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The bright side of being uncertain: The impact of economic policy uncertainty on corporate innovation

Abstract

Purpose: This study aims to theoretically hypothesize and empirically examine the impact of economic policy uncertainty (EPU) on firms' innovation performance as well as the contingency conditions of this relationship.

Design/methodology/approach: This study collects and combines secondary longitudinal data from multiple sources to test for a direct impact of EPU on firms' innovation performance. It further examines the moderating effects of firms' operational and marketing capabilities. A series of robustness checks are performed to ensure the consistency of the findings.

Findings: In contrast to the common belief that EPU reduces the innovativeness of firms, we find an inverted-U relationship between EPU and innovation performance, indicating that a moderate level of EPU actually promotes innovation. Further analysis suggests that firms' operational and marketing capabilities make the inverted-U relationship steeper, further enhancing firms' innovation performance at a moderate level of EPU.

Originality/value: This study adds the emerging literature that investigates the operational implications of EPU, which enhances our understanding of the potential bright side of EPU and broadens the scope of operational risk management.

Keywords: Economic policy uncertainty, Corporate innovation, Organizational capability, Inverted-U relationship, China

Paper type: Research paper

1. Introduction

In recent years, the economic and regulatory landscapes around the globe have undergone significant upheavals. Many events, such as Brexit (Steinberg, 2019), the Sino-US trade war (Benguria *et al*., 2022), the Russia-Ukraine war (Shen and Hong, 2023), and frequent extreme weather shocks (Zhang *et al*., 2023), make it necessary for governments in many countries to frequently adjust economic policies and regulations. In particular, the COVID-19 pandemic provided a real-life example of how uncertain economic policies significantly distorted the vision for the economy and affected many market participants and the global economy's interconnections (Al-Thaqeb *et al*., 2022; Mokni *et al*., 2022; Sharif *et al*., 2020). For instance, Baker *et al*. (2020) offer empirical evidence by employing three indicators to document and quantify the dramatic increase in economic uncertainty and suggest that the COVID-induced uncertainty levels are much higher than those during the 2008 global financial crisis. Indeed, frequent economic policy changes are bound to be accompanied by a rise in economic policy uncertainty (EPU), which means that firms may find it hard to form reasonable expectations of future economic outlooks and operating environments (Gulen and Ion, 2016). EPU thus has profound impacts on diverse corporate decision-makings, spanning operations, finance, accounting, and strategy, making it difficult for firms to assess the risks and opportunities of their investments (Marcus, 1981).

A number of studies have well documented the negative impacts of EPU on firms' financial consequences, such as corporate investment (Gulen and Ion, 2016), foreign direct investment (Choi *et al*., 2021; Nguyen *et al*., 2018), management disclosure (Nagar *et al*., 2019; Wang *et al*., 2022), mergers and acquisitions (Bonaime *et al*., 2018; Nguyen and Phan, 2017), cash holding (Goodell *et al*., 2021; Phan *et al*., 2019), as well as trade credit (D'Mello and Toscano, 2020; Jory *et al*., 2020). In the operations management (OM) field, while prior studies have long investigated many common uncertainties that firms might face in the production and operations processes, such as supply uncertainty (Li *et al*., 2017), demand uncertainty (Biçer *et al*., 2018), and price uncertainty (Mandl and Minner, 2023), very limited knowledge has been developed about EPU's operational implications to date. Similar to the findings in the finance and accounting literature, several recent empirical OM studies show that EPU has adverse effects on some firm-level operating indicators, such as increasing various types of inventories, raising the level of working capital, enhancing vertical integration and product diversification, and lowering firm value (Darby *et al*., 2020; Dbouk *et al*., 2020; Fan and Xiao, 2023; Leung and Sun, 2021).

Yet, some anecdotal evidence suggests that firms' innovation activities, as one of the key drivers of competitive advantage, are not necessarily affected by EPU in a negative way. Within a certain EPU range, i.e., moderate EPU, firms might be incentivized to engage in more innovation activities, leading to better innovation performance. This is partially because EPU creates an unfavorable business environment, forcing firms to change and transform themselves to ensure survival and growth (Chen and Tian, 2022). In addition, a dynamic economic environment with major policy changes leads to new competitive landscapes with both risks and opportunities. For example, Chinese authorities have promulgated a series of anti-trust regulations on technology giants such as Alibaba and enacted a number of related new economic regulations, which have wide economic repercussions. Many Chinese technology companies, including some smaller tech pioneers, have then responded to policy uncertainties by investing more in hardcore technologies. In fact, the law enforcement actions that started with the initial public offering failure of Ant Group have finally led to substantial innovation-oriented investments for many Chinese firms[1] to deal with an uncertain future.

Considering the above conflicting views, we hypothesize a non-linear relationship

[1] https://www.cigionline.org/articles/how-antitrust-facilitates-chinas-goal-to-achieve-technological-self-sufficiency/

between EPU and innovation. By acknowledging the role of cognitive and emotional biases in decision-making, prospect theory provides a more realistic model of human behavior, which has had a profound influence on the study of behavioral economics and the development of decision-making models (Barberis, 2013; Kahneman and Tversky, 1979). For instance, the prospect theory argues that people's choices can change depending on how a decision is framed (i.e., reflection effect). When presented with a decision as a potential gain, individuals tend to be risk-averse. However, when the same decision is framed as avoiding a potential loss, they tend to become more risk-seeking. We therefore leverage the prospect theory as the theoretical lens and postulate that EPU may benefit innovation performance up to a certain threshold, beyond which there is a negative effect, leading to an inverted-U relationship. In addition, a number of examples show that it is not easy for innovative companies to benefit from innovation. Teece (1986) proposed the complementary assets view to explain this phenomenon and suggested that the successful development and commercialization of innovative achievements are inseparable from the support of complementary assets or organizational capabilities such as manufacturing, operations, marketing, distribution, logistics, and after-sales service (Hess and Rothaermel, 2011; Rothaermel and Hill, 2005; Swink and Nair, 2007; Taylor and Helfat, 2009). We therefore argue that firms with higher organizational capabilities, i.e., operational capability and marketing capability, are likely to obtain extra benefits from a moderate level of EPU for their innovation activities. The existence of these complementary capabilities enables firms to create value more efficiently from their core technologies, allowing firms to benefit more from their innovation efforts (Lampert *et al*., 2020; Taylor and Helfat, 2009).

We collect and combine longitudinal secondary data from multiple reliable sources and construct our sample to examine the above postulates. Our result documents an inverted-U shape relationship between EPU and firms' innovation performance. Further moderating effect analysis indicates that firms' operational and marketing capabilities could make the inverted-U curve steeper, highlighting the importance of organizational capabilities at a moderate level of EPU. Moreover, we also find that the simultaneous possession of high operational and marketing capabilities at a moderate level of EPU leads to an extra positive impact, suggesting a positive three-way interactive effect on corporate innovation. These findings are consistent across a battery of robustness tests such as alternative measures, the instrumental variable (IV) approach, and subsample analysis. Our study contributes to the literature in the following three ways. First, it advances operational risk management literature by expanding the applicability of the prospect theory in the firm-level innovation decision-making context and showing that there is an inverted-U relationship between EPU and firms' innovation performance, which challenges the traditional view and highlights the importance of psychological factors in affecting firms' strategic responses to policy uncertainty. Second, our investigation enriches the complementary assets literature by demonstrating the crucial roles of complementary assets (i.e., operational capability and marketing capability) in helping firms yield more innovative benefits when faced with moderate EPU. Finally, our research responds to the recent calls (e.g., Fan and Xiao, 2023; Tokar and Swink, 2019) which encourage to bring policy-related risk into the scope of operations and supply chain risk management by theoretically hypothesizing and empirically examining the non-liner impact of EPU on firms' innovativeness.

2. Theory and hypotheses

2.1. Prospect theory and inverted-U relationship between EPU and innovation

Previous studies usually assume a linear monotonic decreasing relationship between uncertainty and investment through the real options channel, while largely ignoring the varied managerial risk preferences under different scenarios. In this study we adopt prospect theory to theorize and develop our hypothesis. The conventional viewpoint holds that individuals and economic agents typically make rational decisions by calculating expected utility based on the risks and rewards associated with a range of available choices. However, Kahneman and Tversky (1979) as well as Tversky and Kahneman (1981, 1992) provide compelling evidence suggesting that individuals' actual decision-making processes may not conform to the principles of rational calculations. Consequently, prospect theory has attracted considerable attention from practitioners and has been employed as a fundamental theoretical framework in disciplines such as economics, psychology, finance, and management (Shimizu, 2007). Based on the assumption of bounded rationality, prospect theory argues that economic agents will demonstrate distinct risk preferences in various situations. They may exhibit a tendency toward risk aversion when facing gains, and toward risk seeking when facing losses (Kahneman and Tversky, 1979; Zona, 2012). Since an agent's utility typically depends on relative gains or losses rather than absolute income states in the real world, when the potential losses caused by exogenous shock can be controlled within a certain threshold, there will be risk-seeking behaviors, which indirectly provides a theoretical explanation for our hypothesized inverted U-shaped relationship between EPU and firm innovation (Bo and Lensin, 2005). In other words, managers tend not to worry about losses smaller than a threshold value arising from increased uncertainty. Instead, they prefer to undertake risky but promising projects such as innovation activities to achieve target performance (Greve, 2003). Specifically, when the business environment is stable and easily predictable, firms will simply respond to the incidents that have already happened rather than undertake innovative projects. In contrast, the unpredictability of future business conditions encourages firms to pursue more proactive strategies to know what is happening outside and take preventive actions towards upcoming changes (Aragón-Correa and Sharma, 2003; Jahanshahi and Brem, 2020). For example, entrepreneurs could provide a wider variety of products and services and build new capabilities to enrich market information and better deal with the perceived uncertainty (Miller and

Shamsie, 1999). Obviously, an uncertain environment requires entrepreneurs to put forward novel and creative ideas to respond to the challenges as long as the risk-seeking behavior is within the domain of small losses. Moreover, investment in innovation is an active behavior that helps a firm gain a larger market share, consolidate its strategic position, and discourage entrants of potential competitors, especially in a turbulent environment (Kulatilaka and Perotti, 1998; Voss *et al*., 2008). Accordingly, a moderate level of EPU may encourage firms to improve innovation performance.

However, firms' risk tolerance relies on whether the decision-maker views the negative performance as a repairable gap or a threat to survival (Audia and Greve, 2006). When the uncertain environment implies a loss of control over operating decisions and even a threat to firm survival, managers will shift their strategy from seeking risk to avoiding risk to ensure firms' survival (Dutton and Duncan, 1987). If a firm no longer expects to recover performance from a deteriorating environment, the incentive to conduct the problematic search by undertaking risk-taking activities (e.g., innovation projects) will decline as well (Gao *et al*., 2021). Therefore, firms confronted with threatening surroundings are expected to reduce investment in innovative competencies to limit the potential losses (Voss *et al*., 2008). When EPU becomes too high and is even regarded as an extremely adverse condition, its negative effect becomes more salient, so the tendency to make a risky attempt becomes diminished because the chances of benefiting from newly introduced innovations are slim, leading to a decline in innovation performance.

The above discussion indicates that when EPU is at lower levels and less disruptive, firms make strategic investments through innovation to achieve target performance and stay ahead of competitors. However, as EPU further increases to levels where the likelihood of bankruptcy surges, firms will turn more rigid and reduce the deployment of long-term strategic initiatives. Because of these two simultaneous mechanisms, a moderate level of EPU is anticipated to contribute to the development of more creative products within a company, implying that the relation between EPU and innovation performance would not necessarily be a simple linear one. We assume that as EPU increases, its marginal benefits will gradually decrease because the incentive and profitability of problematic search may be more pronounced within a certain range of threats (Kahneman and Tversky, 1979; Shimizu, 2007). However, when threatened by a high level of EPU, a firm would enact strict retrenchment responses and exhibit threat-rigidity, resulting in reduced deployment of long-term strategic initiatives and increased reliance on more conservative short-term alternatives (Shi *et al*., 2018). Accordingly, the dramatically increased costs of maintaining innovation will outweigh its marginal benefits, leading to a decline in innovation performance. In conclusion, a moderate level of EPU will be optimal for firms to innovate, so the impact of EPU on firm innovativeness might be positive up to a certain threshold, beyond which it becomes negative. We therefore hypothesize that:

H1: There is an inverted-U relationship between EPU and innovation performance.

2.2. Moderating effects of complementary capabilities

So far, we have illustrated why there is an inverted-U relationship between EPU and corporate innovation performance. Next, we explain how complementary assets, i.e., operational capability and marketing capability, might moderate the inverted-U link postulated above. We select organizational capabilities as the moderators for two main reasons. On the one hand, a wealth of literature has emphasized that a firm's capabilities play a key role in allocating multiple resources, unlocking resources value, and obtaining sustainable competitive advantage (Teece *et al*., 1997). There is a consensus that it is the proficiency in the use of resources, rather than the stock of resources *per se*, that makes a firm perform better than its competitors (Krasnikov and Jayachandran, 2008; Kwon *et al*., 2022). On the other hand, the prior literature has long acknowledged the importance of relevant organizational capabilities in coping with uncertainty (Tatikonda and Montoya-Weiss, 2001). Although some *ad hoc* measures could help firms temporarily overcome the difficulties caused by uncertainties (Winter, 2003), OM scholars believe that organizational capabilities, especially operational capability, is one of the fundamental means for firms to flexibly cope with uncertainty (Raddats *et al*., 2017). Unlike other short-term, local uncertainties, EPU tends to be regarded as a long-term, systemic uncertainty (Baker *et al*., 2016). In this case, firms need to develop the corresponding capabilities to avoid substantial negative impacts in the face of EPU and even to seize the potential opportunity to achieve growth. Among the various capabilities, we focus on operational and marketing capabilities because they represent a firm's ability to handle complicated internal production processes and respond to the demands of external stakeholders, respectively, and they also encompass the core business processes in a firm (Hirunyawipada and Xiong, 2018; Mishra *et al*., 2022; Rahmandad, 2012).

Operational capability is a relative efficiency indicator, which refers to a firm's ability to generate value-added outcomes from transforming constrained resources, and the extant OM studies often use operational efficiency or operational productivity as its alternative expression (Li *et al*., 2021; Yiu *et al*., 2020). The prior literature suggests that firms with superior operational capabilities are able to perform production and operations activities more efficiently, with lower costs and greater flexibility, as well as to adapt to the dynamic market conditions (Kortmann *et al*., 2014; Krasnikov and Jayachandran, 2008). A number of studies have shown the direct negative impacts of EPU on firms in terms of exacerbation of firms' financial constraints and increasing the operating and external financing costs (D'Mello and Toscano, 2020; Nguyen and Phan, 2017). Innovation activities require significant investment of capital and resources. Although a moderate level of EPU could incentivize firms to engage in more innovative activities, increased financial constraints and higher costs can discourage firms from doing so. High operational capability means that firms could use the limited resources more efficiently even in the face of resource constraints and rising costs. In other words, firms with high operational capability are more likely to achieve better innovation performance when faced with limited resources resulted from EPU.

In addition, OM scholars contend that the central idea of operational capability is that managers need to be competent in deploying the existing resource base for better performance outcomes, which is obtained via benchmarking practices and incremental improvement (Kwon *et al*., 2022). Therefore, operational capability has significant impacts on the enhancement of firms' managerial competency in maximizing short-run profits (Jacobs *et al*., 2016; Saunila *et al*., 2020). When faced with EPU, the improvement of short-term profits caused by operational capability may enable firms to have a more sufficient capital base for innovation activities, enhancing innovation performance and generating long-term innovation returns. Also, firms with efficient, reliable processes and procedures are more likely to maintain a stable environment for idea search and discovery, which is beneficial for firms to conduct R&D activities (Yiu *et al*., 2020; Zollo and Winter, 2002). We therefore hypothesize that:

H2: The inverted-U relationship between EPU and innovation performance is stronger (steeper) when firms' operational capability is high.

Marketing capability refers to a firm's efficiency in converting available marketing-related resources into outputs or marketing performance (Mishra and Modi, 2016; Xiong and Bharadwaj, 2013). The existing marketing literature highlights the significance of marketing capability in a firm. First, firms with high marketing competence are believed to have more ability to manage communication. Better communication could enable firms to have greater awareness of the innovation efforts among various stakeholders such as consumers, suppliers, employees, and the community. In many cases, stakeholders may not have a clear and timely understanding of firms' innovation initiatives. Thus, good communication is important to help firms uncover the potential stakeholder-based resources created by corporate innovation. Also, good communication could reduce stakeholders' perceived risks associated with corporate innovation, which may increase the likelihood of purchasing and adopting innovative products.

In addition, marketing capability also reflects a firm's ability to manage and utilize market information. Firms with high marketing capability do well in identifying customer needs and the factors influencing consumer behavior, which results in excellence in targeting, positioning, and advertising (Vorhies and Morgan, 2005). The significance of the marketing department is that it can make firms perceive and respond to markets and align organizational resources to meet the complex and personalized needs of customers. The existing literature has pointed out that EPU will make firms face more fierce market competition (Jory *et al*., 2020). In this case, to avoid falling into a price war, corporate innovation (e.g., new product development) is naturally an effective way to differentiate a firm from its competitors, but this arrangement is only possible with accurate perceptions of customer needs and preferences (Jansen *et al*., 2006). High marketing capability enables firms to understand the latent demand and to be able to better segment the market and to form well-constructed customer profiles (Hirunyawipada and Xiong, 2018; Xiong and Bharadwaj, 2013). Taken together, marketing capability could help firms increase the benefits of innovation activities when facing EPU, so we propose the following hypothesis:

H3: The inverted-U relationship between EPU and innovation performance is stronger (steeper) when firms' marketing capability is high.

The conceptual model of this study is summarized in Figure 1.

---Please insert Figure 1 about here---

3. Methodology

3.1. Data and sample

We obtain and combine longitudinal secondary panel data of Chinese A-share listed companies from multiple sources to perform our empirical analysis. First, the accounting data of public firms are collected from China Stock Market & Accounting Research (CSMAR) database. The financial information provided by CSMAR is reliable and commonly used by previous empirical studies on Chinese-related issues (e.g., Li *et al*., 2021; Zhu *et al*., 2021). Next, we obtain firms' patent information from Chinese Innovation Research Database (CIRD) as it distinguishes the patent applied by a company on its own and those jointly with other entities and provides complete patent applications of listed companies over a longer time horizon. To measure the degree of uncertainty in economic policies, we employ the EPU index developed by Baker, Bloom & Davis (BBD hereafter, 2016), which has been commonly used in prior relevant studies (e.g., Bhattacharya *et al*., 2017; Gulen and Ion, 2016; Nguyen and Phan, 2017). Our initial sample includes all Chinese A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2000 to 2020. Following prior literature, we exclude firms in financial industries due to their distinct regulatory policies, and observations with missing data on key variables (D'Mello and Toscano, 2020; Zhu *et al*., 2021). Moreover, all independent variables are lagged one year behind to mitigate potential endogeneity risks. Our sample finally consists of 11,769 firm-year observations of 1,392 unique firms between 2000 and 2019. The data set constitutes an unbalanced panel structure due to a lack of observations in certain years. Panels A and B of Table 1 present the sample distribution across industry and year, respectively.

---Please insert Table 1 about here---

3.2. Measures

Economic Policy Uncertainty. We rely on the Chinese BBD news index developed by Baker *et al*. (2016) to examine the impact of EPU on corporate innovation performance[2]. Specifically, Baker *et al*. (2016) first collect the articles in South China Morning Post about

[2] http://www.policyuncertainty.com/scmp_monthly.html

economic uncertainty pertaining to China by picking up all articles that contain at least one keyword from each of the following term sets: {China, Chinese} and {economy, economic} and {uncertain, uncertainty}. Subsequently, they identify the subset of the China economic uncertainty articles that also discuss policy issues. For this purpose, an article is required to satisfy the following text filter: {{policy OR spending OR budget OR political OR "interest rates" OR reform} AND {government OR Beijing OR authorities}} OR tax OR regulation OR regulatory OR "central bank" OR "People's Bank of China" OR PBOC OR deficit OR WTO. Finally, they compute the monthly EPU index by dividing the frequency count of these EPU-related articles by the total number of articles within the same month. The time series is then normalized to a mean value of 100 from 1995 to 2011. Since the index is published every month, we construct an annual index by taking the average of the monthly index in a given year. We compare the trend of the index with important historical events and find that the index jumps around major events (Figure 2), indicating that the index can generally reflect China's economic policy uncertainty. An alternative measure of EPU is the newspaper-based indices derived from two mainland Chinese newspapers: the Renmin Daily and the Guangming Daily, which are used in our robustness test.

Corporate Innovation Performance. R&D expenditure and patent application are the two main proxies applied in prior research to capture innovation investment or productivity. Several studies have contended that patenting activities could better reflect firms' innovation quality and ability than R&D expenditures because the patent application represents innovative outputs and requires a consistent and rigorous examination process (Fang *et al*., 2014). Therefore, patent data is collected to reflect innovation activities. According to China's patent law, there are three basic types of patents: invention, utility model, and design. In this study, we concentrate on the overall patent applications and use filings of invention patents and utility model in our robustness test section.

We focus on the application year of the patents rather than the grant year as the former is closer to the time of actual innovation behavior (Fang *et al*., 2014). Specifically, the natural logarithm of one plus the number of patents is considered as representative of a firm's innovativeness (Liu and Ma, 2020; Wei *et al*., 2020; Xu, 2020; Yuan and Wen, 2018). We add one to the actual application values to retain the firm-year observations with zero patents (Fang *et al*., 2014).

Moderating Variables. We adopt a stochastic frontier estimation approach to estimate operational and marketing capability. The stochastic production function reflects the efficiency of a firm relative to its peers in the same industry by calculating the level of output that can be transformed from a certain level of inputs (Li *et al*., 2010). To measure operational capability, we empirically model a firm's operational efficiency in transforming its operational resources, i.e., number of employees, cost of goods sold, and capital expenditure, into outputs, i.e., operating income, in Equation 1 (Lam *et al*., 2016; Yiu *et al*., 2020). Regarding marketing capability, we use Equation 2 to estimate the transformation process that converts marketing-related input resources, i.e., number of employees, selling, general and administrative expenses, accounts receivable, and intangible assets, into outputs, i.e., sales (Li *et al*., 2010; Mishra and Modi, 2016; Nath *et al*., 2010).

$$In(Operating\ Income)_{ijt} = \beta_0 + \beta_1 In(Employees)_{ijt} + \beta_2 In(COGS)_{ijt} + \beta_3 In(CAEX)_{ijt} + \varepsilon_{ijt} - \gamma_{ijt} \quad (1)$$

$$In(Sales)_{ijt} = \beta_0 + \beta_1 In(Employees)_{ijt} + \beta_2 In(SGA\ expences)_{ijt} + \beta_3 In(account\ receivables)_{ijt} + \beta_4 In(intangible\ assets)_{ijt} + \varepsilon_{ijt} - \gamma_{ijt} \quad (2)$$

where ε_{ijt} is the stochastic random error term and γ_{ijt} reflects the relative inefficiency score of firm *i* in industry *j* (three-digit industry) compared to other firms within the same industry in year *t*. γ_{ijt} ranges from 0 to 1, where 0 means no technical inefficiency. The composite error term $(\varepsilon_{ijt} - \gamma_{ijt})$ is estimated based on the difference between the industry's highest realized operating income and the observed operating income, thereby yielding a consistent estimate of firm-specific operational inefficiency γ_{ijt}. We compute the efficiency term by subtracting the inefficiency score from 1 to capture a firm's operational and marketing capability respectively, with 0 indicating the lowest level of efficiency while 1 indicating the optimal boundary level performed by the "best practice" firm in the transformation process.

Control Variables. Consistent with prior studies, we control for several firm-specific variables that potentially affect firms' innovation outputs (Chang *et al*., 2015; Fang *et al*., 2014; Wei *et al*., 2020). We include return on assets (*ROA*, net income divided by total asset), *Tobin's q* (a firm's market value divided by its book value), *Leverage* (the ratio of the book value of debt to assets), *Firm Size* (the natural logarithm of total assets), *PPE* (net property, plant, and equipment scaled by total assets), *Financial Slack* (the ratio of cash reserves to the book value of total assets) into our estimation. We incorporate *Firm Size* and *PPE* because larger firms and those with higher capital intensity typically possess greater innovation resources and thus generate more patents (Chang *et al*., 2015). Moreover, the inclusion of *ROA* aims to capture operating profitability, while *Tobin's q* is included to delineate a firm's growth prospects, both anticipated to yield a positive impact on innovation performance. However, the impact of *Financial Slack* and *Leverage* on innovation performance remains contentious. While cash reserve is an indispensable resource for fostering innovation, firms with higher free cash flow might be susceptible to managerial resource abuse, potentially impeding firm innovation (Wei *et al*., 2020). The traditional viewpoint contends that debt may be unfavorable for innovation since innovation is inherently risky, and innovation endeavors are not easily deployable to alternative uses. In contrast, other studies have recognized that debt holders may exert a positive impact on innovation outputs by assuming a monitoring role (Choi *et al*., 2016). Further, following previous studies (Leung and Sun, 2021; Liu and Wang, 2022), two macro time-series variables accessed from Chinese National Bureau of Statistics, *CPI index* and *M2 growth*, are added into our model to allow for the influences of economic growth. Additionally, we perform firm fixed effects to remove the effect of unobservable factors that do not vary over time, which could help alleviate the endogeneity bias to a large extent. Haans *et al*. (2016) point out that fixed effects estimation with panel data can remedy the omitted variable bias, strengthen empirical identification, and thus is the best practice to test the quadratic relationship. Similar to Gulen and Ion (2016), Nguyen and Phan (2017), and Phan *et al*. (2019), we do not control for year-fixed effects because the EPU index is the same for all of the firms in a given year. Adopting a year fixed effect will absorb the variation of the EPU.

3.3. Model specification

We introduce the following panel data model as shown in Equation 3 to empirically test the above hypotheses. Hausman test is applied to determine whether fixed effects or random effects estimator is more efficient (Greene, 2012). The null hypothesis of Hausman tests, "no systematic difference in coefficients", is rejected at the 1% significance level, indicating that the fixed effects model is the preferred specification for our dataset. We lag our independent and moderating variables one year behind to alleviate the potential endogeneity concern due to reverse causality and estimate the models with robust standard errors clustered by firm for statistical inference. All continuous variables are winsorized at the 1% and 99% levels to mitigate the potential influence of outliers.

$$Innovation_{i,t+1} = \beta_0 + \beta_1 EPU_t + \beta_2 EPU_t^2 + \beta_3 Operational\ Capability_{i,t} * EPU_t + \beta_4 Operational\ Capability_{i,t} * EPU_t^2 + \beta_5 Marketing\ Capability_{i,t} * EPU_t + \beta_6 Marketing\ \ Capability_{i,t} * EPU_t^2 + \beta_7 Operational\ Capability_{i,t} + \beta_8 Marketing\ \ Capability_{i,t} + \beta_9 Controls_{i,t} + \beta_{10} Macro_t + \eta_i + \varepsilon_{i,t} \quad (3)$$

4. Results

4.1. Descriptive statistics and correlation

Table 2 documents the Pearson correlation matrix and descriptive statistics of the variables.

The average variance inflation factor (VIF) score across all the variables is 2.47, which suggests that multicollinearity is not a major concern. Starting at 55.7 in 2000 and reaching a peak in 2019 of 791.9, EPU index shows an upward trend in our sample period although a quick decline appears in particular years. The large dispersion of the data set helps us find the correlations among variables in the follow-up research. There are 3,555 observations with zero number of patent applications, indicating the absence of patent filings in the respective years. It shows a significant positive correlation between the EPU index and innovation performance without considering the impact of other factors, which preliminarily confirms our hypothesis on prospect theory. Among the control variables, *ROA*, *Leverage*, *Firm Size*, *Financial Slack*, and *CPI index* have positive correlations with innovation outcomes. These findings suggest that firms with a larger scale, better profitability, more cash holdings, and higher levels of leverage are much more likely to achieve better innovation performance.

---Please insert Table 2 about here---

4.2. Baseline results

Table 3 reports the results of fixed effects analysis, where the overall patent application (collaborative innovation and solitary innovation) is the dependent variable. Model 1 only contains the control variables. We then gradually add the variable of our interest into the estimation model step by step. Model 2 puts EPU and its squared term into the equation to examine the inverted U-shape relationship between EPU and innovation performance. Model 3 and Model 4 introduce the interaction terms involving operational and marketing capability respectively to investigate their moderating effects. Model 5 is the full model.

The result of Model 2 shows a positive coefficient for EPU and a negative coefficient for its squared term, both significant at the 1% level, demonstrating the existence of an inverted U-shaped relationship between EPU and corporate innovation performance after including all the predictors but without the interactions. According to the research of Haans *et al*. (2016), the turning point is 412.58 (calculated as -$\beta_1/2\beta_2$) where the curve attains its maximum. The 95% confidence interval of the turning point is (397.92, 427.24), suggesting that the turning point lies well within the data range and removing the doubts that the data only reveal one-half of the curve. We also note that the slope at the lower bound of the EPU data range is 0.00406 ($\beta_1 + 2\beta_2 * EPU_{min}$), yet the upper bound of the data range is -0.00431 ($\beta_1 + 2\beta_2 * EPU_{max}$). The slopes at both ends of the data range are significant at the 1% level, once again showing the existence of an inverted U-shaped relationship. These findings are consistent with Hypothesis 1 that firms are more likely to engage in innovative activities when EPU is neither too high nor too low.

Models 3 and 4 introduce the interaction terms that include operational and marketing capability respectively to examine their moderating effects. The result in Model 3 reveals that the coefficient for the interaction term of EPU and operational capability is positive and significant. In contrast, the interaction term of squared EPU and operational capability has a significantly negative coefficient, implying that a steepening occurs for the inverted U-shaped relationship (Haans *et al.*, 2016). To formally test whether a shift in the turning point occurs, we examine the sign of the Equation 2 and its significance using the *nlcom* command in STATA (Ben-Jebara and Modi, 2021; Haans *et al.*, 2016). The average level of the operational capacity in our sample, that is 0.708, is assigned to perform the test. The results show that the sign of the numerator is negative ($\beta_1\beta_4 - \beta_2\beta_3 < 0$). However, it is critical to note that Equation 4 itself is not significantly different from zero (p value = 0.408), providing less support for the actual shift of the turning point.

$$\frac{\delta(EPU)}{\delta(OP\ Cap)} = \frac{\beta_1\beta_4 - \beta_2\beta_3}{2(\beta_2 + \beta_4 OP\ Cap)^2} \quad (4)$$

---Please insert Figure 3 about here---

The result in Model 4 indicates that the interaction term of EPU and marketing capability has a positive and significant coefficient, whereas the coefficient for the interaction term of the squared EPU and marketing capability is negative and statistically significant. This implies that the captured inverse U-shaped relationship between EPU and innovation performance is steeper. The sign of the numerator in Equation 5 is positive ($\beta_1\beta_6 - \beta_2\beta_5 > 0$). More importantly, Equation 3 as a whole significantly differs from zero, indicating strong support for a right shift occurrence when the marketing capability is strengthened (*p* value = 0.065). Figure 3 graphically illustrates that the inverted U-shaped curve becomes steeper for firms with higher operational and marketing efficiency, which is consistent with H2 and H3.

$$\frac{\delta(EPU)}{\delta(MK\ Cap)} = \frac{\beta_1\beta_6 - \beta_2\beta_5}{2(\beta_2 + \beta_6 MK\ Cap)^2} \quad (5)$$

---Please insert Table 3 about here---

4.3. Robustness checks and endogeneity issues

We consolidate our findings through a series of robustness tests. First, we exclude the patent applications that are filed jointly with other entities during the year and retain those filed by the company independently. Solitary patent applications can better reflect a firm's own innovation capability. The results in Table 4 based on the alternative measure are consistent with previous findings.

---Please insert Table 4 about here---

Second, we perform the IV approach to mitigate the omitted variable bias concern. Although we have controlled for a wide range of firm-specific, time-invariant, and macroeconomic predictors in the estimation model, both EPU and innovation activities may be jointly related to unobservable variables, such as investment opportunities, resulting in a potential biased and inconsistent coefficient estimate (Nguyen and Phan, 2017). Specifically, we employ a two-stage least square (2SLS) estimation to address this endogeneity issue. Following Yuan *et al*. (2022), we choose the natural logarithm of the number of proposals submitted to the National People's Congress (NPC hereafter) in each year as our IV. The NPC exercises its power to formulate and amend the Constitution and the Basic Law of the state. In addition, it has the power to examine and approve the plans for national economic, social development, and state budget, and to monitor their actual implementation. In the context of China, the proposals submitted to the NPC should be a valid IV because they closely correlate with China's EPU and can only influence corporate investment decisions through the independent variable of our interest. Table 5 reports the two-stage results of the IV regression. The dependent variables in the second-stage regression are the overall patent applications, invention patents, and utility model, respectively. The Kleibergen-Paap Wald *F* statistic is significantly larger than the threshold of the Stock-Yogo weak identification critical values, and *LM* statistic is also significant at the 1% level, indicating that our selected IV is relevant and can be fully identified. The results in the second stage are similar to those in Table 3, indicating that the previous quadratic relationship between EPU and innovation performance remains valid after accounting for the omitted variable bias.

---Please insert Table 5 about here---

Third, as suggested by Haans *et al*. (2016) and Qian *et al*. (2010), we split the observations into two subsamples based on the median value of EPU index (179.0) to validate the quadratic relationship again. Panel A of Table 6 identify a significant and positive association between EPU and corporate innovation in the lower samples but a significantly negative one in the upper samples. The opposite slopes are in line with the predicted shape of the curve in H1. Furthermore, we explore the impact of innovation output on firms' financial performance in the following year in both subsamples. The dependent variables in Panels B, C, and D of Table 6 are *Sales Growth*, *ROA*, and *Tobin's q* respectively. We find that the positive correlation between innovation outputs and financial outcome is more pronounced in the lower range of EPU, partially suggesting that innovation efforts could restore firm performance when EPU is not extremely high.

---Please insert Table 6 about here---

Next, we check the robustness of the results by replacing the key variables and estimation strategies. Model 1 in Table 7 replaces the previous EPU index with the newspaper-based indices derived from two major Chinese newspapers: the Renmin Daily and the Guangming Daily. Model 2 in Table 7 uses the natural logarithm of one plus the number of invention patents as a substitute for the dependent variable because invention patents are subject to stricter examination than utility model and design patents (Liu and Ma, 2020). Our findings persist based on these alternative measures. Since the initial innovation application is a count-based variable, we also re-estimate our baseline regression employing a count-based model. The variance of patent counts is much larger than its mean, indicating that the negative binomial model is more suitable than the Poisson model. The empirical results remain robust after we change the estimation strategy (Model 3 in Table 7).

In another robustness check, we dispel the doubts about the measurement errors of the BBD index. Previous research has raised the concern that the BBD index might pick up some other macro-level uncertainties that are unrelated to public policy, leading to potential bias in our estimation results. Thus, related studies in the U.S. context remove the common parts of EPU between the U.S. and Canada and extract the residuals as an alternative regressor (D'Mello and Toscano, 2020; Gulen and Ion, 2016; Leung and Sun, 2021; Nguyen and Phan 2017; Phan *et al*., 2019). Following their approaches, we first regress the Chinese BBD index on the global BBD index and other macroeconomic variables, and then pick up the residual as a proxy for EPU in the baseline model estimation. The reason is that China has established close economic ties with other countries through extensive trade and investment since joining the World Trade Organization (WTO) in 2001. Thus, the worldwide economic shocks will also affect the economic fluctuations in China. Our findings still hold after eliminating the possible confounding factors (Model 4 in Table 7).

Since our benchmark model does not control for time-fixed effects, if the negative shock caused by the global financial crisis results in a surge in EPU and influences firm investment decisions simultaneously, the previous results could be induced by insufficient control for the neglected negative shock (Leung and Sun, 2021). To ensure the robustness of our results, we first follow Bekaert *et al*. (2014) in setting the years 2008 and 2009 as crisis years and show that our findings still hold when we exclude observations during these two years, which indicates this is not a concern in this study (Model 5 in Table 7). Second, although we cannot include time fixed effects in our specifications, we add a linear time trend variable to the regression to disentangle the temporal effect and EPU itself (Yuan *et al*. 2022). Model 6 in Table 7 shows the inverted-U relationship remains significant after accounting for the time trend that potentially affects innovation performance. Moreover, to mitigate potential cyclical variations in annually averaged EPU, we adopt the rolling approach proposed by Fama and French (1992) to calculate each firm's exposure to EPU as such:

$$R_{i\tau} - R_{f\tau} = \beta_0 + \beta_{i\tau}^{EPU} EPU_\tau + \beta_{i\tau}^{MKT} MKT_\tau + \beta_{i\tau}^{SMB} SMB_\tau + \beta_{i\tau}^{HML} HML_\tau + \varepsilon_{i\tau} \quad (6)$$

where $R_{i\tau}$ is the monthly stock return of firm *i* in month τ and $R_{f\tau}$ represents the monthly risk-free rate. EPU_τ is the EPU index in month τ. MKT_τ, SMB_τ, and HML_τ refer to the Fama-French three factors in month τ. We use the absolute value of $\beta_{i\tau}^{EPU}$ in December of each year to measure firm i's exposure to EPU (Francis *et al*. 2014). The past 6 months (τ-5, τ), 36 months (τ-35, τ), 48 months (τ-47, τ) and 60 months (τ-59, τ) are set as the rolling windows, representing short-term and long-term exposure respectively. The quadratic relationship between firms' exposure to EPU and innovation performance still holds after adopting the rolling regression (Model 7 in Table 7).

Finally, we conduct an ad hoc analysis to examine whether possessing both a high level of operational capability and marketing capability would lead to better innovation performance than just having a single capability. This test may help us further understand the synergy effect of diverse organizational capabilities in dealing with EPU. For each of the two capabilities, a dummy variable is created and assigned 1 if a firm's efficiency is more than the median level of the industry in a given year, and 0 otherwise. *Two Cap* is the product of two dummy variables, which is then included in the regression model to perform a two-way interaction among EPU, operational capability, and marketing capability. The result shows that firms with both higher levels of two capabilities will have a significantly steeper inverted-U curve than those with only one capability or neither (Model 8 in Table 7). Furthermore, we investigate the heterogeneity effect of EPU on innovation performance across different industries and find the inverted-U relationship is more pronounced for manufacturing firms, indicating that manufacturing firms may realize better innovation performance from medium levels of EPU. Figure 4 presents the heterogeneity effect across different industries.

---Please insert Table 7 about here---

---Please insert Figure 4 about here---

5. Summary, discussion, and future research

Based on a longitudinal dataset of publicly listed firms from 2000 to 2019, we empirically examine the impact of uncertainty caused by government economic policy changes (EPU) on firms' innovativeness and document an inverted U-shaped relationship in the Chinese context. We conduct a range of additional tests to validate the sensitivity of our results (e.g., alternative measures, IV approach, sub-sample grouping tests) and ultimately reach consistent findings. In addition, our moderating effect analysis shows that firms' operational capability and marketing capability will make the discovered inverted-U relationship steeper. This study provides a new perspective on understanding the EPU-innovation performance link and reconciles the inconsistent findings reported in the prior literature (e.g., Bhattacharya *et al*., 2017; Gulen and Ion, 2016; Pertuze *et al*., 2019; Sarkar, 2021). The research and practical implications of our findings are discussed below.

5.1. Research implications

Our study makes multiple contributions to the literature, challenging conventional wisdom and enriching our understanding of how EPU influences firms' innovation strategies. First, our study extends the application of the prospect theory in the context of firm-level innovation. Kahneman and Tversky (1979) proposed the prospect theory to explain individual decision-making under risk and uncertainty, which finds resonance in the corporate world through its insights into risk attitudes. By hypothesizing an inverted-U relationship between EPU and firms' innovation performance, we align with prospect theory's premise that individuals, and by extension, firms, exhibit nonlinear responses to risk. Our findings suggest that moderate levels of EPU may trigger firms to adopt more risk-seeking behaviors, akin to the "prospect effect", which denotes increased willingness to take risks in the pursuit of gains. This extension of the prospect theory to the corporate domain highlights the relevance of psychological factors in shaping firm-level innovation strategies.

Moreover, the study emphasizes the role of complementary assets in shaping the impact of EPU on innovation performance. The complementary assets view posits that the value and effectiveness of a core asset or innovation are contingent on the presence and alignment of supportive complementary resources (Teece, 1986; Wu *et al*., 2014). Our results corroborate this view by demonstrating that firms' operational and marketing capabilities act as crucial complementary assets, enhancing the relationship between EPU and innovation performance. In addition, when firms possess both operational and marketing capabilities at a higher level, the inverted U-shaped curve becomes even steeper compared to having individual moderating impact of each capability alone. In essence, these capabilities serve as mechanisms to navigate and harness the potential benefits of economic uncertainty (Lampert *et al*., 2020). This finding underscores the importance of considering the interplay between core assets and their complementary counterparts in the OM literature.

Furthermore, our study offers theoretical extensions that warrant exploration in future research. For instance, it prompts a deeper investigation into the underlying mechanisms through which operational and marketing capabilities interact with EPU to promote innovation. This might involve delving into the specific strategies and practices that firms employ when facing moderate EPU levels, such as agile product development, dynamic marketing campaigns, or adaptive supply chain management. These insights could lead to the development of more nuanced theoretical frameworks regarding the interplay between core assets, complementary assets, and external environmental factors.

In short, our study contributes to the theoretical understanding of the relationship between EPU and innovation performance, expanding the applicability of the prospect theory in the corporate context and shedding light on the vital role of complementary assets in navigating EPU. These theoretical insights offer new perspectives on how firms can harness the moderated economic uncertainty to drive innovation, paving the way for a more comprehensive understanding of strategic decision-making in an ever-changing business landscape.

5.2. Practical implications

This study also provides several practical implications for managers and regulators. First, our findings reveal that different degrees of EPU may lead to diametrically opposite innovative outcomes. A moderate level of EPU implies desirable growth opportunities and may encourage firms to embrace innovation, whereas excessive EPU will hinder innovative and risky behavior. This finding is particularly important for corporate managers since the awareness of this tendency could help organizations predict competitors' actions against EPU and make proper allocation of organizational resources in advance. For instance, managers may preempt their opponents' moves and take the lead in grabbing market share as soon as policies change.

Instead, when EPU is extremely high, managers need to be vigilant because its negative impact on firm operations may far outweigh its potential benefits and, under the circumstances, a conservative strategy may be more appropriate. In short, managers should realize the pros and cons of EPU and strategically adjust the operational strategy when facing different levels of EPU.

Second, managers should also be aware of the importance of operational capability and marketing capability in the relationship between EPU and innovation performance. While there is no one-size-fits-all approach to dealing with EPU, a firm is better able to react to customer needs and discover new market opportunities in an uncertain environment by building stronger operational and marketing capabilities. If conditions permit, firms should possess a high level of both capabilities, as this will allow them to achieve better innovation performance.

Finally, policymakers in developing countries might maintain the policy-related uncertainty at a moderate level to avoid unilaterally impeding corporate innovation. Neither invariable nor excessively changing EPU is beneficial for firms to engage in innovation activities. Our findings suggest that policymakers not only consider the impact of the policy itself when exercising power, but also take the uncertainty induced by policy changes into account. Understanding this mechanism will be more helpful for governments to develop scientific and accurate policies.

5.3. Limitations and future directions

Like other secondary data-based OM research, this study is not without limitations, which also provide several avenues for future research. First, our sample is only limited to publicly listed firms in China. Although it is acceptable to select Chinese firms when focusing on emerging economies, subsequent research scenarios can be shifted to other developing countries (e.g., Brazil, India, Russia, and South Africa) to test the generalizability of our results.

We believe that policy-related studies in emerging market economies will be a promising direction for future empirical OM research. Besides, future studies can also investigate whether our findings are applicable to non-public firms, which face more challenges and are more vulnerable to EPU.

Second, our sample period begins in 2000 and ends in 2019 due to data availability. Another noticeable issue is that the BBD index and innovation data are both captured on an annual basis, which largely reduces the overall sample size. Therefore, more data from other countries and longer time horizons could be supplemented in future research. Such investigations can better reveal the EPU-strategic firm behavior linkage and help verify the conclusions drawn in our research.

Finally, in terms of the theoretical lens, despite that prospect theory fits our research purpose, we suggest that other theoretical perspectives be deployed in future related studies. For instance, signaling theory could be used to interpret how the macro-level signals related to policy variation and industry-level signals correlated with resource availability are perceived by the firms (Connelly *et al*., 2011). Complementary or competing theories can provide diverse insights and shed additional light on this issue. Accordingly, other contingent factors could also be explored to enhance our understanding of the boundary conditions of the impacts of EPU in the future.

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Table 1
Descriptive statistics of sample firms.

Panel A: Distribution of sample firms across industries

CSRC industry code	Industry	Frequency	Percentage (%)
A	Agriculture, forestry, animal husbandry and fishery	673	5.72
B	Mining	773	6.57
C	Manufacturing	7,464	63.42
D	Utilities	129	1.10
E	Construction	629	5.34
G	Transportation, warehousing, and postal services	842	7.15
H	Accommodation and catering	33	0.28
I	Information transmission, software, and IT services	209	1.78
M	Scientific research and technical services	244	2.07
N	Water conservancy, environment, and public facilities management	370	3.14
O	Residential service, repair and other services	40	0.34
P	Education	15	0.13
R	Culture, sports and entertainment	348	2.96
Total sample size		11,769	100.00

Panel B: Distribution of sample firms across years

Year	Frequency	Percentage (%)
2000	280	2.38
2001	302	2.57
2002	319	2.71
2003	345	2.93
2004	372	3.16
2005	364	3.09
2006	382	3.25
2007	434	3.69
2008	470	3.99
2009	491	4.17
2010	568	4.83
2011	642	5.46
2012	698	5.93
2013	680	5.78
2014	684	5.81
2015	755	6.42

2016	830	7.05
2017	1,001	8.51
2018	1,065	9.05
2019	1,087	9.24
Total sample size	11,769	100.00

Table 2
Correlation matrix and descriptive statistics.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
F. Patent Applications	1.000											
EPU Index	0.241***	1.000										
ROA	0.117***	-0.036***	1.000									
Tobin's q	-0.082***	-0.035***	0.058***	1.000								
Leverage	0.100***	-0.059***	-0.351***	-0.194***	1.000							
Firm Size	0.458***	0.211***	0.039***	-0.356***	0.376***	1.000						
PPE	-0.202***	-0.181***	-0.034***	-0.105***	0.040***	0.042***	1.000					
Financial Slack	0.009	-0.040***	0.244***	0.076***	-0.347***	-0.151***	-0.334***	1.000				
Operational Capability	0.259***	0.108***	0.342***	-0.066***	-0.101***	0.073***	-0.127***	0.121***	1.000			
Marketing Capability	0.097***	0.032***	0.135***	-0.121***	0.086***	0.093***	-0.018**	0.031***	0.402***	1.000		
CPI Index	0.030***	0.053***	0.044***	-0.080***	0.019**	0.028***	-0.006	0.052***	-0.014	-0.016*	1.000	
M2 growth	-0.270***	-0.648***	0.015	0.036***	0.087***	-0.194***	0.187***	0.051***	-0.098***	-0.012	-0.131***	1.000
Mean	2.155	259.1	0.034	1.805	0.445	21.93	0.257	0.173	0.708	0.606	102.4	13.65
Standard deviation	1.813	209.6	0.059	1.066	0.200	1.299	0.163	0.127	0.289	0.285	1.550	4.735
Minimum	0.000	55.69	-0.277	0.883	0.053	19.40	0.002	0.009	0.000	0.000	99.20	8.100
Maximum	8.779	791.9	0.191	8.379	0.908	25.85	0.730	0.671	1.000	1.000	105.9	28.50

Table 3
Results of fixed-effects regression analysis.

Variables	Model1	Model2	Model3	Model4	Model5
*EPU Index * Marketing Capability*				0.00363***	0.00301***
				(4.82)	(3.75)
EPU Index^2 * *Marketing Capability*				-3.84e-06***	-2.86e-06***
				(-4.93)	(-3.38)
*EPU Index * Operational Capability*			0.00269***		0.00151*
			(3.68)		(1.94)
EPU Index^2 * *Operational Capability*			-3.47e-06***		-2.36e-06***
			(-4.38)		(-2.72)
EPU Index		0.00469***	0.00275***	0.00248***	0.00175***
		(19.17)	(4.65)	(4.62)	(2.62)
EPU Index^2		-0.00001***	-3.15e-06***	-3.34e-06***	-2.20e-06***
		(-24.78)	(-4.91)	(-6.06)	(-3.12)
Operational Capability	0.09637	0.07159	-0.23083**	0.07170	-0.06893
	(1.56)	(1.20)	(-2.14)	(1.20)	(-0.60)
Marketing Capability	-0.12601	-0.05513	-0.05494	-0.53045***	-0.47359***
	(-1.64)	(-0.73)	(-0.73)	(-4.13)	(-3.54)
ROA	1.00206***	0.97738***	0.96472***	0.99072***	1.00846***
	(3.63)	(3.69)	(3.64)	(3.76)	(3.82)
Tobin's q	0.15225***	0.13048***	0.13206***	0.13044***	0.13073***
	(10.29)	(9.01)	(9.10)	(9.05)	(9.05)
Leverage	-0.19644	-0.07921	-0.07764	-0.06606	-0.06491
	(-1.19)	(-0.49)	(-0.48)	(-0.41)	(-0.40)
Firm Size	0.93284***	0.85463***	0.85455***	0.84934***	0.85124***
	(21.44)	(18.50)	(18.48)	(18.49)	(18.48)
PPE	-0.22389	-0.13587	-0.13020	-0.12431	-0.11785
	(-1.19)	(-0.74)	(-0.71)	(-0.68)	(-0.65)
Financial Slack	-0.02391	-0.10616	-0.09010	-0.08995	-0.09242
	(-0.15)	(-0.66)	(-0.56)	(-0.56)	(-0.57)
CPI Index	-0.00646	0.01386**	0.01477**	0.01357**	0.01409**
	(-0.93)	(2.00)	(2.13)	(1.97)	(2.03)
M2 growth	-0.01640***	-0.00428	-0.00400	-0.00432	-0.00405
	(-4.20)	(-1.15)	(-1.08)	(-1.16)	(-1.09)
Constant	-17.572***	-18.732***	-18.621***	-18.308***	-18.342***
	(-12.93)	(-13.67)	(-13.60)	(-13.39)	(-13.41)
Firm Fixed Effect	YES	YES	YES	YES	YES
N	11,769	11,769	11,769	11,769	11,769
Within R^2	0.3143	0.3630	0.3645	0.3653	0.3661

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All the p-values are two-tailed. t statistics in parentheses.

Table 4
Robustness test-Alternative measure of dependent variable.

Variables	Model1	Model2	Model3	Model4	Model5
*EPU Index * Marketing Capability*				0.00350***	0.00275***
				(4.54)	(3.33)
*EPU Index^2 * Marketing Capability*				-3.59e-06***	-2.47e-06***
				(-4.47)	(-2.84)
*EPU Index * Operational Capability*			0.00287***		0.00182**
			(3.87)		(2.28)
*EPU Index^2 * Operational Capability*			-3.62e-06***		-2.69e-06***
			(-4.45)		(-3.03)
EPU Index		0.00432***	0.00225***	0.00219***	0.00132**
		(16.65)	(3.81)	(4.10)	(2.00)
EPU Index^2		-0.00001***	-2.72e-06***	-3.18e-06***	-1.89e-06***
		(-21.94)	(-4.20)	(-5.72)	(-2.65)
Operational Capability	0.08998	0.07016	-0.26000**	0.07047	-0.10886
	(1.50)	(1.20)	(-2.41)	(1.21)	(-0.94)
Marketing Capability	-0.11440	-0.04258	-0.04264	-0.50965***	-0.43631***
	(-1.47)	(-0.55)	(-0.55)	(-3.89)	(-3.19)
ROA	0.86009***	0.78401***	0.76356***	0.79552***	0.80674***
	(3.09)	(2.93)	(2.85)	(2.98)	(3.01)
Tobin's q	0.14843***	0.12814***	0.12992***	0.12803***	0.12857***
	(10.32)	(9.11)	(9.23)	(9.16)	(9.17)
Leverage	-0.26261	-0.16434	-0.16286	-0.15109	-0.15034
	(-1.58)	(-1.01)	(-1.00)	(-0.93)	(-0.93)
Firm Size	0.88661***	0.82323***	0.82262***	0.81768***	0.81940***
	(20.36)	(17.73)	(17.72)	(17.73)	(17.73)
PPE	-0.18383	-0.10788	-0.10267	-0.09625	-0.09012
	(-0.94)	(-0.56)	(-0.53)	(-0.50)	(-0.47)
Financial Slack	0.05711	-0.02934	-0.01088	-0.01480	-0.01522
	(0.34)	(-0.18)	(-0.07)	(-0.09)	(-0.09)
CPI Index	-0.00792	0.01134*	0.01231*	0.01104	0.01167*
	(-1.15)	(1.66)	(1.80)	(1.62)	(1.71)
M2 growth	-0.01642***	-0.00661*	-0.00634*	-0.00665*	-0.00636*
	(-4.23)	(-1.80)	(-1.73)	(-1.81)	(-1.73)
Constant	-16.520***	-17.797***	-17.662***	-17.371***	-17.396***
	(-12.27)	(-13.06)	(-12.97)	(-12.78)	(-12.79)
Firm Fixed Effect	YES	YES	YES	YES	YES
N	11,769	11,769	11,769	11,769	11,769
Within R^2	0.2825	0.3283	0.3299	0.3305	0.3314

Notes: *p < 0.1, **p < 0.05, ***p < 0.01. All the p-values are two-tailed. t statistics in parentheses.

Table 5
Robustness test-Instrumental Variable (IV) approach.

Variables	First stage		Second stage		
	EPU	EPU^2	Patent	Invention Patent	Utility Model
BILL	1302.6^{***}	1732995^{***}			
	(9.79)	(13.35)			
$BILL^2$	-104.5^{***}	-132287^{***}			
	(-10.13)	(-13.14)			
Instrumented EPU			0.01371^{***}	0.00905^{***}	0.01289^{***}
			(20.39)	(16.90)	(22.90)
Instrumented EPU^2			-0.00001^{***}	-0.00001^{***}	-0.00001^{***}
			(-17.51)	(-12.36)	(-22.56)
Operational Capability	40.80^{***}	30586.2^{***}	-0.10697^{*}	-0.11721^{**}	-0.04162
	(5.71)	(4.38)	(-1.85)	(-2.52)	(-0.85)
Marketing Capability	51.74^{***}	54851.5^{***}	-0.20114^{***}	-0.19439^{***}	-0.08734
	(6.67)	(7.25)	(-3.01)	(-3.51)	(-1.51)
ROA	-497.2^{***}	-451396.8^{***}	3.24934^{***}	2.42688^{***}	2.22473^{***}
	(-15.46)	(-14.38)	(8.26)	(7.75)	(6.84)
Tobin's q	-6.468^{***}	-6602.4^{***}	0.09847^{***}	0.08310^{***}	0.08333^{***}
	(-3.58)	(-3.74)	(7.62)	(7.82)	(7.29)
Leverage	-103.1^{***}	-76510.5^{***}	0.57155^{***}	0.40517^{***}	0.45991^{***}
	(-6.99)	(-5.31)	(4.35)	(3.59)	(3.91)
Firm Size	77.89^{***}	66371.3^{***}	0.32572^{***}	0.32459^{***}	0.31649^{***}
	(23.77)	(20.76)	(5.21)	(6.42)	(6.06)
PPE	-50.79^{***}	-43433.0^{**}	0.25849^{*}	0.12859	0.08144
	(-2.94)	(-2.57)	(1.89)	(1.16)	(0.69)
Financial Slack	-89.84^{***}	-93529.0^{***}	0.19879	0.19151^{*}	0.08494
	(-5.39)	(-5.75)	(1.44)	(1.75)	(0.72)
CPI Index	-2.680^{***}	2676.8^{***}	0.02977^{***}	0.00996^{*}	0.01428^{**}
	(-2.82)	(2.89)	(4.06)	(1.78)	(2.31)
M2 growth	-16.95^{***}	-12016.4^{***}	0.07818^{***}	0.05220^{***}	0.05013^{***}
	(-42.12)	(-30.61)	(8.10)	(7.15)	(6.53)
Constant	-4943.7^{***}	-7072131^{***}	-11.87^{***}	-9.35^{***}	-9.84^{***}
	(-11.92)	(-17.48)	(-8.36)	(-7.94)	(-7.94)
Firm Fixed Effect	YES	YES	YES	YES	YES
N	11,693	11,693	11,693	11,693	11,693
Kleibergen-Paap rk LM statistic			208.711^{***}	208.711^{***}	208.711^{***}
Kleibergen-Paap rk Wald F statistic			115.132	115.132	115.132
Cragg-Donald Wald F statistic			69.173	69.173	69.173
Stock-Yogo 10% critical value			7.03	7.03	7.03
Sargan statistic			0.000	0.000	0.000

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All the p-values are two-tailed. t statistics in parentheses.

Table 6
Regression results in subsamples.

Panel A: Two subsamples of observations split according to the median value of EPU index

Variables	Low EPU	High EPU
EPU Index	0.00266***	-0.00182***
	(6.47)	(-17.95)
Operational Capability	0.11598*	0.13577
	(1.76)	(1.50)
Marketing Capability	-0.07866	0.00830
	(-0.81)	(0.09)
ROA	0.36874	1.36682***
	(1.04)	(4.58)
Tobin's q	0.16249***	0.04251**
	(7.62)	(2.25)
Leverage	-0.26243	-0.24735
	(-1.16)	(-1.47)
Firm Size	1.02316***	0.45210***
	(17.36)	(8.80)
PPE	0.09218	0.03600
	(0.43)	(0.15)
Financial Slack	-0.21933	-0.11116
	(-1.08)	(-0.57)
CPI Index	0.02579***	0.00379
	(3.18)	(0.17)
M2 growth	0.00758*	-0.15209***
	(1.85)	(-17.35)
Constant	-23.802***	-5.456***
	(-15.05)	(-1.93)
Firm Fixed Effect	YES	YES
N	5,863	5,906
Within R^2	0.3355	0.2582

Panel B: The impact of innovation output on firms' sales growth in two subsamples

	F.Sales Growth			
	Low EPU	High EPU	Low EPU	High EPU
Patent	0.05761**	0.05491		
	(2.13)	(1.38)		
Invention Patent			0.07556*	0.09069
			(1.86)	(1.61)
Controls	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
N	5,856	5,906	5,856	5,906
Within R^2	0.0053	0.0180	0.0053	0.0188

Panel C: The impact of innovation output on firms' ROA in two subsamples

	F.ROA			
	Low EPU	High EPU	Low EPU	High EPU
Patent	0.00253**	0.00079		
	(2.36)	(0.74)		
Invention Patent			0.00295**	0.00020
			(2.26)	(0.17)
Controls	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
N	5,863	5,906	5,863	5,906
Within R^2	0.0655	0.0638	0.0652	0.0637

Panel D: The impact of innovation output on firms' *Tobin's q* in two subsamples

	F.*Tobin's q*			
	Low EPU	High EPU	Low EPU	High EPU
Patent	0.10609***	0.01446		
	(6.27)	(0.94)		

Invention Patent			0.14651***	0.01446
			(6.46)	(0.94)
Controls	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES
N	5,863	5,906	5,863	5,906
Within R^2	0.0234	0.0939	0.0251	0.0939

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All the *p*-values are two-tailed. *t* statistics in parentheses.

Table 7
Robustness test.

	Alternative newspaper	Invention patents	Negative binomial model	U.S. EPU	Deletion of 2008 & 2009	Time trend	Rolling regression: 6 months	Rolling regression: 36 months	Rolling regression: 48 months	Rolling regression: 60 months	Two capabilities
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7				Model 8
EPU Index	0.01623***	0.00284***	0.0042***	0.00212***	0.00413***	0.00244***					0.00249***
	(22.61)	(14.11)	(19.29)	(7.82)	(16.30)	(10.80)					(4.76)
EPU Index^2	-0.00004***	-3.16e-06***	-3.84e-06***	-0.00001***	-0.00001***	-4.05e-06***					-1.70e-06*
	(-25.48)	(-16.54)	(-17.94)	(-16.24)	(-22.27)	(-19.74)					(-1.79)
*EPU Index * Two Cap*											0.00196**
											(2.11)
EPU Index^2 * *Two Cap*											-3.33e-06**
											(-1.96)
EPU Exposure							21.60***	63.52*	262.96***	439.32***	
							(4.02)	(1.81)	(4.05)	(4.06)	
EPU Exposure^2							-1224.1***	-2512.7*	-65516.2**	-161255.5*	
							(-5.56)	(-1.82)	(-2.17)	(-1.85)	
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time trend	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	NO
N	11,769	11,769	12,369	11,769	10,808	11,769	11,244	9,931	9,931	9,931	9,855
Log likelihood	No	No	-36866.0	No	No	No	No	No	No	No	No
Within R^2	0.3810	0.3459	No	0.3452	0.3835	0.3909	0.3395	0.3371	0.3387	0.3402	0.3891

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All the p-values are two-tailed. t statistics in parentheses.

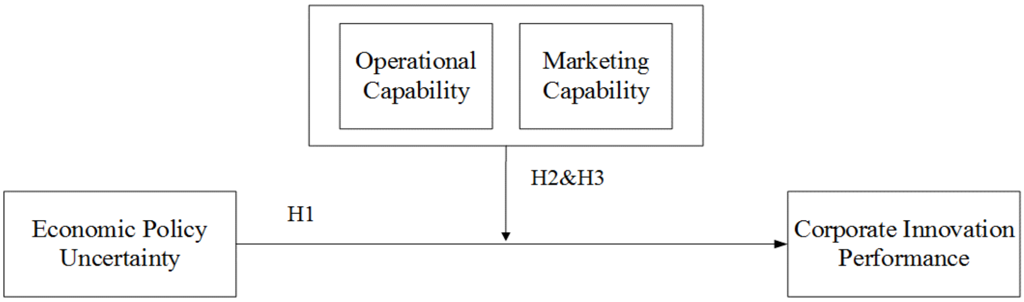

Figure 1. Conceptual model.

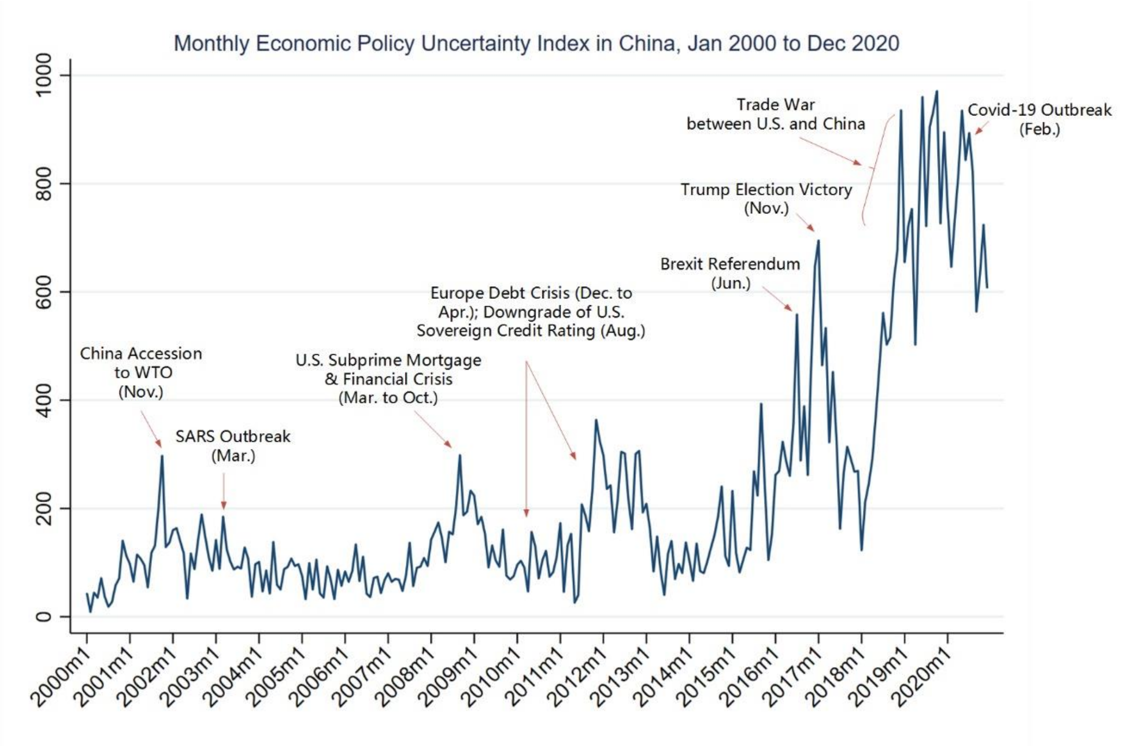

Figure 2. The monthly EPU index.

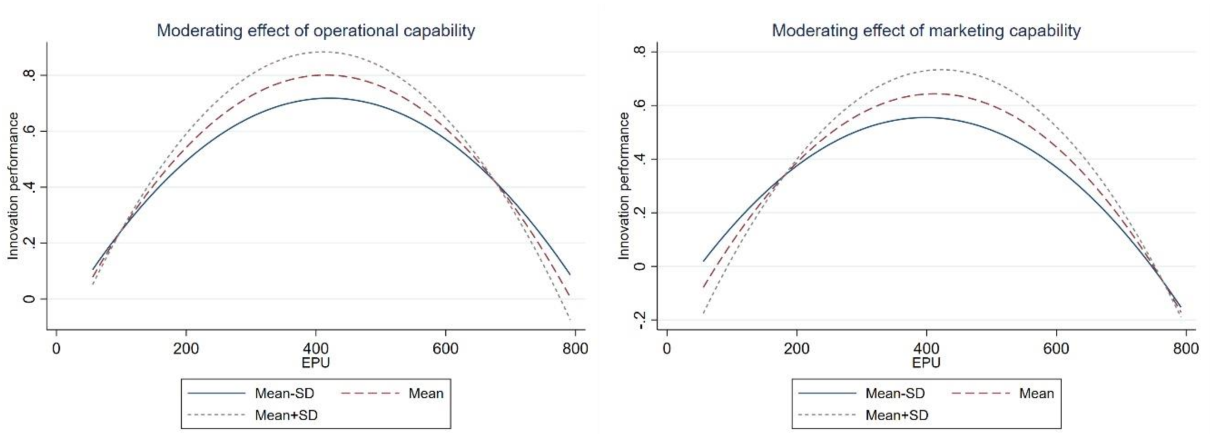

Figure 3. The moderating effects of operational capability and marketing capability.

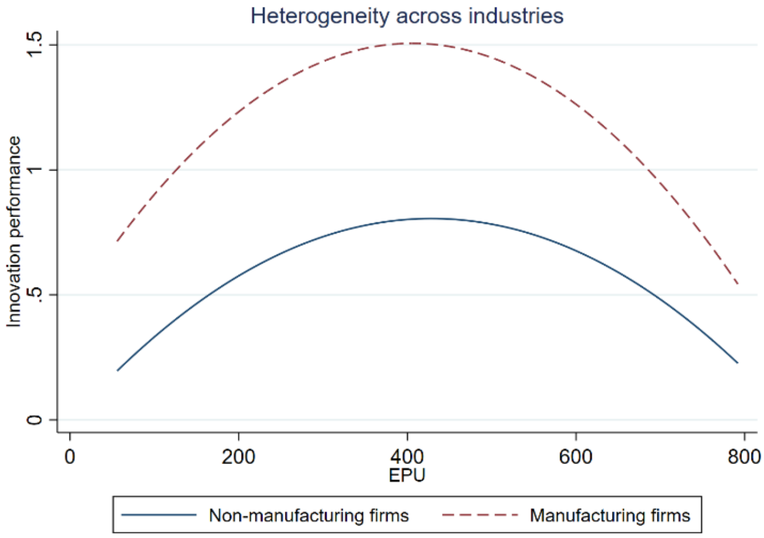

Figure 4. The heterogeneity effect across industries.