Theoretical Economics Letters, 2024, 14, 2212-2235
https://www.scirp.org/journal/tel
ISSN Online: 2162-2086
ISSN Print: 2162-2078

The Firm Innovation under the Uncertainty of Industry-Level Demand—Evidence from China

Jie Cai[1], **Qi Wang**[2], **Anping Liu**[1], **Xiangyun Xu**[2*]

[1]School of International Economics and Business, Nanjing University of Finance and Economics, Nanjing, China
[2]School of International Trade and Economics, Anhui University of Finance and Economics, Bengbu, China
Email: *xuxiangyun_ecnu@sina.com

How to cite this paper: Cai, J., Wang, Q., Liu, A. P., & Xu, X. Y. (2024). The Firm Innovation under the Uncertainty of Industry-Level Demand—Evidence from China. *Theoretical Economics Letters, 14,* 2212-2235.
https://doi.org/10.4236/tel.2024.146109

Received: October 10, 2024
Accepted: November 14, 2024
Published: November 21, 2024

Abstract

Voluminous studies have investigated the impact of uncertainty on investment or innovation, but few focus on the relationship between industry-level demand uncertainty and firm innovation. This paper uses the standard deviation of the industry's sales growth rate to represent the uncertainty of demand. It employs the panel data of listed manufacturing firms in China for empirical analysis. Our results show that demand uncertainty inhibits the firm innovation activities. However, such a focal effect depends on the size, ownership of the firm, and the character of the industry to which the firm belongs, which indicates that the heterogeneity of firms is crucial for absorbing demand uncertainty shock. In addition, we also find that the aggregate and industry-specific demand uncertainty affect firm innovation negatively.

Keywords

Industry-Level Demand, Uncertainty, Firm Innovation, Heterogeneity, Manufacturing Firms

1. Introduction

The impact of uncertainty on innovation is a complex and crucial topic in economics and management. Uncertainty can arise from various factors—market shifts, policy changes, and institutional dynamics—each affecting firm innovation differently, with both positive and negative outcomes. Some research indicates that, while challenging, uncertainty can foster innovation by creating opportunities for flexibility and adaptability in complex environments. The classical "Oi-Hartman-Abel" theory suggests that firms may take more risks and increase investment to offset potential losses from increased uncertainty (Abel, 1983; Hartman, 1972; Oi, 1961). Additionally, the "growth option" theory (Dixit & Pindyck,

1994) posits that firms might invest more in innovation, treating it as an option for future profitability under uncertain conditions. Since R&D and technological advancements are essential for sustainable growth in competitive markets (Aghion et al., 2005; Jens, 2017), increased uncertainty could incentivize firms to enhance innovation to secure their survival and profits (Van Vo & Le, 2017; García-Quevedo et al., 2017; Ross et al., 2018). Supporting this view, York and Venkatraman (2010) argue that innovation is driven more by motivation and creativity than by regulatory stability, suggesting that an uncertain environment may push innovators to pursue riskier, unconventional paths. This is echoed by Sartorius (2006), who emphasizes that "fundamental uncertainty" from dynamic interactions between stakeholders can promote new forms of collaboration, often leading to breakthrough innovations. In such contexts, uncertainty can encourage creative problem-solving and adaptive strategies that would likely not emerge in more stable, predictable settings.

However, more scholars hold the opposite opinion and believe the increase in uncertainty will inhibit the investment of firms (Bloom et al., 2007; Nguyen & Trinh, 2023), which in turn may produce an innovation-reducing effect, no matter whether the uncertainty originates from political disturbance (Julio & Yook, 2012; Jens, 2017; Cao et al., 2019), change of government authority (An et al., 2016), or economic policy including fiscal and monetary policy (Baker et al., 2016; Fernández-Villaverde et al., 2015). Bunches of studies hold this opinion, covering areas like economic policy (Geng et al., 2023), climate policy (Sun et al., 2024), fiscal and tax policies (Wen et al., 2022; Chen & Jin, 2023), and trade policy (Liu & Ma, 2020). First, the "real option" theory (Dixit & Pindyck, 1994) points out that when investment costs associated with innovation activities are sunk and irreversible, the value of "wait and see" increases with rising uncertainty at the industry level. In such situations, decision-makers find it difficult to precisely predict the firm's revenue, liabilities, and asset prices, even the operation of the supply chain, which will delay investments in innovation activities (Bloom et al., 2007; Bloom, 2009; Baum et al., 2006; Song & Lee, 2012). For example, Meng et al. (2022) find that demand unpredictability raises the supply chain risk in the manufacturing industry by utilizing the data of Chinese firms. Second, higher uncertainty may trigger pessimistic expectations about future market demand, which may induce them to adjust firm's investment plans and reduce innovation investments (Barrero et al., 2017). Third, the firm's financing costs will rise, and the availability of bank loans will decrease due to the uncertainty. Firms with severe financial constraints are more likely to restrict funding for R&D investment (Alessandri & Bottero, 2020).

Though the relationship between investment or innovation and uncertainty can be negative or positive theoretically, voluminous empirical studies have verified the negative effect of uncertainty, including demand uncertainty on the investment of firms (Bernanke, 1983; Dixit & Pindyck, 1994; Ogawa & Suzuki, 2000), and some papers focused on the uncertainty and innovation get similar conclusion, which indicates a reduction in innovation activities under high uncertainty and supports the "real option" theory. For example, He et al. (2020) apply the EPU index as the measurement of uncertainty and find that a considerably high level of uncertainty inhibits a firm's innovation. By constructing the indicator of perception of uncertainty from the management team, Yu et al. (2021) find that managers' interpretations of the environment will affect their innovative incentives, and uncertainty leads to a decrease in the number of patent filings. Bhattacharya et al. (2017) propose that innovative activities drop significantly during times of national elections.

Based on previous literature, this paper focuses on the impact of industry-level demand uncertainty on firm innovation. We use the data from the Annual Survey of Industrial Production (ASIP) conducted by the National Bureau of Statistics of China (Abbreviated as NBSC) to construct indicators to depict the demand uncertainty in China's manufacturing industries. Combined with the firm-level data of the A-share listed manufacturing firms from 2004 to 2019, our empirical results verify that increased industry-level demand uncertainty indeed inhibits innovation significantly in China's manufacturing firms. By decomposing the demand uncertainty, we reveal that both aggregate and industry-specific demand uncertainty reduce firm innovation. In addition, we also explore the impact of demand uncertainty on the innovation of heterogeneous manufacturing firms with different sizes, ownership, and the character of the industry to which the firm belongs.

While the impact of demand uncertainty on investment or certain kinds of uncertainty, such as EPU and political disturbance on innovation, have been extensively studied, it still needs to be explored for the role of demand uncertainty on innovation. This is surprising because demand uncertainty is the most important type of uncertainty that firms face directly. Other types of uncertainty, such as policy or political uncertainty, will turn into demand factors and affect the innovation activities of firms. So, this paper seeks to address this gap. It contributes to literature in several notable ways. First, the paper focuses on the impact of industrial-level demand uncertainty on firm innovation and explores the heterogeneous reaction of firms to demand uncertainty. It not only confirms the inhibitory impact of demand uncertainty on firm innovation but also demonstrates such a focal effect depending on the size, ownership of the firm, and the character of the industry to which the firm belongs. To the best of our knowledge, the paper is the first one to try to do it. Second, this study compares the role of aggregate and industry-specific demand uncertainty on innovation by decomposing the industry-level demand uncertainty. Theoretically, such uncertainty originates partially from aggregate and industry-specific demand shock, and the two kinds of uncertainty may have different impacts on the behavior of firms. Third, this paper also examines the influence of higher-order moments of uncertainty on firm innovation by introducing the skewness of manufacturing industry-level demand, which extends to the existing literature such as De Sousa et al. (2020).

The remainder of the paper is organized as follows: Section 1 is an introduction. Section 2 presents variables and an empirical model. Section 3 shows the variables and data. Section 4 presents the regression results and the robustness test, and the final section concludes.

2. Hypotheses Development

A firm must choose whether and when to invest; when demand uncertainty affects a firm's decision to invest in innovation, the firm may postpone its decision while it waits for new information to address this uncertainty. The firm may stick to its original strategy and proceed with the investment if the demand uncertainty has no bearing on the project. Businesses are more cautious because the delay option is more useful at significant costs (Bloom et al., 2007; Bloom, 2009). One of the primary objectives of a firm is to maximize returns. From the net present value standpoint, the firm decides to invest in innovation only when the benefits of innovation (cash inflow) brought by the innovation project outweigh the innovation expenses (cash outflow). Uncertainty makes a firm's innovation project more volatile and makes forecasting how new ventures will develop harder. In such cases, the business decides to delay or halt innovative endeavors. Similarly, the firm's costs rise due to uncertainty in demand. The firm requests financing when internal finance is insufficient to raise the necessary funding. The firm is under financial pressure and must cut its investment in innovation due to the high level of uncertainty around the project (Kara & Yook, 2022). According to Gilchrist et al. (2013), business default rates rise when macroeconomic uncertainty is high, and financing costs follow suit. Managers will reduce a firm's finances in reaction to increased financing costs. Due to the firm's increasing financial constraints, Jeong (2002) also demonstrates that reducing investment is a wise decision in situations of high uncertainty. So, we propose hypothesis 1.

Hypothesis 1: *Industry-level demand uncertainty suppresses innovation, negatively affecting the innovation activities of listed firms.*

Firm innovation is impacted by ownership heterogeneity. Technology-based firms need fixed assets that may be mortgaged because the returns from technical R&D operations are unclear and time-consuming. According to Brandt and Roberts (2005), commercial banks engage in "ownership discrimination," favoring lending to firms with fixed assets over those without them (Stiglitz & Weiss, 1981). Demand uncertainty can alter the supply of bank credit and distort the allocation of loanable funds because enterprises with diverse ownership have varying access to commercial bank loans (Alessandri & Bottero, 2020; Kara & Yook, 2022). The inadequate supply of external financing leads firms to rely too much on internal cash flows for investment, constraining their investment in fixed and intangible assets (Bloch, 2005). A rising body of research indicates that direct finance is preferred as the main source of R&D funding in economies with higher levels of technological innovation (Brown et al., 2013). According to Feng et al. (2021), enterprise investment is negatively correlated with economic policy uncertainty, which is more significant in non-state-owned enterprises (non-SOEs) than state-owned enterprises (SOEs). According to Li et al. (2021), uncertainty causes financial mismatches to worsen, which lowers firms' growth in total factor productivity. This effect is especially significant in non-SOEs.

State-owned commercial banks with monopolistic positions frequently practice lending discrimination and favor SOEs over other borrowers. In comparison to private businesses, SOEs are better able to get more lending from financial institutions and secure funding for innovative investments due to their political connections. When market demand is highly uncertain, SOE financing costs are lower than those of non-SOEs. The "ownership discrimination" is particularly striking when there is a lot of uncertainty around market demand. As a result, we suggest hypothesis 2.

Hypothesis 2: *Increasing industry-level demand uncertainty has a more significant inhibitory effect on the innovation activity of non-SOEs than that of SOEs.*

Firm size heterogeneity also plays an important role when faced with uncertainty shocks because firms of different sizes have different abilities to take risks and seize opportunities (Khan et al., 2020). Specifically, there are some differences between large and small firms in terms of financing and governance structure. Commercial banks and investors prefer larger firms over smaller ones because the latter have fewer collateral assets and less perfect financial systems (Kang et al., 2014). Jefferson et al. (2006) use data from Chinese medium and large manufacturing firms to explore the determinants of R&D expenditures and sales income of new products. The findings indicate a positive correlation between firm size and the level of innovative activity within the firms. The study of Tovar & Wall (2012) illustrates that demand uncertainty affects firms' marginal costs. A firm can only lower marginal costs and advance its development by embracing economies of scale and economics of scope.

According to the growth option theory, although the irreversibility of investment makes deferred options more valuable under conditions of uncertainty, for some firms, the cost of waiting may be so expensive that holding an option is not feasible. When there is a high level of industry competition, the firm should thoroughly evaluate how competitors would perceive the technological innovation project when deciding whether to adopt it or not, in addition to how the technological innovation will affect the firm itself. In many cases, to avoid losing the first-mover advantage and market share in the future, firms will choose to enter the market in advance, especially some large and high-tech firms. Even if the innovation investment project's NPV (net present value) is negative, the firm may carry out the innovation project. Despite the high degree of uncertainty in demand, firms consider their competitors' responses to technological innovation activities the most important factors to consider (Trigeorgis, 1996). Compared to small and medium-sized firms, large firms may be more concerned about the future value of innovative investments and are likely to invest more in R&D, even with uncertainty (Boulding & Christen, 2003, 2008). Thus, the impact of industry-level demand uncertainty on the innovative performance of large firms will be smaller than on small firms. Therefore, we propose hypothesis 3 as follows:

Hypothesis 3: *Keep other things equal, larger firm size weakens the negative effect of industry-level demand uncertainty on innovation in manufacturing.*

Industry heterogeneity is a notable factor affecting innovative activities when firms face uncertainty. Raman & Chatterjee (1995) point out that in a market with demand uncertainty, high-tech firms should pay more attention to the impact of uncertainty. According to Kafouros et al. (2008), businesses that invest in sectors with brighter technological prospects benefit more from knowledge spillovers, have much stronger organizational frameworks, and are more capable of innovation. Jakubovskis (2017) makes distinctions between capital-intensive and labor-intensive technology sectors to examine the differences in how firms' strategic decisions are affected by demand uncertainty.

Increased market demand uncertainty suggests that firms, particularly those in the high-technology sector, have a better possibility of acquiring larger profits. High-tech firms have a greater willingness and capacity to seek out new innovative activities because technological innovation activities in high-tech industries are characterized by high knowledge and skill intensity, high revenue levels, and high market competition, which require firms to respond quickly to changes in the market environment. Firms in high-tech industries have more options than traditional businesses to take advantage of opportunities created by uncertainty and enhance the effectiveness of their operational management by quickening the speed of technological innovation. Therefore, we hypothesize as follows:

Hypothesis 4: *Compared to high-tech firms, industry-level demand uncertainty has a more significant inhibitory effect on the innovation activities of non-high-tech firms.*

3. Variables and Model Specification

3.1. Key Explanatory Variable

The key explanatory variable in this paper is the industry-level demand uncertainty. There are four methods to calculate the demand uncertainty in literature (Ogawa & Suzuki, 2000;; Campbell, 2007; Banker et al., 2014; Liang et al., 2023), including the standard deviation of the sales growth rate based on a traditional formula using past few years' information, the magnitude of the standard error of regression which implies the growth rate follows an auto-regressive (AR) process, unexpected sales divided by forecast sales (Chuang et al., 2019), and conditional standard deviation of an ARCH model which assumes the growth rate follows a second-order AR model, and the error term follows an ARCH (1) model, respectively. We use the first method (also the traditional method) to measure the industry-level demand uncertainty for three reasons: 1) the data of forecast sales is hard to obtain; 2) the ARCH-type method needs to utilize the full information set, including the future information to get the conditional standard deviation, which seems less realistic from the empirical point of review; 3) the correlation coefficient between the measures based on the first two methods is high (Ogawa & Suzuki, 2000; Liang et al., 2023). Exactly, we use the past two years' information (with

22 monthly observations[1]) to compute the demand uncertainty of industry j ($Uncer_{j,t}$).

$$Uncer_{j,t} = \frac{1}{22}\sqrt{\sum_{n=1}^{11}\left(R_{t-1+\frac{n}{11},j} - \widehat{R_{t-1\sim t}}\right)^2 + \sum_{n=1}^{11}\left(R_{t+\frac{n}{11},j} - \widehat{R_{t-1\sim t}}\right)^2} \tag{1}$$

where $R_{t+\frac{n}{11},j}$ is the sales growth rate of industry j at the nth month of year t, and $\widehat{R_{t-1\sim t}}$ is the average growth rate of industry j during the year $t-1$ to t. The sales growth rate of each industry in the manufacturing sector refers to the year-on-year growth rate of the main business income of firms above the designated size, and the data comes from the Annual Survey of Industrial Production (ASIP) of China, which can be downloaded from the official website of NBSC.

3.2. Dependent Variable

Firm innovation serves as the explanatory variable in this study. R&D expenditures and innovation output are typically the indicators of firm innovation (Shefer & Frenkel, 2005; Mancusi & Vezzulli, 2010). However, there are some disadvantages to quantifying innovation by R&D expenditures. First, R&D expenditure data may suffer from sample selection bias because some firms are unwilling to publish their investment in R&D; no data does not necessarily mean a lack of innovation activities. Second, firm R&D expenditures don't necessarily convert into R&D output (Griliches, 1990). In contrast, the number of patent applications granted is a more effective measure of firm innovation, which can visually characterize the quality of firms' innovation output (Griliches, 1990). Third, the China Stock Market Accounting Research (CSMAR) database provides data on patent applications and authorizations of listed firms in China since 1989, while the data on the R&D expenditures of listed firms in China is only from 2007. There will be more observations to use the patent data than R&D expenditures data.

Therefore, referring to Hall et al. (2005), Fang et al. (2014), Van Vo & Le (2017), and Pertuze et al. (2019), we use patent applications to measure firm innovation, which includes invention patents (Inv), utility model patents (Uti), design patents (Des), and the total of patents (All). Considering that the number of patent applications can be zero, we take the logarithm of one plus the number of patent applications according to the method of existing literature.

3.3. Control Variables

Following Kaplan & Zingales (1997), Hall et al. (2005), Shefer & Frenkel (2005), and Pham et al. (2018), we choose firm size, profitability, Tobin's Q, asset-liability ratio, cash flow ratio, tangible asset ratio, equity concentration, and firm age as control variables. **Table 1** displays the definition of each variable. Except for industry-level demand uncertainty, which is calculated by data from the NBSC website, other variables' data come from the CSMAR database.

[1]As the length of time window to calculate the demand uncertainty is subjective, we also use the past three years' information as one robust test in Section 5.3.

Table 1. Variable definition and data source.

Variable Type	Definition	Symbol	Explanations
Dependent Variables	Total patents	$\ln\left(1+All_{i,j,t}\right)$	The logarithm of (1+ all patent applications)
	Invention patents	$\ln\left(1+Inv_{i,j,t}\right)$	The logarithm of (1+ invention patent applications)
	Utility model patents	$\ln\left(1+Uti_{i,j,t}\right)$	The logarithm of (1+ utility model patent applications)
	Design patents	$\ln\left(1+Des_{i,j,t}\right)$	The logarithm of (1+ design patent applications)
Explanatory Variable	Industry-level demand uncertainty	$Uncer_{j,t}$	The industry revenue growth's standard deviation over the previous 22 months
Control Variables	Firm size	$lnSize_{i,t}$	The logarithm of the firm's total assets
	Profitability	$Roa_{i,t}$	The return of total asset
	Cash flow ratio	$Cfo_{i,t}$	The ratio of cash flow to total assets
	Asset-liability ratio	$Lev_{i,t}$	The ratio of total liabilities to total assets
	Equity concentration	$First_{i,t}$	The largest shareholder's holdings/total number of shares
	Tobin's Q	$TobQ_{i,t}$	The ratio of the sum of market value of equity and market value of net debt to the total assets
	Tangible asset ratio	$Tange_{i,t}$	The ratio of tangible assets to total assets
	Age of the firm	$Age_{i,t}$	The length of the firm's founding years

3.4. Sample Explanation and Descriptive Statistics

We match the industry classification of manufacturing firms listed in A-shares with the Industry Classification of National Economy (GB T4754-2011) based on the Guideline of Industry Classification of Listed Firms issued by the China Securities Regulatory Commission (CSRC) in 2012. We drop the firms with ST or ST* from our sample to reduce the influence of outliers. The sample covers from 2002-2019 as the data of the sales growth rate of each industry only starts from February 2001 on the website of the NBSC, and NBSC has changed the indicator "main business income of firms" into another indicator "sales revenue of firms" since 2019, to reflect the scale and operational status of industrial enterprises more comprehensively. Ultimately, we get 21728 observations. It should be noted that there are a few missing data for some variables because the CSMAR database does not provide full information for certain listed companies. Table 2 displays the descriptive statistics for all variables of the observations.

4. Model Specification and Empirical Results

4.1. Model Specification

Based on the previous analysis, we set the baseline regression model as follows.

$$Innovation_{i,j,t} = \alpha + \beta Uncer_{j,t-1} + \sum \gamma_k Control_{i,t-1} + \mu_j + \eta_t + \varepsilon_{i,t} \quad (2)$$

Table 2. Descriptive statistics of variables.

Variables	N	Mean	Medium	St. Dev.	Min	Max
$\ln\left(1+All_{i,j,t}\right)$	21,728	2.416	2.485	1.665	0	8.904
$\ln\left(1+Inv_{i,j,t}\right)$	21,728	1.670	1.609	1.442	0	4.836
$\ln\left(1+Uti_{i,j,t}\right)$	21,728	1.688	1.754	1.606	0	5.697
$\ln\left(1+Des_{i,j,t}\right)$	21,728	0.663	1.548	1.111	0	3.871
$Uncer_{j,t}$	21,728	0.0420	0.0290	0.0330	0.008	0.128
$lnSize_{i,t}$	21,717	21.76	21.61	1.185	16.51	27.47
$Roa_{i,t}$	21,728	0.0450	0.0430	0.187	−6.714	20.79
$TobQ_{i,t}$	21,302	2.007	1.575	1.971	0.153	122.2
$Lev_{i,t}$	21,728	0.441	0.407	1.032	0	96.96
$Cfo_{i,t}$	21,728	0.169	0.127	0.503	−0.165	71.55
$Tange_{i,t}$	21,728	0.940	0.960	0.0710	0	1
$First_{i,t}$	20,341	35.56	33.67	14.96	3	89.99
$Age_{i,t}$	21,421	16.21	16	6.400	1	65

Source: Authors' computation based on NBSC and CSMAR database.

where *i*, *j*, and *t* represent the firm, the industry to which the firm belongs, and the year, respectively. $Innovation_{i,j,t}$ denotes the innovation output of firm *i*, $Uncer_{j,t-1}$ denotes industry-level demand uncertainty of industry *j*, $Control_{i,t-1}$ is a set of control variables, including firm size, profitability, Tobin's Q, asset-liability ratio, cash flow ratio, tangible asset ratio, equity concentration, and firm age; μ_j and η_t represent industry-fixed effects and time-fixed effects, respectively, $\varepsilon_{i,t}$ denotes random disturbance term. We lagged dependent variables by one year because their effects take some time to materialize.

4.2. Empirical Results

4.2.1. Baseline Regression Results

The Hausman test indicates that the fixed effect model should be adopted[2]. Table 3 shows the results of the benchmark regression. Columns (1) to (4) display the regression results for different dependent variables: the patent applications of the total, invention, utility model, and design, respectively. The results in columns (1) to (3) show a significant negative relationship between the industry-level demand uncertainty and the patent applications of the total, invention, or utility models of listed manufacturing firms. The estimated coefficients are −0.83, −1.73, and −0.83, respectively, among which the impact of industry-level demand uncertainty has

[2]The Chi-square statistic of the Hausman test is 6.20 with the value of *p* is 0.023. Therefore, we select the fixed effect model.

the greatest inhibitory effect on invention patents. This is because the invention patents, always seen as the best indicator of a firm's capacity for innovation, are the most difficult to apply, involve more R&D expenditures, longer processing time, and larger investment risk, and would be affected by demand uncertainty deeper compared with other types of patents, no matter from the channels of real option, expectation or financing costs. Column (4) shows that the impact of industry-level demand uncertainty on design patent applications is insignificant, probably because design patents are more accessible to apply and do not need much investment. Overall, the regression results in Table 3 verify that industry-level demand uncertainty indeed inhibits firm innovation, and the results are consistent with Hypothesis 1.

Table 3. Baseline regression results.

	(1)	(2)	(3)	(4)
	$\ln\left(1+All_{i,j,t}\right)$	$\ln\left(1+Inv_{i,j,t}\right)$	$\ln\left(1+Uti_{i,j,t}\right)$	$\ln\left(1+Des_{i,j,t}\right)$
$Uncer_{j,t-1}$	-0.81^{**}	-1.71^{***}	-0.81^{**}	-0.16
	(-2.08)	(-4.84)	(-2.09)	(-0.50)
$lnSize_{i,t-1}$	0.61^{***}	0.55^{***}	0.55^{***}	0.24^{***}
	(40.88)	(41.05)	(38.38)	(19.66)
$Roa_{i,t-1}$	1.48^{***}	1.08^{***}	1.49^{***}	0.61^{***}
	(8.23)	(6.65)	(8.42)	(4.24)
$TobQ_{i,t-1}$	0.01	0.03^{***}	-0.01	0.01^{*}
	(1.05)	(2.64)	(-0.51)	(1.75)
$Lev_{i,t-1}$	-0.14^{**}	0.01	0.04	-0.03
	(-1.96)	(0.17)	(0.55)	(-0.60)
$Cfo_{i,t-1}$	-0.04	0.05	-0.10	0.06
	(-0.52)	(0.62)	(-1.34)	(0.89)
$Tange_{i,t-1}$	-0.48^{***}	-0.28^{*}	-0.46^{***}	-0.09
	(-2.87)	(-1.85)	(-2.80)	(-0.64)
$First_{i,t-1}$	-0.00	-0.00	-0.00	0.00^{**}
	(-1.53)	(-1.05)	(-1.03)	(2.19)
$Age_{i,t-1}$	-0.01	-0.00	-0.00	0.00
	(-1.59)	(-1.33)	(-1.11)	(0.46)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observation	17478	17478	17478	17478
R^2	0.4565	0.4503	0.4353	0.0879

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. t-statistics are in parentheses. Standard errors are clustered by firm and year. Source: Author's Computation.

As to the control variables, the coefficients of the firm's total assets ($lnSize_{i,t-1}$), return on assets ($Roa_{i,t-1}$), and Tobin's Q ($TobQ_{i,t-1}$) are almost significantly positive in all columns, which indicates that the larger, more profitable, and better-growing firms have more innovation output. This is because innovation is a high-risk and high-input activity, and the larger, more cash-flow and higher-growing firms can better afford the high investment in innovation. Moreover, a firm can invest more resources in innovation projects and become more innovative as it grows larger and more successful. The tangible asset ratio ($Tange_{i,t-1}$) has a significant negative impact because the high tangible asset ratio implies the firm has a high degree of asset irreversibility and belongs to the traditional industry. But the asset-liability ratio ($Lev_{i,t-1}$), cash flow ratio ($Cfo_{i,t-1}$), equity concentration ($First_{i,t-1}$), and age of the firm ($Age_{i,t-1}$) seem to have no impact on the innovation. The above regression results of the control variables are generally consistent with the findings of most existing studies.

4.2.2. Differentiating the Role of Aggregate and Industry-Specific Demand Uncertainty

It is crucial to separate the sources of demand uncertainty when analyzing the economic implications of uncertainty (Baker et al., 2016). Different sources of demand uncertainty, such as aggregate and industry-specific demand uncertainty, may have different impacts of uncertainty on firms' innovation activities. The former originates from the volatility of macroeconomic or aggregate demand, and the latter originates from the industry-specific demand shock after controlling the aggregate demand uncertainty. For example, certain industries may endure substantial downward pressure even though the overall economy flourishes.

We use a traditional regression approach to decompose industry-specific demand uncertainty and examine how it affects a firm's innovation. In particular, we calculate the aggregate demand uncertainty ($Uncer\_all_{t-1}$) by using the data of sales growth rate of the manufacturing sector in China and then regress Equation (3).

$$Uncer_{j,t} = \alpha_j + \beta_j Uncer\_all_t + e_{j,t} \tag{3}$$

We can get the residual ($e\_indus_{j,t}$) from Equation (3) and use it as the proxy for industry-specific demand uncertainty, then add $Uncer\_all_{t-1}$ and $e\_indus_{j,t-1}$ into baseline Equation (2) by replacing the $Uncer_{j,t-1}$.

Table 4 displays the results of the regression. Industry-specific demand uncertainty significantly reduces the innovation of manufacturing firms, with the greatest influence on invention patents. Similarly, the coefficients of aggregate demand uncertainty are also significantly negative for all types of innovation outputs. This result shows that demand uncertainty at the aggregate level and industry-specific level will inhibit firms' innovation activities.

4.2.3. Heterogeneity of Firms

1) Heterogeneity in Ownership

According to the ownership of the controller, the CSMAR database classifies the firms into four types: state-owned, private-owned, foreign-owned, and others. We divide the sample into two categories: SOEs and non-SOEs (including

Table 4. Regression results of aggregate and industry-specific demand uncertainty.

	(1) $\ln\left(1+All_{i,j,t}\right)$	(2) $\ln\left(1+Inv_{i,j,t}\right)$	(3) $\ln\left(1+Uti_{i,j,t}\right)$	(4) $\ln\left(1+Des_{i,j,t}\right)$
$e\_indus_{j,t-1}$	-1.09^{**} (−2.53)	-1.69^{***} (−4.32)	-1.57^{***} (−3.68)	0.21 (0.61)
$Uncer\_all_{t-1}$	-14.86^{***} (−9.12)	-20.24^{***} (−13.52)	-0.75^{**} (−2.49)	-4.61^{***} (−3.36)
$lnSize_{i,t-1}$	0.61^{***} (40.94)	0.55^{***} (41.12)	0.55^{***} (38.46)	0.24^{***} (19.69)
$Roa_{i,t-1}$	1.47^{***} (8.22)	1.08^{***} (6.68)	1.49^{***} (8.44)	0.61^{***} (4.21)
$TobQ_{i,t-1}$	0.01 (1.19)	0.03^{***} (2.76)	−0.00 (−0.37)	0.01^{*} (1.76)
$Lev_{i,t-1}$	-0.13^{*} (−1.95)	0.01 (0.22)	0.03 (0.48)	−0.03 (−0.59)
$Cfo_{i,t-1}$	−0.04 (−0.51)	0.04 (0.61)	−0.11 (−1.36)	0.06 (0.88)
$Tange_{i,t-1}$	-0.46^{***} (−2.73)	-0.26^{*} (−1.70)	-0.44^{***} (−2.70)	−0.08 (−0.58)
$First_{i,t-1}$	−0.00 (−1.56)	−0.00 (−1.11)	−0.00 (−1.08)	0.00^{**} (2.18)
$Age_{i,t-1}$	−0.01 (−1.64)	−0.00 (−1.39)	−0.00 (−1.13)	0.00 (0.43)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observation	17513	17513	17513	17513
R^2	0.4044	0.4170	0.4116	0.0769

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. t-statistics are in parentheses. Standard errors are clustered by firm and year. Source: Author's Computation.

private-owned, foreign-owned, and others), and carry out the baseline regression, respectively. Table 5 shows the regression results while considering the heterogeneity of firms' ownership. In terms of patent applications for invention, industry-level demand uncertainty has significant negative impact on both SOEs and non-SOEs, but the impact on non-SOEs is greater. In terms of patent applications for utility model, industry-level demand uncertainty tends to inhibit non-SOEs' innovation but has no impact on SOEs. The results are consistent with Hypothesis 2 and indicate non-SOEs need more policy support from the government to keep the innovation activities when facing high demand uncertainty.

2) Heterogeneity in Size

In order to verify the moderating effect of firm size on the relationship between

Table 5. Regression results after considering the heterogeneity in firm's ownership.

	Non-SOEs			SOEs		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(1+Inv_{i,j,t})$	$\ln(1+Uti_{i,j,t})$	$\ln(1+Des_{i,j,t})$	$\ln(1+Inv_{i,j,t})$	$\ln(1+Uti_{i,j,t})$	$\ln(1+Des_{i,j,t})$
$Uncer_{j,t-1}$	−1.83*** (−3.75)	−1.11** (−2.08)	0.00 (0.00)	−1.69*** (−3.32)	−0.54 (−0.96)	−0.30 (−0.69)
$lnSize_{i,t-1}$	0.54*** (29.36)	0.53*** (27.26)	0.30*** (17.51)	0.57*** (26.12)	0.56*** (23.71)	0.19*** (10.18)
$Roa_{i,t-1}$	1.28*** (6.10)	1.56*** (6.84)	0.50*** (2.58)	0.87*** (3.34)	1.38*** (4.85)	0.78*** (3.47)
$TobQ_{i,t-1}$	0.05*** (3.80)	0.02* (1.67)	0.04*** (3.44)	0.01 (0.47)	−0.05** (−2.51)	−0.02 (−1.13)
$Lev_{i,t-1}$	0.02 (0.19)	0.14* (1.65)	−0.04 (−0.50)	−0.18* (−1.76)	−0.21* (−1.93)	−0.10 (−1.12)
$Cfo_{i,t-1}$	−0.06 (−0.66)	−0.19** (−1.99)	0.08 (1.01)	0.06 (0.48)	−0.01 (−0.04)	0.11 (0.98)
$Tange_{i,t-1}$	−0.25 (−1.41)	−0.31 (−1.59)	0.09 (0.57)	−0.46 (−1.51)	−0.72** (−2.19)	−0.37 (−1.39)
$First_{i,t-1}$	−0.01 (−0.83)	−0.002 (−0.20)	0.00** (2.04)	0.00 (1.12)	0.00 (0.38)	0.001*** (2.60)
$Age_{i,t-1}$	−0.01* (−1.85)	−0.01 (−1.31)	−0.00 (−0.85)	−0.01* (−1.71)	−0.01* (−1.73)	0.01 (1.13)
Time FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Observation	10579	10579	10579	6934	6934	6934
R^2	0.3003	0.3572	0.0768	0.5003	0.4595	0.0908

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. t-statistics are in parentheses. Standard errors are clustered by firm and year. Source: Author's Computation.

demand uncertainty and firm innovation, the interaction term of firm size and uncertainty ($Uncer_{j,t-1} * lnSize_{i,t-1}$) is introduced into the regression. The results are displayed in Table 6. The coefficients are significantly positive in column 1 and column 2, which confirms that the inhibitory effect of uncertainty on firm innovation diminishes as firm size increases, and Hypothesis 3 is verified.

3) Heterogeneity in the Character of Industry to Which the Firm Belongs

Similar to firm's ownership, we construct a dummy variable ($Hightech_{i,t}$) and assign a value of 1 if the firm belongs to a high-tech industry and 0 otherwise, then add the interaction term $Hightech_{i,t-1} * Uncer_{j,t-1}$ into the baseline equation. Referring to *the Industry Classification Guidelines for Listed Firms* issued by the China Securities Regulatory Commission in 2012, we classify the pharmaceutical manufacturing, aerospace manufacturing, and information transmission, software,

Table 6. Regression results after considering the heterogeneity in firm's size.

	(1)	(2)	(3)
	$\ln(1+Inv_{i,j,t})$	$\ln(1+Uti_{i,j,t})$	$\ln(1+Des_{i,j,t})$
$Uncer_{j,t-1}$	-8.47^{**} (−2.25)	-13.73^{***} (−3.33)	2.43 (0.72)
$lnSize_{i,t-1}$	0.54^{***} (34.77)	0.52^{***} (31.64)	0.24^{***} (17.52)
$Uncer_{j,t-1} * lnSize_{i,t-1}$	0.31^{*} (1.80)	0.59^{***} (3.14)	−0.12 (−0.78)
$Roa_{i,t-1}$	1.08^{***} (6.65)	1.49^{***} (8.43)	0.61^{***} (4.24)
$TobQ_{i,t-1}$	0.02^{**} (2.50)	−0.01 (−0.72)	0.02^{*} (1.80)
$Lev_{i,t-1}$	0.01 (0.21)	0.04 (0.62)	−0.03 (−0.62)
$Cfo_{i,t-1}$	0.06 (0.78)	−0.08 (−1.07)	0.05 (0.83)
$Tange_{i,t-1}$	-0.28^{*} (−1.83)	-0.45^{***} (−2.77)	−0.09 (−0.65)
$First_{i,t-1}$	−0.00 (−1.03)	−0.00 (−1.00)	0.00^{**} (2.18)
$Age_{i,t-1}$	−0.00 (−1.28)	−0.00 (−1.01)	0.00 (0.43)
Time FE	YES	YES	YES
Industry FE	YES	YES	YES
Observation	17513	17513	17513
R^2	0.4352	0.4403	0.0879

Note: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. t-statistics are in parentheses. Standard errors are clustered by firm and year. Source: Author's Computation.

and information technology industries as high-tech industries. The results in Table 7 show that the coefficients of the interaction terms are both significantly positive in column (1) and (2), which indicates that the impact of demand uncertainty on innovation is less for high-tech firms, and are also consistent with Hypothesis 4.

5. Robustness Tests

As the industry-level demand uncertainty is an exogenous variable for firm innovation, the endogeneity problem originating from reverse causality in this research is very slight. However, the empirical results may be affected by the omitted variable, the different measurements of the dependent variable and the key

Table 7. Regression results after considering the heterogeneity in character of industry to which the firm belongs.

	(1) $\ln(1+Inv_{i,j,t})$	(2) $\ln(1+Uti_{i,j,t})$	(3) $\ln(1+Des_{i,j,t})$
$Uncer_{j,t-1}$	-1.94^{***} (−5.21)	-1.06^{***} (−2.60)	−0.03 (−0.09)
$Hightech_{i,t-1} * Uncer_{j,t-1}$	0.82^{*} (1.80)	0.86^{*} (1.72)	−0.49 (−1.21)
$Hightech_{i,t-1}$	1.67^{***} (3.92)	2.08^{***} (4.54)	1.38^{***} (3.63)
$lnSize_{i,t-1}$	0.56^{***} (41.14)	0.55^{***} (38.49)	0.24^{***} (19.62)
$Roa_{i,t-1}$	1.07^{***} (6.57)	1.47^{***} (8.37)	0.61^{***} (4.22)
$TobQ_{i,t-1}$	0.03^{***} (2.78)	−0.00 (−0.34)	0.01^{*} (1.72)
$Lev_{i,t-1}$	0.01 (0.19)	0.03 (0.51)	−0.04 (−0.63)
$Cfo_{i,t-1}$	0.04 (0.62)	−0.11 (−1.35)	0.06 (0.87)
$Tange_{i,t-1}$	-0.26^{*} (−1.74)	-0.45^{***} (−2.74)	−0.08 (−0.56)
$First_{i,t-1}$	−0.00 (−1.08)	−0.00 (−1.07)	0.00^{**} (2.20)
$Age_{i,t-1}$	−0.00 (−1.40)	−0.00 (−1.15)	0.00 (0.45)
Time FE	YES	YES	YES
Industry FE	YES	YES	YES
Observation	17513	17513	17513
R^2	0.4047	0.4113	0.0770

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. t-statistics are in parentheses. Standard errors are clustered by firm and year. Source: Author's Computation.

explanatory variable. Therefore, we conduct three robustness tests as follows.

5.1. Considering the Mean and Skewness of Sales Growth Rate of Industry

Besides the variance of the sales growth rate, which is the proxy for demand uncertainty, the mean and skewness of the sales growth rate can reflect the average level and the asymmetry of the distribution of industry-level demand growth, and may also affect the firm innovation. For example, several studies have found that skewness of demand growth can influence firms' decisions (Arunraj & Ahrens, 2015; Zhang et al., 2020) as downside losses may have more impact on the utility of decision-makers than upside gains because of the loss aversion according to the "perspective theory" in behavior economics (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). To keep consistent with the demand uncertainty, we also use the information from the past two years (22 monthly observations) to calculate the mean and skewness of industry-level demand growth. Exactly, let $\widehat{R_{t-1\sim t}}$ be the mean of industry-level demand growth ($mean_{j,t}$), and denotes $skew_{j,t}$ as the skewness of demand growth in industry *j*. Then,

$$skew_{j,t} = \frac{22*\left(\sum_{n=1}^{11}\left(R_{t-1+\frac{n}{11},j} - \widehat{R_{t-1\sim t}}\right)^3 + \sum_{n=1}^{11}\left(R_{t+\frac{n}{11},j} - \widehat{R_{t-1\sim t}}\right)^3\right)}{21*20*sd_{j,t-1\sim t}^3} \tag{4}$$

The meanings of $R_{t+\frac{n}{11},j}$ and $\widehat{R_{t-1\sim t}}$ are same as in Equation (1), and $sd_{j,t-1\sim t}$ is the standard deviation of monthly sales growth rate in industry *j* during the year $t-1$ to *t*.

Table 8 shows the results by adding the mean and skewness of industry-level demand growth into baseline regression. The coefficients of $mean_{j,t-1}$ are significantly positive except for column (4), which indicates the average growth rate of industry-level demand will foster firm innovation. Similarly, the coefficients of $skew_{j,t-1}$ are significantly positive except for column (3). The results are in line with expectations because the higher absolute value of a negative skewness represents the larger tail risk of loss during a certain period and will impose a more adverse impact on firm innovation. The impacts of $Uncer_{j,t-1}$ are unchanged compared with **Table 3** after controlling the mean and skewness of demand growth, suggesting that the negative relationship between demand uncertainty and firm innovation is robust.

Table 8. Regression results after adding the mean and skewness of industry-level demand growth.

	(1)	(2)	(3)	(4)
	$\ln(1+All_{i,j,t})$	$\ln(1+Inv_{i,j,t})$	$\ln(1+Uti_{i,j,t})$	$\ln(1+Des_{i,j,t})$
$skew_{j,t-1}$	0.03^{**} (2.51)	0.03^{***} (2.97)	−0.01 (−0.46)	0.02^{**} (2.14)
$mean_{j,t-1}$	1.93^{***} (9.39)	1.46^{***} (7.87)	1.85^{***} (9.14)	0.03 (0.17)
$Uncer_{j,t-1}$	-1.00^{**} (−2.57)	-1.83^{***} (−5.19)	-1.08^{***} (−2.79)	−0.12 (−0.37)
$lnSize_{i,t-1}$	0.62^{***} (41.53)	0.56^{***} (41.57)	0.56^{***} (39.04)	0.24^{***} (19.65)
$Roa_{i,t-1}$	1.62^{***} (9.03)	1.19^{***} (7.31)	1.63^{***} (9.21)	0.61^{***} (4.22)

Continued

$TobQ_{i,t-1}$	0.02** (2.17)	0.03*** (3.56)	0.01 (0.52)	0.02* (1.81)
$Lev_{i,t-1}$	−0.14** (−2.08)	0.00 (0.06)	0.03 (0.40)	−0.04 (−0.63)
$Cfo_{i,t-1}$	−0.03 (−0.43)	0.05 (0.68)	−0.10 (−1.26)	0.06 (0.87)
$Tange_{i,t-1}$	−0.46*** (−2.78)	−0.26* (−1.75)	−0.45*** (−2.75)	−0.08 (−0.58)
$First_{i,t-1}$	−0.00* (−1.76)	−0.00 (−1.25)	−0.00 (−1.24)	0.00** (2.16)
$Age_{i,t-1}$	−0.01* (−1.70)	−0.01 (−1.43)	−0.00 (−1.18)	0.00 (0.43)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observation	17513	17513	17513	17513
R^2	0.4433	0.4043	0.3985	0.0655

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. t-statistics are in parentheses. Standard errors are clustered by firm and year. Source: Author's Computation.

5.2. Using the Alternative Indicators to Proxy Firm Innovation

We adopt a new indicator to measure firm innovation for a robust test. Compared with the number of patent applications, the number of granted patents can better reflect the quality and efficiency of innovation activities (Hirshleifer et al., 2013). Therefore, we use the number of granted patents instead of the number of patent applications as the proxy for firm innovation. The regression results are shown in **Table 9**. The coefficients of industry-level demand uncertainty remain significantly negative in columns (1) to (3), indicating that our results are solid across different indicators of firm innovation.

Table 9. Regression results by replacing alternative indicators for firm innovation.

	(1)	(2)	(3)	(4)
	$\ln(1+All_{i,j,t})$	$\ln(1+Inv_{i,j,t})$	$\ln(1+Uti_{i,j,t})$	$\ln(1+Des_{i,j,t})$
$Uncer_{j,t-1}$	−1.18*** (−2.80)	−1.40*** (−3.29)	−0.92** (−2.15)	−0.20 (−0.51)
$lnSize_{i,t-1}$	0.56*** (30.81)	0.45*** (28.24)	0.55*** (30.31)	0.27*** (15.66)
$Roa_{i,t-1}$	1.19*** (5.32)	1.06*** (4.84)	1.40*** (6.18)	0.58*** (2.76)
$TobQ_{i,t-1}$	0.02 (1.55)	0.07*** (6.15)	0.02 (1.51)	0.02 (1.33)

Continued

$Lev_{i,t-1}$	−0.01 (−0.17)	−0.25*** (−3.16)	0.12 (1.35)	−0.02 (−0.19)
$Cfo_{i,t-1}$	−0.13 (−1.36)	−0.16* (−1.76)	−0.04 (−0.42)	0.03 (0.36)
$Tange_{i,t-1}$	−0.03 (−0.14)	0.23 (1.17)	−0.31 (−1.44)	−0.14 (−0.72)
$First_{i,t-1}$	−0.00 (−1.52)	−0.00 (−1.05)	−0.00 (−1.61)	0.00 (1.10)
$Age_{i,t-1}$	−0.00 (−0.78)	−0.01* (−1.79)	−0.00 (−0.21)	0.00 (0.78)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observation	11375	11375	11375	11375
R^2	0.2650	0.3698	0.3596	0.0452

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. t-statistics are in parentheses. Standard errors are clustered by firm and year. Source: Author's Computation.

5.3. Expanding the Time Window Length When Constructing the Key Explanatory Variable

There seems to be no consensus on the selection of the length of a time window to calculate the demand uncertainty. For example, Ogawa & Suzuki (2000) use the past five years' information on the sales growth rate, which only has five observations, while Liang et al. (2023) use 21 yearly observations of the sales growth rate. In this section, we recalculate the industry-level demand uncertainty using the monthly observations of the past three years ($Uncer\_3_{j,t-1}$) and replace $Uncer_{j,t-1}$ into the baseline regression. As shown in **Table 10**, the results are same as in **Table 3**, which also indicates that the conclusions of this paper are robust.

Table 10. Regression results by expanding the time window length of key explanatory variables.

	(1) $\ln(1+All_{i,j,t})$	(2) $\ln(1+Inv_{i,j,t})$	(3) $\ln(1+Uti_{i,j,t})$	(4) $\ln(1+Des_{i,j,t})$
$Uncer\_3_{j,t-1}$	−0.73* (−1.72)	−2.01*** (−5.27)	−0.80* (−1.93)	−0.03 (−0.10)
$lnSize_{i,t-1}$	0.61*** (40.89)	0.55*** (41.00)	0.55*** (38.42)	0.24*** (19.69)
$Roa_{i,t-1}$	1.47*** (8.18)	1.07*** (6.63)	1.48*** (8.39)	0.61*** (4.22)
$TobQ_{i,t-1}$	0.01 (1.12)	0.02*** (2.59)	−0.00 (−0.45)	0.01* (1.77)

Continued

$Lev_{i,t-1}$	−0.13* (−1.96)	0.01 (0.13)	0.03 (0.48)	−0.03 (−0.60)
$Cfo_{i,t-1}$	−0.04 (−0.53)	0.04 (0.54)	−0.11 (−1.38)	0.06 (0.88)
$Tange_{i,t-1}$	−0.46*** (−2.75)	−0.26* (−1.74)	−0.45*** (−2.73)	−0.08 (−0.58)
$First_{i,t-1}$	−0.00 (−1.51)	−0.00 (−0.99)	−0.00 (−1.03)	0.00** (2.18)
$Age_{i,t-1}$	−0.01 (−1.62)	−0.00 (−1.33)	−0.00 (−1.11)	0.00 (0.43)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observation	17513	17513	17513	17513
R^2	0.4168	0.4049	0.4112	0.0769

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. t-statistics are in parentheses. Standard errors are clustered by firm and year. Source: Author's Computation.

6. Conclusion and Implications

This study investigates the relationship between firm innovation and industry-level demand uncertainty using data from Chinese manufacturing firms listed between 2004 and 2019. We find that both the aggregate and industry-specific demand uncertainty have adverse impacts on firm innovation. Moreover, the inhibitory effect of demand uncertainty on innovation activities is contingent upon the firm's size, ownership, and character of the industry to which the firm belongs. These findings enhance our understanding of the influence of uncertainty on firm innovation and highlight the importance of government support for investment activities, particularly for small firms and non-SOEs, during periods of high demand uncertainty.

The findings of this study have some policy implications for corporate and governmental decision-making. Local governments can provide appropriate policy support or economic subsidies to private firms and traditional manufacturing industries impacted by the uncertainty of industry-level demand because global conflicts will likely keep the uncertainty high in the foreseeable future. When making strategic decisions, firms should take into account the risks and opportunities associated with their innovation activities to ensure survival and growth in the long term.

Although this paper explores the impact of industry-level demand uncertainty on firm innovation, there are still some limitations that may include: First, due to limited access to firm-level data, this paper just tests the overall impact rather than using a specific model to empirically assess the impact mechanism. Second, because of the limitation of data disclosure, a large number of unlisted manufacturing firms' data are difficult to obtain, so the samples of empirical analysis in this paper are all listed firms. Since unlisted firms cannot be included in the empirical model, the applicability of the paper's conclusions is constrained. These are the areas that need to be explored further for upcoming research.

Funding Information

Humanities and Social Sciences Foundation of the Ministry of Education, Grant/Award Numbers: 22YJC790149; Post-funded Project of the National Social Science Fund, Grant/Award Numbers: 22FGJB008.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

Abel, A. B. (1983). Optimal Investment under Uncertainty. *The American Economic Review, 73,* 228-233.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2005). Competition and Innovation: An Inverted-U Relationship. *Quarterly Journal of Economics, 120,* 701-728. https://doi.org/10.1162/0033553053970214

Alessandri, P., & Bottero, M. (2020). Bank Lending in Uncertain Times. *European Economic Review, 128,* Article ID: 103503. https://doi.org/10.1016/j.euroecorev.2020.103503

An, H., Chen, Y., Luo, D., & Zhang, T. (2016). Political Uncertainty and Corporate Investment: Evidence from China. *Journal of Corporate Finance, 36,* 174-189. https://doi.org/10.1016/j.jcorpfin.2015.11.003

Arunraj, N. S., & Ahrens, D. (2015). A Hybrid Seasonal Autoregressive Integrated Moving Average and Quantile Regression for Daily Food Sales Forecasting. *International Journal of Production Economics, 170,* 321-335. https://doi.org/10.1016/j.ijpe.2015.09.039

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

Banker, R. D., Byzalov, D., & Plehn-Dujowich, J. M. (2014). Demand Uncertainty and Cost Behavior. *The Accounting Review, 89,* 839-865. https://doi.org/10.2308/accr-50661

Barrero, J. M., Bloom, N., & Wright, I. (2017). *Short and Long Run Uncertainty.* NBER Working Papers No. 23676, National Bureau of Economic Research.

Baum, C. F., Caglayan, M., Ozkan, N., & Talavera, O. (2006). The Impact of Macroeconomic Uncertainty on Non-Financial Firms' Demand for Liquidity. *Review of Financial Economics, 15,* 289-304. https://doi.org/10.1016/j.rfe.2006.01.002

Bernanke, B. S. (1983). Irreversibility, Uncertainty, and Cyclical Investment. *The Quarterly Journal of Economics, 98,* 85-106. https://doi.org/10.2307/1885568

Bhattacharya, U., Hsu, P., Tian, X., & Xu, Y. (2017). What Affects Innovation More: Policy or Policy Uncertainty? *Journal of Financial and Quantitative Analysis, 52,* 1869-1901. https://doi.org/10.1017/s0022109017000540

Bloch, C. (2005). R&D Investment and Internal Finance: The Cash Flow Effect. *Economics of Innovation and New Technology, 14,* 213-223. https://doi.org/10.1080/1043859042000312710

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica, 77,* 623-685.

Bloom, N., Bond, S., & Van Reenen, J. (2007). Uncertainty and Investment Dynamics. *Review of Economic Studies, 74,* 391-415. https://doi.org/10.1111/j.1467-937x.2007.00426.x

Boulding, W., & Christen, M. (2003). Sustainable Pioneering Advantage? Profit Implications of Market Entry Order. *Marketing Science, 22,* 371-392. https://doi.org/10.1287/mksc.22.3.371.17736

Boulding, W., & Christen, M. (2008). Disentangling Pioneering Cost Advantages and Disadvantages. *Marketing Science, 27,* 699-716. https://doi.org/10.1287/mksc.1070.0324

Brandt, L., Li, H., & Roberts, J. (2005). Banks and Enterprise Privatization in China. *Journal of Law, Economics, and Organization, 21,* 524-546. https://doi.org/10.1093/jleo/ewi022

Brown, J. R., Martinsson, G., & Petersen, B. C. (2013). Law, Stock Markets, and Innovation. *The Journal of Finance, 68,* 1517-1549. https://doi.org/10.1111/jofi.12040

Byeongju, J. (2002). Policy Uncertainty and Long-Run Investment and Output across Countries. *International Economic Review, 43,* 363-392. https://doi.org/10.1111/1468-2354.t01-1-00019

Campbell, S. D. (2007). Macroeconomic Volatility, Predictability, and Uncertainty in the Great Moderation: Evidence from the Survey of Professional Forecasters. *Journal of Business & Economic Statistics, 25,* 191-200. https://doi.org/10.1198/073500106000000558

Cao, C., Li, X., & Liu, G. (2019). Political Uncertainty and Cross-Border Acquisitions. *Review of Finance, 23,* 439-470. https://doi.org/10.1093/rof/rfx055

Chen, W., & Jin, R. (2023). Does Tax Uncertainty Affect Firm Innovation Speed? *Technovation, 125,* Article ID: 102771. https://doi.org/10.1016/j.technovation.2023.102771

Chuang, H. H., Oliva, R., & Heim, G. R. (2019). Examining the Link between Retailer Inventory Leanness and Operational Efficiency: Moderating Roles of Firm Size and Demand Uncertainty. *Production and Operations Management, 28,* 2338-2364. https://doi.org/10.1111/poms.13055

De Sousa, J., Disdier, A., & Gaigné, C. (2020). Export Decision under Risk. *European Economic Review, 121,* Article ID: 103342. https://doi.org/10.1016/j.euroecorev.2019.103342

Dixit, A. K., & Pindyck, R. S. (1994). *Investment under Uncertainty.* Princeton University Press.

Fang, V. W., Tian, X., & Tice, S. (2014). Does Stock Liquidity Enhance or Impede Firm Innovation? *The Journal of Finance, 69,* 2085-2125. https://doi.org/10.1111/jofi.12187

Feng, X., Luo, W., & Wang, Y. (2021). Economic Policy Uncertainty and Firm Performance: Evidence from China. *Journal of the Asia Pacific Economy, 28,* 1476-1493. https://doi.org/10.1080/13547860.2021.1962643

Fernández-Villaverde, J., Guerrón-Quintana, P., Kuester, K., & Rubio-Ramírez, J. (2015). Fiscal Volatility Shocks and Economic Activity. *American Economic Review, 105,* 3352-3384. https://doi.org/10.1257/aer.20121236

García-Quevedo, J., Pellegrino, G., & Savona, M. (2017). Reviving Demand-Pull Perspectives: The Effect of Demand Uncertainty and Stagnancy on R&D Strategy. *Cambridge Journal of Economics, 41,* 1087-1122. https://doi.org/10.1093/cje/bew042

Gilchrist, S., Zakrajsek, E., Albero, C. F., &Caldara, D. (2013). *On the Identification of Financial and Uncertainty Shocks.* 2013 Meeting Papers 965, Society for Economic Dynamics.

Griliches, Z. (1990). Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature, 28,* 1661-1707.

Hall, B., Jaffe, A., & Trajtenberg, M. (2005). Market Value and Patent Citations. *Rand Journal of Economics, 36,* 16-38.

Hartman, R. (1972). The Effects of Price and Cost Uncertainty on Investment. *Journal of Economic Theory, 5,* 258-266. https://doi.org/10.1016/0022-0531(72)90105-6

He, F., Ma, Y., & Zhang, X. (2020). How Does Economic Policy Uncertainty Affect Corporate Innovation?—Evidence from China Listed Companies. *International Review of Economics & Finance, 67,* 225-239. https://doi.org/10.1016/j.iref.2020.01.006

Hirshleifer, D., Hsu, P., & Li, D. (2013). Innovative Efficiency and Stock Returns. *Journal of Financial Economics, 107,* 632-654. https://doi.org/10.1016/j.jfineco.2012.09.011

Jakubovskis, A. (2017). Strategic Facility Location, Capacity Acquisition, and Technology Choice Decisions under Demand Uncertainty: Robust vs. Non-Robust Optimization Approaches. *European Journal of Operational Research, 260,* 1095-1104. https://doi.org/10.1016/j.ejor.2017.01.017

Jefferson, G. H., Bai, H. M., Guan, X. J., &Yu, X. Y. (2006). R&D Performance in Chinese Industry. *Economics of Innovation and New Technology, 15,* 345-366. https://doi.org/10.1080/10438590500512851

Jens, C. E. (2017). Political Uncertainty and Investment: Causal Evidence from U.S. Gubernatorial Elections. *Journal of Financial Economics, 124,* 563-579. https://doi.org/10.1016/j.jfineco.2016.01.034

Julio, B., & Yook, Y. (2012). Political Uncertainty and Corporate Investment Cycles. *The Journal of Finance, 67,* 45-83. https://doi.org/10.1111/j.1540-6261.2011.01707.x

Kafouros, M. I., Buckley, P. J., Sharp, J. A., & Wang, C. (2008). The Role of Internationalization in Explaining Innovation Performance. *Technovation, 28,* 63-74. https://doi.org/10.1016/j.technovation.2007.07.009

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica, 47,* 263-292. https://doi.org/10.2307/1914185

Kang, W., Lee, K., & Ratti, R. A. (2014). Economic Policy Uncertainty and Firm-Level Investment. *Journal of Macroeconomics, 39,* 42-53. https://doi.org/10.1016/j.jmacro.2013.10.006

Kaplan, S. N., & Zingales, L. (1997). Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints? *The Quarterly Journal of Economics, 112,* 169-215. https://doi.org/10.1162/003355397555163

Kara, G. I., & Yook, Y. (2022). Policy Uncertainty and Bank Mortgage Credit. *Journal of Money, Credit and Banking, 55,* 783-823. https://doi.org/10.1111/jmcb.12967

Khan, M. A., Qin, X., Jebran, K., & Ullah, I. (2020). Uncertainty and R&D Investment: Does Product Market Competition Matter? *Research in International Business and Finance, 52,* Article ID: 101167. https://doi.org/10.1016/j.ribaf.2019.101167

Li, K., Guo, Z., & Chen, Q. (2021). The Effect of Economic Policy Uncertainty on Enterprise Total Factor Productivity Based on Financial Mismatch: Evidence from China. *Pacific-Basin Finance Journal, 68,* Article ID: 101613. https://doi.org/10.1016/j.pacfin.2021.101613

Liang, J., Yang, S., & Xia, Y. (2023). The Role of Financial Slack on the Relationship between Demand Uncertainty and Operational Efficiency. *International Journal of Production Economics, 262,* Article ID: 108931. https://doi.org/10.1016/j.ijpe.2023.108931

Liu, Q., & Ma, H. (2020). Trade Policy Uncertainty and Innovation: Firm Level Evidence from China's WTO Accession. *Journal of International Economics, 127,* Article ID: 103387. https://doi.org/10.1016/j.jinteco.2020.103387

Mancusi, M. L., & Vezzulli, A. (2010). *R&D, Innovation, and Liquidity Constraints*. Kites Working Papers No. 30, Kites, Centre for Knowledge, Internationalization and Technology Studies, Universita' Bocconi.

Meng, M., Lin, Q., & Wang, Y. (2022). The Risk Assessment of Manufacturing Supply Chains Based on Bayesian Networks with Uncertainty of Demand. *Journal of Intelligent & Fuzzy Systems, 42,* 5753-5771. https://doi.org/10.3233/jifs-212207

Nguyen, M. H., & Trinh, V. Q. (2023). U.K. Economic Policy Uncertainty and Innovation Activities: A Firm-Level Analysis. *Journal of Economics and Business, 123,* Article ID: 106093. https://doi.org/10.1016/j.jeconbus.2022.106093

Ogawa, K., & Suzuki, K. (2000). Uncertainty and Investment: Some Evidence from the Panel Data of Japanese Manufacturing Firms. *The Japanese Economic Review, 51,* 170-192. https://doi.org/10.1111/1468-5876.00145

Oi, W. Y. (1961). The Desirability of Price Instability under Perfect Competition. *Econometrica, 29,* 58-64. https://doi.org/10.2307/1907687

Pertuze, J. A., Reyes, T., Vassolo, R. S., & Olivares, N. (2019). Political Uncertainty and Innovation: The Relative Effects of National Leaders' Education Levels and Regime Systems on Firm-Level Patent Applications. *Research Policy, 48,* Article ID: 103808. https://doi.org/10.1016/j.respol.2019.103808

Pham, L. T. M., Vo, L. V., Le, H. T. T., & Le, D. V. (2018). Asset Liquidity and Firm Innovation. *International Review of Financial Analysis, 58,* 225-234. https://doi.org/10.1016/j.irfa.2017.11.005

Raman, K., & Chatterjee, R. (1995). Optimal Monopolist Pricing under Demand Uncertainty in Dynamic Markets. *Management Science, 41,* 144-162. https://doi.org/10.1287/mnsc.41.1.144

Ross, J., Fisch, J. H., & Varga, E. (2018). Unlocking the Value of Real Options: How Firm-specific Learning Conditions Affect R&D Investments under Uncertainty. *Strategic Entrepreneurship Journal, 12,* 335-353. https://doi.org/10.1002/sej.1275

Shefer, D., & Frenkel, A. (2005). R&D, Firm Size and Innovation: An Empirical Analysis. *Technovation, 25,* 25-32. https://doi.org/10.1016/s0166-4972(03)00152-4

Song, K., & Lee, Y. (2012). Long-Term Effects of a Financial Crisis: Evidence from Cash Holdings of East Asian Firms. *Journal of Financial and Quantitative Analysis, 47,* 617-641. https://doi.org/10.1017/s0022109012000142

Stiglitz, J. E., & Weiss, A. (1981). Credit Rationing in Markets with Imperfect Information. *American Economic Review, 71,* 393-410.

Sun, G., Fang, J., Li, T., & Ai, Y. (2024). Effects of Climate Policy Uncertainty on Green Innovation in Chinese Enterprises. *International Review of Financial Analysis, 91,* Article ID: 102960. https://doi.org/10.1016/j.irfa.2023.102960

Tovar, B., & Wall, A. (2012). Economies of Scale and Scope in Service Firms with Demand Uncertainty: An Application to a Spanish Port. *Maritime Economics & Logistics, 14,* 362-385. https://doi.org/10.1057/mel.2012.12

Trigeorgis, L. (1996). *Real Options-Managerial Flexibility and Strategy in Resource Allocation*. MIT Press.

Tversky, A., & Kahneman, D. (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty, 5,* 297-323. https://doi.org/10.1007/bf00122574

Vo, L. V., & Le, H. T. T. (2017). Strategic Growth Option, Uncertainty, and R&D Investment.

International Review of Financial Analysis, 51, 16-24. https://doi.org/10.1016/j.irfa.2017.03.002

Wen, H., Lee, C., & Zhou, F. (2022). How Does Fiscal Policy Uncertainty Affect Corporate Innovation Investment? Evidence from China's New Energy Industry. *Energy Economics, 105,* Article ID: 105767. https://doi.org/10.1016/j.eneco.2021.105767

York, J. G., & Venkataraman, S. (2010). The Entrepreneur-Environment Nexus: Uncertainty, Innovation, and Allocation. *Journal of Business Venturing, 25,* 449-463. https://doi.org/10.1016/j.jbusvent.2009.07.007

Yu, Z., Xiao, Y., & Li, J. (2021). Firm-Level Perception of Uncertainty and Innovation Activity: Textual Evidence from China's A-Share Market. *Pacific-Basin Finance Journal, 68,* Article ID: 101555. https://doi.org/10.1016/j.pacfin.2021.101555

Zhang, Y., De Zoysa, A., & Cortese, C. (2020). The Directionality of Uncertainty Expressions and the Foreign Language Effect. *Meditari Accountancy Research, 28,* 543-563. https://doi.org/10.1108/medar-09-2018-0377