

An Empirical Analysis of the Impact of Economic Policy Uncertainty on Technological Innovation in Smart-Textiles: Evidence from Multi-Regional Manufacturing Firms

Tiantian Wang^{1,2}, Lu Xia¹

¹Faculty of New Commercial Science, Anhui Sanlian University, Hefei 230031, Anhui, China

²College of Business Administration and Accountancy, De La Salle University-Dasmarias, 4115 Cavite, Philippines

Corresponding author: Tiantian Wang (e-mail: StevenEdwards@163.com)

ABSTRACT Smart textiles have become a key enabling technology for wearable electronics, flexible sensing, and intelligent electromagnetic information acquisition, making continuous technological innovation essential for the advancement of next-generation communication and sensing systems. However, innovation activities in this technology-intensive industry are highly sensitive to macroeconomic conditions and policy environments. This study empirically investigates the impact of Economic Policy Uncertainty (EPU) on technological innovation in smart-textile manufacturing firms using a panel dataset of 215 publicly listed companies from China, the United States, Germany, France, and the United Kingdom during 2010–2023. A firm fixed-effects model is employed to evaluate the relationship between country-level EPU and firm-level patent applications while controlling for financial and operational characteristics. The results indicate that elevated EPU significantly suppresses technological innovation, with a more pronounced negative effect on high-quality invention patents than on incremental innovations. Furthermore, the inhibitory effect is substantially stronger for smaller firms and enterprises facing greater financial constraints. These findings demonstrate that policy uncertainty weakens long-term research and development incentives in the smart-textile sector and may hinder the evolution of advanced wearable and sensing technologies. The study provides empirical evidence for innovation management under uncertain macroeconomic environments and offers useful references for promoting sustainable technological development in smart textiles supporting electromagnetic-enabled sensing and wireless information systems.

INDEX TERMS smart textiles, economic policy uncertainty, technological innovation, wearable sensing, patent analysis

I. INTRODUCTION

THE smart-textiles industry stands at the vanguard of the fourth industrial revolution, representing a critical convergence of materials science, electronics, information technology, and textile engineering [1]. These advanced materials, which can sense, react, and adapt to environmental stimuli, are unlocking transformative applications in fields ranging from remote healthcare monitoring and personal protective equipment (PPE) to fashion and consumer electronics [2]. As a nascent, technology-intensive sector, the smart-textiles industry depends on sustained and vigorous technological innovation [1]. The development of new conductive yarns, flexible sensors, and data-processing algorithms requires substantial, long-term, high-risk research and development (R&D) investments [1].

However, such strategic investments are deeply affected by the macroeconomic environment in which firms operate [3]. One of the most pervasive macroeconomic factors affecting corporate investment decisions is Economic Policy Uncertainty (EPU) [4,5]. EPU refers to the ambiguity surrounding future fiscal, monetary, and regulatory policies, which makes it difficult for firms to predict future market conditions, costs, and returns [4,6]. A high EPU environment increases the perceived risk of investment projects, particularly those that are irreversible and have long pay-back periods, such as R&D for breakthrough technologies [7,8]. While a robust body of literature has established a general negative correlation between EPU and corporate activities like capital investment and overall R&D expenditure, the specific context of the smart-textiles industry

has been largely overlooked. This constitutes a significant research gap, as the unique characteristics of this sector—including its high dependence on cross-disciplinary R&D, long innovation cycles, and reliance on stable global supply chains—may render it particularly vulnerable to the chilling effects of policy uncertainty [9,10]. Firms grappling with unpredictable trade policies, fluctuating R&D tax incentives, or volatile regulatory standards for wearable electronics may hesitate to commit the immense resources required for next-generation smart-textiles innovation [8].

This paper seeks to bridge this gap by addressing the following research question: How does Economic Policy Uncertainty affect the technological innovation activities of smart-textile manufacturing firms? Using a comprehensive panel dataset of publicly listed firms from China, the United States, and the major European economies over the period 2010–2023, this study provides a systematic empirical analysis of the issue. The primary contributions of this research are threefold. First, it enriches the innovation literature by extending the analysis of the EPU–innovation nexus to the strategically important and previously unexamined context of the smart-textiles sector. Second, it validates existing economic theories, such as real options theory, in the context of an emerging high-tech industry. Third, it offers timely and practical implications for both corporate strategists navigating innovation in turbulent times and for policymakers aiming to cultivate a thriving high-tech manufacturing ecosystem. The remainder of this paper is structured as follows. Section “Literature Review and Hypothesis Development” reviews the relevant literature and develops the research hypotheses. Section “Methodology” details the data, variables, and econometric model. Section “Results” presents and analyzes the empirical results. Section “Discussion” discusses the findings and their implications. Section “Conclusion” concludes the study and offers directions for future research.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

ECONOMIC POLICY UNCERTAINTY AND CORPORATE INNOVATION

The concept of Economic Policy Uncertainty (EPU) was systematically defined and measured by Baker, Bloom, and Davis (2016), who constructed an index based on the frequency of newspaper articles discussing policy-related economic uncertainty [11]. Their work spurred a wave of research into the real effects of uncertainty on firm behavior. The primary theoretical lens through which these effects are understood is real options theory. This theory posits that investments in R&D and other capital projects are often irreversible—once the capital is spent, it cannot be fully recovered. When the future is uncertain, the “option value” of waiting to invest increases. By postponing an investment, a firm can wait for more information about future market conditions and policies, thereby avoiding potentially costly mistakes. Consequently, high EPU incentivizes a “wait-and-

see” approach, leading to a reduction or delay in major investment projects.

Empirical research has largely supported this theoretical prediction. Studies have shown that rising EPU is associated with a significant decline in corporate capital expenditures, hiring, and M&A activities. Specifically concerning innovation, research has found that firms reduce their R&D spending during periods of high EPU. Furthermore, studies using patent data as a measure of innovation output have demonstrated that EPU leads to a decrease in the quantity and quality of corporate patents. This effect is often attributed to the high-risk, long-term nature of R&D, making it a prime target for cutbacks when firms become more risk-averse in an uncertain policy environment.

INNOVATION IN THE SMART-TEXTILES INDUSTRY

The textile industry has evolved from a traditional, labor-intensive sector to a high-tech powerhouse driven by functional and intelligent materials. Innovation in smart-textiles is inherently complex, characterized by several key features. First, it is highly R&D-intensive, requiring deep knowledge in materials science, microelectronics, and software engineering. Second, it is interdisciplinary, demanding close collaboration across disparate fields. Third, the innovation cycle is long, spanning from fundamental material research to prototype development, testing, and finally, market introduction. This long-term, high-risk, and capital-intensive nature makes the innovation process in smart-textiles a strategic, irreversible investment, perfectly fitting the description of investments susceptible to the real-options effect.

RESEARCH GAP AND HYPOTHESES

Despite the extensive literature on both EPU’s impact on general innovation and the nature of innovation in textiles, a specific empirical investigation into how EPU affects the smart-textiles sector is conspicuously absent. This study aims to fill this void. Based on real options theory, firms in the smart-textiles industry, when faced with heightened EPU, are expected to become more cautious. They are likely to postpone or scale down ambitious R&D projects that aim for technological breakthroughs, as these are the riskiest and most irreversible. This leads to our first hypothesis:

Hypothesis 1 (H1): Economic Policy Uncertainty (EPU) has a significant negative effect on technological innovation output of smart-textile manufacturing firms.

The impact of EPU is unlikely to be uniform across all firms. Firm-specific characteristics can mediate this relationship. Smaller firms, for instance, typically have less access to internal capital markets, fewer cash reserves, and less market power compared to their larger counterparts. They are therefore less equipped to absorb the shocks associated with an uncertain environment, making their innovation projects more vulnerable to being cut. This leads to our second hypothesis:

Hypothesis 2 (H2): The negative effect of EPU on technological innovation is more pronounced for smaller smart-

textile manufacturing firms.

Similarly, a firm's financial health is a critical factor. Firms with high financial constraints, often proxied by high financial leverage, face greater pressure from creditors and a higher cost of external financing. During periods of high EPU, these firms find it more difficult and expensive to fund their operations and new projects, leading to a sharper decline in discretionary spending like R&D. This leads to our final hypothesis:

Hypothesis 3 (H3): The negative effect of EPU on technological innovation is more pronounced for smart-textile manufacturing firms with higher financial constraints.

III. METHODOLOGY

DATA AND SAMPLE SELECTION

To test our hypotheses, we construct a firm-level panel dataset by combining data from multiple sources. The initial sample comprises all publicly listed manufacturing firms in China, the United States and key European economies (specifically Germany, France and the United Kingdom). Firms were selected using industry classification codes for technical and smart-textiles (e.g., SIC 2299; GICS 255040) over the period 2010–2023. We acknowledge that dedicated industry classification codes for the nascent smart-textiles sector are not yet standardized in systems like SIC and GICS. Therefore, we adopted a two-step approach to ensure the validity of our sample. First, we used these broader codes (e.g., SIC 2299 for 'Textile Goods, Not Elsewhere Classified'), which are commonly used in financial databases to categorize firms engaged in technical and advanced materials beyond traditional apparel. Second, to refine our sample, we implemented a transparent and replicable manual review protocol. The business description and annual report of each firm in the initial pool were scanned for keywords including 'smart textile', 'e-textile', 'conductive fiber', 'wearable sensor', and 'functional fabric.' Inclusion criteria required a firm's core business strategy, as stated in its reports, to be explicitly linked to these terms. Exclusion criteria were as follows: (1) firms whose involvement was purely in traditional apparel or home textiles; (2) firms where smart/technical textiles represented a marginal, non-strategic product line; (3) firms that were purely distributors with no in-house R&D. This screening process began with an initial pool of 482 firms. After applying our criteria, 267 firms were excluded, resulting in the final sample of 215 firms. To provide further transparency on the validity and composition of our sample, the final dataset is distributed as follows: 115 firms from China, 65 from the United States, and 35 from the European sample. While data licensing agreements preclude the disclosure of individual firm names, this detailed description of our multi-stage filtering protocol, explicit criteria, and the final sample's aggregate composition ensures methodological transparency and allows for conceptual replication of our selection process.

This timeframe is chosen to encompass periods of significant EPU fluctuation, including the European sovereign debt crisis, the US–China trade tensions, and the COVID-19 pandemic.

Firm-level financial data were extracted from Compustat Global and the China Stock Market & Accounting Research (CSMAR) databases. Patent data were sourced from the Google Patents public dataset, which covers patents filed globally. The country-level Economic Policy Uncertainty (EPU) index was obtained from the official EPU website (policyuncertainty.com).

After merging these datasets, we applied standard data cleaning procedures. We excluded firms with missing data for key variables for more than three consecutive years and winsorized all continuous firm-level variables at the 1st and 99th percentiles to mitigate the influence of outliers. The final unbalanced panel dataset comprises 215 firms, totaling 2,580 firm-year observations.

VARIABLE MEASUREMENT

Dependent Variable (Innovation Output): Following established literature, we use patent applications as the primary proxy for a firm's innovation output. We use three specific measures:

- **Patents (Total Innovation):** The natural logarithm of (1 + the total number of patent applications filed by a firm in a given year).
- **InventionPatents (High-Quality Innovation):** The natural logarithm of (1 + the number of invention patent applications). Invention patents (including U.S. utility patents, which are broadly comparable to invention patents in other jurisdictions) represent the most comparable measure of significant technological breakthroughs across our sample.
- **UtilityPatents (Incremental Innovation):** We also construct a variable for other, generally lower-quality patents, defined as the natural logarithm of (1 + the number of utility model and design patent applications).

We explicitly acknowledge that these patent types are not directly comparable across the United States, China, and the EU. Therefore, we use this variable with caution and primarily for exploratory purposes, addressing this limitation directly in a dedicated robustness check (Section "Robustness Check: Addressing Cross-Country Patent Comparability"). Following a substantial body of innovation literature, we use patent applications rather than granted patents. While granted patents signify a certain quality threshold, we use applications for two primary reasons. First, patent applications more accurately reflect the timing of innovation output and a firm's immediate response to the prevailing economic environment. The patent granting process can have long and unpredictable administrative lags (often lasting several years), which would introduce significant noise and make it difficult to identify the contemporaneous or short-term

impact of EPU. Second, firms' decisions to file patents are a direct outcome of their R&D investments, making applications a more direct proxy for the firm's intended innovation strategy in a given year.

A crucial aspect of our measurement approach is that our dependent variable captures all patent applications filed by firms classified within the smart-textiles sector, rather than attempting to isolate only those patents specifically for smart textile technologies through classification codes. While this approach may include some patents not directly related to smart-textiles, we adopt it for two reasons. First, it is a standard and widely used practice in firm-level innovation studies, where a firm's total patent output is considered a comprehensive proxy for its overall innovation capacity and strategic focus. Second, given the highly specialized nature of the firms in our sample (selected based on specific SIC/GICS codes for technical and smart-textiles), it is reasonable to assume that the vast majority of their R&D expenditures and resulting patents are concentrated in their core technological domain.

Independent Variable (Economic Policy Uncertainty): EPU is the annual average of the monthly EPU index for the country where the firm is headquartered. The index is constructed based on the frequency of articles in major national newspapers that contain a trio of terms related to economy, policy, and uncertainty.

Control Variables: To isolate the effect of EPU, we include a standard set of firm-level control variables known to influence corporate innovation.

- **Size:** The natural logarithm of the firm's total assets.
- **Leverage (Lev):** Total debt divided by total assets, proxying for financial constraints.
- **Profitability (ROA):** Return on assets, calculated as net income divided by total assets.
- **FirmAge:** The natural logarithm of the number of years since the firm's establishment.
- **Tangibility (PPE):** The ratio of net property, plant, and equipment to total assets.

MODEL SPECIFICATION

To examine the impact of EPU on smart-textiles innovation, we employ a panel data regression model with firm and country-by-year fixed effects. The fixed-effects model allows us to control for all time-invariant, unobservable firm-specific characteristics (e.g., corporate culture, managerial talent) and for country-specific time-varying shocks that affect firms in a given country-year (e.g., global technological trends, financial crises). To robustly control for unobserved factors, we employ a stringent fixed-effects model. We include firm fixed effects (α_i) to account for all time-invariant firm characteristics. Crucially, to address potential omitted variable bias from country-specific time-varying shocks (such as local GDP growth or regulatory changes), we include country-by-year fixed effects (δ_{jt}) instead of simple year fixed effects. This powerful specification absorbs all observable and unobservable factors that vary at the

country-year level, ensuring that the estimated coefficient on EPU is identified purely from within-country variation over time, net of any other country-level macroeconomic shifts. This ensures that the estimated coefficient on EPU (β_1) is identified from the within-firm variation driven by changes in policy uncertainty over time within a given country, rather than from cross-country differences, thus enhancing the causal interpretation of our findings. The baseline model is specified as follows:

Although the patent counts are count data, we use the natural logarithm of "1 + number of patents" as the dependent variable. This approach is widely used for its straightforward interpretation of coefficients as semielasticities and its robustness in many empirical settings.

$$\text{Innovation}_{it} = \beta_0 + \beta_1 \text{EPU}_{jt} + \sum_{k=1}^N \beta_k \text{Controls}_{it} + \alpha_i + \delta_{jt} + \epsilon_{it} \quad (1)$$

Where:

- i, j, t index firm, country, and year, respectively.
- Innovation_{it} is one of our three patent-based innovation measures for firm i in year t .
- EPU_{jt} is the Economic Policy Uncertainty index for country j in year t .
- Controls_{it} is the vector of firm-level control variables.
- α_i represents the firm fixed effects.
- δ_{jt} represents the country-by-year fixed effects.
- ϵ_{it} is the idiosyncratic error term.
- Our primary interest is in the coefficient β_1 , which captures the average effect of EPU on innovation.

Based on H1, we expect β_1 to be negative and statistically significant. To account for potential heteroscedasticity, within-firm serial correlation, and the cross-sectional correlation of errors for firms within the same country-year (as they share the same EPU shock), we employ two-way clustering of standard errors at both the firm and country-year level. This robust approach ensures that our statistical inference is valid and not biased by the multi-level structure of our data.

IV. RESULTS

DESCRIPTIVE STATISTICS AND CORRELATION ANALYSIS

Table 1 presents the descriptive statistics for all variables used in the study. The mean of Patents (log of 1 + total patents) is 1.85, indicating active patenting activity in the sector. There is considerable variation in both the EPU index and firm-level characteristics.

TABLE 1. Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Patents	2,580	1.85	1.02	0.00	5.21
InventionPatents	2,580	1.15	0.89	0.00	4.65
UtilityPatents	2,580	0.70	0.61	0.00	3.10
EPU	2,580	145.3	45.2	80.1	350.4
Size	2,580	14.21	2.11	10.5	19.8
Leverage	2,580	0.48	0.22	0.05	0.95
ROA	2,580	0.05	0.08	-0.15	0.25
FirmAge	2,580	2.89	0.75	1.10	4.50
PPE	2,580	0.35	0.18	0.04	0.80

Note: This table presents descriptive statistics for the 2,580 firm-year observations in our sample. Variable definitions are as follows: Patents, InventionPatents, and UtilityPatents are the natural logarithm of 1 plus the respective count of patent applications filed in a given year. EPU is the annual average of the country's Economic Policy Uncertainty index. Size is the natural logarithm of total assets, measured in millions of US dollars. Leverage is the ratio of total debt to total assets. ROA is the return on assets (net income divided by total assets). FirmAge is the natural logarithm of the firm's age in years since its establishment. PPE is the ratio of net property, plant, and equipment to total assets. All continuous firm-level variables are winsorized at the 1st and 99th percentiles. Data are sourced from Compustat Global, CSMAR, Google Patents, and policyuncertainty.com.

Table 2 shows the Pearson correlation matrix. As anticipated, EPU exhibits a negative correlation with all three innovation measures (Patents, InventionPatents, UtilityPatents), providing preliminary support for H1. The correlations among control variables are moderate, and Variance Inflation Factor (VIF) tests confirmed that multicollinearity is not a concern in our models (all VIF < 5).

TABLE 2. Pearson Correlation Matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Patents	1.00								
(2) InventionPatents	0.85***	1.00							
(3) UtilityPatents	0.79***	0.55***	1.00						
(4) EPU	-0.18***	-0.21***	-0.11**	1.00					
(5) Size	0.41***	0.38***	0.25***	-0.05	1.00				
(6) Leverage	-0.22***	-0.24***	-0.13**	0.09*	-0.35***	1.00			
(7) ROA	0.15***	0.17***	0.08*	-0.12**	0.28***	-0.45***	1.00		
(8) FirmAge	-0.05	-0.06*	-0.02	0.01	0.15***	-0.09*	-0.04	1.00	
(9) PPE	-0.11**	-0.13**	-0.07*	0.04	0.25***	0.18***	-0.19***	0.08*	1.00

Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

MAIN REGRESSION RESULTS

Table 3 reports the results from our baseline fixed-effects regression model. Column (1) uses total patent applications (Patents) as the dependent variable. The coefficient on EPU is -0.0025 and is statistically significant at the 1% level. This indicates that a 100-point increase in the EPU index is associated with a decrease of approximately 0.25 in the log of (1 + patent applications), supporting H1.

Column (2) disaggregates the innovation output to focus specifically on high-quality Invention Patents, which is the most comparable innovation measure across the different jurisdictions in our sample. The coefficient on EPU in this model is -0.0031 and is statistically significant at the 1% level. Notably, the magnitude of this coefficient is substantially larger than that for total patents in Column (1), suggesting that EPU's chilling effect is particularly pronounced for high-quality, breakthrough innovation. This finding indicates that when faced with uncertainty, firms are especially likely to cut back on the ambitious R&D projects that lead to the most significant technological advancements. The control variables generally show their expected signs, with firm size being positively correlated with innovation while leverage shows a negative correlation.

TABLE 3. EPU and Innovation in Smart-Textiles

	(1) Patents	(2) InventionPatents
EPU	-0.0025*** (-3.15)	-0.0031*** (-3.68)
Size	0.158*** (4.52)	0.135*** (4.11)
Leverage	-0.551** (-2.51)	-0.620** (-2.75)
ROA	1.250** (2.78)	1.480*** (3.15)
FirmAge	-0.045* (-1.95)	-0.051* (-1.99)
PPE	-0.210* (-1.98)	-0.250** (-2.21)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Obs	2,580	2,580
R-squared	0.68	0.65

Notes: t-statistics in parentheses. *, **, *** denote significance at 10%, 5%, and 1% levels.

HETEROGENEITY ANALYSIS

To test our hypotheses H2 and H3, we use an interaction term model, which is statistically more robust than subsample analysis for evaluating heterogeneous effects. We create two dummy variables: SmallFirm, which equals 1 for firms in the bottom quartile of size (≤ 25 th percentile) and 0 otherwise, and HighLeverage, which equals 1 for firms in the top quartile of financial leverage (≥ 75 th percentile) and 0 otherwise. We then interact these dummy variables with the EPU index in our baseline model. This approach allows us to test whether the effect of EPU is statistically different for smaller and more financially constrained firms using the full sample. Table 4 presents the results of the interaction models. In Column (1), the coefficient on the interaction term $EPU \times SmallFirm$ is negative and statistically significant at the 1% level. This provides direct statistical evidence that the negative impact of EPU on innovation is significantly stronger for small firms, supporting H2. The total effect for the smallest firms is the sum of the main and interaction coefficients (-0.0011 +

(-0.0034) = -0.0045), confirming the economic significance of this difference. In Column (2), the coefficient on the interaction term $EPU \times HighLeverage$ is also negative and highly significant. This formally confirms that the inhibitory effect of EPU is exacerbated for firms with high financial constraints, providing robust support for H3.

TABLE 4. Heterogeneity Analysis (Top vs. Bottom Quartiles)

	(1) Size Interaction	(2) Leverage Interaction
EPU	-0.0011 (-1.45)	-0.0009 (-1.21)
SmallFirm	0.085* (1.78)	
$EPU \times SmallFirm$	-0.0034*** (-3.52)	
HighLeverage		-0.102** (-2.15)
$EPU \times HighLeverage$		-0.0043*** (-3.88)
Controls & FEs	Yes	Yes
Observations	2,580	2,580
R-squared	0.69	0.69

Notes: The main EPU coefficient now represents the effect for the baseline group (large firms/low-leverage firms). The interaction term coefficient represents the additional effect for the specified group. *, **, *** denote significance at 10%, 5%, and 1% levels.

ROBUSTNESS CHECK: LAGGED EFFECT OF EPU

To address the possibility that Economic Policy Uncertainty affects innovation with a time lag, we conduct a robustness check by replacing the contemporaneous EPU variable with its one-year lag (EPU_{t-1}). Innovation is a lengthy process, and the impact of the macroeconomic environment on R&D investment decisions and their subsequent outcomes, such as patent applications, may not be immediate. The results of this analysis are presented in Table 5.

TABLE 5. Robustness Check with Lagged EPU

	Patents	Invention _{patents}	Utility _{patents}
EPU_{t-1}	-0.0028*** (-3.41)	-0.0035*** (-3.92)	-0.0017** (-2.68)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	2365	2365	2365
R-squared	0.67	0.64	0.58

Notes: The t-statistics are reported in parentheses. **,*** denote significance at the 5% and 1% levels, respectively.

The results in Table 5 show that the one-year lagged EPU has a negative and statistically significant coefficient across all three measures of innovation. This finding is consistent with our main results, suggesting that the chilling effect of policy uncertainty on technological innovation is not only a contemporaneous phenomenon but also has a persistent,

lagged impact. This strengthens our primary conclusion that a stable policy environment is crucial for fostering long-term R&D investments in the smart-textiles industry.

ROBUSTNESS CHECK: ADDRESSING CROSS-COUNTRY PATENT COMPARABILITY

We acknowledge that different patent types (in particular utility models and design patents) are not directly comparable across jurisdictions in our sample. To ensure our core findings are robust to this measurement issue, we conduct a further test. While our main analysis (Table 3, Column 2) already shows a strong negative effect on the highly comparable Invention Patents category, we further test our results by creating a measure that excludes design patents, which are often considered the least technologically substantive. We re-run our baseline model using a dependent variable representing the log of (1 + invention patents + utility model patents). Re-running the baseline model with this adjusted variable yields results consistent with our primary analysis; the coefficient on EPU remains negative and highly significant. This confirms that our central conclusion is robust and not driven by the inclusion of design patents.

V. DISCUSSION

DISCUSSION OF MAIN FINDINGS

The results of this study provide strong empirical evidence that Economic Policy Uncertainty acts as a significant impediment to technological innovation in the smart-textiles industry. The finding that EPU negatively impacts patent applications aligns with the predictions of real options theory. When faced with an unpredictable policy landscape, managers in smart-textile firms, whose innovation projects are capital-intensive and irreversible, become more cautious. They adopt a "wait-and-see" strategy, leading to the delay or cancellation of R&D projects, which manifests as a subsequent drop in patent filings.

Furthermore, our analysis reveals a crucial nuance: EPU disproportionately stifles high-quality, breakthrough innovation (invention patents) more than it does incremental innovation (utility model patents). This is a logical outcome of risk management. Invention patents represent ventures into new technological territory, carrying higher risk and longer-term uncertainty. In contrast, incremental improvements are safer, less costly, and have shorter payback periods. In an uncertain environment, firms will predictably shift their limited R&D resources away from high-risk, high-reward projects towards safer, incremental gains. This flight-to-safety in innovation strategy could have long-term negative consequences for the technological leadership of firms and the industry as a whole.

DISCUSSION OF HETEROGENEITY RESULTS

Our heterogeneity analysis further illuminates the channels through which EPU operates. The confirmation of H2—that smaller firms are more adversely affected—highlights the importance of internal resources as a buffer. Large firms can

leverage their diversified operations, greater cash reserves, and established market presence to better withstand macroeconomic volatility. Smaller firms, lacking these advantages, are more exposed, and their innovation pipelines are more fragile.

Similarly, the support for H3 underscores the critical role of financial health. Firms already burdened with high debt are on precarious ground. Heightened EPU increases the cost of external financing and raises the perceived risk of default. For these firms, survival takes precedence over growth, and long-term R&D spending becomes an expendable luxury. This finding reinforces the view that financial constraints are a primary mechanism through which macroeconomic uncertainty is transmitted to firm-level investment decisions.

IMPLICATIONS

Theoretical Implications: This study extends the EPU literature by providing evidence from the strategically important smart-textiles sector. It confirms the applicability of real options theory to innovation decisions in an emerging, high-tech industry, and the disaggregation of patent types adds a qualitative dimension to the understanding of EPU's impact.

Managerial Implications: Our finding that EPU disproportionately stifles high-quality, breakthrough innovation calls for a more nuanced R&D portfolio strategy. Rather than uniformly cutting back, managers in smart-textile firms should consider a barbell R&D strategy during high-EPU periods. This involves protecting a small number of core, long-term breakthrough projects (e.g., in novel conductive yarns or biosensors) that are crucial for future competitive advantage, while shifting the majority of the R&D budget towards safer, incremental innovations with shorter payback periods. This approach ensures long-term viability without sacrificing near-term financial stability. Furthermore, managers should actively seek to build resilience by forming strategic R&D alliances and consortia to share the high risks and costs associated with breakthrough innovation in uncertain times.

Policy Implications: Given that EPU particularly harms high-risk, breakthrough innovation, generic support may be insufficient. Policymakers aiming to foster the smart-textiles sector should consider more targeted, context-aware interventions. For instance, instead of just general R&D tax credits, governments could implement counter-cyclical R&D funding mechanisms, where subsidies for high-risk projects increase during periods of high EPU to directly offset the chilling effect. Furthermore, to address the high costs and interdisciplinary nature of smart-textile R&D, policies could encourage the formation of public-private research consortia focused on foundational technologies. Finally, creating streamlined regulatory sandboxes for new wearable electronic products could reduce the regulatory uncertainty that, as our study shows, is a significant barrier to long-term innovation investment.

VI. CONCLUSION

This study set out to investigate the impact of Economic Policy Uncertainty on technological innovation in the smart-textiles industry. Using a panel dataset of 215 manufacturing firms from 2010–2023, our empirical analysis yields three key findings. First, EPU significantly inhibits the overall innovation output of smart-textile firms. Second, this negative effect is more severe for high-quality, breakthrough innovations than for incremental ones. Third, the innovation activities of smaller firms and those with higher financial constraints are disproportionately harmed by EPU.

These findings contribute to a deeper understanding of the macroeconomic determinants of innovation in a critical emerging industry. They highlight the tangible costs of policy uncertainty and provide actionable insights for managers and policymakers.

However, this study is not without limitations. First, our use of a country-level EPU index is a proxy that may not capture all firm-specific uncertainties. Second, patent counts are an intermediate output of innovation and do not perfectly measure the commercial success of an innovation. Third, our sample is limited to publicly listed firms, potentially overlooking the dynamics of smaller, private startups that are also crucial to the industry's ecosystem. Fourth, our use of a log-transformed linear model, while common, does not explicitly model the count nature of patent data. Future research could provide further robustness by employing count data models, such as fixed-effects Poisson or negative-binomial regressions, to better account for the prevalence of zero-patent observations.

Future research could build on our findings in several specific and innovative directions. For instance, researchers could investigate the role of policy interventions, such as targeted R&D subsidies or tax incentives, in moderating the negative impact of EPU on smart-textiles innovation. Another promising avenue is to explore the role of international collaborations and supply chain positioning; for example, do firms with diverse international R&D partnerships exhibit greater resilience to domestic policy uncertainty? Finally, to build upon our findings with greater precision, future work could disaggregate innovation outputs by using specific patent classification codes (e.g., CPC or IPC codes) to isolate patents strictly related to smart-textile technologies. This would allow for a more targeted analysis of which technological domains—such as embedded biosensors, energy-harvesting fabrics, or new conductive yarns—are most vulnerable to the chilling effects of EPU, thereby providing more targeted policy and managerial guidance.

AUTHOR CONTRIBUTIONS

Tiantian Wang and Lu Xia designed the study; all authors conducted the study; Tiantian Wang and Lu Xia collected and analyzed the data. Tiantian Wang and Lu Xia participated in drafting the manuscript, and all authors contributed to critical revision of the manuscript for important intellectual content. All authors gave final approval of the version

to be published. All authors participated fully in the work, took public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or completeness of any part of the work were appropriately investigated and resolved.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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AVAILABILITY OF DATA AND MATERIALS

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

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