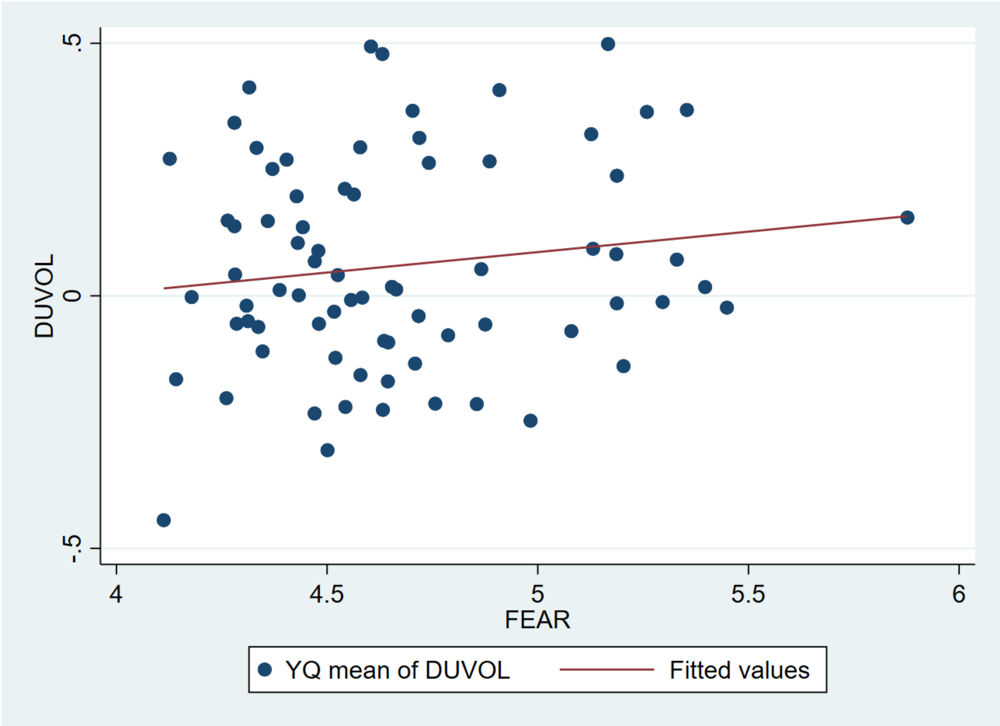

Figure 3: The figure depicts the correlation and trend between $MFEAR$ and $DUVOL$.

Table 1: **Pairwise Correlations**

This table shows the pairwise correlations between the variable of this study. Reference numbers in columns and rows refer to the variables associated with the pairwise correlation. * and ◇ indicate 1%, and 5% significance levels, respectively.

obs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) $NCSKEW$	1										
(2) $DUVOL$	0.950*	1									
(3) $MFEAR$	0.004◇	0.005*	1								
(4) $DTURN$	-0.021*	-0.023*	0.017*	1							
(5) $RETURN$	-0.680*	-0.683*	0.002	0.036*	1						
(6) MTB	-0.036*	-0.037*	0.055*	0.034*	0.046*	1					
(7) ROA	-0.014*	-0.015*	-0.062*	0.008*	0.073*	-0.156*	1				
(8) $SIZE$	0.004◇	0.001	0.041*	0.004	0.065*	-0.289*	0.365*	1			
(9) LEV	-0.007*	-0.006*	0.029*	0.020*	0.010*	-0.246*	0.001	0.360*	1		
(10) $KURT$	0.008*	0.008*	0.032*	0.047*	-0.017*	0.005◇	0.043*	-0.003◇	-0.014*	1	
(11) $SIGMA$	0.028*	0.023*	-0.064*	0.126*	-0.121*	0.111*	-0.349*	-0.439*	-0.096*	0.039*	1

Table 2: **Descriptive Statistics**
This table shows summary statistics of variables of the study. All the variables are winsorized at 1% level in both tails of the distribution before the summary statistics are calculated. Appendix A defines the variables.

Variable	N	Mean	p25	p50	p75	Max	Min	SD
$NCSKEW$	285254	0.055	-0.822	0.062	0.936	2.757	-2.631	1.197
$DUVOL$	285106	0.060	-0.866	0.049	0.981	3.419	-3.262	1.383
$MFEAR$	285353	4.660	4.428	4.584	4.866	5.877	4.112	0.356
$DTURN$	281346	0.004	-0.067	-0.002	0.064	1.068	-0.952	0.242
$RETURN$	285353	-0.184	-0.835	-0.108	0.547	3.417	-4.378	1.326
MTB	282073	1.563	0.655	1.071	1.825	10.030	0.118	1.620
ROA	264336	0.008	0.004	0.019	0.037	0.129	-0.302	0.062
$SIZE$	285349	6.410	4.891	6.419	7.839	15.010	-6.908	2.181
LEV	285243	0.561	0.336	0.553	0.789	1.425	0.041	0.287
$KURT$	285306	3.014	2.190	2.696	3.482	7.410	1.519	1.176
$SIGMA$	285306	0.053	0.029	0.045	0.070	0.151	0.011	0.031
VIX	285353	20.430	15.140	17.640	25.490	33.320	11.300	6.305
LEI	285353	94.130	86.630	95.490	101.600	111.500	77.000	9.101
$UNEMPLOY$	285353	5.916	4.620	5.530	6.170	9.630	3.670	1.711
$INFLATION$	285353	2.148	1.586	2.270	2.853	3.839	-0.356	1.034

Table 3: **The Impact of Migration Fear on Crash Risk**
This table presents the results of estimating Equation (4) to investigate the impact of migration fear ($MFEAR$) on stock price crash risk (proxied by $NCSKEW_{T+1}$ and $DUVOL_{T+1}$). Panel A showcases the estimation results, while Panel B demonstrates the marginal effect. Appendix A provides clear definitions for each variable. We report clustered standard errors by firm in parentheses, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		$NCSKEW_{T+1}$			$DUVOL_{T+1}$	
$MFEAR$	0.0603***	0.222***	0.101***	0.0792***	0.273***	0.122***
	(0.00542)	(0.0126)	(0.00873)	(0.00628)	(0.0146)	(0.0101)
$CRASH$		-0.117***	-0.115***		-0.136***	-0.133***
		(0.00438)	(0.00439)		(0.00507)	(0.00508)
$DTURN$		0.0300***	0.0244***		0.0278**	0.0216**
		(0.00935)	(0.00933)		(0.0109)	(0.0109)
$RETURN$		0.118***	0.119***		0.136***	0.137***
		(0.00227)	(0.00227)		(0.00268)	(0.00267)
MTB		0.100***	0.101***		0.115***	0.115***
		(0.00285)	(0.00283)		(0.00334)	(0.00332)
ROA		-1.328***	-1.251***		-1.577***	-1.495***
		(0.0782)	(0.0776)		(0.0909)	(0.0902)
$SIZE$		0.106***	0.0887***		0.119***	0.101***
		(0.00459)	(0.00431)		(0.00537)	(0.00505)
LEV		-0.0763***	-0.107***		-0.0880***	-0.122***
		(0.0148)	(0.0148)		(0.0174)	(0.0173)
$KURT$		0.000548	9.66e-05		0.000566	5.43e-05
		(0.00201)	(0.00201)		(0.00232)	(0.00232)
$SIGMA$		0.886***	1.039***		1.042***	1.225***
		(0.103)	(0.0991)		(0.120)	(0.115)
VIX			0.00309***			0.00428***
			(0.000371)			(0.000430)
LEI			-0.00420***			-0.00392***
			(0.000494)			(0.000576)
$UNEMPLOY$			-0.000190			0.00212
			(0.00257)			(0.00299)
$INFLATION$			-0.0129***			-0.0162***
			(0.00215)			(0.00249)
EPU			0.00404			0.00391
			(0.0102)			(0.0118)
Constant	-0.225***	-1.630***	-0.754***	-0.308***	-1.950***	-0.999***
	(0.0253)	(0.0655)	(0.0753)	(0.0293)	(0.0760)	(0.0866)
Year FE	No	Yes	No	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	318,550	318,550	279,299	318,390	318,390	279,160
R-squared		0.001	0.044		0.001	0.044
Number of gvkey	9,851	9,851	9,171	9,851	9,851	9,170
Panel B - marginal effect						
% Δ			16.8%			18.9%

Table 4: **Differential Impact of Migration Fear on Crash Risk: Industries with Most Immigrant Workers**

This table presents estimates of Equation (4) with a focus on industries with high shares of immigrant workers. Based on Pew Research Centre data, the top industries in the US by immigrant share of workers are manufacturing (including computer and electronic products, food manufacturing, textile, apparel and leather manufacturing, and other unspecified manufacturing), construction, and agriculture and extraction. We estimate Equation (4) separately for firms belonging to these industries ($IND_{IMMIGRANTS} = 1$) and for all other sectors ($IND_{IMMIGRANTS} = 0$). Appendix A provides clear definitions for each variable. We report clustered standard errors by firm in parentheses, with statistical significance denoted by *, **, and *** indicating levels of 10%, 5%, and 1%, respectively.

Panel A : Industries with most immigrant workers				
	(1)	(2)	(3)	(4)
	$NCSKEW_{T+1}$		$DUVOL_{T+1}$	
VARIABLES	Most immigrant workers	All other sectors	Most immigrant workers	All other sectors
$MFEAR$	0.150***	0.084***	0.182***	0.098***
	(0.012)	(0.011)	(0.014)	(0.013)
Constant	-0.493***	-0.435***	-0.687***	-0.596***
	(0.105)	(0.096)	(0.122)	(0.112)
CONTROLS	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	143,741	176,306	143,687	176,205
Panel B: Marginal Effect				
%Δ	25.9%	15.7%	28.1%	16.4%

Table 5: **Robustness Results: 2SLS Regressions**

This table reports the results of a Two-Stage Least Squares (2SLS) regression analysis. The instrumental variable is the average migration fear index scores of France, Germany, and the United Kingdom during the sample period. Panel A presents the results of the first-stage regressions, while Panel B reports the second-stage regression results. Appendix A provides clear definitions for each variable. We report clustered standard errors by firm in parentheses, with statistical significance denoted by *, **, and *** indicating levels of 10%, 5%, and 1%, respectively.

Panel A: 2SLS first-stage	
	$MFEAR$
Fear_average	0.002***
	0.000
Firm FE	Yes
CONTROLS	Yes
Observations	283015
Underidentification Test: χ^2-statistic	4375
p-value	0.000
Cragg-Donald Wald F statistic	85411
Kleibergen-Paap rk Wald F statistic	230000
p-value	0.000

Panel B : 2SLS second-stage		
	(1)	(2)
VARIABLES	$NCSKEW_{T+1}$	$DUVOL_{T+1}$
$MFEAR$	0.170***	0.213***
	(0.016)	(0.018)
CONTROLS	Yes	Yes
Firm FE	Yes	Yes
Observations	283,015	282,865
R-squared	0.045	0.044
Number of gvkey	8,993	8,982

Table 6: **Robustness Results: First-difference Regressions**

This table reports the results of a first-difference specification to control for time-invariant effects that may be specific to stock price crash risk. Appendix A provides clear definitions for each variable. We report clustered standard errors by firm in parentheses, with statistical significance denoted by *, **, and *** indicating levels of 10%, 5%, and 1%, respectively.

	(1)	(2)
VARIABLES	$\Delta NCSKEW_{T+1}$	$\Delta DUVOL_{T+1}$
$\Delta MFEAR$	0.185***	0.232***
	(0.011)	(0.012)
$\Delta CONTROLS$	Yes	Yes
Constant	-0.011***	-0.013***
	(0.001)	(0.001)
Firm FE	Yes	Yes
Observations	271,333	271,196
R-squared	0.269	0.290
Number of gvkey	8,984	8,973

Table 7: **Robustness Results: Sub-sample Analysis**

This table presents the results of estimating Equation (4) using a sub-sample of periods with heightened migration fear that includes 2001q3 and 2001q4 (September 11 attack), 2006q2 (Comprehensive Immigration Reform Act), 2015q3 and 2015q4 (European migrant crisis), 2016 and 2017 (Trump's reforming American Immigration for a Strong Economy Act). Appendix A provides clear definitions for each variable. We report clustered standard errors by firm in parentheses, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
VARIABLES	$NCSKEW_{T+1}$	$DUVOL_{T+1}$
$MFEAR$	0.328***	0.412***
	(0.019)	(0.023)
CONTROLS	Yes	Yes
Firm FE	Yes	Yes
Constant	-8.076***	-9.813***
	(0.559)	(0.645)
Observations	35,520	35,508
R-squared	0.084	0.087

Table 8: **Channel Testing: Is the impact of migration fear on crash risk stronger for firms with higher information asymmetry?**

This table presents the results of estimating Equation (4) while doing a sub-sample analysis. Using two measures of (il)liquidity ($AMIHUD$ and $SPREAD$), we split the sample based on the top and bottom 20% values of these two measures and estimate each sub-sample separately. Appendix A provides clear definitions for each variable. We report clustered standard errors by firm in parentheses, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% levels, respectively.

Asymmetric information				
	High	Low	High	Low
	(1)	(2)	(3)	(4)
VARIABLES	$NCSKEW_{T+1}$	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$DUVOL_{T+1}$
Panel A - $AMIHUD$				
$MFEAR$	0.136***	0.0339*	0.167***	0.0434*
	(0.0188)	(0.0198)	(0.0219)	(0.0228)
CONTROLS	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	56,974	56,808	56,925	56,770
R-squared	0.054	0.042	0.054	0.041
Panel B - $SPREAD$				
$MFEAR$	0.120***	0.0431**	0.140***	0.0513**
	(0.0186)	(0.0199)	(0.0218)	(0.0229)
CONTROLS	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	57,195	57,662	57,142	57,624
R-squared	0.054	0.047	0.054	0.047

Table 9: **Mitigating factors on the relationship between migration fear and crash risk**
This table presents the results of estimating Equation (4) while testing the mitigating effect of regulated industries, ESG, management's sentiment and cash flow volatility on the relationship between migration fear and crash risk. Panel A, splits the sample to firms belonging to regulated and unregulated industries. Panels B, C and D, split the sample based on the bottom and top 20% values of ESG, $SENTIMENT_{MNG}$ and CFV. All specifications include firm-fixed effect and control variables. Appendix A provides clear definitions for each variable. We report clustered standard errors by firm in parentheses, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$NCSKEW_{T+1}$	$DUVOL_{T+1}$
Panel A - Industry regulations				
	Regulated industries		Unregulated industries	
$MFEAR$	0.007	-0.016	0.105***	0.128***
	(0.038)	(0.045)	(0.009)	(0.010)
Constant	-0.470	-0.548	-0.767***	-1.020***
	(0.315)	(0.367)	(0.077)	(0.089)
Observations	12,426	12,417	270,905	270,775
R-squared	0.030	0.030	0.045	0.045
VARIABLES	$NCSKEW_{T+1}$		$DUVOL_{T+1}$	
Panel B - ESG				
	Low	High	Low	High
$MFEAR$	0.282***	0.155***	0.332***	0.177***
	(0.037)	(0.034)	(0.043)	(0.039)
Constant	-3.956***	-2.192***	-4.666***	-2.149***
	(0.528)	(0.404)	(0.631)	(0.465)
Observations	13,918	14,068	13,914	14,065
R-squared	0.058	0.037	0.057	0.036
Panel C - Managerial sentiment				
	Low	High	Low	High
$MFEAR$	0.158***	0.066***	0.189***	0.079***
	(0.021)	(0.022)	(0.024)	(0.025)
Constant	-1.561***	-0.829***	-2.086***	-0.985***
	(0.294)	(0.282)	(0.339)	(0.321)
Observations	48,883	46,045	48,844	46,032
R-squared	0.054	0.061	0.055	0.062
Panel D - Cash flow volatility				
	Low	High	Low	High
$MFEAR$	0.099***	0.184***	0.120***	0.233***
	(0.024)	(0.024)	(0.027)	(0.028)
Constant	-0.652***	-2.234***	-0.928***	-2.820***
	(0.244)	(0.268)	(0.283)	(0.311)
Observations	41,798	41,456	41,777	41,431
R-squared	0.055	0.062	0.054	0.062

Table 10: **Robustness Results: Alternative Definition of Migration Fear**

This table re-test Equation (4) employing and alternative definition of migration fear, i.e. $REFUGEES$. $REFUGEES$ measures the pressure upon states caused by the forced displacement of large communities as a result of social, political, environmental or other causes, and is available at the Fragile States Index website. Appendix A provides clear definitions for each variable. We report clustered standard errors by firm in parentheses, with statistical significance denoted by *, **, and *** indicating levels of 10%, 5%, and 1%, respectively.

	(1)	(2)
VARIABLES	$NCSKEW_{T+1}$	$DUVOL_{T+1}$
$REFUGEES$	0.042***	0.045***
	(0.004)	(0.004)
Constant	-1.322***	-1.423***
	(0.118)	(0.137)
CONTROLS	Yes	Yes
Firm FE	Yes	Yes
Observations	196,553	196,469
R-squared	0.045	0.044
Number of gvkey	7,178	7,177

Appendix A

This table provides variable definitions. Columns 1 and 2 provide the variable name and definition, and Column 3 provides the data source.

Variable	Definition	Data Sources
$MFEAR$	The natural logarithm of Baker et al. (2015) textual-based fear index, see Section 3.2 for more details.	Available at footnote[19]
$NCSKEW$	Negative skewness is a measure of stock price crash risk, constructed in Section 3.1.	Compustat
$DUVOL$	Down and up volatility is a measure of stock price crash risk, constructed in Section 3.1.	Compustat
ROA	The ratio of operating income before depreciation to total assets.	Compustat
$SIZE$	The logarithm of a firm's total assets.	Compustat
MTB	The ratio of market value of equity plus total liabilities over book value of equity plus total liabilities.	Compustat
$DTURN$	The change in the average quarterly share turnover from the previous quarter, where share turnover is calculated as the quarterly share trading volume divided by the average number of shares outstanding during the specified year-quarter period.	Compustat
$RETURN$	The average of firm-specific weekly returns over the specified year-quarter period.	CRSP
LEV	The ratio of total liabilities to total assets.	Compustat
$KURT$	The kurtosis of firm-specific weekly returns in year-quarter YQ.	CRSP
$SIGMA$	The standard deviation of firm-specific weekly returns in year-quarter YQ.	CRSP
VIX	The Chicago Board Options Exchange's CBOE Volatility Index .	Chicago Board Options Exchange
LEI	The Leading economic index representing the global economic movements, developed by the University of Michigan.	The Conference Board.
$UNEMPLOY$	The total unemployment as a percentage of total labor force.	The World Bank Database
$INFLATION$	The US inflation rate.	The World Bank Database
EPU	The natural logarithm of Baker et al. (2016) quarterly three component economic policy uncertainty index.	Available at footnote[20]

[19] www.policyuncertainty.com
[20] www.policyuncertainty.com

Variable	Definition	Data Sources
$IND_{IMMIGRANTS}$	A dummy variable representing top industries in the US by immigrant share of workers. It is equal one for firms belonging to manufacturing (including computer and electronic products, food manufacturing, textile, apparel and leather manufacturing, and other unspecified manufacturing), construction, and agriculture and extraction sectors, and zero otherwise.	Pew Research Centre
$AMIHUD$	The (Amihud, 2002) price impact of trading (il)liquidity measure, calculated as daily return over daily dollar traded volume, averaged over a quarter.	CRSP
$SPREAD$	The (il)liquidity measure based on bid-ask spreads constructed by (Corwin and Schultz, 2012) as daily ask minus bid prices over the average of ask and bid prices. The quarterly $SPREAD$ is the quarterly average of daily $SPREADS$.	CRSP
$IND_{REGULATED}$	A dummy variable equal one for firms belonging to industries with Standard Industrial Classification (SIC) codes 4811–4899, 4922–4924, 4931, and 4941, and zero otherwise.	(Kothari et al., 2009)
ESG	A firm's overall ESG score, and is the percentile ranked score based on the three self-reported information in the environmental, social and corporate governance pillars. 0% is the lowest (where firms have not reported any of the pillars), and 100% is the highest value Boubakri, Guedhami, Kwok and Wang (2019).	Asset-4 database in Thomson Reuters
$SENTIMENT_{MNG}$	A firm-level textual-based measure of managerial sentiment is calculated using the filings database by Loughran and McDonald (2016). It is computed as the difference between the number of positive words and the number of negative words, divided by the total number of words.	From the website of Loughran and McDonald (2016)[21]
CFV	The rolling standard deviation of quarterly cash flows divided by total assets, employing an 8-quarter window.	Compustat

[21] https://sraf.nd.edu

Variable	Definition	Data Sources
REFUGEES	An alternative proxy for migration fear measures the pressure upon states caused by the forced displacement of large communities as a result of social, political, environmental or other causes.	Available at footnote[22].

[22] https://fragilestatesindex.org/