Managers, Analysts, and Political Risk

Evidence from Chinese Firms

(Preliminary Draft)

Dongwei Xu

xud@bu.edu

May 2018

1 Introduction

Inspired by Hassan et al. [2017], in this paper I aim to answer the following five questions. The first is, how high the political risk is among firms in *China* compared to that among firms in the United States; the second question is, given a measurement of political risk of a firm at a given time, how much of it is inferred from *corporate voluntary disclosure* and how much is from *market following.* Given a certain level of firm-level political risk, the third question is, how substantial the contributions of political risk from different geographic origins at various aggregation levels are; the next question is, given a certain level of firm-level political risk, what its impact on the firm's political risk management is, in equity price and volatility, investment and hiring (passive), and in donation to campaigns and connection with politicians (active); the last question is, how firm-level political risk is related to different political topics.

In this preliminary draft, I describe the dataset used to construct firm-level political risk, explain the measurement, and provide first-pass answers to the first two questions. With answers to the first two questions, the firm-level political risk is decomposed into two parts that are mutually exclusive, the managers' and analysts' perspectives on the political risk a firm faces at a given time. The statistical differences between the two parts (as to be shown) put forward sensible reasons to believe answers to the last three questions might differ immensely when asked separately about the two parts[1], and therefore, deliver more specific implications to firms' decision makers and institutional investors.

To construct the dataset, I define the universe of firms in the *main* dataset the Chinese firms that are or were traded in the United States or in Hong Kong. This choice has two benefits: these firms hold regular, English earnings conference calls, and they are potentially subject to a broader range of political risks (e.g., regulations from both US and China). I also define an *extended* dataset that additionally includes all firms listed in (Mainland) China (the Shanghai Stock Exchange and the Shenzhen Stock Exchange). A caveat about these additional firms is that, the earnings conference calls they hold are in Chinese, meaning analysis of them demands new computational linguistic approaches and tools.

The input for political risk faced by a firm at a given time is the transcript of a call. A plain-vanilla call starts with a Prepared Remarks session in which firm representatives give presentations; the call moves to the Question-and-Answer session in which call participants discuss question raised by analysts. Therefore, I intuitively separate and name the two sessions the *presentation* and *discussion* parts of a call. Such separation sheds light on the relative contribution of the two parts to the political-risk measurement, and more importantly, allows the identification of firm-level political risk attributed to corporate voluntary disclosure by managers and to disclosure prompted by questions from participating analysts.

[1] Working with earnings conference calls from the United States, Brockman et al. [2015] finds that investors (particularly institutional investors) react more strongly to analyst tones than to manager tones; Brockman et al. [2017], on the other hand using Hong Kong data, finds stock prices are significantly sensitive to manager tones- but insignificantly sensitive to analyst tones.

I follow Hassan et al. [2017] to measure firm-level political risk using sequence-classification method developed in computational linguistics. The measurement is applied to both the presentation and discussion parts, the sum of which gives the political risk.

The main finding is as follows. Despite the private and social cost of disclosure, the political risk origins from the presentation part is significantly higher than that from the discussion part, suggesting the voluntary disclosure might serve as clarification in the first place. Furthermore, I find the dispersion of firm-level political risk in cross-section rises when the average firm-level political risk is high. Such dispersion comovement exists as well in presentation and discussion parts when treated separately.

In what follows, I explain the dataset to construct and measurement of political risk in Section 2 and Section 3, respectively. Empirical results are presented in Section 4. I further discuss plans for next-step in Section 5.

2 Data

The current dataset contains 2896 earnings conference calls from 177 Chinese firms that are or were traded in the United States. The calendar quarters of these calls span from 2005:Q3 to 2018:Q1. Of the 177 firms, 96 are or were listed in NASDAQ, NYSE or AMEX, while the remaining (81) firms are or were traded in Over-the-counter (OTC) markets as American Depositary Receipts (ADRs)[2]. As a result, the current dataset has 96 firms with 1915 firm-quarter calls that are in the dataset of Hassan et al. [2017][3].

Transcripts of calls are collected from the Seeking Alpha website (seekingalpha.com), redirected from the official NASDAQ website (nasdaq.com). I use automated algorithms (Web-crawling and Web-scraping) to construct the *raw* dataset. By doing so, I take advantage of plain-text format's accuracy and efficiency in linguistic computation. Furthermore, I deliberately familiarize myself with the implementation of such automated algorithms since the earnings conference calls from firms listed in mainland China are not integrated into any dataset and hence require such techniques.

A plain-vanilla call contains two sessions. In the first session, firm representatives present the Prepared Remarks; in the second, they answer further questions from the floor (Question-and-Answer), consisted usually of financial analysts representing institutional investors. The transcript of a call, on the other hand, contains additional immaterial contents. At the beginning of a transcript (call), it is common practice for a firm representative, usually the Investor Relations (IR) manager, to read a Safe Harbor statement[4]; at the end of a transcript, additional disclaimer statements (e.g., copyright statement) are attached by the transcripts vendor; throughout a transcript (call), an Operator is involved to organize the presentations and questions.

[2] The ADR is a stock that is traded in the United States but represents a certain percentage (number) of share(s) of a foreign firm that is listed in an overseas market. An ADR gives investors pro-rata benefits, such as dividends, in US dollars.

[3] As is shown later, due to the cleaning of data, and the differences in measurements and libraries, the numbers in here are not directly comparable to those in Hassan et al. [2017]; this comparison is a task in the next-step plan and detailed in Section 5.

[4] A Safe Harbor statement, including sentences like "... does not undertake any obligation to update any forward-looking statement, except as required under applicable law...", serves to limit the firm's liability should actual results prove different from the discussed in the call. The Safe Harbor statement is irreverent to the main contents of a call.

To mitigate the potential bias from these contents, I clean the transcripts by use only presentations, questions and answers of a call.

As a result, in a transcript, I define *presentation* part (presentations by firm representatives other than IR manager in Prepared Remarks session) and *discussion* part (questions and answers by call participants other than the Operator in Question-and-Answer session). Therefore, I am able to link directly the presentation part to *managers* and the discussion part to *analysts*[5], and treat them individually.

The raw difference between presentation and discussion lies in the length. To understand the firm's political risk from managers' vs analysts' perspectives, it is essential to examine such difference between the presentation and discussion parts across time and firms. I define the length as the number of words. In Table 1, I show that the discussion part of a call is consistently longer than presentation part, and it exhibits larger length dispersion in the cross-section.

In Table 1, I calculate the means and standard deviations of the length of the presentation and discussion parts of calls and compare these two moments from the two parts in various ways, demonstrating that, the length of discussion part is longer and has larger cross-sectional dispersion than that of presentation part. Focus first on rows (1)-(10), which tabulate the results of all firms in current dataset. Rows (3)-(4) show the yearly and sample means of length of the presentation (P, row (3)) and discussion (D, row (4)) parts as portions of the total length of a call (row (1)). Over all the years in sample, the discussion part accounts for about 57% of a call, roughly 15% higher than the portion of presentation part; reading across columns of these two rows, I find the portion of presentation part increases over time. Row (7) facilitates a better comparison by showing the ratio (P/D) of the two means; similarly, this ratio rises over time. A possible cause for the discussion part's portion to decrease might be the surged and concentrated market following immediately after a firm's IPO. As a result, the separation of the presentation and discussion parts is central to gaining insights about *measuring* political risk.

Turning to the cross-sectional dispersion, the mean-adjusted standard deviation (standard deviation over mean) in rows (5)-(6) reveals that the discussion part manifests higher dispersion of length. Rows (8)-(9) compare the mean-adjusted and non-adjusted standard deviations of the presentation and discussion parts, and corroborate the higher dispersion of length from discussion part. In rows (11)-(13), I repeated the same calculation using only firms in in NASDAQ, NYSE or AMEX; i.e., firms and calls in Hassan et al. [2017], the message that discussion part is longer in words and is more volatile in length is unchanged.

Without imposing assumptions, this section shows that the presentation and discussion parts of a call differ in nature. The most intuitive reason for the cross-sectional dispersion of discussion part is perhaps market following[6]. In a classic study, Bhushan [1989] finds several firm characteristics that are major determinants of analysts' following; in another direction, Hong et al. [2000] shows analysts' following is related to firms' cost of capital. Therefore, this section also produces facts that are ripe for future investigation.

[5]The discussion of managers' behavior during answering questions is beyond the scope of this paper; further research could be conducted due to the clean format of the dataset. Interesting analyses have contributed to such discussion, for example, Hollander et al. [2010] find investors treat silence during managers' answering negatively.

[6]See Healy and Palepu [2001] for an inclusive literature survey.

3 Measurement

I adopt a similar measurement of political risk as in Hassan et al. [2017]. As to be shown, the biggest variation from that measurement is that instead of using a fixed window of (20) words, I use a floating window of words defined by paragraphs of a call. I explain the choice of floating window at the end of this section, after introducing the measurement, to make the reason clear.

Let $j = 1, 2, \cdots, J$ and $t = 1, 2, \cdots, T$ index the set of firms and quarters, respectively. Denote as C_{jt} the (number of words in) a call from firm j at quarter t[7]. Furthermore, let $\mathbb{C}^1_{ijt}$ be the set of single-word terms from the i-th paragraph in a call from firm j at quarter t where i indexes the paragraphs of the call. Similarly, let $\mathbb{C}^2_{ijt}$ be the set of bigram terms from the i-th paragraph, and $\mathbb{C}^x_{ijt}$ be the set of all possible consecutive x-word terms from the i-th paragraph. For any $\mathbb{C}^x_{ijt}$, x is capped by some fixed number $\bar{x}$.

Within each paragraph, I define the political risk as the product of two numbers, the number of occurrences of terms categorized as political, and a binary indicator of risk synonyms. In particular,

$$\text{PolR}_{ijt} = \frac{1}{C_{jt}} \Big(\sum_{x=1}^{\bar{x}} \sum_{w \in \mathbb{C}^x_{ijt}} \mathbf{1}[w \in \mathbb{P}] \Big) \times \mathbf{1}[(\mathbb{C}^1_{ijt} \cap \mathbb{R}) \neq \emptyset] \tag{1}$$

where $\mathbf{1}[\cdot]$ is the binary indicator function, and $\mathbb{P}$ and $\mathbb{R}$ are, respectively, the sets of political terms and risk synonyms. Therefore, the two sums in parenthases left of the multiplication sign in Eq. (1) is the number of occurrences of terms that are political and the part right to is the binary indicator of risk synonyms. Together, they capture *whether or not* this paragraph is on a political risk topic, and *how intensively* political risk is discussed.

Next, I define three paragraph index sets. Let $\mathbb{I}$ be the paragraph indices of an arbitrary call, and $\mathbb{I}^P$ and $\mathbb{I}^D$ the paragraph indices of the presentation and discussion parts of this arbitrary call. As a result, I define the political risk of firm j at quarter t the sum of political risk measuring from paragraphs in the call,

$$\text{PolR}_{jt} = \sum_{i \in \mathbb{I}} \text{PolR}_{ijt} \tag{2}$$

and hence $\text{PolR}_{jt} = \text{PolR}^P_{jt} + \text{PolR}^D_{jt}$, where PolR^P_{jt} and PolR^D_{jt} are political risk inferred from the presentation and discussion parts, defined following Eq. (2). I interpret PolR^P_{jt} and PolR^D_{jt}, respectively, as the firm's political risk from *managers*' and *analysts*' perspectives.

The risk synonyms are obtained by Oxford Dictionary. Specifically, following Hassan et al. [2017], the $\mathbb{R}$ includes "risk", "risky", "uncertainty" and "uncertain", and single-word synonyms of these four words from Oxford Dictionary excluding "question", "questions", "unknown", "venture", and "prospect"[8]. The political terms in $\mathbb{P}$ are modified from Baker et al. [2016] and Baker et al. [2013] to capture the political discussion

[7] Throughout I use blackboard font (e.g. $\mathbb{C}$) to denote a set and regular (e.g., C) to a number.

[8] I am grateful to Tarek Hassan, Stephan Hollander, Laurence van Lent and Ahmed Tahoun for making their synonyms available (Hassan et al. [2017], p67 Appendix Table 3.)

related to both the United States and China. $\mathbb{P}$ contains single words (e.g., political), bigrams (e.g., Federal Reserve), trigrams (e.g., Supreme People's Procuratorate), and quadrigram (e.g., People's Bank of China). $\mathbb{P}$ includes only unique terms and Eq. (1) need not adjust for *term frequency*; therefore, the political risk measurement in Eq. (2) is the *exact* share of a call devoted to discussion of risks associated with political topics.

Now the reason for the choice of floating instead of fixed window in measuring political risk is as follows. The $\mathbb{P}$ consists terms of different length; therefore, in this context, the fixed window might be an inconsistent measure of distance to risk synonyms. However, for certain political-related terms such as "People's Bank of China", the truncated bigrams and trigrams will result in upward bias.

4 Empirical Results

In this section, I summarize my current findings. I make two caveats to my findings. First, I aggregate the cross-sectional observations to interpret the time-series properties of the political risk. Second, I randomly sample 420 calls from the main dataset, and truncate $\mathbb{P}$ and $\mathbb{R}$ to both contain precisely 20 elements; I do this to ease the computational complication.

In Table 2, I show the means and standard deviations of political risk inferred from the call PolR, and from presentation PolR^P and discussion PolR^D parts. As is discussed in Section 3, I interpret the political risk inferred from the presentation and discussion parts as the political risk faced by a firm from the managers' and analysts' perspectives. Given the private and social costs of disclosure (Admati and Pfleiderer [2000]), the speculation about the relative portions of the two in total political risk measurement PolR is that firms are reluctant to disclose the usually unhedgeable political risk and thus the analysts increase PolR by raising political risk-related questions, i.e., PolR^D.

Interestingly, this is not the case in data. From rows (4)-(5) of Table 2, PolR^P continually serves as a more substantial portion in PolR than PolR^D, suggesting the willingness of firms to disclose political risk-related issues voluntarily. Several studies have found voluntary disclosure profitable in various countries[9]. Even though the results here are specific to political risk, future studies can link such voluntary disclosure on political risk matters to similar settings.

Rows (7)-(8) of Table 2 calculate the standard deviation of PolR^P and PolR^D within years. I interpret the standard deviation as the cross-sectional *dispersion* of firm-level political risk. Similar to Hassan et al. [2017], I find the dispersion increases when the average firm-level political risk is high; this pattern is shared unanimously by PolR, PolR^P, and PolR^D. In Fig. 1, I plot cross-sectional mean and dispersion of PolR, PolR^P and PolR^D in panel (A)-(C), respectively. The comovement is strongest in PolR^D, with a correlation coefficient of 0.62. As pointed out by Hassan et al. [2017], such dispersion might interact with frictions to reduce growth (Bloom et al. [2018]; Gilchrist et al. [2014]) or induce misallocation and dampen productivity

[9]Among others, Bradbury [1992]: New Zealand; Chow and Wong-Boren [1987]: Mexico; Hossain and Adams [1995]: Australia; Raffournier [1995]: Switzerland; Scott [1994]: Canada.

(Hsieh and Klenow [2009]). Therefore, the result from here can also be combined with firm-level data to investigate the economic magnitudes of political risk in aggregate level and quantify the impact from political risk on firms.

5 Conclusion

In this section, I elaborate more on steps to taken in this paper.

To begin with, the preferred dataset contains earnings conference calls of three sources, the United States-traded, the Hong Kong-traded and the mainland China-traded Chinese firms. The current dataset contains calls from the first source yet not the latter two. The task on dataset construction remains.

The third and fourth questions in the beginning of Section 1 require linkage from the dataset of earnings conference calls to firm-quarter financial statements data from Compustat as well as other vendors. By doing so, I can see how these firms' business are operated in the United States and China, and how these firms make decisions in face of political risk.

Furthermore, given only part of firms in my dataset are subject to Lobbying Disclosure Act (LDA), firms' lobbying-related actions are hard to identify for the majority of firms in my dataset. Potentially, firms can directly lobby in the United States under the Foreign Agents Registration Act (FARA), but it is super useful to think of other factors ("Lobby Proxy") that play in China's efforts to lobby in the United States (Wagreich [2013]). A even more interesting question would be that, in face of political risk, what a Chinese firm may act in the form of donation to campaigns and connection with politicians, official diplomatic conversations, or pressuring the United State business partners, to affect and alter the political environment of a particular industry (e.g., e-commerce), and hence put an impact on the firms of the same industry.

Last but not least, as is pointed out in Section 2, other latent factors, such as IPO indicator, might contribute to the time-series variation of the discussion part's length and hence require caution during measuring political risk. I plan to refine the political risk measurement to achieve efficiency while preserving the original "taste" of political term, and to find the measurement that can best capture the concept of political risk within this dataset.

Table 1. Call Transcript Length Difference Between Presentation And Discussion Parts.

This table tabulates the key statistics of call transcripts lengths across years. The length of a call transcript is defined as the number of words, where the transcript is cleaned by steps mentioned in Section 2. From rows (1)-(10), all firms in the dataset are used in calculation. I report the yearly mean and standard deviation (as percentage of mean) of transcripts' lengths of calls from that calendar year, in rows (1)-(2), respectively. In rows (3)-(6), I report the same statistics of presentation (rows (3)&(5)) and discussion (rows (4)&(6)) parts. The rows (7)-(9) are at the heart of this table; they show the ratios (as percentages) of means, mean-adjusted standard deviations, and standard deviations from presentation and discussion parts. Finally, the number of firm-quarter observations is given in rows (10). In rows (11)-(14), a subsample that overlaps the dataset of Hassan et al. [2017] is used in calculation. Rows (11)-(13) reports the same ratios between presentation and discussion parts as rows (7)-(9); row (14) gives the number of observations across years.

	Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	All
	Whole Call														
(1)	Mean	6276	6143	6558	6146	6171	5900	5478	4966	5282	4683	4368	4794	4697	5214
(2)	St.D./Mean (%)	0.24	0.28	0.33	0.32	0.37	0.32	0.39	0.60	0.42	0.46	0.49	0.46	0.50	0.45
	Mean (Portion of Whole Call)														
(3)	- P(resentation)	0.33	0.41	0.40	0.36	0.39	0.42	0.44	0.45	0.42	0.44	0.47	0.46	0.49	0.43
(4)	- D(iscussion)	0.67	0.59	0.60	0.64	0.61	0.58	0.56	0.55	0.58	0.56	0.53	0.54	0.51	0.57
	St.D./Mean														
(5)	- P	0.49	0.68	0.53	0.43	0.58	0.53	0.41	0.48	0.41	0.38	0.42	0.51	0.48	0.48
(6)	- D	0.37	0.58	0.58	0.45	0.52	0.55	0.65	0.86	0.61	0.71	0.75	0.73	0.86	0.69
	Ratio of P/D														
(7)	- Mean	0.49	0.70	0.66	0.56	0.64	0.72	0.79	0.83	0.72	0.78	0.87	0.86	0.96	0.75
(8)	- St.D./Mean	1.32	1.17	0.90	0.97	1.11	0.96	0.64	0.56	0.67	0.53	0.56	0.70	0.56	0.70
(9)	- St.D.	0.65	0.82	0.59	0.54	0.71	0.69	0.50	0.46	0.48	0.42	0.48	0.60	0.54	0.53
(10)	# of Obs.	100	114	99	117	111	134	277	474	406	359	332	307	66	2896
	Ratio of P/D														
(11)	- Mean	0.53	0.60	0.72	0.58	0.68	0.76	0.85	0.81	0.76	0.85	0.92	0.92	0.85	0.78
(12)	- St.D./Mean	1.43	1.24	0.99	1.03	1.15	0.94	0.60	0.56	0.58	0.47	0.48	0.68	0.49	0.67
(13)	- St.D.	0.75	0.74	0.71	0.60	0.79	0.71	0.50	0.46	0.44	0.40	0.44	0.62	0.41	0.52
(14)	# of Obs.	69	78	61	83	71	83	169	295	264	245	234	223	40	1915

Table 2. Political Risk Inferred From Presentation And Discussion Parts.

This table tabulates the key cross-sectional statistics of political risk $PolR$ across years. The political risk measurement is defined by Eqs. (1) and (2). Row (1) shows the cross-sectional average of $PolR$. Row (2)-(3) tabulates that of $PolR^P$ and $PolR^D$, respectively; row (4)-(5) gives the portion of $PolR^P$ and $PolR^D$ in $PolR$. The cross-sectional dispersion of political risk is captured by the standard deviation of political risk across firms. Row (6) shows the dispersion of $PolR$, and rows (7)-(8) the dispersion of $PolR^P$ and $PolR^D$, respectively. Row (9)-(11) gives the mean-adjusted standard deviations (standard deviation over respective mean) of $PolR$, $PolR^P$ and $PolR^D$, respectively. Finally, the number of firm-quarter observations is given in rows (12).

	Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	All
	Mean (*100)													
(1)	PolR	4.15	4.26	3.33	4.94	3.10	3.36	2.79	3.08	3.00	3.85	3.81	4.27	3.66
(2)	PolR^P	1.62	2.63	1.83	3.30	1.60	2.66	1.86	2.25	1.82	2.04	2.03	2.95	2.22
(3)	PolR^D	2.53	1.62	1.50	1.64	1.50	0.69	0.93	0.84	1.18	1.81	1.78	1.32	1.45
	Portion													
(4)	PolR^P/PolR	0.39	0.62	0.55	0.67	0.52	0.79	0.67	0.73	0.61	0.53	0.53	0.69	0.61
(5)	PolR^D/PolR	0.61	0.38	0.45	0.33	0.48	0.21	0.33	0.27	0.39	0.47	0.47	0.31	0.39
	St.D. (*100)													
(6)	PolR	3.21	3.81	2.20	5.42	1.66	2.84	2.56	3.48	3.20	3.72	3.06	5.24	3.37
(7)	PolR^P	2.38	3.11	1.40	4.67	1.25	2.18	2.15	3.34	2.51	2.70	2.10	3.92	2.64
(8)	PolR^D	1.47	1.29	1.52	1.65	1.40	1.10	1.41	1.15	1.93	2.69	2.30	2.13	1.67
	St.D./Mean													
(9)	PolR	0.77	0.89	0.66	1.10	0.53	0.85	0.92	1.13	1.07	0.97	0.80	1.23	0.91
(10)	PolR^P	1.47	1.18	0.77	1.41	0.78	0.82	1.15	1.48	1.38	1.32	1.03	1.33	1.18
(11)	PolR^D	0.58	0.79	1.01	1.00	0.93	1.58	1.52	1.38	1.63	1.48	1.29	1.61	1.23
(12)	# of Obs.	19	15	26	16	25	30	75	52	52	48	51	11	420

Figure 1. Firm-Level political Risk Dispersion

This figure show the firm-level political risk dispersion increases when average firm-level political risk is high. In panel (A)-(C), I depict respectively the firm-level political risk measurement PolR, and its components originating from presentation PolR^P and from discussion PolR^D. In any panel, the blue line indicates the cross-sectional mean while the red dashed line the cross-sectional standard deviation, the measure of dispersion. In all plots, the shaded areas are NBER recessions. The dataset covers 2007:Q1 to 2018:Q1.

References

Anat R Admati and Paul Pfleiderer. Forcing firms to talk: Financial disclosure regulation and externalities. *The Review of financial studies*, 13(3):479–519, 2000.

Scott R Baker, Nicholas Bloom, Steven J Davis, and Xiaoxi Wang. A measure of economic policy uncertainty for china. *U Chicago, work in progress*, 2013.

Scott R Baker, Nicholas Bloom, and Steven J Davis. Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636, 2016.

Ravi Bhushan. Firm characteristics and analyst following. *Journal of Accounting and Economics*, 11(2-3): 255–274, 1989.

Nicholas Bloom, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J Terry. Really uncertain business cycles. *forthcoming, Econometrica*, 2018.

Michael E Bradbury. Voluntary disclosure of financial segment data: New zealand evidence. *Accounting & Finance*, 32(1):15–26, 1992.

Paul Brockman, Xu Li, and S McKay Price. Differences in conference call tones: Managers vs. analysts. *Financial Analysts Journal*, 71(4):24–42, 2015.

Paul Brockman, Xu Li, and S McKay Price. Conference call tone and stock returns: Evidence from the stock exchange of hong kong. *Asia-Pacific Journal of Financial Studies*, 46(5):667–685, 2017.

Chee W Chow and Adrian Wong-Boren. Voluntary financial disclosure by mexican corporations. *Accounting review*, pages 533–541, 1987.

Simon Gilchrist, Jae W Sim, and Egon Zakrajšek. Uncertainty, financial frictions, and investment dynamics. Technical report, National Bureau of Economic Research, 2014.

Tarek A Hassan, Stephan Hollander, Laurence van Lent, and Ahmed Tahoun. Firm-level political risk: Measurement and effects. 2017.

Paul M Healy and Krishna G Palepu. Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, 31(1-3):405–440, 2001.

Stephan Hollander, Maarten Pronk, and Erik Roelofsen. Does silence speak? an empirical analysis of disclosure choices during conference calls. *Journal of Accounting Research*, 48(3):531–563, 2010.

Harrison Hong, Terence Lim, and Jeremy C Stein. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance*, 55(1):265–295, 2000.

Mahmud Hossain and Mike Adams. Voluntary financial disclosure by australian listed companies. *Australian Accounting Review*, 5(10):45–55, 1995.

Chang-Tai Hsieh and Peter J Klenow. Misallocation and manufacturing tfp in china and india. *The Quarterly journal of economics*, 124(4):1403–1448, 2009.

Bernard Raffournier. The determinants of voluntary financial disclosure by swiss listed companies. *European accounting review*, 4(2):261–280, 1995.

Thomas William Scott. Incentives and disincentives for financial disclosure: Voluntary disclosure of defined benefit pension plan information by canadian firms. *Accounting review*, pages 26–43, 1994.

Samuel Wagreich. Lobbying by proxy: A study of china's lobbying practices in the united states 1979-2010 and the implications for fara. *The Journal of Politics and Society*, 24(1):130–159, 2013.