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# Understanding the impact of trade policy effect uncertainty on firm-level innovation investment: A deep learning approach

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# Understanding the Impact of Trade Policy Effect Uncertainty on Firm Innovation Investment: A Deep Learning Approach

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**Abstract:** Integrating the real options perspective and resource dependence theory, this study examines how firms adjust their innovation investments to trade policy effect uncertainty (TPEU), a less studied type of firm specific, perceived environmental uncertainty in which managers have difficulty predicting how potential policy changes will affect business operations. To develop a text-based, context-dependent, time-varying measure of firm-level perceived TPEU, we apply Bidirectional Encoder Representations from Transformers (BERT), a state-of-the-art deep learning approach. We apply BERT to analyze the texts of mandatory Management Discussion and Analysis (MD&A) sections of annual reports for a sample of 22,669 firm-year observations from 3,181 unique Chinese public firms during the period of 2007-2019. The results of econometric analyses show that firms experiencing higher TPEU tend to reduce innovation investments. Furthermore, this effect is stronger for firms within industries with lower competition, involving more foreign sales, and not owned by the state. Our inferences persist when utilizing the abnormal TPEU derived from a two-stage analysis, and when filtering out other potential confounding effects. We further fortify the causal effect of TPEU by showing its impact on innovation investments was stronger after the outbreak of the ongoing U.S.-China trade war since 2018. These findings help to explain prior mixed findings by demonstrating that policy effect uncertainty, in contrast to policy state uncertainty, exerts a salient influence on firms' innovation investment decisions, and by highlighting resource dependence factors as important contingencies.

**Keywords:** Effect uncertainty, Trade policy uncertainty, Real options theory, Resource dependence theory, Innovation investment, Deep learning

## 1. INTRODUCTION

Public policy changes exert important influences and constraints on a firm's business operations (Charpin, 2022; Tokar and Swink, 2019). For example, as a direct consequence of government trade policy changes, the recent Brexit referendum and the 2018 "trade war" between the U.S. and China seriously undermined the global business landscape and the world economy (China Daily, 2019; Financial Times, 2020).[1] Not only can changes to international trade agreements destroy decades of efforts on trade globalization (Fajgelbaum et al., 2020), they also create a high level of environmental uncertainty for many businesses, making it difficult for them to make proper operational decisions. Whereas decision-making under environmental uncertainty has drawn decades of research interest in Operations and Supply Chain Management (OSCM), extant OSCM literature largely focuses on the implications of market- or technology-related uncertainties to firm operations (Kocabasoglu et al., 2007; Ulu and Smith, 2009). Scholars are only recently giving more attention to impacts of government policy uncertainty (such as foreign trade policy uncertainty) on firm-level operational decisions (Tokar and Swink, 2019). Because a firm's operational decision-making is frequently shaped by public policy-related uncertainty including the timing, content, and impact of policy decisions (Gulen and Ion, 2016; Leung and Sun, 2021), it is essential to explore how public policy uncertainty affects firm-level operations management. Accordingly, in recent years, researchers have increasingly called for studies on decision-making driven by public policy uncertainties in the field of OSCM (Helper et al., 2021; Joglekar et al., 2016; Tokar and Swink, 2019).

The current study responds to these calls by examining the impacts of policy uncertainties stemming from changing international trade restrictions or protections on corporate investments in innovation, an important operational activity that is particularly sensitive to changes in environmental uncertainty (Tokar and Swink, 2019). To fulfill this objective, we first draw upon a classic environmental uncertainty

[1] Google's English dictionary defines a trade war as "a situation in which countries try to damage each other's trade, typically by the imposition of tariffs or quota restrictions." See China Daily at: http://www.chinadaily.com.cn/a/201906/29/WS5d16bf8aa3103dbf1432af4d.html, and Financial Times at: https://www.ft.com/content/6124beb8-5724-11ea-abe5-8e03987b7b20.

framework (Milliken, 1987) to introduce the concept of trade policy effect uncertainty (TPEU), a firm-specific form of environmental uncertainty. We then apply the real options perspective (Pennings and Sereno, 2011) and resource dependency theory (Pfeffer and Salancik, 1978) to address two specific research questions: 1) How does TPEU influence corporate resource investments in innovation activities? 2) What contingent factors moderate the influence of TPEU on innovation investment decisions?

Trade policy uncertainty potentially influences many types of resource investment decisions. We focus on the implications of TPEU for firm innovation investments, for three reasons. First, innovation investment is one of the most significant, risky, and sensitive operational determinants of firm sustainable competitive advantage and long-term viability (Aghion et al., 2013; Bellamy et al., 2014; Dong et al., 2020). Firm innovations enhance an organization's capacity to produce intangible assets and to drive growth and financial performance (Eroglu and Hofer, 2014; Mackelprang et al., 2015; Swink and Jacobs, 2012). However, unlike other capital investments, returns on innovation investments are among the most difficult to predict during the pre-investment decision-making stage, because innovation is an uncertain enterprise (Mackelprang et al., 2015). While OSCM research has addressed the effects of uncertainty to individual aspects of innovation, it lacks studies of how firm-level innovation investment is related to trade policy effect uncertainty.

Second, because innovation investments directly impact a firm's markets and competitive position, they are likely to be more sensitive to firm-specific competitive factors and resource dependencies that can change the risk-reward calculus for investments made in uncertain conditions. For example, high levels of competition for resources likely raises the risk of innovation investments in times of high environmental uncertainty. Decisions for other types of capital investment such as for facility expansion or workforce development might also be impacted by environmental uncertainty, but such decisions are likely not as sensitive to external competitive factors and resource dependencies. As such, both policymakers and operations managers need greater understanding of how trade policy dynamics impact business operations in general, and innovation activities in particular.

Third, our study proposes TPEU as a new means for explaining the mixed findings of prior studies of trade policy uncertainty and innovation investment. Prior studies of trade policy uncertainty consistently demonstrate its negative effects on capital investment decisions (Baker et al., 2016; Cong and Howell, 2021; Jens, 2017; Julio and Yook, 2012). However, studies of innovation investment decisions show mixed results. Our updated review of the literature suggests that a lack of distinction among different types of environmental uncertainty in this line of literature may explain these mixed findings. In this study, we take advantage of the conceptual work of Milliken (1987) to differentiate *effect uncertainty* from *state uncertainty*. Milliken defines state uncertainty as the *unpredictability of the future state of the external environment* (e.g., competitors' moves, suppliers' offerings, government policy decisions, etc.). In contrast, effect uncertainty is the unpredictability of the *impacts of potential environmental changes on a given organization* (Milliken, 1987). State uncertainty pertains to what environmental changes might occur; effect uncertainty pertains to how such changes might impact a specific firm in a specific context. Firms may react differently to state and effect uncertainties (Aragon-Correa and Sharma, 2003), including their investment sensitivities (Pindyck,1993). Thus, empirical research focusing on firm-specific perceptions of TPEU may offer a useful lens with which to better understand firm level innovation investment behaviors.

Drawing upon real options theory, we argue that high TPEU increases the value of preserving options by postponing firm innovation investments (Pennings and Sereno, 2011). In practice, top managers who experience high TPEU must spend significant amounts of time and resources to identify and develop an understanding of the effects of environmental threats and opportunities (Milliken, 1987). Such efforts divert resources away from other mission critical operations (Aragon-Correa and Sharma, 2003). Therefore, firms may prefer to take a wait-and-see strategy, postponing innovation investments rather than taking costly actions perceived to be increasingly risky due to policy uncertainty. To shed light on whether wait-and-see behavior is moderated by firm context, we turn to resource dependence theory, which identities three external stakeholder groups (competitors, customers, and government) that can constrain a firm's access to necessary resources. We posit that the negative relationship between TPEU and firm innovation activities is moderated by three factors reflecting these groups: product market competition, dependence on foreign customers for sales, and state ownership.

We acknowledge the methodological challenge in measuring firm-specific perception of effect uncertainty, which might explain the paucity of existing theoretical evidence establishing a causal effect of policy uncertainty on operational decision-making in prior OSCM literature. We address this research gap by developing an instrument to measure TPEU using Bidirectional Encoder Representations from Transformers (BERT), a context-dependent natural language processing (NLP) algorithm originated from computational linguistics (Devlin et al., 2019). Our novel firm-specific measure of TPEU captures *the degree to which a firm's leaders lack understanding of the specific impacts of trade policy changes on its own businesses*. We construct and validate a time-varying, idiosyncratic TPEU measure by using deep learning algorithms to analyze the Management Discussion and Analysis (MD&A) disclosures contained in annual reports of publicly listed businesses in China. In addition, we collect archival financial and innovation data from multiple sources to study 3,181 unique China-based public firms, with a sample of 22,669 firm-year observations covering the period of 2007 to 2019. Our analysis shows that corporate innovation investment significantly declines when its leaders perceive a high level of TPEU. Furthermore, the negative impact of TPEU on innovation investments is more pronounced for firms within less competitive industries, for firms with more foreign sales, and for firms not characterized as State Owned Enterprises (SOE).

This study makes several contributions to the OSCM literature. It is the first to highlight the concept of perceived *trade policy effect uncertainty* to the OSCM discipline. By integrating economics and organizational theories, we explicate why and how firm-specific perception is a more appropriate lens for researchers to view corporate investment decision-making amid public trade policy uncertainty, as opposed to the broader state uncertainty conceptualizations used in most foregoing research. In addition, we provide large-scale empirical evidence regarding a specific application of the broad conceptual developments by Aragon-Correa and Sharma (2003) on the theoretical relationship between effect uncertainty and environmental strategy. Managers may use our findings to better understand implied tradeoffs they make when considering innovation investment decisions. Our findings may also alert policy makers to unintended consequences of policy changes (Tokar and Swink, 2019).

Methodologically, this study provides an early demonstration of the potential of deep learning approaches (e.g., BERT) to be further employed in OSCM research to address the challenges of extracting measures from textual data. Our validation of the TPEU measure should be useful in forwarding further research into questions involving firm-specific policy uncertainty.

Our study thus points to both uncertainty measurement and contextual factors as potential explanations for the mixed findings of prior studies. By clearly delineating the impacts of effect versus state uncertainty, by applying a more precise measure of uncertainty, and by taking resource-based contextual factors into account, we expect that future researchers can develop a more consistent and nuanced understanding of how environmental uncertainty affects firm investment decisions.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 describes the data, constructs the measure of corporate TPEU, and introduces our research design. Section 4 presents the empirical results. Section 5 discusses the contributions, limitations, and future research.

## 2. LITERATURE AND HYPOTHESES

Many OSCM scholars have studied influences of environmental uncertainty on operational decision making. However, most studies examine relationships of market uncertainties to operating performance or to the development of operations capabilities. Relatively few published works focus on relationships between environmental uncertainty and innovation investment. Several researchers consider the influence of technological uncertainty on innovation. For example, Koufteros et al. (2002) find that firms operating in environments that are uncertain due to rapid technological change adopt higher levels of integrated product development practices. Li et al. (2003) develop a stochastic program to model technology acquisition decisions under different levels of technology progress uncertainty. Similarly, Ulu and Smith (2009) use dynamic programming to model the technology adoption problem considering evolving information about the technology's benefits. Pennings and Sereno (2011) develop a model suggesting that both technology and economic uncertainties positively impact pharmaceutical R&D option value.

Other OSCM researchers evaluate the influences of broader business uncertainty on innovation. Kocabasoglu et al. (2007) find that business uncertainty, which they define as a state uncertainty deriving from industry conditions (munificence, dynamism, hostility, competition), encourages investments in reverse supply chain innovations. This tendency toward investment is mediated by the firm's risk propensity. Wang et al. (2020) show that a changing business environment moderates the influence of information technology-enabled capabilities on innovation activities.

Until recently, OSCM research has mostly neglected the study of policy uncertainty, a gap that researchers have highlighted. Public policy reflects actions (and nonactions) of lawmakers and governmental agencies in response to specific problems relevant to state or public interests (Birkland, 2019; Helper et al., 2021). Because of the pivotal role that government plays in shaping firms' decision-making (Davis-Sramek et al., 2017; Gulen and Ion, 2016; Leung and Sun, 2021), the environment in which firms operate is frequently susceptible to decisions/policies made by governments or equivalent authorities (Gulen and Ion, 2016). As such, both policy makers and operations managers are paying increasing attention to ways in which uncertainties stemming from regulatory or public policy-related (in)actions affect OSCM practices (Helper et al., 2021; Joglekar et al., 2016; Tokar and Swink, 2019). As noted above, few of OSCM studies address innovation. We thus look to broader economic and financial literatures to identify relevant foregoing research.

### *2.1 Research on policy uncertainty and investment*

Before addressing the theoretical underpinnings of our study, it is necessary to address the limitations inherent in the ways that policy uncertainties have been conceptualized and operationalized in prior research. The economics and finance literatures contain active research streams that address public policy uncertainty, largely focusing on macro-level uncertainties resulting from changes of economic policies or from political elections. For example, Baker et al. (2016) construct a newspaper-based index of aggregate economic policy uncertainty (EPU) that combines measures of overall policy uncertainty, uncertainty about future changes in federal tax policies, and uncertainty about fiscal and monetary policies. Building on their work, a series of studies report that such an overall level of economic policy uncertainty shapes a firm's customer-base concentration (Leung and Sun, 2021), supply chain structures (Charoenwong et al., 2022), capital investment (Gulen and Ion, 2016), R&D investment (Shen and Hou, 2021), and mergers and acquisitions (Bonaime et al., 2018). Similarly, Davis et al. (2019) apply a dictionary approach to create a time-series newspaper-based index of macro policy uncertainty.

Table 1 provides a brief review of the studies that examine the relationship between broad measures of policy uncertainty and innovation investments, sorted by type of uncertainty measure. These studies use the aforementioned indices or events such as elections to proxy levels of policy uncertainty. The inconsistent findings evidenced in Table 1 may exist because measures of macroeconomics policy uncertainty do not adequately capture the uncertainty perceptions of individual firms (Handley and Limão, 2022). For example, newspaper-based indices are unable to distinguish the variances of policy uncertainty experienced by different firms that have different information access and processing capabilities. Such differences can lead to different perceptions of uncertainty, even for the same macro event (Bloom, 2014). Moreover, different sources of uncertainty may produce diverse economic consequences (Pindyck, 1993). Thus, to better understand the effects of policy uncertainty on firms' operational decisions it seems essential to construct time-varying and firm-specific measures of policy uncertainty that reflect managers' idiosyncratic perceptions.

**Table 1: Summary of research on the relationship between policy uncertainty and innovation investment**

| **Study** | **Uncertainty measure** | **Dependent variable** | **Relevant findings** | **Uncertainty-investment relationship** | **Discipline** |
|---|---|---|---|---|---|
| Marcus (1981) | Literature review of policy uncertainty studies | Technological innovation | Policy uncertainty effects vary based on policy type, industry, and firm size. | Inconsistent | Management |

| | | | | | |
|---|---|---|---|---|---|
| Atanassov et al. (2019) | Policy uncertainty stemming from US gubernatorial elections | R&D investment | Uncertainty over government policy stimulates firm R&D investment, especially in close elections, politically sensitive and hard-to-innovate industries, and for firms with high growth options and high competition. | Positive | Finance |
| Shen and Hou (2021) | Baker et al. (2016) EPU index | R&D investment and patents | Trade policy uncertainty spurs innovation investment: effect is reduced by government subsidy and managerial ownership. | Positive | Economics |
| Guan et al. (2021) | Davis et al. (2019) EPU index (China) | Patent applications | Economic policy uncertainty encourages technological innovation. | Positive | Finance |
| Liu and Ma (2020) | China accession to the World Trade Organization | Patent applications | Trade liberalization induces innovation, moderated by firm productivity, ownership, exporting status, and investment irreversibility. | Negative | Economics |
| Cong and Howell (2021) | China suspension of IPOs | Patent applications and grants | Uncertainty created by temporary suspensions of access to public equity reduces investment | Negative | Finance |

A recent stream of research takes steps in this direction, exploring specifically how international trade policy uncertainty (TPU) affects business firms' decisions and outcomes – see Charpin (2022) and Handley and Limão (2022) for recent comprehensive reviews of TPU studies. Both Benguria et al. (2022) and Caldara et al. (2020) employ a simple dictionary approach based on firm's quarterly or annual reports to construct a firm-level TPU. Hassan et al. (2019) also develop a dictionary-based measure of political risk faced by individual U.S. firms, based on discussions taking place during earnings conference calls. While such approaches provide more focused assessments of TPU as opposed to the more general EPU studies above, they still suffer important limitations. Among others, a primary limitation of simple dictionary approaches is context independence (i.e., they ignore the order and context of the words embedded in text or conversations) (Devlin et al., 2019; Loughran and McDonald, 2016).

As such, there is a need for a novel empirical approach to precisely capture time-varying, firm-specific perception of trade policy effect uncertainty, based upon a solid conceptual foundation, and more importantly to help with comprehending how idiosyncratic perception of TPEU may affect firm decision-making on innovation activities.

***2.2. State uncertainty and effect uncertainty***

In her seminal thesis, Milliken (1987) distinguishes three types of perceived environmental uncertainty by companies: *state uncertainty*, *effect uncertainty*, and *response uncertainty*. Response uncertainty is associated with an organization's lack of knowledge on what response options are available to them, and therefore is not of interest to this study. Instead, we briefly focus on conceptual differences between state uncertainty and effect uncertainty to explain why effect uncertainty is a more appropriate lens through which to explore the implications of trade policy uncertainty to firm-level operational decisions.

According to Milliken (1987), business executives experience state uncertainty when they perceive their organizational environment, or certain elements of that environment, to be hard to predict. State uncertainty may also involve deficient knowledge of the inter-connections between environmental components. As such, state uncertainty reflects a general degree of unpredictability of the external environment (Kocabasoglu et al., 2007). Such an inability to forecast industry, political, or market events stems in part from the challenges similarly faced by all firms in an industry (Miller and Shamsie, 1999). For example, trade policy state uncertainty creates difficulty for firms to tell how parts of the competitive environment (e.g., customers, government, shareholders, etc.) might change due to an unexpected trade war between two countries. In this case, decision makers' inabilities to predict the future state of the environment are largely similar across firms (Miller and Shamsie, 1999).

Whereas state uncertainty refers to the unpredictability of the future state of the external business environment, effect uncertainty is defined as "an inability to predict what the nature of the impact of a future state of the environment or environmental change will be on the organization" (Milliken 1987, p137). Although effect uncertainty is not completely orthogonal to state uncertainty (i.e., effect uncertainty is also influenced by the macro environment), effect uncertainty describes a different level of uncertainty in that it occurs when decision makers find it difficult to understand or anticipate the future impact of environmental events on their business operations. While state uncertainty may be experienced similarly by many firms, effect uncertainty is firm-specific; it is often a function of resources and market opportunities available to a given firm (Miller and Shamsie, 1999). Another differentiation of the two types of uncertainty stems from the types of information that organizational decision makers lack (Milliken, 1987). In the case of state uncertainty, decision makers lack information on the nature of the future environment. For example, they may lack reliable predictions of which available options policymakers will choose to pursue. In contrast, effect uncertainty is indicated in the degree to which firms' decision makers differ in their abilities to predict how policy option choices will affect their operations and business prospects.

Differentiating between these two types of uncertainty should promote a better understanding of firm-level strategic and operational changes, while also clarifying some of the noticeably mixed results reported in past research. We argue that, even for firms with comparable views of trade policy state uncertainty (e.g., how many countries will be involved, how long the trade policy changes will last, how many industry sectors may be affected, etc.), they likely will exhibit diverse levels of trade policy effect uncertainty (i.e., what are the likely impacts of the uncertain trade policy changes on their businesses). Consequently, firms will vary in their competitive responses to TPEU.

### *2.3. Linking TPEU to innovation investment*

Despite the significant importance of innovation for firm-level competitiveness, the profits of investment in innovation behaviors tend to be distant, and the probability of success for most innovation investments is low (Eroglu and Hofer, 2014; Mackelprang et al., 2015). As shown in Table 1, innovation investment under policy uncertainty has been analyzed and understood in the literatures of multiple disciplines, but the results of empirical tests have been decidedly mixed. On the one hand, some researchers document that trade policy uncertainty leads firms to lower investments because they consider the uncertainty to be fraught with risks (Cong and Howell, 2021; Liu and Ma, 2020). On the other hand, firms can view uncertainty as offering opportunities, and thus choose to increase innovation activities to gain competitive advantages (Atanassov et al., 2019; Guan et al., 2021). An early review of policy uncertainty studies reveals no clear and consistent relationship between environmental uncertainty and technological investment decisions (Marcus, 1981).

A possible explanation for these inconsistent findings is that these studies fail to distinguish differences in types of perceived environmental uncertainty that may exert different influences on firm investment decisions. In a conceptual paper, Aragon-Correa and Sharma (2003) propose that firms facing higher state uncertainty tend to be more preemptive, take greater risk, and pursue product innovation (e.g., to increase product variety) in order to prepare for the unknown scenarios. However, firms experiencing greater effect uncertainty may find it difficult to allocate sufficient resources to develop proactive responses to changes in the environment. In this study, we suggest that TPEU (i.e., the lack of knowledge on implications of environment changes to individual businesses) more directly explains corresponding firm-level actions (Milliken, 1987).

Real options theory (ROT) (Pennings and Sereno, 2011) provides a useful frame with which to examine the impacts of firm-specific TPEU on innovation investment decisions. ROT applies option valuation methods to capital budgeting decisions. A real option is the right, not the obligation, to launch particular business initiatives such as postponing, dumping, growing, altering, or switching an investment project (Trigeorgis and Reuer, 2017). Unlike traditional financial options, real options often are created or discovered by management. Therefore, the value of a real option's underlying project can be directly influenced by the holder (i.e., the managers) of the option. Furthermore, it is unlikely for management to measure uncertainty only in terms of volatility; they more likely make decisions based upon their interpretations of alternative sources of uncertainty.

Based upon ROT, we suggest that firms experiencing greater TPEU are likely to reduce spending in innovation activities, because high levels of effect uncertainty increase the option value of waiting for future innovation investment opportunities (Bloom, 2009; Bloom et al., 2007; Dixit et al., 1994; Mcdonald and Siegel, 1986). First, ROT suggests the wait option is generally valuable when an investment has a highly irreversible nature and low probability of success (Grenadier, 2002; Jiang et al., 2015). General investment research offers empirical evidence that high uncertainty amplifies the real-option value of waiting (Bloom, 2009; Bloom et al., 2007). Since business innovation typically involves exploring unknown and risky technologies, commands long trial-and-error testing duration, and occupies high probability of failure (Aghion and Tirole, 1994; Mackelprang et al., 2015; Manso, 2011), the option value of waiting is even more important for innovation investments (Pennings and Sereno, 2011). For example, Miller and Shamsie (1999) find that greater effect uncertainty led to reduced investments in product variety in the Hollywood film industry. Accordingly, we expect that firms tend to postpone innovation investments under greater TPEU.

Second, we expect that firms that experience higher policy effect uncertainty will spend more time and effort collecting information to better understand concrete impacts of unavoidable environmental changes to their organizations, including specific threats and/or opportunities (Milliken, 1987). In this case, it is hard for firms to quickly devote sufficient resources to develop the required capabilities for innovation needs (Aragon-Correa and Sharma, 2003). Thus, we expect that TPEU will compel top managers to reduce investment in innovation activities and take a wait-and-see strategy.

***Hypothesis 1:*** *TPEU is negatively associated with corporate innovation investments.*

### *2.4. Moderators of the TPEU – innovation investment relationship*

While ROT argues for a direct negative relationship between TPEU and firm-level innovation investment, we are also interested in understanding how the strength of the proposed relationship may vary across organizational characteristics, particularly, differences in resources. Resource dependence theory (RDT) (Pfeffer and Salancik, 1978) suggests that firms are open systems that depend on external environments for resources to survive or prosper; it is difficult to be “internally self-sufficient” regarding critical resources (Pfeffer and Salancik, 1978). As specified by Pfeffer and Salancik (1978, p.1): “to understand the behavior of an organization you must understand the context of that behavior—that is, the ecology of the organization". Darby et al. (2020) apply RDT to argue that policy uncertainty destabilizes operations as it brings into question a firm's access to critical resources and market opportunities. They show that policy uncertainty encourages firms to increase their inventories as buffers against resource scarcities. Similarly, we suggest that integrating the ROT with RDT offers a more comprehensive explanation of how firms react to TPEU.

Pfeffer and Salancik (1978) name competitors, customers, and government as important constituencies that provide or restrict access to resources. Considering our research context, we examine three resource dependencies: product market competition, foreign sales, and ownership structure.

#### *2.4.1. Product market competition*

Product market competition describes the degree of competition that a company faces within a given industry or industry segments. More intensive market competition increases the threat of preemption by competitors (Weeds, 2002). In this respect, firms operating in industries of varying competition levels have differing levels of access to sources of product demand and supply. Viewing these markets as resources (i.e., sources of demand and supply), competition likely conditions the ways that firms are likely to behave under a certain level of TPEU.

Firms who operate in highly competitive markets feel the urgency to react quickly to competitors' actions so as to retain or improve their market positions. Prior investment literature suggests that competition reduces the option value of postponing investments because firms fear that their competitors may seize competitive advantages by investing first (Grenadier, 2002). In other words, the value of a wait-and-see strategy diminishes for firms encountering intense competition, because the expected competitive benefits of preemptive action outweigh the option value of delay (Aguerrevere, 2009; Weeds, 2002). As a result, firms may strive to increase innovation activities in order to head off rivals in capturing resources (Bhaskaran and Ramachandran, 2011) required for survival and/or success (Brown and Eisenhardt, 1995). Consistent with this mechanism, ROT researchers have empirically documented that competition dampens the negative impact of uncertainty on irreversible investments (Bulan, 2005), such as R&D investments (Czarnitzki and Toole, 2013). Consequently, we expect that firms within highly competitive industries will exhibit smaller decreases in resources allocated to innovation activities in response to increased TPEU.

***Hypothesis 2:*** *Higher levels of product market competition weaken the negative effect of TPEU on innovation investments.*

***2.4.2. Dependence on foreign markets***

We expect the association between TPEU and a firm's innovation investments also to be shaped by the extent to which the firm relies upon foreign sales generated by overseas customers. RDT would suggest that participation in foreign markets enables firms to gain resources (e.g., knowledge of different customer preferences and demands) that are unavailable in the domestic market (Salomon and Jin, 2008; Salomon, 2006). However, when facing increased TPEU, firms having an extensive dependence on sales from foreign customers are more likely to cut innovation spending, for several reasons. First, TPEU increases the option value of wait-and-see more significantly for firms relying more on foreign markets than on domestic ones, because access to foreign markets becomes increasingly uncertain. Hence, returns on innovations targeting foreign customers become more equivocal and the special resources associated with foreign markets becomes less valuable. Second, efforts to develop, understand, and retain foreign markets compete for organizational resources with efforts to innovate, and innovation itself becomes more resource intensive (Roper and Love, 2002). For example, Kumar (2009) finds a negative relationship between participation in exporting activities and product diversification. Similarly, Sowell (2009) document that exporting to foreign markets exerts a negative effect on productivity, and explain that the uneven distribution of costs produced by exports (e.g., quasi-rents) are likely to overwhelm procompetitive impacts such as innovation. As we explained earlier, TPEU compels firms to allocate more resources to understand the specific implications of trade policy issues to their businesses. Under resource scarcity, firms with larger foreign exposure are more likely to use resources for this purpose rather than to make innovation investments.

***Hypothesis 3:*** *Higher levels of dependence on foreign markets strengthen the negative effect of TPEU on innovation investments.*

***2.4.3. Ownership structure***

RDT highlights the essential role of governments as both direct and indirect resource providers to businesses (Pfeffer and Salancik, 1978). We investigate the impact of government by considering whether or not a firm is owned by the state. In general, SOEs receive greater inputs from government, which has the power to shape the landscape of an economy or industry (Gao et al., 2010). Compared to non-SOEs, SOEs are more likely to obtain direct financial inputs from the government, such as government contracts (Eckerd and Girth, 2017) and corporate bailouts (Faccio et al., 2006). In addition, SOEs enjoy closer political connections with the government, suffer less from information asymmetries, and benefit from more favorable subsidies (Wang et al., 2008). Using China as an example, it is much easier for SOEs to receive loans from banks (Xu and Zhang, 2008) because most Chinese banks themselves are SOEs and they prefer to transact with other SOEs in order to obtain perks or to pursue political/personal goals not attainable from non-SOEs (Brandt and Li, 2003; Chen et al., 2014).

State ownership has been shown to be positively associated with organizational innovation activities (Zhou et al., 2017). Government provided resources, including financial, regulatory, and information support, lower the risk of innovation, thus lowering the value of wait-and-see options. In addition, we expect that the resource advantages of SOEs enhance decision makers' capacities to wrestle with heightened TPEU, as they expect to experience less resource deficiencies than non-SOEs counterparts under the same TPEU conditions. These resource effects suggest that SOEs' innovation activities will be less affected than those of non-SOEs.

***Hypothesis 4:*** *State ownership weakens the negative effect of TPEU on innovation investments.*

Figure 1 depicts the research model that encapsulates the above hypotheses.

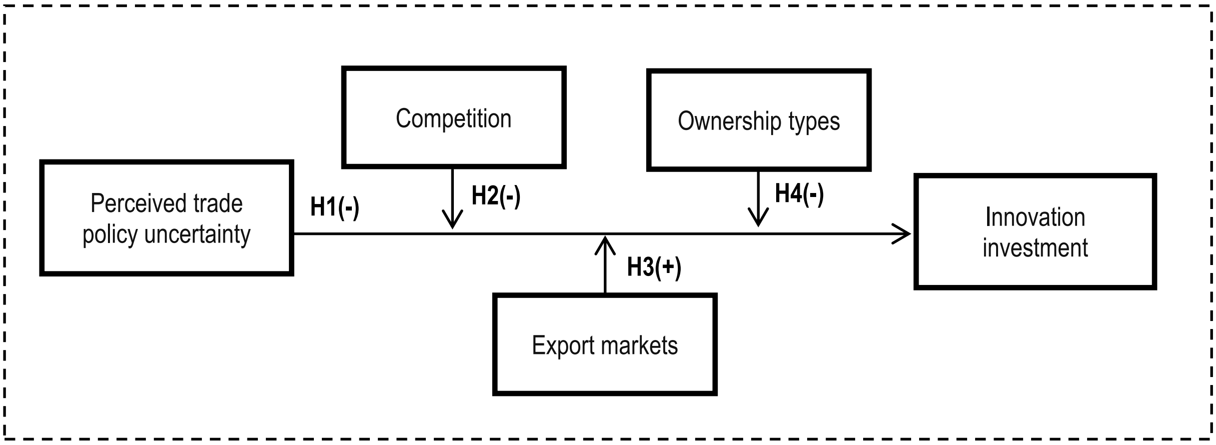


**Figure 1 Conceptual Model**

## 3. METHODOLOGY

### *3.1. Sample and data*

Our sample frame consists of all public Chinese firms listed on A-share Shanghai and Shenzhen Stock Exchanges for the sample period from 2007[2] to 2019. We first download all annual reports from Wingodata.com, which is a leading textual analytics platform collecting and pre-processing various financial disclosures of companies publicly traded in the two Chinese stock exchanges. Similar to the approach adopted by Li (2010) and Muslu et al. (2015), we subsequently extract the MD&A sections from these filings. The MD&A disclosures offer an appropriate platform for us to assess managers' perceptions of trade policy effect uncertainty for two reasons. First, theoretical evidence from prior linguistics literature (Pennebaker et al., 2003; Tausczik and Pennebaker, 2010) suggests that the words human use offer rich information on their perceptions such as beliefs, fears, thinking patterns, etc. Second, MD&A disclosures are mandated by China Securities Regulatory Commission (CSRC) for all public firms to provide managerial views on a variety of environmental aspects (e.g., production and market risks) that could affect their operations. As such, MD&A disclosures provide valid sources to develop effective measure reflecting idiosyncratic firm perception on TPEU.

[2] We use 2007 as the starting year when constructing the sample because the new Chinese Accounting Standards (CAS) has been in effect since this year. Besides, Chinese firms began to disclose R&D expenditures in 2007.

The research hypotheses of the study are examined using data from numerous sources. We gather data on firm fundamentals and overseas businesses from the CSMAR (China Securities Markets and Accounting Research) database and Wind database[3], respectively. We eliminate firms in the financial service industry because their financial statements are prepared following different accounting standards. Firms under Special Treatment and observations with missing data are also excluded.[4] We further drop observations containing less than 200 words[5] in the MD&A narrative and observations with missing data. After such considerations, the final sample of the study contains 22,669 firm-year observations from 3,181 firms. To address the potential effect of outliers, all continuous variables are winsorized at the bottom and top one percent level.

### *3.2. Developing and validating the measure of trade policy effect uncertainty*

#### *3.2.1. Constructing TPEU using BERT*

We now describe the process of developing a firm-specific, time-varying measure of TPEU (i.e., *the degree to which a firm lacks understanding of the specific impacts of trade policy changes on its own businesses*). Extracting trade policy uncertainty-related information from financial disclosures is a complex topic that is closely related to the context of words. As such, we use BERT, a context-dependent language model, for such a task because it addresses the key challenges in simple dictionary methods (e.g., context independence) (Devlin et al., 2019), exhibits decisive advantages for dealing with complex topics (Varini et al., 2020), and performs better on various NLP tasks than traditional context-free machine learning models (Bochkay et al., 2022; Devlin et al., 2019; Huang et al., 2021; Kölbel et al., 2020), including Word2Vec (Mikolov et al., 2013), GloVe (Pennington et al., 2014), and FastText (Joulin et al.,

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[3] Both CSMAR and Wind databases are comprehensive and leading databases that compile all Chinese publicly listed firms. They are similar to Compustat and CRSP databases, and have been used in a set of recent high-quality papers, including but not limited to Xiong and Yu (2011),Fang et al. (2017), Zhou et al. (2017), and Jia et al. (2019).

[4] Firms are regarded as Special Treatment Firms by the Stock Exchanges if they are financially distressed (i.e., two continuous years of financial loss).

[5] Since our analysis is dependent on having a material MD&A section, following Davis and Tama-Sweet (2012), we exclude MD&A narratives of less than 200 words which generally occurs when our extraction process does not capture the MD&A.

2017). Our TPEU measure is first estimated at the single sentence-level (i.e., whether a sentence is related to TPEU)[6] and then aggregate to the document level.

Our BERT approach, like most of the recent deep learning-based language models, involves two steps: the pre-training step and the fine-tuning step (Devlin et al., 2019).[7] In the pre-training step, the BERT language model learns contextual relationships between words in large-scale unlabeled training data by jointly considering both preceding and following context of words, reflected in a huge number of parameters.[8] However, because BERT is an English pre-trained language model on Wikipedia and BookCorpus with 3.3 billion word tokens (Devlin et al., 2019), to get started, we pre-train our BERT model for Chinese natural language processing using various financial narratives disclosed by public Chinese firms as data input, including quarterly/annual reports, IPO prospectuses, conference call transcripts, corporate social responsibility (CSR) reports, and management reporting on internal control (MRIC) transcripts. Following Devlin et al. (2019), we pre-train BERT by using a masked language model to mitigate the unidirectionality constraint of the context and by solving a next sentence prediction task to understand sentence relationships.

In the fine-tuning step, the language model starts with the parameters learned from the pre-training step and simultaneously updates such parameters and parameters related to a TPEU classification problem that requires a manually annotated TPEU dataset. For this annotated process, a sentence is labeled as a TPEU related sentence (i.e., “1”) if it contains the information of managerial perspectives or commentaries on the potential effect of trade policy uncertainty on firm-level operations. Specifically, every sentence is independently labeled by three researchers with significant background knowledge on

[6] We develop our measure at the sentence level (instead of the word or the text line level), because 1) a sentence is the minimum integral unit of text to convey a message (Ivers, 1991), and a natural place to see meaning flowing from thought to language (Perry, 2013); 2) BERT's creator set the max length limit of a document to be less than 512 tokens because they notice a significant decrease in performance when using documents longer than 512 tokens. The underlying reason is the space complexity of the self-attention model is $O(n^2)$, which makes the modes very resource heavy to fine-tune. As a results, longer sentence will be truncated automatically in Bert model. Hence, we split our MD&A text into sentence, classifier each sentence, and combine the results to the document level.
[7] In this article, we provide a brief introduction on how BERT works. For a more comprehensive understanding of this novel algorithm, please refer to the emerging literature, including Devlin et al. (2019), Rogers et al. (2020), among others.
[8] BERT has 110 million parameters.

financial markets and policy uncertainty. A sentence is labeled as a TPEU related sentence only if all three researchers judge it to belong to TPEU.[9] Our fine-tuned model is based on a sample of 5,300 labeled sentences from our text corpus, of which 592 are related to TPEU, and 4,708 are not related.[10] To be more specific, we randomly partition the full sample of labeled sentences into three parts based on a standard proportion in deep learning algorithms: 80% for training, 10% for validation, and the other 10% for testing (i.e., 4,240, 530, and 530 sentences, respectively). We choose to use a batch size of 8, set the fine-tuning learning rate as $2e^{-5}$, and set the dropout probability to 0.1.

The result of our fine-tuned BERT is the probability that the sentence is related to TPEU. Following the convention of deep learning algorithms in classification tasks, we set the threshold to 0.5.[11] That is, if the probability of a sentence is above 0.5, we identify it as one (i.e., as a TPEU-related sentence), and zero otherwise. The results based on the testing dataset indicate superior performance of the BERT model with an accuracy rate of 99.62%, a recall rate of 96.61%, and an F1 score of 98.28%.

Since the fine-tuned BERT model has reached very high accuracies in identifying TPEU, in the following stage, we apply this model to the MD&A of all the rest A-share listed companies in China during the period of 2007-2019. For each firm year, we first obtain the probability of every sentence in its MD&A being related to TPEU, and then classify that sentence to be a TPEU-related sentence if its probability is equal or greater to the given threshold (i.e., 0.5). Finally, we construct our TPEU measure by counting the number of TPEU-related sentences, scaled by total number of sentences in the MD&A document, formulated as follows:

[9] For instance, the sentence "*These trade policy-related environmental changes made it difficult for the company to predict whether they are opportunities or challenges for us*" is related to trade policy effect uncertainty.

[10] Consistent with Fleiss (1971), we calculate the Fleiss' Kappa statistic (a way to measure agreement between three or more raters) to assess interrater reliability across the three researchers who independently labeled a sentence as a TPEU related sentence or not. Out of an initial sample of randomly selected 6,000 sentences from MD&A disclosures, we kept 5,300 sentences that three researchers universally judge to be related to TPEU (592 sentences) or not related to (4708 sentences). Our estimated Fleiss' Kappa value is 0.76 (i.e., >0.75), suggesting a substantial reliability (Hallgren, 2012; Landis and Koch, 1977).

[11] We find robust results if we set other thresholds such as 0.8 in Kölbel et al. (2020) or the median threshold of our sample as in Siano and Wysocki (2021), suggesting that our final model can effectively discriminate between non-TPEU and TPEU-related sentences.

$$TPEU_{i,t} = \frac{\sum_{s=1}^{S_{it}}\{\mathbf{1}[P_s \geq 0.5]\}}{S_{i,t}} = \frac{\sum_{s=1}^{S_{it}}\{\mathbf{1}[s \in Sentences\ related\ to\ TPEU]\}}{S_{i,t}}, \qquad (1)$$

where the subscripts *i* and *t* denote firm and year, respectively. $S_{i,t}$ is the total number of sentences in the MD&A document and $s = 0, 1, 2, \ldots; S_{i,t}$ are the sentences embedded in a given MD&A document. $\mathbf{1}[\bullet]$ is the indicator function. $P_s$ is the probability for sentence $s$ belongs to TPEU. For expositional purposes, we multiply the measure by 100. Since our TPEU measure is built on the firm-specific MD&A disclosures, it thus dynamically and accurately captures the intensity of trade policy effect uncertainty perceived by top managers of individual firms.

#### *3.2.2. Validations of the TPEU measure*

In order to verify that our newly developed TPEU measure truly captures the idiosyncratic managerial perceptions of trade policy effect uncertainty at the firm level, in this section we provide some empirical patterns and statistical properties of our TPEU measure. Given the nature of TPEU, we believe its measure should not be time-fixed and firm-fixed; it should exert large within-firm variations over time. For validation, we examine **content validity** (i.e., content wise, *does TPEU indeed reflect the management's perception of trade policy effect uncertainty related to firm-level operations?*), **variance decomposition** (i.e., *is TPEU truly idiosyncratic at the firm level?*), and **predictive validity** (i.e., does *TPEU provide significant explanatory power in predicting theoretically expected firm outcomes?*).

**(1) Content validity**

Content validity is "the degree to which a measure captures the domain of which it is intended" (Nunnally and Bernstein, 1994). Following Short et al. (2010), we assess the content validity of TPEU by providing a contextual meaning analysis. Specifically, we first randomly select sentences from MD&A disclosures with a probability above the given threshold (i.e., 0.5), indicating they are related to TPEU classified by the BERT model. Then we manually read these sentences to detect whether they reflect the degree to which a firm's leaders lack understanding of the specific impacts of trade policy changes on its own businesses. Table A1 of the Online Supplement provides exemplar texts suggesting the content validity of our TPEU measure.

**(2) Variance decomposition**

To bolster our claim that the proposed measure indeed captures variation in managers' perceptions of trade policy effect uncertainty at the firm level, we next analyze the extent to which the TPEU measure quantifies firm-level (idiosyncratic) variation. We expect to observe that the majority of the variation in measured TPEU exists at the level of the firm-period, rather than across time or industry (Hassan et al., 2019). We perform variance decomposition by examining how much of the variance in TPEU can be explained by various sets of fixed effects (Hassan et al., 2019).[12] Following Hassan et al. (2019), we estimate TPEU along several specifications and assess the $R^2$ values to capture the portion of the variance of TPEU that is accounted for by fixed effects.

Table A2 of the Online Supplement summarizes the estimated results. Year fixed effects explain 13.0% of the variance in TPEU; industry fixed effects account for an additional 6.0%. Thus, most of the variance in measured TPEU (81.0%) exists at the firm-period level. The results further indicate that firm fixed effects account for 39.9% portion of the variance in TPEU while the residuals capture the majority of the variation, 41.1% (= 81.0% - 39.9%). These findings offer substantial evidence that our measure of TPEU is truly idiosyncratic at the firm level.(i.e., within-firm variation) (Hassan et al., 2019).

**(3) Predictive validity**

Finally, we follow Hassan et al. (2019) and probe the predictive validity of TPEU by assessing the ability of TPEU to predict firm actions/outcomes that result from the underlying construct. Consistent with Hassan et al. (2019), all regressions include firm size, as well as year and industry fixed effects. Table A3 of the Online Supplement documents that TPEU has significantly negative impacts on employment growth rate, suggesting that firms reduce hiring to manage heightened idiosyncratic trade policy effect

[12] Variance decomposition is a well-established and widely accepted approach proposed and applied by economists and management scholars to probe the contributions of a measure at varying (e.g., aggregate-, industry-, or firm-) level of analysis based on the sources of variation (Fitza, 2014; Hassan et al., 2019; Sautner et al., 2022; Sharapov et al., 2021).

uncertainty. A separate regression (reported later in Table 4 of Section 4) indicates that TPEU is significantly negatively associated with firm capital investments. Taken together, these results provide solid evidence showing that TPEU provides significant explanatory power in predicting firm outcomes consistent with the notion that TPEU indeed captures variation in trade policy effect uncertainty.

### *3.3. Measuring firm-level innovation investment*

Following precedence in OSCM and other related disciplines (Chen and Miller, 2007; Eroglu and Hofer, 2014; Gentry and Shen, 2013; Kim and Zhu, 2018; Mackelprang et al., 2015), we use R&D intensity (*RDI*), measured as total R&D expenditures divided by total sales, to capture firm-level innovation investment. As elaborated by Schildt et al. (2012), RDI accurately reveals the relative amount of resources available for knowledge creation and management. Also following prior literature (Cohen et al., 2019; Hirshleifer et al., 2012; Kim and Zhu, 2018), we replace missing R&D values with zeros in our main analysis[13] .

### *3.4. Measuring the moderators*

*Product market competition*. To test Hypothesis 2, we follow prior literature (Gu, 2016; Jiang et al., 2015; Wani et al., 2018) to use the Herfindahl–Hirschman Index (*HHI*) to measure product market competition. The HHI is calculated as the sum of squared market shares:

$$HHI_{jt} = \sum_{i=1}^{N_j} s_{ijt}^2,$$

where $s_{ijt}$ represents the market share of firm *i* in industry *j* in year *t*, $N_j$ is the number of firms in industry *j* in year *t.* The market share of a firm is the ratio of the firm's sales to the total sales of the entire industry. It is important to note that higher HHI indicates weaker product market competition.

*Dependence on foreign sales*. To test Hypotheses 3, we use the proportion of total foreign sales generated by a firm's overseas customers to its total sales to capture the dependence of the firm on its

[13] Please refer to Koh and Reeb (2015) for a review of how previous studies deal with missing values of R&D. Our results are robust if we drop observations with missing R&D expenditures or include an indicator variable for observations with missing R&D values.

foreign markets (*Dependence*). A higher share of foreign sales implies a greater dependence on foreign markets.

*Ownership types.* To test Hypothesis 4, we code the conditioning variable, *SOE*, as one for SOE firms, and zero otherwise.

### *3.5. Control variables*

Consistent with extant research (Fang et al., 2014; Gentry and Shen, 2013; Kim and Zhu, 2018), we control for a set of firm-specific variables including: profitability (*ROA*), indicated by return on assets; firm size (*Size*), calculated as natural logarithm of market capitalization; financial leverage (*Leverage*), computed as total liabilities divided by total assets; sales growth (*Growth*), the change in year-to-year total sales over last year's value; firm age (*Age*), calculated as the number of years since a firm has been publicly listed; stock return (*Return*), defined as the annual return on individual shares without cash dividends reinvestment; tangible assets (*PPE*), which is the net value of property, plant, and equipment scaled by total assets; book-to-market ratio (*BM*), measured as book value divided by market capitalization; capital investment (*CAPITAL*), computed as the percentage of capital expenditures divided by total assets; institutional investors ownership (*IO*), calculated as the proportion of firm shares owned by institutional investors; bankruptcy risk (*Z-Score*), indicated by Altman's Z score. Appendix 1 offers detailed definitions and operationalizations of the variables. We bring in year and industry fixed effects (i.e., two-digit CSRC industrial code) to control for the potential inter-temporal and cross-industry variations. Standard errors are clustered at the firm and year level to alleviate the potential autocorrelation problems (Petersen, 2009).

In short, we estimate the baseline regression as follows:

$$RDI_{i,t} = \beta_0 + \beta_1 TPEU_{i,t-1} + \sum Controls_{i,t-1} + YearFE + IndustryFE + \varepsilon_{i,t}. \quad (2)$$

where the subscripts *i* and *t* denote firm and year, respectively. To capture the causal effect, the main variable of interest is one-year lagged *TPEU,* which allows firms to acquire and respond to information derived from trade policy uncertainty in their investment activities.

## 4. EMPIRICAL RESULTS

### *4.1. Descriptive statistics*

Table 2 reports the means, medians, standard deviations, and correlations among the variables used in our baseline analysis. We observe that the mean value of TPEU is 1.591 with a standard deviation of 1.862, indicating considerable variation across companies. On average, firms in our sample invest 2.9% of their total sales revenue in R&D activities. In addition, we report a significantly negative correlation (-0.168) between TPEU and R&D intensity, which provides preliminary support that a firm's investment in innovation decreases when it perceives increasing trade policy effect uncertainty to its operations.

**Table 2: Descriptive statistics and correlation**

| | Variable | Mean | Median | Std. Dev. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | RDI(t) | 2.888 | 1.620 | 3.949 | **1.000** | | | | | | | | | | | | | | |
| 2 | TPEU(t-1) | 1.591 | 0.990 | 1.862 | **-0.168** | **1.000** | | | | | | | | | | | | | |
| 3 | ROA(t-1) | 0.043 | 0.039 | 0.059 | **0.092** | **-0.095** | **1.000** | | | | | | | | | | | | |
| 4 | Size(t-1) | 15.185 | 15.141 | 1.061 | **-0.022** | **-0.089** | **0.178** | **1.000** | | | | | | | | | | | |
| 5 | Leverage(t-1) | 0.445 | 0.442 | 0.211 | **-0.369** | **0.088** | **-0.364** | **0.151** | **1.000** | | | | | | | | | | |
| 6 | Growth(t-1) | 0.213 | 0.124 | 0.514 | **-0.020** | **-0.079** | **0.234** | **0.018** | **0.046** | **1.000** | | | | | | | | | |
| 7 | Age(t-1) | 10.850 | 10.000 | 6.475 | **-0.303** | **0.016** | **-0.154** | **0.322** | **0.334** | **-0.023** | **1.000** | | | | | | | | |
| 8 | Return(t-1) | 0.195 | -0.037 | 0.746 | **-0.100** | **-0.030** | **0.097** | **0.136** | **0.056** | **0.090** | **-0.038** | **1.000** | | | | | | | |
| 9 | PPE(t-1) | 0.232 | 0.198 | 0.172 | **-0.223** | **0.165** | **-0.132** | -0.002 | **0.102** | **-0.085** | **0.052** | **0.040** | **1.000** | | | | | | |
| 10 | BM(t-1) | 0.606 | 0.606 | 0.241 | **-0.222** | **0.158** | **-0.201** | **-0.106** | **0.334** | -0.006 | **0.113** | **-0.367** | **0.118** | **1.000** | | | | | |
| 11 | Capital(t-1) | 5.221 | 3.736 | 4.963 | **0.030** | **0.050** | **0.134** | **-0.055** | **-0.070** | **0.026** | **-0.240** | -0.004 | **0.300** | **0.021** | **1.000** | | | | |
| 12 | IO(t-1) | 0.464 | 0.489 | 0.237 | **-0.279** | **0.086** | **0.112** | **0.333** | **0.216** | **0.051** | **0.219** | **0.069** | **0.145** | **0.151** | **0.037** | **1.000** | | | |
| 13 | Z-Score(t-1) | 2.642 | 2.143 | 2.110 | **0.313** | **-0.055** | **0.422** | **-0.108** | **-0.767** | **-0.014** | **-0.280** | **-0.041** | **-0.192** | **-0.240** | 0.013 | **-0.136** | **1.000** | | |
| 14 | HHI (t-1) | 0.046 | 0.010 | 0.075 | **-0.027** | **-0.074** | **-0.023** | **-0.053** | **0.047** | **0.032** | **0.023** | -0.016 | **-0.104** | **0.017** | **-0.045** | 0.014 | **-0.030** | **1.000** | |
| 15 | Dependence (t-1) | 0.117 | 0.007 | 0.199 | **0.098** | **0.289** | -0.006 | **-0.054** | **-0.088** | -0.008 | **-0.143** | **-0.018** | **0.034** | **-0.027** | **0.096** | **-0.070** | **0.064** | **-0.118** | **1.000** |
| 16 | SOE (t-1) | 0.450 | 0.000 | 0.498 | **-0.306** | **0.115** | **-0.120** | **0.196** | **0.297** | **-0.059** | **0.409** | **0.041** | **0.222** | **0.199** | **-0.053** | **0.414** | **-0.230** | **0.058** | **-0.130** |

***Note:*** This table reports summary statistics and the Pearson correlations of variables in our baseline analysis. A correlation coefficient in bold indicates a significance level of 1% or less. Variables are defined in Appendix 1.

### *4.2. Results of hypotheses testing*

Hypothesis 1 predicts that firms facing a high level of TPEU will retrench corporate innovation investments. The results presented in Column (1) of Table 3 support this prediction. We show that the coefficient of *TPEU* is negatively significant at the 1% level (coefficient= -0.069, t-statistic= -7.54), suggesting that firms are more cautious investing in innovation activities when they perceive a high level of firm-level uncertainty unleashed through general trade policy changes. Statistically, the results indicate that a one-standard-deviation increase in TPEU is accompanied by a 12.8% (= 0.069*1.862) decrease in a firm's R&D investment, corresponding to a decrease of 4.4% (= 0.128/2.888*100%) relative to the sample mean. Thus, our main hypothesis is supported.

**Table 3 Results of perceived trade policy effect uncertainty on innovation investment**

| DV= RDI (t) | (1) Main effect | (2) HHI | (3) Export markets | (4) SOE |
|---|---|---|---|---|
| TPEU (t-1) | -0.069*** | -0.059*** | -0.065*** | -0.136*** |
| | (-7.54) | (-5.57) | (-5.62) | (-9.58) |
| TPEU (t-1) * Condition (t-1) | | -0.251* | -0.088** | 0.134*** |
| | | (-1.67) | (-2.43) | (7.92) |
| Condition (t-1) | | -4.255*** | 0.571*** | -0.258*** |
| | | (-5.00) | (3.48) | (-4.28) |
| ROA (t-1) | -3.247*** | -3.202*** | -3.195*** | -3.122*** |
| | (-6.36) | (-6.29) | (-6.26) | (-5.98) |
| Size (t-1) | 0.245*** | 0.234*** | 0.244*** | 0.221*** |
| | (10.27) | (9.91) | (10.26) | (9.14) |
| Leverage (t-1) | -1.702*** | -1.697*** | -1.696*** | -1.545*** |
| | (-9.56) | (-9.52) | (-9.52) | (-8.66) |
| Growth (t-1) | -0.036 | -0.040 | -0.041 | -0.049 |
| | (-0.90) | (-1.00) | (-1.04) | (-1.32) |
| Age (t-1) | -0.096*** | -0.094*** | -0.095*** | -0.095*** |
| | (-27.27) | (-26.80) | (-26.87) | (-24.88) |
| Return (t-1) | -0.179*** | -0.207*** | -0.181*** | -0.169*** |
| | (-3.66) | (-4.28) | (-3.70) | (-3.47) |
| PPE (t-1) | -2.023*** | -1.998*** | -2.035*** | -1.883*** |
| | (-15.93) | (-15.80) | (-16.08) | (-14.74) |
| BM (t-1) | -1.940*** | -1.921*** | -1.929*** | -1.880*** |
| | (-18.15) | (-17.99) | (-18.00) | (-17.43) |
| Capital (t-1) | 0.040*** | 0.040*** | 0.039*** | 0.040*** |
| | (8.63) | (8.60) | (8.31) | (8.41) |
| IO (t-1) | -1.207*** | -1.177*** | -1.200*** | -1.134*** |
| | (-12.02) | (-11.74) | (-11.95) | (-10.78) |
| Z-Score (t-1) | 0.169*** | 0.173*** | 0.169*** | 0.182*** |
| | (6.95) | (7.10) | (6.92) | (7.39) |
| Constant | 0.949*** | 1.378*** | 0.901*** | 1.191*** |
| | (2.74) | (3.99) | (2.60) | (3.39) |
| Industry FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Observations | 22,669 | 22,669 | 22,669 | 21,609 |
| $R^2$ | 0.466 | 0.469 | 0.466 | 0.468 |

***Note:*** Variables are defined in Appendix 1. The decreased sample size in Column (4) is due to the missing value of *SOE*. *, ** and *** correspondingly indicates level of significance at 10%, 5% and 1%.

To examine the moderating effects of product market competition (Hypothesis 2), the dependence on foreign markets (Hypotheses 3), and state ownership (Hypothesis 4), we assess the models in Table 3 (i.e., columns 2-4) which include these condition variables (i.e., *HHI*, *Dependence*, and *SOE*) and their interactions with *TPEU*, respectively. As shown in Column (2), the *HHI(t-1)* interaction term coefficient is significantly negative (coefficient= -0.251, t-statistic= -1.67). Because an increasing value of *HHI* represents less product market competition, the result supports Hypothesis 2, which claims that an increase in production market competition will attenuate the negative effect of TPEU on innovation investments. In Column (3), we observe a negative and significant coefficient for the *Dependence(t-1)* interaction term (coefficient= -0.088, t-statistic= -2.43), implying that in firms more dependent on foreign markets, higher levels of TPEU lead to lower innovation investments. This finding supports Hypothesis 3. Results in Column (4) show that the estimated coefficient for the *SOE(t-1)* interaction term is positive and significant at the 1% level (coefficient= 0.134, t-statistic= 7.92), suggesting that SOEs experience a lower decrease in R&D investments when encountered with higher TPEU. Thus, Hypothesis 4 is supported.

### *4.3. Robustness checks*

We perform a battery of robustness checks to fortify our inferences and report the results in Table 4. First, following Cohen et al. (2019), we address the issue of missing R&D expenditure data in two ways. Column (1) in Table 4 presents results of the baseline regression, omitting observations with missing R&D data. Column (2) presents the full data model with an added indicator variable for observations with missing values. Both models provide results that are qualitatively similar to those reported in Table 3. Second, following Kivimaki et al. (2000) and Barker and Mueller (2002), we repeat our baseline results using two alternative R&D intensity measures: 1) the proportion of number of employees with R&D roles to total number of employees (*RDPE*) and 2) the total R&D expenditures spent per employee (*RDEE*) (divided 1000). These analyses also provide consistent results. Third, we replace industry fixed effects with firm fixed effects in our main regression, and find our inferences remain the same. Fourth, as mentioned earlier, we examine the relationship of TPEU to capital investment, a fundamental determinant of firm-level productivity and future performance (Biddle and Hilary, 2006). The results in column (6) indicate that TPEU negatively affects firm-level capital investment, consistent with the findings of prior studies that use broader measures of policy uncertainty (Baker et al., 2016; Cong and Howell, 2021; Jens, 2017; Julio and Yook, 2012). Fifth, we test an alternative TPEU measure, *Exposure*, defined by an indicator variable that equals one if TPEU>0 and zero otherwise. The results shown in Panel B of Table 4 confirm the significant moderating effects supporting hypotheses H2-H4.

**Table 4 Robustness tests: perceived trade policy effect uncertainty and innovation investment**

Panel A: Robustness tests of main effect

| | (1) RDI (t) | (2) RDI (t) | (3) RDPE (t) | (4) RDEE (t) | (5) RDI (t) | (6) Capital (t) |
|---|---|---|---|---|---|---|
| | Drop observations with missing R&D expenses | Control for missing R&D expenses | Alternative innovation measure | Alternative innovation measure | Firm Fixed Effects | Capital investment |
| TPEU (t-1) | -0.126*** | -0.065*** | -0.085*** | -0.354*** | -0.024** | -0.037*** |
| | (-7.84) | (-7.35) | (-3.48) | (-3.45) | (-2.43) | (-2.68) |
| ROA (t-1) | -6.892*** | -3.308*** | -2.810** | 4.016 | -0.954** | 0.692 |
| | (-8.39) | (-6.64) | (-2.16) | (0.84) | (-2.32) | (1.19) |
| Size (t-1) | 0.382*** | 0.196*** | 0.740*** | 6.138*** | 0.311*** | 0.153*** |
| | (10.21) | (8.41) | (10.87) | (23.06) | (8.19) | (5.07) |
| Leverage (t-1) | -2.658*** | -1.472*** | -1.746*** | 2.242 | -0.462** | -0.071 |
| | (-9.24) | (-8.47) | (-3.93) | (1.32) | (-2.38) | (-1.62) |
| Growth (t-1) | -0.223** | -0.022 | 0.519*** | 1.999*** | -0.102*** | 0.000*** |
| | (-2.48) | (-0.58) | (4.57) | (4.79) | (-3.12) | (7.62) |
| Age (t-1) | -0.059*** | -0.067*** | -0.225*** | -0.733*** | -0.087 | -0.045*** |
| | (-11.24) | (-19.13) | (-22.16) | (-19.34) | (-0.64) | (-9.26) |
| Return (t-1) | -0.345*** | -0.180*** | -0.903*** | -1.395*** | -0.075** | 0.209*** |
| | (-4.09) | (-3.79) | (-6.64) | (-3.09) | (-2.19) | (3.66) |
| PPE (t-1) | -3.013*** | -1.820*** | -5.653*** | -24.949*** | -0.188 | 1.432*** |
| | (-13.54) | (-14.93) | (-16.37) | (-17.69) | (-1.01) | (6.91) |
| BM (t-1) | -2.953*** | -2.091*** | -5.030*** | -1.830* | 0.130 | -0.538*** |
| | (-17.89) | (-20.12) | (-17.51) | (-1.70) | (0.97) | (-3.88) |
| Capital (t-1) | 0.061*** | 0.036*** | -0.055*** | -0.071* | 0.024*** | 0.547*** |
| | (8.03) | (7.80) | (-5.16) | (-1.73) | (5.43) | (57.23) |
| IO (t-1) | -1.157*** | -1.105*** | -3.649*** | -10.065*** | -0.724*** | 0.420*** |
| | (-8.85) | (-11.18) | (-13.05) | (-10.13) | (-3.89) | (3.41) |
| Z-Score (t-1) | 0.205*** | 0.165*** | -0.034 | 1.453*** | 0.101*** | -0.006 |
| | (5.98) | (6.90) | (-0.63) | (7.41) | (4.31) | (-1.37) |
| MissingRD (t-1) | ___ | -2.024*** | ___ | ___ | ___ | ___ |
| | ___ | (-40.07) | ___ | ___ | ___ | ___ |
| Constant | 3.333*** | 3.199*** | 1.268 | -66.467*** | -2.360*** | 0.380 |
| | (5.15) | (9.36) | (1.29) | (-17.01) | (-2.75) | (0.85) |
| Year FE | YES | YES | YES | YES | YES | YES |
| Industry FE | YES | YES | YES | YES | NO | YES |
| Firm FE | NO | NO | NO | NO | YES | NO |
| Observations | 14,949 | 22,669 | 22,669 | 22,669 | 22,669 | 22,663 |
| $R^2$ | 0.381 | 0.491 | 0.509 | 0.362 | 0.828 | 0.435 |

Panel B: Robustness tests of moderation effects

| DV= RDI (t) | (1) Competition | (2) Export markets | (3) SOE |
|---|---|---|---|
| Exposure (t-1) | -0.043 | -0.022 | -0.296*** |
| | (-0.86) | (-0.41) | (-4.12) |
| Exposure (t-1) * Condition (t-1) | -0.472*** | -0.904*** | 0.498*** |
| | (-3.52) | (-2.63) | (5.50) |
| Condition (t-1) | -3.859*** | 1.224*** | -0.390*** |
| | (-4.61) | (3.64) | (-4.60) |
| ROA (t-1) | -3.123*** | -4.152*** | -3.053*** |
| | (-6.14) | (-7.93) | (-5.85) |
| Size (t-1) | 0.231*** | 0.254*** | 0.219*** |
| | (9.79) | (10.45) | (9.04) |
| Leverage (t-1) | -1.705*** | -1.613*** | -1.544*** |
| | (-9.56) | (-8.89) | (-8.65) |
| Growth (t-1) | -0.035 | -0.006 | -0.038 |
| | (-0.89) | (-0.16) | (-1.01) |
| Age (t-1) | -0.095*** | -0.108*** | -0.097*** |
| | (-26.99) | (-29.98) | (-25.46) |
| Return (t-1) | -0.204*** | -0.135*** | -0.168*** |
| | (-4.22) | (-2.70) | (-3.46) |
| PPE (t-1) | -2.046*** | -2.680*** | -1.953*** |
| | (-16.18) | (-20.97) | (-15.29) |

| | | | |
|---|---|---|---|
| BM (t-1) | -1.964*** | -1.771*** | -1.940*** |
| | (-18.39) | (-16.32) | (-17.99) |
| Capital (t-1) | 0.041*** | 0.037*** | 0.041*** |
| | (8.71) | (7.74) | (8.63) |
| IO (t-1) | -1.179*** | -1.260*** | -1.161*** |
| | (-11.76) | (-12.18) | (-11.04) |
| Z-Score (t-1) | 0.171*** | 0.154*** | 0.182*** |
| | (7.03) | (6.19) | (7.38) |
| Constant | 1.386*** | 0.814** | 1.292*** |
| | (4.01) | (2.30) | (3.65) |
| Industry FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Observations | 22,669 | 22,669 | 21,609 |
| $R^2$ | 0.468 | 0.437 | 0.468 |

***Note:*** The definitions of the variables are provided in Appendix 1. *, ** and *** correspondingly represents significance level at 10%, 5% and 1%.

### *4.4. Addressing endogeneity*

The foregoing results provide strong support for the validity of our TPEU measure and robust support for our hypotheses. However, the potential for TPEU to be correlated with trade policy state uncertainty raises the prospect of endogeneity. We address this concern in two ways. Our first strategy is to examine the different net impacts of effect uncertainty and state uncertainty on firm innovation investment (Sections 4.4.1 and 4.4.2). Our second strategy is to apply a quasi-natural experiment to alleviate this and other potential endogeneity concerns (Section 4.4.3).

#### *4.4.1. The effect of trade policy state uncertainty*

Aragon-Correa and Sharma (2003) predict that perceived state uncertainty influences a firm's proactive activities to prepare for the unpredictable situations. Therefore, trade policy state uncertainty, omitted in our baseline analysis, could endogenously drive our findings regarding the TPEU-innovation investment relationship. To address this potential problem, we use an aggregate trade policy uncertainty index derived from newspapers in mainland China developed by Davis et al. (2019) (Davis–Liu–Sheng index, hereafter *DLS Index*)[14] to proxy for trade policy state uncertainty. Such a proxy seems appropriate because it reflects a macro-level public perception of the predictability of the future state (Milliken, 1987). We estimate two models to evaluate the impacts of trade policy state uncertainty. In the first model, we

[14] The data are available on the website at: https://www.policyuncertainty.com/china_monthly.html by the curtesy of the authors.

replace TPEU with the DLS index. In the second model, we include both the DLS index and our firm-specific TPEU.[15]

The results in Table 5, Column (1) show that the coefficient of DLS index (3.216) alone is positively significant at the 1% level (t= 21.05), implying that macro-level trade policy uncertainty (i.e., trade policy state uncertainty) generally propels firms to increase innovation investments. Statistically, the results indicate that a one-standard-deviation increase in the DLS index is accompanied by a 50.5% (= 3.216*0.157)[16] increase in a firm's R&D investment, corresponding to an increase of 17.5% (= 0.505/2.888*100%) relative to the sample mean. The results of the second model, reported in Column (2) confirm that firm-specific TPEU remains negatively associated with firm R&D investments, while trade policy state uncertainty (i.e., DLS index) is still positively associated with firm innovation investment. These opposing effects of TPEU and the DLS index are in line with the theoretical predictions by Aragon-Correa and Sharma (2003).

**Table 5 The effect of perceived state uncertainty on innovation investment**

| | (1) RDI (t) | (2) RDI (t) |
|---|---|---|
| TPEU (t-1) | ___ | -0.156*** |
| | ___ | (-17.74) |
| DLS Index (t-1) | 3.216*** | 2.987*** |
| | (21.05) | (19.46) |
| ROA (t-1) | -4.463*** | -4.598*** |
| | (-8.70) | (-9.00) |
| Size (t-1) | 0.488*** | 0.460*** |
| | (22.81) | (21.48) |
| Leverage (t-1) | -2.478*** | -2.388*** |
| | (-13.84) | (-13.35) |
| Growth (t-1) | -0.024 | -0.056 |
| | (-0.62) | (-1.42) |
| Age (t-1) | -0.091*** | -0.090*** |
| | (-25.40) | (-25.09) |
| Return (t-1) | -0.424*** | -0.428*** |
| | (-14.15) | (-14.38) |
| PPE (t-1) | -2.518*** | -2.322*** |
| | (-19.24) | (-17.76) |
| BM (t-1) | -1.758*** | -1.585*** |
| | (-16.84) | (-15.15) |
| Capital (t-1) | 0.035*** | 0.035*** |
| | (7.26) | (7.28) |
| IO (t-1) | -1.793*** | -1.697*** |
| | (-17.80) | (-16.90) |
| Z-Score (t-1) | 0.163*** | 0.168*** |

[15] Due to the inclusion of *DLS Index*, we don't include year fixed effects in the table as they are perfectly collinear with each other (Wooldridge, 2009).
[16] The DLS index has a mean value of 0.158 with a standard deviation of 0.157.

| | | |
|---|---|---|
| | (6.61) | (6.85) |
| Constant | -0.797** | -0.333 |
| | (-2.50) | (-1.05) |
| Industry FE | YES | YES |
| Observations | 22,669 | 22,669 |
| $R^2$ | 0.433 | 0.438 |

***Note:*** Variables are defined in Appendix 1. *, ** and *** correspondingly represents significance level at 10%, 5% and 1%.

### *4.4.2. Two-stage regression analysis*

To further minimize the endogeneity concern that TPEU may be affected by trade policy state uncertainty, we construct a measure of *abnormal* trade policy effect uncertainty (*ATPEU*) by performing a two-stage regression analysis. In the first step, we regress the raw value of TPEU on our proxy for trade policy state uncertainty (i.e., the DLS index) and a series of firm-level fundamental characteristics that might affect TPEU, as formulated in the regression model below:

$$TPEU_{i,t} = \alpha_0 + \alpha_1 Size_{i,t} + \alpha_2 ROA_{i,t} + \alpha_3 Loss_{i,t} + \alpha_4 Coverage_{i,t} + \alpha_5 BM_{i,t}$$

$$+\alpha_6 RetVol_{i,t} + \alpha_7 DLS\ Index_{i,t} + IndustryFE + \varepsilon_{i,t}. \quad (3)$$

where the subscripts *I* and *t* denote firm and year, respectively. Control variables include firm size (*Size*), financial performance captured by return on assets (*ROA*) and financial losses (*Loss*), analyst coverage (*Coverage*), the book-to-market ratio (*BM*), firm-specific stock return volatility (*RetVol*), and trade policy state uncertainty (*DLS Index*). Table A4 of the Online Supplement provides detailed descriptions of this analysis and the results.

We estimate *ATPEU* as the residual from the regression. Since we include a measure of trade policy state uncertainty in the first-stage analysis, the residual reflects the firm-specific (idiosyncratic) TPEU that, statistically speaking, is orthogonal to trade policy state uncertainty. In our second-stage analysis, we replace *TPEU* with *ATPEU*, and include the DLS index in the model. Results are tabulated in Table 6. We find that ATPEU and the DLS index still have significant and opposing effects (negative and positive, respectively) on firm innovation investment. The signs, magnitudes, and statistical significances of the corresponding coefficients are qualitatively consistent with those reported in Table 5. These results again support the validity of the TPEU measure and our findings regarding its effect on innovation investment.

**Table 6 Two-stage analysis: Perceived trade policy effect uncertainty and innovation investment**

| | (1) RDI (t) |
|---|---|
| ATPEU (t-1) | -0.153*** |
| | (-16.88) |
| DLS Index (t-1) | 3.144*** |
| | (20.60) |
| ROA (t-1) | -4.342*** |
| | (-8.50) |
| Size (t-1) | 0.475*** |
| | (22.18) |
| Leverage (t-1) | -2.395*** |
| | (-13.38) |
| Growth (t-1) | -0.057 |
| | (-1.44) |
| Age (t-1) | -0.090*** |
| | (-25.26) |
| Return (t-1) | -0.440*** |
| | (-14.75) |
| PPE (t-1) | -2.332*** |
| | (-17.83) |
| BM (t-1) | -1.797*** |
| | (-17.23) |
| Capital (t-1) | 0.035*** |
| | (7.39) |
| IO (t-1) | -1.699*** |
| | (-16.90) |
| Z-Score (t-1) | 0.169*** |
| | (6.85) |
| Constant | -0.699** |
| | (-2.20) |
| Industry FE | YES |
| Observations | 22,660 |
| $R^2$ | 0.437 |

***Note:*** Variables are defined in Appendix 1. The decreased sample size is due to the one-year lagged *ATPEU*. *, ** and *** correspondingly represents significance level at 10%, 5% and 1%.

### *4.4.3. Difference-in-differences analysis: A quasi-natural experiment*

The year 2018 witnessed the outbreak of an escalating trade war, primarily between the United States and China. This period of events involving the world's two largest GDP economies generates plausibly exogenous variation in TPEU and thus offers a natural setting to strengthen our baseline analysis (Lam et al., 2022). We predict that the negative effect of TPEU on firm innovation investment is exacerbated after the 2018 trade war.

To test this prediction, we run a difference-in-differences analysis, formulated as follows:

$$RDI_{i,t} = \beta_0 + \beta_1 TPEU_{i,t-1} + \beta_2 POST2018 * TPEU_{i,t-1} + \beta_3 Treat_i * TPEU_{i,t-1}$$
$$+ \beta_4 POST2018 * Treat_i * TPEU_{i,t-1} + \beta_5 POST2018 * Treat_i + \beta_6 Treat_i$$
$$+ \sum Controls_{i,t-1} + YearFE + IndustryFE + \varepsilon_{i,t}. \quad (4)$$

Where *POST2018* is a dummy variable equal to one for the periods after year 2018, and zero otherwise. *Treat* is also a dummy variable equal to one if a firm's dependence on sales from overseas market is above the sample median in the year prior to the 2018 US-China trade war (i.e., year 2017), and zero otherwise. We classify firms that are more dependent on foreign market sales as treatment firms because they are more vulnerable to trade policy uncertainty. In this analysis, we limit our sample to firms that were publicly listed in the year prior to 2018 US-China trade war. Our independent variable of interest is the three-way interaction term *Treat*POST2018*TPEU(t-1)*.

Table 7 reports the corresponding results, including a significantly negative coefficient on the three-way interaction term (coefficient= -0.189, t-statistic= -2.49). This result indicates that, relative to control firms, treatment firms experienced greater decreases in innovation activities under heightened perceived trade policy effect uncertainty after the unexpected outbreak of the 2018 U.S.-China trade war.

**Table 7 Difference-in-differences analysis: A quasi-natural experiment**

| | (1) RDI (t) |
|---|---|
| TPEU (t-1) | -0.033** |
| | (-2.26) |
| POST2018 * TPEU (t-1) | -0.080* |
| | (-1.70) |
| Treat * TPEU (t-1) | -0.043** |
| | (-2.31) |
| Treat * POST2018 * TPEU (t-1) | -0.189** |
| | (-2.49) |
| Treat * POST2018 | 0.681*** |
| | (4.64) |
| Treat | 0.236*** |
| | (3.40) |
| ROA (t-1) | -3.154*** |
| | (-6.09) |
| Size (t-1) | 0.231*** |
| | (9.51) |
| Leverage (t-1) | -1.686*** |
| | (-9.32) |
| Growth (t-1) | -0.055 |
| | (-1.36) |
| Age (t-1) | -0.093*** |
| | (-25.92) |
| Return (t-1) | -0.174*** |
| | (-3.50) |
| PPE (t-1) | -1.997*** |
| | (-15.54) |
| BM (t-1) | -1.960*** |
| | (-18.20) |
| Capital (t-1) | 0.040*** |
| | (8.33) |
| IO (t-1) | -1.157*** |

| | |
|---|---|
| | (-11.47) |
| Z-Score (t-1) | 0.178*** |
| | (7.16) |
| Constant | 0.939*** |
| | (2.67) |
| Industry FE | YES |
| Year FE | YES |
| Observations | 22,376 |
| $R^2$ | 0.468 |

***Note:*** Variables are defined in Appendix 1. *, ** and *** correspondingly indicates significance level at 10%, 5% and 1%.

## 5. DISCUSSION

Trade policy changes are among the most challenging externalities to predict, mainly because policymakers have a wide array of varied interests (Aharoni et al., 1981). Our study responds to concerns that prior OSCM research has paid scant attention to the implications of policy dynamics (Fugate et al., 2019; Helper et al., 2021; Tokar and Swink, 2019). Tokar and Swink (2019) highlight trade restrictions as one of the most prominent policy issues affecting OSCM in recent years. They note that uncertainties caused by events such as the U.S.-China and U.S.-EU trade wars and Brexit have been largely ignored by OSCM researchers. Such events shape priorities and options for operations mangers who must make strategic decisions affecting capital investments, sourcing decisions, location and network strategies, and, as we demonstrate in this study, innovation investments.

Hassan et al. (2019) observe that the greatest variation in impacts from policy uncertainties occurs at the firm level. Hence, firms implement various strategies to mitigate policy risks (Darby et al., 2020). Both ROT and RDT suggest that firms facing intense uncertainty will evaluate and pursue options that protect their operational activities against threats of resource shortage (Pfeffer and Salancik, 1978). Accordingly, the findings from our study indicate that such firms reduce their innovation investments, likely taking a wait-and-see posture to mitigate risks associated with TPEU. Even though broader trade policy state uncertainty tends to encourage innovation, firm operational leaders appear to be more cautious when making long-term innovation investments under high level of trade policy effect uncertainty. However, we also find that the negative impact of TPEU to firm innovation investments is less significant for firms that operate in three environments where resource conditions lower the value of a wait-and-see option. First, in highly competitive product markets, access to demand and supply are threatened by a wait-and-see option. The cost of not innovating is higher, as it risks loss of competitive advantage or even loss of continued market participation. Second, when firms mostly compete domestically (have lower foreign sales), the negative influence of TPEU on innovation is lessened because firm performance is less dependent on trade policy uncertainties. In this situation, losing access to foreign demand because of a wait-and-see approach is less important to firm performance. Third, state ownership provides advantageous access to resources, thereby serving as a hedge against the risks of trade policy uncertainties and lessoning the value of a wait-and-see approach. Interestingly, the estimates from our data models indicate that, at their highest levels, these moderating effects overcome the direct effect of TPEU, such that TPEU would not be that important as a predictor of the innovation investment of state-owned firms who operate in highly competitive, domestically focused markets.

These findings extend literature that examines resource dependency factors as important contingencies to the effects of environment on operational decisions (Handfield, 1993; Paulraj and Chen, 2007; Singh et al., 2011). More specifically, our theory and findings help to explain the inconsistent results of prior studies of the impacts of policy uncertainty on firm innovation investments. Comprehensions of varying measurements of policy uncertainty and resource dependence are useful in interpreting foregoing studies. Table 1 lists three studies that demonstrate a positive relationship between policy uncertainty and firm innovation activity (Atanassov et al., 2019; Guan et al., 2021; Shen and Hou, 2021). Shen and Hou (2021) and Guan et al. (2021) measure policy uncertainty using the newspaper-announcement-based indices developed by Baker et al. (2016) and Davis et al. (2019), respectively. Both measures assess state uncertainty; they are not firm specific. The positive uncertainty-innovation relationships uncovered in these studies are confirmed by our finding that trade policy state uncertainty encourages innovation investment. Moreover, Shen and Hou (2021) find that the strength of the positive uncertainty-innovation relationship is weakened for state-owned firms; and Guan et al. (2021) find that rising product market competition amplifies the positive uncertainty-innovation relationship. A resource dependence perspective explains these effects. The relationship between uncertainty and innovation is weakened when access to resources is at lower risk (i.e., guaranteed by state-ownership), and strengthened when innovation is a means for acquiring resources (i.e., competition for access to demand and supply markets).

Atanassov et al. (2019) employ a different proxy for policy state uncertainty. Their study of political uncertainty regarding election outcomes and policies also demonstrates a positive uncertainty-innovation relationship. Again, this finding is consistent with our finding regarding trade policy state uncertainty (i.e., DLS index). In addition, RDT helps to explain the moderating effects of industry specific characteristics uncovered in the Atanassov et al. (2019) study. They find that the positive uncertainty-innovation relationship is strengthened for firms in highly regulated industries, in high competition and high growth industries, and in "hard-to-innovate" industries (characterized by long and technically uncertain innovation projects). In each of these industry settings, innovation is a more important basis for competition and access to resources.

The two studies that report a negative relationship of uncertainty and innovation (Table 1) are qualitatively different than the foregoing three studies, in ways underscored by our findings. Liu and Ma (2020) provide empirical support for the argument that trade liberation (China's accession to WTO) reduces uncertainty about firms' access to markets, thereby increasing their incentives to innovate. Similar to our finding regarding resource access enabled by state-ownership, the Liu and Ma (2020) result suggests that more certain access to resources (demand and supply markets) encourages innovation, or at least makes a firm less susceptible to the negative influence of TPEU. Similarly, Cong and Howell (2021) find that the Chinese government's suspension of initial public offering (IPO) approvals increases uncertainty regarding access to public equity (capital resources), thereby decreasing firm innovation activity. This result is consistent with our finding that less preferential access to resources (i.e., the non-SOEs) increases the negative effect of TPEU on innovation.

In sum, the foregoing mixed findings of policy uncertainty-innovation research can be reconciled when one considers the opposing effects of state and effect uncertainty while also considering the influences of policy uncertainty and innovation activities to resource access risk. When increases in trade policy state uncertainty put resource access at risk, firms tend to respond by increasing innovation investments. In other words, resource dependent firms (e.g., those that participate in competitive, regulated, or otherwise challenging industries, and are not state-owned) will increase innovation investments when state uncertainty is high to maintain or improve resource access and to capitalize on opportunities. This positive innovation effect, especially in contexts where innovation is necessary to acquire resources, counters the influence of trade policy effect uncertainty on firm innovation, which is uniformly negative.

Our study highlights the need to clearly delineate and measure trade policy state and effect uncertainties in future research. A more complete understanding of how effect uncertainty contributes to firm-level operations decisions seems a promising objective. However, a key barrier for scholars to move forward lies in the difficulty to appropriately quantify firm-specific effect uncertainty. We offer our application of a state-of-the-art deep learning algorithm, BERT, as a useful approach to develop a context-dependent measure of firm-specific TPEU. This advanced deep learning approach outperforms conventional textual analysis methods by addressing the key challenges in traditional methods: context independence (Devlin et al., 2019; Loughran and McDonald, 2016); susceptibility to human error (Liu et al., 2020); incapability of adapting to dynamic business world (Li et al., 2021); understatement of the importance of the narrative information (Donovan et al., 2021); and a high rate of Type I errors (Brown et al., 2021). Our approach appears to provide a valid proxy of trade policy effect uncertainty that is distinct from broader measures used in the literature. Existing measures appear to more closely reflect state uncertainty, rather than firm-specific effect uncertainty (Baker et al., 2016). Our state-of-the-art method allows us to significantly improve upon older NLP methods, contributing to a small but growing literature that uses NLP methods to extract trade policy uncertainty-relevant information in text-based data. This novel measurement approach might be extended to enable researcher to address the more specific strategic responses to environmental uncertainty envisioned by Aragon-Correa and Sharma (2003) conceptual thesis. In particular, they suggest that firms facing state uncertainty tend to be more preemptive and risk taking, while firms facing effect uncertainty pursue less resource intensive tactics. Moreover, the concept of TPEU is readily applicable to studies across multiple reference disciplines of OSCM such as Strategic Management, Economics, Finance, and Accounting. Presumably our measurement approach could be of use in those domains.

### *5.1. Theoretical and managerial implications*

This study makes several contributions to the OSCM literature. First, we enrich the literature on the impacts of environmental uncertainty on firm-level decisions. Whereas most prior OSCM research addresses environmental uncertainty stemming from changes in demand or technology, we address trade policy uncertainty, a factor that appears to be of rising importance to operational decision makers (Helper et al., 2021; Tokar and Swink, 2019). Second, we add to the growing interest of OSCM researchers in policy effects on operational decisions and behaviors; our study fits the first "type" of public policy research identified by Helper et al. (2021, p. 792): "uncovering the impact of public policy on the operations and supply chains of organizations outside the public sector." Recent studies of firm-level operational impacts focus on factors such as political risk (Charpin et al., 2021), social and environmental regulations (Cousins et al., 2020; Dhanorkar et al., 2018; Sautner et al., 2020), and government interventions in markets (Jia and Zhao, 2017; Nguyen and Kim, 2019; Phadnis and Joglekar, 2021; Roca and O'Sullivan, 2020). Along with Darby et al. (2020), our study is one of the first in the OSCM literature to address trade policy as a driver of operational decisions, thus addressing the "Finance and Financial Sector" area of policy research identified by Tokar and Swink (2019). Moreover, Helper et al. (2021, p. 791) note that public policy studies in OSCM "tilt heavily towards certain policy domains, most notably healthcare and the environment"; they encourage OSCM researchers to address broader issues. We believe that our study meets this encouragement.

Importantly, the foregoing discussion of our findings in light of the mixed findings of prior research provides a useful step toward a unifying view of policy uncertainty's effects on innovation, and perhaps other firm investment activities. It appears that a clearer understanding of uncertainty operationalization issues, coupled with a resource dependence perspective can serve to harmonize past findings while also providing a foundation for future research designs. We expect that a greater understanding of how effect uncertainty affects operational decisions will help to provide indications of the unintended consequences of policy decisions for firm behaviors (Tokar and Swink, 2019).

Our findings extend several considerations for managers and policymakers. Managers have options in how they respond to policy risk, including engaging in political action (e.g., lobbying), buffering (e.g., hedging, inventory, or capacity), and reducing resources at risk (e.g., minimizing commitments or investments). Before pursuing these options, however, managers should consider the costs and benefits of reducing the uncertainties that drive risk. Our results indicate that trade policy effect uncertainty (as proxied by TPEU) varies significantly across firms. Assuming that effect uncertainty can be managed, managers should consider the potential for investments in research, scanning, and analysis to lower idiosyncratic effect uncertainty. Such improvements could prove to be a source of competitive advantage. Moreover, institutional theory suggests that firms imitate each other (Zhu et al., 2013), specifically when environments are highly uncertain, so it is essential for managers to comprehend how firm-specific effect uncertainty is driven by policy risk as opposed to the actions of competitors. These possibilities lead to other important questions: How good are managers at gaging the long-term costs of postponed or reduced innovation investments? How are current policy uncertainties influencing resource requirements and resource access risk in our competitive environment? What are the trade-offs between resource requirements for innovation and resource access created by innovation? While a wait-and-see approach offers option value (by preserving certain options), innovation projects also offer option value (e.g., through learning and new market opportunities) that may be undervalued in times of uncertainty.

Policymakers face decision-making environments that are complex and ambiguous, while also involving many stakeholders (Helper et al., 2021). The challenge of unintended consequences is well recognized (Tokar and Swink, 2019), yet time constraints and political processes often hinder thorough consideration of a policy's non-immediate impacts on all stakeholders (Sowell, 2009; Tokar and Swink, 2019). Our findings indicate that policy makers should consider the effects of both trade policy state uncertainty and effect uncertainty, not only on current economic conditions, but on longer term suppression of market and technology advances via reduced innovation investments. Political leaders might improve the quality of their decisions if they had a more nuanced understanding not only of the general uncertainty introduced by policy dynamics, but of difficulties that potentially innovative firms might have in interpreting and effectively responding to policy changes. Our results indicate that the influences of idiosyncratic trade policy effect uncertainty effects are quite substantial, driving 10% or more reductions in firm innovation investments that likely have very large impacts on future economic value. Such impacts could be viewed as another instance in which significant future gains are sacrificed for short-term economic or political ends (Tokar and Swink, 2019). Given these important impacts, policymakers should consider ways in which they could reduce both state and effect uncertainties. Darby et al. (2020) suggest that published regulatory impact analyses could help. We also suggest that clear statements of timeframes and areas of application will aid innovation managers who seek to estimate the relative values of the risk mitigation approaches available to them. In summary, our findings imply that, when making policies, government should not only deliberate possible effect of their decisions on one narrow domain (i.e., trades, supply chains, etc.); they should also think about the impacts of broader uncertainties engendered by policy decisions.

### *5.2. Limitations and implications for future studies*

This study exhibits several limitations. First, while the sample frame of the study comprises of publicly listed firms in China, i.e., an ideal setting to examine the impacts of trade policy effect uncertainty, we acknowledge the generalizability of our findings to studies taking places in other economies might be limited. Future studies that replicate ours in other countries such as in the U.S and EU are greatly encouraged. Further, research could explore the broader effects on stakeholders affected by firm-level innovation decisions. The long-term effects of TPEU-induced reductions in innovation are not known. Future research of both the firm-level and industry-level impacts of innovation reductions might bring further insight to policy makers who drive trade policy uncertainty. For example, what are the longer-term effects on firms in trade-partner nations (i.e., major customers)? What are the effects on the suppliers of innovating firms? Second, we investigate how firms react to the TPEU in their innovation resources allocation; future research can explore the implications of TPEU to other operations decisions, such as changes to distribution and supply networks, inventory stock levels, capacity expansions and contractions, among others. Third, we focus on understanding trade policy effect uncertainty, while controlling for broader state uncertainty. Aragon-Correa and Sharma (2003) conceptualize a third type of uncertainty, "decision response uncertainty," that may also be relevant to the policy environment we study. Moreover, future research might consider further improvements on operationalizations and measurements of these factors, as well as how they may interact to affect decision making.

## Appendix 1 Variable definitions

| Variable | Definitions |
|---|---|
| TPEU | Measure of perceived trade policy effect uncertainty at the firm level, measured as the percentage of the number of perceived trade policy effect uncertainty sentences on total number of sentences in the MD&A section of annual reports. |
| Exposure | An indicator variable that equals one if the firm is subject to trade policy effect uncertainty (i.e., TPEU>0), and zero otherwise. |
| RDI | The percentage of total R&D expenses on total sales. Missing R&D values are set to zero. |
| DLS Index | A monthly measure of macro trade policy uncertainty derived from newspapers in mainland China developed by Davis et al. (2019). We calculate the annual DLS index as the average of monthly indexes within a year and scale it by $10^3$. |
| Size | Natural logarithm of market capitalization, calculated at the end of the fiscal year as price close multiplied by the number of shares outstanding. |
| Growth | The change in year-to-year total sales over last year's value. |
| Loss | A dummy variable equal to one if the firm reports negative earnings. |
| Coverage | The number of analysts issuing estimates during a fiscal year before the earnings announcement. Missing values are set to zero. |
| BM | Book-to-market ratio, measured as book value divided by market capitalization. |
| Age | The number of years since a firm has been publicly listed. |
| RetVol | The standard deviation of the monthly stock returns over the fiscal year. |
| ROA | Return on assets defined as net income before extraordinary items scaled by total assets. |
| Leverage | Total liabilities divided by total assets. |
| Return | Annual return on individual shares without cash dividends reinvestment. |
| PPE | Net value of property, plant, and equipment scaled by total assets. |
| Capital | The percentage of capital expenditures divided by total assets. |
| IO | The proportion of firm shares owned by institutional investors. |
| Z-Score | Measured as 1.2 * (current asset – current liabilities) / total assets + 1.4 * retained earnings / total assets + 3.3 * earnings before interest and taxes / total assets + 0.6 * market value of equity / total liabilities + 0.999 * sales / total assets. |
| RDPE | Number of R&D personnel scaled by total number of employees. Missing values are set to zero. |
| RDEE | Total R&D expenses scaled by total number of employees and then divided by $10^3$. Missing values are set to zero. |
| HHI | The sum of squared market shares for all firms in the same industry, where the market share of an individual firm is the proportion of the firm's sales to the entire industry's sales. |
| SOE | A dummy variable equal to one if the firm is a state-owned enterprise, and zero otherwise. |
| Dependence | The ratio of foreign sales to total sales. |
| POST2018 | A dummy variable equal to one for the periods after year 2018, and zero otherwise. |
| Treat | A dummy variable equal to one if a firm's dependence on sales from overseas market is above the sample median in the year prior to the 2018 US-China trade war (i.e., year 2017), and zero otherwise. |

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