Management Science Letters 13 (2023) 251–256

Contents lists available at GrowingScience

Management Science Letters

homepage: www.GrowingScience.com/msl

Does economic policy uncertainty exacerbate the gap between firms' words and actions? Evidence from China's digital transformation

Shutter Zor[a*]

[a]*School of Management, Xiamen University, China*

C H R O N I C L E

Article history:
Received: March 1, 2023
Received in revised format: March 29 2023
Accepted: June 22, 2023
Available online: June 22, 2023

Keywords:
Economic policy uncertainty
Digital transformation
Strategic disclosure

A B S T R A C T

This paper analyses the impact of economic policy uncertainty at the firm level on the inconsistency of words and actions in their digital transformation. Using new quantitative indicators of the gap as well as robust models, we find that firm economic policy uncertainty can exacerbate the gap between what firms say and do about digital transformation. In light of these findings, the paper concludes that there tends to be a certain amount of digital transformation hype among listed firms.

1. Introduction

Economic policy uncertainty has been extensively developed and studied over time (Baker et al., 2016; Li & Wei, 2022; Boitani and Dragomirescu-Gaina, 2023; Mamman et al., 2023). At the same time, with the building of Industry 4.0 and the urging of a long-term vision for sustainable development, academics have begun to pay more and more attention to the digital transformation behavior of companies (Li et al., 2022). Some of these scholars have astutely captured the connection between the two (Cheng & Masron, 2022). However, they probably overlooked the hype effect that companies may have on their digital transformation behavior. Based on the potentially self-interested behavior of companies, we argue that there may be some problems with measuring companies' digital transformation by textual analysis. Therefore, this paper proposes a method that can quantify the gap between what companies say and do in terms of digital transformation. We will also further discuss the role of economic policy uncertainty in exacerbating the gap between what companies say and do, from the perspective of digital transformation.

The remainder of the paper is structured as follows. Section 2 describes our data, model, and methodology. Section 3 reports the results and discusses the findings. Section 4 is the conclusion.

2. Data and Method

2.1. Data and Sample

According to the comparison of existing works, we identified a suitable research sample and data pre-processing method for this paper. First, our initial sample was from listed Chinese A-share companies (2007-2021). Secondly, we did some sample

* Corresponding author.

E-mail address: shutter_z@outlook.com (S. Zor)

doi: 10.5267/j.msl.2023.6.002

deletions as follows: (1) We excluded listed companies in the financial sector as usual. These industries have their specific accounting standards and can be an outlier in terms of some indicators, hence we excluded these industries. (2) We exclude companies that have been exposed to special treats. These companies were warned and punished by the SEC for some actions that endangered investors and several of them will be relisted after delisting through restructuring, etc. They will perform very abysmally in some sheets (e.g., balance sheet, income statement, and equity statement), hence we excluded these companies. (3) We exclude companies that are listed in multiple regions or stock markets. We use data from the consolidated financial statements of companies that are excluded due to different accounting standards in different regions, which can lead to significant differences in the statements.

2.2. Economic policy uncertainty

Baker et al. (2016) pioneered a method to measure economic policy uncertainty (EPU) in the macro environment through newspaper texts. At the same time, several scholars have built on his work to further discuss other potential impacts of EPU (Mamman et al., 2023). However, it is worth noting that these words often cannot be translated by direct translation to fit the Chinese context, considering the differences in context and word usage. Therefore, Davis et al. (2019) translated the original English EPU word list on the top of the former and modified it to finally refine the words applicable to uncertainty measurement in the Chinese macroeconomic environment. Although the revised Chinese words can measure the EPU index in the macro environment well, after all, the original text comes from publicly available newspapers, not corporate annual reports.

We have drawn on some of the literature and reconstructed a new firm-level economic policy uncertainty index (FEPU). We first introduce some directly relevant words as the input layer of the Word2Vec neural network to obtain several similar words and use these words, including input words and output words, as the bag of words for our FEPU. Next, we calculate the firm's EPU by following four steps: (1) Extracting the management discussion and analysis (MD&A) part of the annual reports by regular expressions. (2) Removing stop words, i.e., words with inadequate information, such as inflection words, and some ordinal numbers. (3) Using the words that we have trained to count the information about "economy", "policy" and "uncertainty" in the pure text (MD&A fragments with meaningful Chinese characters only). (4) The FEPU is calculated according to Eq. (1).

$$FEPU_{i,t} = \frac{\sum_{w} tf_{w,i,j}}{Text_{i,j}} \tag{1}$$

where $tf_{w,i,j}$ represents the number of occurrences of the word w in the FEPU dictionary in the text of the firm i's annual report in year j. $Text_{i,j}$ represents the text length of the MD&A fragment in the firm i's annual report in year j. Figure 1 shows our FEPU compared to the EPU indexes of Baker et al. (2016) and Davis et al. (2019).

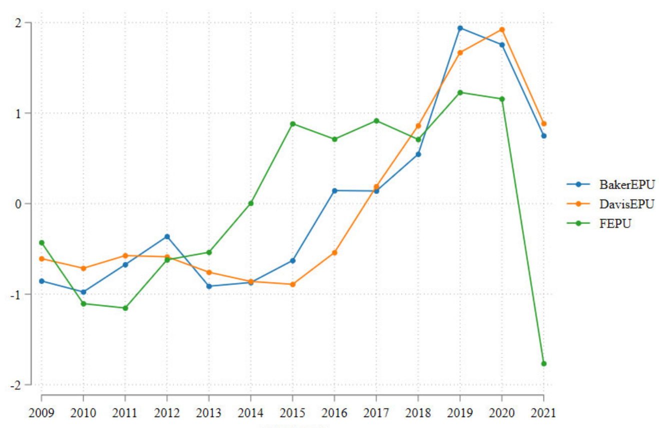

Fig. 1. Different economic policy uncertainty indexes (After standardization)

2.3. The gap between the words and actions of companies from a digital transformation perspective

2.3.1 Digital transformation at the corporate annual report level (Words)

In this section, we use textual analysis to identify the digital transformation of companies in terms of rhetoric. This was done by counting the number of occurrences of all words in the dictionary from the MD&A section of the company's annual report, based on our dictionary about digitization. The data was then deflated using the total number of words in the MD&A section.

$$DTWords_{i,t} = \frac{\sum DWF_{i,t}}{MDAText_{i,t}} \tag{2}$$

where $DTWords_{i,t}$ is the digital transformation of companies in words, $\Sigma DWF_{i,t}$ is the total number of occurrences of all words relating to digitization in the company's annual report, $MDAText_{i,t}$ is the total number of words in the MD&A section of the company's annual report.

2.3.2 Digital transformation at the company's actual input level. (Actions)

In this section, we use the total proportion of digital assets in the enterprise's intangible assets breakdown to express this. This section provides a good measure of the proportion of digital transformation that companies are putting in, rather than superficial work.

$$DTActions_{i,t} = \frac{DIA_{i,t}}{IA_{i,t}} \tag{3}$$

where $DTActions_{i,t}$ is the digital transformation of companies in action, $DIA_{i,t}$ is the total number of digital intangible assets, and $IA_{i,t}$ is the total number of intangible assets.

2.3.3 Quantifying the Variations in Words and Actions

To quantify the gap between the words and actions of companies in digital transformation, we refer to the calculation of earnings management (Proença et al., 2023), introduce the residuals of the regression, and use this to represent digital differences or digital manipulation.

$$DTActions_{i,t} = \alpha_0 + \alpha_1 DTWords_{i,t-1} + \sum \beta Controls + \gamma_i + \mu_t + \varepsilon_{i,t} \tag{4}$$

Among the control variables, we introduced the number of positive words, the number of negative words, and the total length in MD&A. It also controls for the model's individual fixed effects and year fixed effects. Finally, we use the residuals ($\widehat{DTActions} - DTActions$) of the model to represent the gap (*DTDiff*) between the words and actions of companies on digital transformation. Also, Fig. 2 shows the mean values of digital transformation discourses, behaviors, and differences in words and actions from 2010 to 2020.

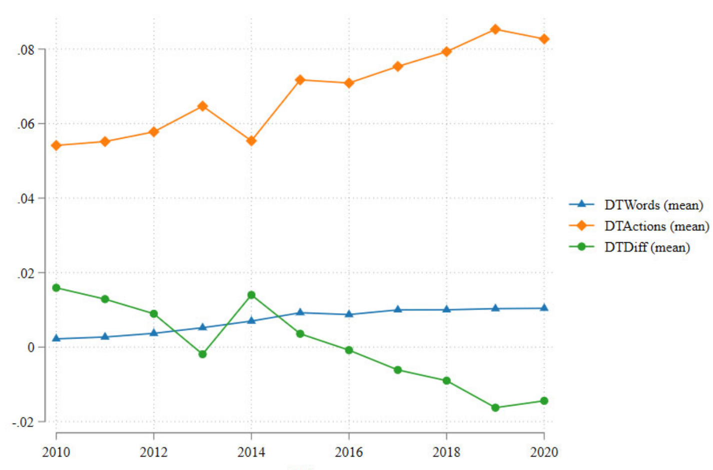

Fig. 2. Digital transformation in business rhetoric, action, and the difference between words and deeds

In addition, some suitable control variables have been introduced to improve the accuracy of the model as well as to mitigate endogeneity issues, based on some existing studies.

Table 1
Control variables and their definitions

Variables	Definition
Lev	The gearing ratio is the ratio of total liabilities to total assets.
ROA	Return on total assets, the ratio of net profit to total assets.
Growth	Operating income growth rate.
Size	Enterprise size is expressed using the natural logarithm of total fixed assets.
Age	Enterprise age is the number of years from the beginning of its establishment to the year of observation.
Big4	Whether the business is audited by a Big 4 accounting firm, dummy variable.

2.3. Fixed effects regression model

The fixed effects regression model used in this paper is as follows.

$$DTDiff_{i,t} = \alpha_0 + \alpha_1 FEPU_{i,t} + \sum \alpha Controls + \beta + \gamma + \mu + \varepsilon \tag{5}$$

where *Controls* include all the control variables in Table 1, and α are their coefficients. β, γ, μ denote individual, year, and industry-fixed effects respectively. ε is the model error. Also, in the follow-up results, we used robust standard errors.

3. Empirical Results and Discussion

According to the results in Table 2, it can be found that the variable *DTDiff*, which takes values ranging from -0.977 to 0.193, shows a left-skewed trend. Meanwhile, the median is 0.054. The combination of the two pieces of evidence reveals that more than 5.4% of digital transformation hype exists in greater than 50% of the observed sample in this paper. That is, these companies said 5.4% more than they did about digital transformation this year.

Table 2
Descriptive statistics

Variables	Obs	Mean	SD	Median	P25	P75	Min	Max
DTDiff	10655	0.000	0.184	0.054	0.025	0.067	-0.977	0.193
FEPU	10655	0.011	0.003	0.011	0.009	0.013	0.000	0.043
Lev	10655	0.491	0.187	0.502	0.354	0.634	0.082	0.861
ROA	10655	0.042	0.055	0.034	0.014	0.063	-0.644	0.478
Growth	10655	0.148	0.368	0.093	-0.025	0.233	-0.518	2.376
Size	10655	22.699	1.365	22.571	21.732	23.564	19.046	28.636
Age	10655	2.961	0.297	2.996	2.773	3.178	1.099	3.738
Big4	10655	0.093	0.290	0.000	0.000	0.000	0.000	1.000

Therefore, we can tentatively conclude that there is a digital transformation among companies that do not match words with deeds. Next, we observe the intuitive link between FEPU and the digital transformation rhetoric of the enterprise, as shown in Figure 3. When FEPU increases, companies will be more inclined to disclose their digital transformation strategies in the text of their annual reports. And, these companies don't commit to the act of digital transformation to match the language.

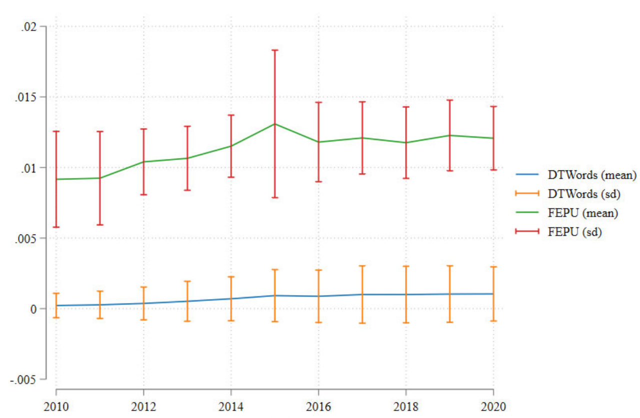

Fig. 3. FEPU and the digital transformation rhetoric in corporate annual reports (Means & Standard Deviations)

Finally, the results of our regression model are introduced, as shown in Table 3.

Table 3
Regression results

	(1) *DTDiff*	(2) *DTDiff*
FEPU	1.259**	1.281**
	(2.19)	(2.24)
Size		0.013***
		(3.08)
Lev		-0.073***
		(-4.40)
ROA		-0.098***
		(-3.08)
Age		0.047
		(1.56)
Big4		-0.033**
		(-2.42)
Growth		0.004
		(0.78)
_cons	-0.014**	-0.417***
	(-2.14)	(-3.32)
N	10655	10655
R^2	0.619	0.621
adj. R^2	0.582	0.584
Firm	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes

Note: *t* statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Based on the suggestion of the regression results, we can find that a rise in FEPU leads to a worsening of the inconsistency between what companies say and do in terms of digital transformation.

4. Conclusion

In this paper, we examine the impact of corporate economic policy uncertainty on the inconsistency between the words and actions of Chinese listed companies in terms of digital transformation over the period 2007 to 2021. Using completely new quantitative indicators of the gap as well as robust models, we find that corporate economic policy uncertainty can exacerbate the rhetoric of Chinese listed companies about their digital transformation at the expense of actual investment. This means that companies may be more likely to issue false growth announcements when uncertainty is high.

References

Baker, S.R., Bloom, N., & Davis, S.J., (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics, 131*(4), 1593-1636. https://doi.org/10.1093/qje/qjw024

Boitani, A., & Dragomirescu-Gaina, C. (2023). News and narratives: A cointegration analysis of Russian economic policy uncertainty. *Economics Letters, 226,* 111094. https://doi.org/10.1016/j.econlet.2023.111094

Cheng, Z., & Masron, T. A. (2022). Economic policy uncertainty and corporate digital transformation: evidence from China. *Applied Economics*, 1-17. https://doi.org/10.1080/00036846.2022.2130148

Davis, S.J., Liu, D., & Sheng, X.S., (2019). Economic policy uncertainty in China since 1949: The view from mainland newspapers, *Fourth Annual IMF-Atlanta Fed Research Workshop on China's Economy Atlanta.* pp. 1-37.

Li, R., & Wei, N. (2022). Economic policy uncertainty and government spending multipliers. *Economics Letters, 217*, 110693. https://doi.org/10.1016/j.econlet.2022.110693

Mamman, S. O., Zhanqin, W., & Iliyasu, J. (2023). Commonality in BRICS stock markets' reaction to global economic policy uncertainty: Evidence from a panel GARCH model with cross sectional dependence. *Finance Research Letters*, 103877. https://doi.org/10.1016/j.frl.2023.103877

Proença, C., Augusto, M., & Murteira, J. (2023). The effect of earnings management on bank efficiency: Evidence from ECB-supervised banks. *Finance Research Letters, 51*, 103450. https://doi.org/10.1016/j.frl.2022.103450