Foreign Political Risk and Technological Change

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Abstract

This paper studies how innovation reacts to foreign political risk and shapes its economic consequences. In a model with foreign political shocks that can disrupt foreign supply, we show that greater political risk abroad increases domestic innovation, thereby lowering reliance on risky sourcing countries. We then combine data on sector-level technology development with time-varying measures of industry-level exposure to foreign political risk and report three sets of empirical findings. First, sectors and commodities with higher exposure to foreign political risk exhibit significantly greater innovative activity. This finding holds across sectors in the US, across country-sector pairs in a global sample, and across critical minerals. Second, the response of innovation is particularly strong when risk emanates from geopolitical adversaries. This is consistent with our finding that trade restrictions are more likely to emerge between non-allies following a rise in political risk in either country. Third, directed innovation reduces countries' reliance on imports from risky foreign markets. In doing so, technological change abroad amplifies the negative effects of domestic political risk on export performance.

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1 Introduction

Foreign political risk and geopolitical conflict can affect access to key inputs, shaping productivity and well-being. Motivated by rising global tension and the clear relationship between politics and international economic ties, there is growing interest in modeling optimal government intervention in environments where countries can exert their influence over foreign nations (e.g., Clayton, Maggiori, and Schreger, 2023, 2025; Maggi and Ossa, 2023; Mohr and Trebesch, 2025). However, there is little evidence documenting how firms and countries react in practice to foreign threats to production and whether these responses mediate the economic impacts of political turmoil.

A range of examples suggest that innovation may be an important mechanism of adaptation to foreign political risk. For example, rising investment in US rocketry coincided with mounting political risk in Russia, which had been supplying the engine for the Atlas V rocket used in US launches. In a 2014 senate hearing, Elon Musk argued that "the Atlas V cannot possibly be described as providing assured access to space [...] when supply of the main engine depends on President Putin's permission" (Business Insider, 2014). Similarly, in response to rising political uncertainty in the US after the 2024 election, the European Union made a major push to invest in research and development for military capabilities in order to free itself from what it views as excessive reliance on US weapons and equipment (Atlantic Council, 2025). There are many examples of innovation in mineral extraction and processing in response to rising violence in regions with mineral deposits, in an effort to insure against the loss of key inputs (e.g., Vespignani and Smyth, 2024). Thus, a broad set of cases highlights how innovation can react to foreign political threats, potentially reshaping their impacts on domestic production and foreign reliance.

This paper investigates how innovation, both in the US and around the world, reacts to foreign political risk. Does technology development systematically shift toward more risk-exposed industries? If so, what are the underlying mechanisms? And how does induced innovation mediate the impacts of political risk on international sourcing patterns?

We begin our analysis with a simple model to formalize the relationship between foreign political risk, innovation, and trade. There are two countries, Home and Foreign. Producers in Home can produce using either a domestic or an imported input, are heterogeneous in their productivity, and can invest in innovation to increase their productivity at a cost. With some likelihood, political risk abroad will lead to production disruptions or trade restrictions of some intensity, increasing import costs. In this way, foreign political risk potentially generates both bad news and uncertainty.[1] A rise in the likelihood or intensity of foreign political shocks drives greater domestic innovation, raising productivity and reducing reliance on foreign inputs. Foreign loses exports to Home even when the adverse shock does not materialize, and the effect scales with the intensity of Home's technological response. Moreover, to the extent that trade restrictions (e.g., tariffs and sanctions) are more likely to emerge between geopolitical adversaries, the response should be larger for threats emanating from non-allies. Beneath these aggregate effects are complicated firm-level responses, driven by intermediate-productivity firms innovating for "insurance" and high-productivity firms responding to equilibrium price changes—all while, paradoxically, the most import-exposed firms never innovate. This motivates an empirical analysis at the sector level, where the model makes clear and testable predictions and where the direction of innovation and patterns of trade are determined.

To investigate these questions empirically, we combine data on global innovation and political risk. We compile the universe of patents filed in the US from the PatentsView database. This allows us to measure technology investment by topic or sector over time, along with detailed information about the inventors and citation patterns. As an alternative proxy for technology development, we collect data on all R&D investments by US public firms from Compustat. To measure time-varying political risk (e.g., internal conflict, expropriation) we use the International Country Risk Guide (ICRG), the longest-running comprehensive database cataloging country-level political risk and turmoil. We combine all ICRG political risk measures into a single index for each country and year. To measure political ties across *country pairs*, we assemble data on political alliances between countries from Correlates of War (CoW) and Alliance Treaty Obligations and Provisions Project (ATOP), as well as information on UN voting similarity.

We begin with a case study of political risk and innovation in an economically important field where risk-exposure is (in part) geographically determined: minerals. Supply risk and innovation related to minerals have received substantial attention because of both the importance of many minerals inputs to many modern technologies and the fact that mineral deposits are concentrated in regions with substantial political turmoil (e.g., Schulz, 2017). To measure exposure to political risk at the level of each mineral and year, we weight political risk in each country-year by that country's mineral-specific deposit share. We find that increased exposure to political risk for a given mineral are followed

[1]Thus, our use of the word "risk" aligns with its common usage: "possibility of loss or injury" (Merriam-Webster, 2025). We are not studying the effects of pure second moment (uncertainty) shocks.

by an increase in both patents that mention that mineral and citations thereof. The effect is larger over longer time horizons, perhaps because innovation takes time to ramp up and is more responsive to persistent changes in risk. This is a first indication that increases in political risk are met with innovative activity to mitigate their adverse consequences.

To determine whether this finding is systematic and to investigate its underlying mechanisms, we study the relationship between foreign supply risk and innovation across all US sectors. We construct a measure of foreign political risk exposure that varies at the sector-year level, weighting political risk in each foreign country by the extent to which US imports in that sector were concentrated in each foreign country during a fixed pre-period. We then build on methods from Lybbert and Zolas (2014) and Goldschlag, Lybbert, and Zolas (2020) to measure patenting activity over time in each production sector (NAICS 6-digit) and aggregate data from Compustat to measure R&D investment at the same level. We estimate the dynamic relationship between sector-level exposure to foreign political risk and sector-level innovation, fully absorbing both sector and time effects.

We first show that foreign political risk in a sector has a large, positive effect on subsequent patenting activity in the US. This effect is similar when we focus on highly-cited patents; groundbreaking patents, as determined by their textual similarity to prior and subsequent innovation (as in Kelly, Papanikolaou, Seru, and Taddy, 2021); or high-value patents, as captured by changes in the patenting firm's stock market value around the patent grant date (as in Kogan, Papanikolaou, Seru, and Stoffman, 2017). The positive effect on overall innovative activity seems to be driven both by an expansion of innovative activity among already-innovating firms, as well as the entry of new firms into innovation as a sector becomes more exposed to political threats abroad. We find no evidence of pre-existing trends in innovation—changes in sector-level innovative activity take place only in the years following an increase in political risk.

We then investigate the mechanisms underpinning this baseline relationship. First, we examine heterogeneity across patenting firms and, consistent with our model's predictions, show that the finding is driven by firms with intermediate levels of innovation activity. We also detect a positive response among firms with the highest levels of innovation activity, consistent with some role for price effects. Second, separating patenting activity by the type of inventor, we find that the results are mostly driven by private-sector patenting and not patenting by universities or the government. We also separate patents based on whether they are classified as "government interest," meaning that the technology was funded by the US government, and separate sectors based on whether they are defined by the US International Trade Association as "critical" for functioning US supply chains. While we find slightly larger effects for critical industries, we continue to find positive effects in technologies and sectors that are not explicitly supported by the government. Third, we use firm-level data from Compustat to identify the technology space of each firm (based on the areas in which it patents) and the product market space of each firm (based on the main sector of its output), and separately estimate the effect of political risk shocks to each. We find that the innovation responses are only driven by technology space shocks, suggesting that our findings capture the impact of supply risk in areas where firms innovate rather than changes in product market competition. Finally, we find suggestive evidence of positive innovation spillovers from shocks to upstream sectors in the supply chain, again consistent with the input supply risk mechanism highlighted by the model.

We next broaden our analysis to analyze how innovation reacts to foreign political risk across all country-sector pairs. Beyond expanding the scope of our results, this allows us both to investigate the role of geopolitical relationships in mediating the response to political risk and to assess the impact of innovation on global patterns of trade.

We first study the relationship between innovation and political risk exposure in the global sample. By exploiting variation across countries, we can include all two-way fixed effects that fully absorb any unobserved sector-specific or country-specific trends. This includes any changes in sector-level technological capabilities or demand. Our empirical specification exploits the fact that fluctuations in country-specific political risk differentially affect a given sector in every other country depending on bilateral import linkages at baseline. Despite this more conservative design, we find strong evidence that technology development re-directs toward sectors with increased exposure to political risk. This effect remains true for the most influential patents, and we again verify that there are no pre-trends between innovation and political risk exposure: innovation rises following increases in risk exposure, but not before. The baseline estimate, however, is driven largely by markets with a high innovation stock at baseline. Thus, only certain countries may be able to weather foreign political risk shocks via innovation and production on-shoring.

Second, we investigate the role that geopolitical ties play in shaping our findings. So far, we have treated risk emanating from all foreign countries as equal. However, political risk emanating from geopolitical adversaries may lead to more severe economic risks (Farrell and Newman, 2023). In our model, this would be the case if countries are more likely to impose trade-restricting policies (e.g., sanctions) on their adversaries than their allies in response to a rise in political risk. We measure whether each pair of countries is allied or not using information both about formal alliances and about UN voting patterns. We find that the effect of political risk in *non-allies* on innovation is substantially stronger than the effect of political risk in *allies*, with the latter effect often indistinguishable from zero. As is intuitive, the differential response to risk in allied versus non-allied countries is driven by types of political risk that are due to government behavior and thus could be mediated by geopolitical incentives (e.g., democratic backsliding, military control of government), and not by sources of risk that would likely disrupt supply regardless of the geopolitical context (e.g., internal or external wars).

As one potential mechanism underlying this differential response between allies and non-allies, we show direct evidence that governments erect barriers to trade only in response to rising political turmoil in non-allies. Combining our empirical design with trade policy data since 2008 from the Global Trade Alert (GTA) database, we find that following a political risk shock, both the shocked country and its trading partners are substantially more likely to erect barriers to trade if they are non-allies. Compared to a rise in political risk in an allied trading pair, a rise in political risk in a non-allied pair increases the likelihood of a new trade-restricting policy by nearly fifteen percentage points.

Finally, we investigate how the endogenous technological response to foreign political risk reshapes the economic consequences of political shocks. Following a domestic political risk shock, all exports decrease. However, they decrease disproportionately more in sectors that initially exported to more innovation-intensive markets, where we have shown that innovation is more elastic to foreign political risk. This finding is robust to controlling for a broad set of additional export-market characteristics and is similar using an alternative identification strategy that exploits variation in exports within origin-sector pairs and across destination markets. Thus, technological development seems to successfully reduce reliance on risky foreign imports for the handful of markets with large innovation ecosystems. In doing so, however, it exacerbates the domestic economic consequences of political shocks—as countries with rising levels of political risk are "innovated out" of the trade network—and reshapes revealed comparative advantage.

Related Literature. Our analysis builds on several bodies of work. First, we contribute to a literature studying economic and policy responses to international political tension. While scholars have long studied the economic underpinnings of national power (e.g., Hirschman, 1945), there has been a surge of recent research modeling optimal government responses to foreign political risk (Martin, Mayer, and Thoenig, 2008; Clayton, Maggiori, and Schreger, 2023, 2024, 2025; Becko and O'Connor, 2024; Kooi, 2024; Liu, Rotemberg, and Traiberman, 2024). Other work documents mechanisms through which governments can use their influence to affect the actions of foreign nations (e.g., Kuziemko and Werker, 2006; Becko, Grossman, and Helpman, 2025; Liu and Yang, 2025; Meyer and Wesseler, 2025). While existing work focuses on how economic capabilities affect policy actions, our findings show that foreign political tension endogenously affects technology itself.

Another strand of literature studies the relationship between international conflict, trade flows, and global fragmentation (e.g., Schiller, 1955; Morrow, Siverson, and Tabares, 1998; Blanga-Gubbay and Rubínová, 2023; Eppinger, Felbermayr, Krebs, and Kukharskyy, 2023; Gopinath, Gourinchas, Presbitero, and Topalova, 2024; Broner, Martin, Meyer, and Trebesch, 2025; Fan, Wo, and Xiang, 2025). Our results suggest that innovation could be an important link between political conflict and economic disintegration and "decoupling." By showing that innovation resulting from foreign political risk affects patterns of trade, we also add to the few existing studies showing how international political ties and foreign intervention affect comparative advantage (Berger, Easterly, Nunn, and Satyanath, 2013).

We also build on studies investigating the economic consequences of foreign political turmoil. While most work on this topic is theoretical (e.g., Grossman, Helpman, and Lhuillier, 2023; Becko and O'Connor, 2024), a growing number of studies directly measure exposure to aggregate input supply risk (Baldwin, Freeman, and Theodorakopoulos, 2023) and whether re-allocation makes it possible to weather foreign political shocks (Moll, Schularick, and Zachmann, 2023). Our paper complements these studies by highlighting innovation as an important mechanism of adaptation to foreign political risks.

Finally, this paper extends existing work on innovation and directed technological change (e.g., Acemoglu, 2002). A small body of work studies how politics shapes the direction of innovation (Acemoglu and Johnson, 2023; Beraja, Kao, Yang, and Yuchtman, 2023; Beraja, Yang, and Yuchtman, 2023; Atanassov, Julio, and Leng, 2024). Other work highlights how public investments during international conflicts can have long-run effects on innovation (e.g., Gross and Sampat, 2023; Kantor and Whalley, 2023). Our findings also relate to a broader set of studies investigating how scarcity or "necessity" can drive invention (e.g., Popp, 2002; Acemoglu, 2010; Hanlon, 2015; Moscona and Sastry, 2023; Moscona, 2025; Dugoua and Gerarden, 2023; Ilzetzki, 2024), including recent work on the effects of US export controls on firm-level innovation in China (Liu, Liu, Makarin, and Wen, 2025). Our analysis shows that technological development reacts systematically to geopolitical tensions and how induced innovation in one country can exacerbate the consequences of negative shocks in others.

2 Conceptual Framework

We begin with a simple model to formulate hypotheses for how innovation and trade are affected by foreign political risk that influences domestic access to goods and inputs.

2.1 Model Set-Up

Production. There are two time periods $t \in \{0, 1\}$ and two countries, Home (H) and Foreign (F). In Home, there is a continuum of goods sectors, indexed by $k \in [0, 1]$, and each sector contains a continuum of varieties indexed by $i \in [0, 1]$. Each variety producer can use domestic labor or an input sourced from Foreign to produce output:

$$Y^i_{k,t} = A^i_{k,t} L^i_{k,t} + X^i_{k,F,t} \tag{2.1}$$

where $A^i_{k,t}$ is the productivity of using domestic labor $L^i_{k,t}$ to produce variety i of good k in period t, $X^i_{k,F,t}$ is the amount of inputs sourced from Foreign, and foreign inputs and domestic labor are substitutes in production within variety.[2] Note that this model accommodates the import of final goods, for example by wholesalers, who would simply import a good and market it domestically. The total output of the economy is given by:

$$Y_t = \left(\int_{[0,1]} \int_{[0,1]} (Y^i_{k,t})^{\frac{\eta-1}{\eta}} \, \mathrm{d}i \, \mathrm{d}k \right)^{\frac{\eta}{\eta-1}} \tag{2.2}$$

which is a constant elasticity of substitution (CES) aggregator of each firm's production with an elasticity of $\eta > 2$. The good sourced from Foreign is produced by perfectly competitive suppliers with productivity $A_{F,t}$:

$$Y_{k,F,t} = A_{k,F,t} L_{k,F,t} \tag{2.3}$$

Moreover, both foreign and domestic labor is supplied at wage w and w^F that we henceforth normalize to 1.[3]

[2] While these inputs are perfect substitutes at the firm level, we show in the Appendix A.1 that this model generates an endogenous CES production structure with imperfect substitution at the sector level:

$$Y_{k,1} = \left(\alpha_{k,1} X^{\frac{\eta-1}{\eta}}_{k,F,1} + (1 - \alpha_{k,1}) \mathbb{E}_G \left[(A^i_{k,1} L^i_{k,1})^{\frac{\eta-1}{\eta}} \mid A^i_{k,1} \geq P^{-1}_{k,F,1} \right] \right)^{\frac{\eta}{\eta-1}}$$

where G is the distribution of $A^i_{k,1}$, $\alpha_{k,1} = G(P^{-1}_{k,F,1})$, and $X_{k,F,1}$ is the imports of the sector.

[3] This amounts to redefining aggregate productivity and is without loss of generality for our analysis.

Innovation Decisions. Domestic firms in sector k are endowed with some random draw of productivity $A^i_{k,0} \sim H$ in the first period, where H is a cumulative distribution function supported on $\mathbb{R}_+$. They can innovate by investing final output in order to increase their productivity to $A^i_{k,1} \geq A^i_{k,0}$ in the second period. The cost of doing so is given by:

$$C(A^i_{k,1}, A^i_{k,0}) = \kappa \left[\left(\frac{A^i_{k,1}}{A^i_{k,0}} \right)^{\delta} - 1 \right] \tag{2.4}$$

where $\kappa > 0$ shifts the cost of innovation and δ shifts the curvature of innovation. We assume that $\delta > \eta - 1$ so that firms' optimal innovation decisions will be interior.

Political Risk. We model political risk in F as a disruption that hits sector k. Formally, we assume that $A_{k,F,0} \equiv A_{k,F}$ is known at $t = 0$ but that at date $t = 1$ a political shock can occur such that:

$$A_{k,F,1} = (1 - \tau_{k,1}) A_{k,F} \tag{2.5}$$

where $\tau_{k,1} = \tau > 0$ with probability p and $\tau_{k,1} = 0$ with probability $1 - p$. Intuitively, a political shock takes place with *likelihood* p and, if it does, then the productivity of sector k goes down with *intensity* τ. Conversely, in the absence of a political shock, there is no effect on productivity.[4] Modeling the outcome of policies in terms of the "as if" production distortion they induce is a standard approach, following Restuccia and Rogerson (2008), to model the consequences of a multitude of policies without taking a stand on the fine details of what policies induce these distortions. As we shortly detail, this set-up can also capture geopolitical risk via trade-restricting policies that may be shaped by whether the two countries are allies or adversaries. Proofs of all results are in Appendix A.

2.2 Political Risk, Innovation, and International Input Dependence

We now characterize firms' innovation choices, how they respond to changes in political risk, and the resulting implications for Home's reliance on imports from Foreign.

How Innovation Responds to Political Risk. We say that there is an increase in political risk under (p', τ') relative to (p, τ) if $p' \geq p$ and $\tau' \geq \tau$. We say that there is an increase in innovation at the sector level after a change in political risk if the equilibrium distribution of A^i_1 in any given sector k is greater after the change than before in the

[4] In practice, there may be many foreign countries from which Home can source. The present model accommodates this as a situation in which Home imports a bundle of inputs and foreign political risk affects the price of that bundle.

sense of first-order stochastic dominance. We say that an increase in innovation at the sector level is driven by a set of firms $\mathcal{I}$ if only the members of $\mathcal{I}$ strictly increased their innovation when political risk increased.

Proposition 1 (The Innovation Response to Political Risk)**.** *If political risk increases in Foreign, then innovation at the sector level increases. This increase is driven by firms with intermediate initial productivity,* $\mathcal{I} = \{i \in [0,1] : A_0^i \in (A_*, A^*)\}$ *where* $0 \leq A_* \leq A^*$.

Thus, increased foreign political risk leads to an endogenous sector-level increase in innovation at Home. However, underlying this aggregate response are complicated firm-level responses that are not linearly or monotonically related to variation in foreign exposure across firms. This motivates our empirical focus on sector-level variation in political risk exposure and innovation, where theory generates testable and interpretable predictions.

To understand this result, consider how changes in political risk affect innovation incentives for different firms. In Appendix A.2, we show that equilibrium features an endogenous segmentation of firms into (at most) three groups. First, there are *laggards* who always import and never engage in innovation. For laggards, increases in political risk reduce the expected profits from always importing the good, leading them to begin engaging in innovation if and only if the potential shock becomes severe enough to lead them to use the domestic technology (an *extensive* margin effect). Second, there are *insurance innovators* who innovate to mitigate the risk of facing high input prices when adverse political shocks hit, while retaining the option of using imports if they do not. For insurance innovators, increases in political risk make it more likely that they will rely on their own technology as the adverse shock occurs more frequently, increasing their incentives to innovate (an *intensive* margin effect). Third, there are *classical innovators* who are so productive that they never rely on the foreign input and their innovation decisions are affected only by the standard market size effect. For classical innovators, political risk has no effect on innovation since firms in this group do not import so changes in foreign risk have no direct effect on profits.[5] Thus, firms with intermediate productivity and innovation levels increase innovation when political risk rises.

To this point, we have treated political risk as an exogenous change in the probability or severity of input supply disruption. However, this model allows us to consider how trade-restricting policies enacted in response to political risk in allied *vs.* adversarial

[5] In Appendix A.5, we show that in an extended version of the model with different elasticities of substitution across and within sectors, classical innovators can also respond to changes in foreign political risk. This response is ambiguous in sign due to competing price effects.

countries affect innovation (see Clayton, Maggiori, and Schreger, 2023, 2024; Becko and O'Connor, 2024, for analyses of why such barriers may emerge). Proposition 1 implies that innovation will be more extreme in response to political risk in non-ally countries if restrictions to trade are more likely to emerge among non-allies in response to rising risk.

How Imports Respond to Political Risk. A further implication of our model is that when Foreign becomes politically riskier, domestic innovation will erode productivity advantages held abroad, leading domestic imports from abroad to decrease:

Proposition 2 (The Import Response to Political Risk)**.** *If political risk increases in Foreign, then the value and quantity of imports from Foreign decrease, both when the political shock happens and when it does not.*

The arguments underlying this result show that both the value and quantity of imports will be more elastic to changes in political risk whenever innovation is more elastic.

Extension: Competition. In this simple framework, innovation incentives arise from changes in input costs. In Appendix A.6, we adapt our baseline model to focus explicitly on the market for final goods and competition in the product market. In this setting, adverse shocks abroad generate a similar incentive to innovate domestically since the potential returns to being the lowest-cost domestic producer in a given sector increase. Indeed, we show that Propositions 1 and 2 generalize as written to such a setting. Thus, our approach does not hinge on whether foreign political risk affects input risk, final good access, or both. This notwithstanding, we will later present tests consistent with the input risk mechanism in the baseline version of the model (see Sections 4 and 5.3).

Summary of Predictions. The model makes four clear predictions at the sector level for any composite change in risk that increases the intensity and/or likelihood of future political shocks: (i) innovation will increase, (ii) if governments respond to political risk by restricting trade with non-allies, then this increase in innovation will be driven by political risk emanating from non-allies, (iii) reliance on foreign inputs will decrease, (iv) and reliance on foreign inputs will decrease by more in sectors whose innovation is more elastic to changes in political risk. While not our primary interest, our model also predicts that firms of intermediate innovation activity will respond most to increases in political risk. We proceed to test these predictions, exploiting variation in political risk across many sectors and trading partners, and study the mechanisms that underlie them.

3 Data and Measurement

We begin our empirical analysis by describing our main data sources and how we construct our baseline measures of innovation and exposure to political risk.

3.1 Data

Our key goals are to measure innovation and exposure to political risk across industries and over time. To measure changes over time in country-level political risk, we rely on the International Country Risk Guide (ICRG). The ICRG publishes annual reports on the sources and level of political risk for 147 countries. We average the 12 political risk components used by the ICRG into a single measure of risk exposure for each country since 1984. The ICRG is the longest-running and most comprehensive database of political risk. These data have been used widely in policy documents, in reports by international organizations (e.g., the IMF), and in academic research in economics and political science.[6]

Figure A.1 maps country-level changes in political risk for each decade during our sample period. On average, political risk was declining around the world during the 1990s but increasing during the 2010s. However, there are large differences in political risk trends across regions and across countries within regions. Figure A.2 displays the time-series pattern in the political risk measure for China and Russia. Measured political risk in both countries fluctuates substantially over the sample period, with increases coinciding with episodes of political tension (e.g., the consolidation of Putin's power and annexation of Crimea, the Tiananmen Square Protests and more recent "zero COVID" policies) and decreases coinciding with the opposite (e.g., the end of the First and Second Chechen Wars, Deng's Southern Tour). This is the variation that underlies our analysis.

As validation of this measure and its relevance for economic decision making, in Figure A.3a we show that the ICRG country-by-year measure of political risk is strongly associated with earnings call mentions (2002-2021) of political risk by exposed firms, as reported by Hassan, Hollander, Van Lent, and Tahoun (2019). However, it is *not* associated with mentions of non-political sources of risk, indicating that it captures potential disruption due to politics but not broader economic trends or events (Figure A.3b).[7] While we are

[6] See, for example: Filippou, Gozluklu, and Taylor (2018), Casanova, Cerutti, and Pradhan (2024), Catalán, Fendoglu, and Tsuruga (2024), Kanga (2024), Keefer and Knack (2002), Montes de Oca Leon, Hagen, and Holz (2024), Kim (2025), and Pellegrino, Spolaore, and Wacziarg (2025).

[7] We further shows that our main measure of political risk is strongly correlated with a news-based measure of geopolitical risk developed by Caldara and Iacoviello (2022), which exists only for a small subset of the countries in our main analysis (see Figure A.3c).

reassured by this exercise, we do not use these text-based measures in our main analysis due to a major endogeneity concern: the intensity of discussion of foreign political risk (e.g., in firm earnings calls) is intrinsically correlated with the ability to mitigate that risk, including via innovation. The ICRG measure, on the other hand, is based solely on political developments that are likely independent from foreign firm- or sector-level innovation trends, making it a more appropriate measure of political risk for our analysis.

To capture bilateral relationships between countries, which may mediate the consequences of the unilateral measure of political risk described above, we use several strategies to measure geopolitical "friendship" across country pairs. These include data on military and strategic alliances from the Correlates of War (COW) project; a database of all signed international alliance agreements from The Alliance Treaty Obligations and Provisions Project (ATOP); and data on UN voting, which we use to build a voting similarity measure based on methods developed by Bailey, Strezhnev, and Voeten (2017). These measures capture formal alliances between countries, military and non-military agreements between countries, and how similar their viewpoints are when voting on an international stage. We use all three to proxy bilateral friendship between country pairs.

Turning to innovation, we compile data on all patents filed in the United States using PatentsView, which also contains information on the patent industry classification, location and characteristics of the inventor(s) and assignee(s), and citation counts. We link patents to NAICS six-digit industry codes using validated "algorithmic links with probabilities" methods developed by Lybbert and Zolas (2014) and extended in Goldschlag, Lybbert, and Zolas (2020). We use several approaches to capture the potential importance of each patent, including measuring the number of citations each patent receives within five years of publication; measuring the dollar value of each patent issued to a public firm as determined by the excess stock market return of the patenting firm around the filing date (see Kogan, Papanikolaou, Seru, and Stoffman, 2017); and measuring each patent's textual similarity to subsequent relative to past innovation (see Kelly, Papanikolaou, Seru, and Taddy, 2021). We use these data to measure both US innovation, using the sample of US-based inventors, as well as global innovation, using the full sample of inventors linked to their countries of origin.[8] As a complementary measure of research effort, we compile data on all research and development (R&D) investments made by publicly traded firms

[8]We focus throughout on patents issued in the U.S. because its consistent patent policies (such as applying the same inclusion criteria and quality thresholds) ensure a comparable sample of technologies. Moreover, patents for which assignees incurred the cost of U.S. patent protection likely reflect more significant innovations than domestic-only patents.

using Compustat and aggregate these data to the sector level. Together, these data make it possible to paint a detailed picture of innovation trends in each sector and country.

We rely on a range of additional data sources for various parts of our empirical analysis, mentioned briefly here and described in greater detail in Appendix B. To construct our measure of political risk for minerals, we use data from the United States Geological Survey (USGS) on the location of all known deposits of each mineral around the world. This allows us to measure the exposure of the supply of each mineral to risk episodes in each country. To measure trade flows between countries at the six-digit NAICS level, we use the UN Comtrade database. Finally, to measure policy interventions that restrict trade, we use data from the Global Trade Alert (GTA) database, which has compiled information on all types of trade interventions made by governments since 2008. This allows us to investigate whether endogenous changes in trade policy following episodes of domestic and foreign political risk are an important intervening mechanism.

3.2 Measuring Political Risk Exposure

Our measure of political risk combines variation across country-years in political risk with variation across sectors in exposure to different countries. That is, we define political risk exposure (PRE) in each sector-year as:

$$\text{PRE}_{it} = \sum_{c} \text{PoliticalRisk}_{ct} \cdot \text{Exposure}_{ic} \tag{3.1}$$

where i indexes sectors, c indexes countries and t indexes time periods. $\text{PoliticalRisk}_{ct}$ is level of political risk for country c in year t, measured using the ICRG data. Exposure_{ic} is potential exposure of sector i to episodes of political risk in country c. An increase in this measure implies that sector i is increasingly exposed to potential political risk.

In the first part of our analysis (Section 4), i indexes different minerals and we consider a mineral to be more exposed to political risk if its deposits are concentrated in countries with high political risk. That is, in the formula above, we replace Exposure_{ic} with the squared deposit share of mineral i in country c, according to data from the USGS. Intuitively, values of this measure are higher when the deposits of mineral i are more concentrated in countries with high values of $\text{PoliticalRisk}_{ct}$.

When we turn to our analysis of innovation across all US sectors (Section 5), i indexes

NAICS 6-digit sectors and we define political risk exposure in sector i and time t as:

$$\text{PRE}_{it}^{\text{US}} = \sum_c \text{PoliticalRisk}_{ct} \cdot (\text{ImportShare}_{ict})^2 \tag{3.2}$$

where ImportShare_{ict} is the share of total imports to the US of sector i sourced from country c in year t. Values of $\text{PRE}_{it}^{\text{US}}$ are higher if US imports in sector i are concentrated in countries with higher levels of political risk. This measure combines time-series variation in both country-level political risk and in US import shares. Both sources of variation are potentially important. From the perspective of the US, import risk in a sector could increase either because of increased risk levels in an existing sourcing relationship or because of a shift in imports toward a country that is politically risky.

While foreign changes in country-level political risk levels are plausibly independent from the sector-specific innovation trends in the US, import patterns may not be. As a result, for most of our analysis, we fix import weights at their average *prior* to the year 2000 ($\text{ImportShare}_{ict_0}$). This only exploits changes over time in the distribution of political risk across foreign countries, and how that differentially affects sectors with heterogeneous baseline exposure to foreign nations. We validate this measure of political risk exposure by showing that it is associated with large contemporaneous declines in profits and capital investments by firms in more exposed industries (see Table A.1).

Our use of the squared import share in the baseline PRE_{it} measure has the intuitive appeal of corresponding to a Herfindahl–Hirschman index of supply concentration, which is commonly used in policy reports and analysis of supply risk (e.g., Grohol and Veeh, 2023, a report produced by the European Commission). It is also motivated theoretically by the non-linear relationship between the control of a sector and political power, described by Clayton, Maggiori, and Schreger (2024). Nevertheless, we show throughout the analysis that our results are similar if we use the level of exposure shares rather than the squared.

Figures A.1 and A.4 highlight the variation underlying this measure. Our main identification strategy will exploit foreign changes in political risk—plausibly exogenous with respect to US sector-level innovation trends—interacted with the differential reliance of each sector on imports from each foreign market. Figure A.1 shows decadal changes in political risk in each country and Figure A.4 displays US import reliance on each country for three sectors (automobiles, oil and gas, and semiconductors) before 2000. Changes in a given country's risk level will affect sectors very differently depending on the extent to which they rely on imports from that country at baseline. For example, changes in political risk in parts of the Middle East, West Africa, and South America will affect risk exposure for oil and gas, but not for the other two sectors, while changes in political risk in Japan will affect both automobiles and semiconductors, but not oil and gas. Meanwhile, rising political tension in China and Southeast Asia affects political risk exposure for semiconductors, but not for automobiles.

When we extend our analysis to a global sample (Section 6), exploiting variation in political risk not only across sectors and time but also across countries, we measure political import risk across countries, sectors, and years as:

$$\text{PRE}_{cit}^{\text{Global}} = \sum_{k \neq c} \text{PoliticalRisk}_{kt} \cdot (\text{ImportShare}_{k \to c, it_0})^2 \tag{3.3}$$

Here, variation derives both from differential changes in country-specific political risk and variation in each country's pre-period and sector-specific international sourcing patterns.

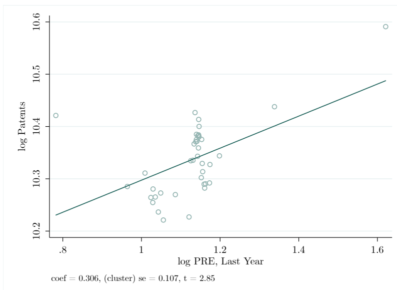
4 Case Study: Political Risk and Innovation in Minerals

To provide a concrete case study of our hypotheses, we first analyze the effect of political risk on innovation in minerals. The central role of mineral inputs across many sectors of the economy, combined with the fact that deposits of many minerals are concentrated in volatile regions, has led to mounting concerns about political threats to mineral supply (Schulz, 2017; Alfaro, Fadinger, Schymik, and Virananda, 2025). Moreover, the fact that mineral source locations are geographically determined and mineral-specific patents can be extracted directly using patent text, makes this a particularly compelling setting for measurement and identification.

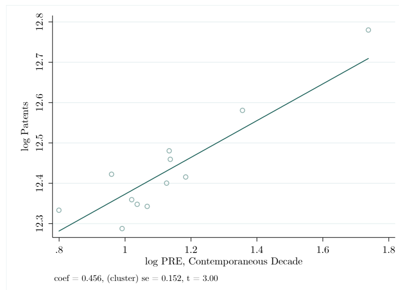
Several examples highlight the importance of political risks to mineral supply and innovation as a potential adaptation mechanism. In particular, growing concern about the concentration of copper and aluminum deposits has led to price spikes (Bloomberg News, 2024; Bastin, 2024) and calls for new strategies to "de-risk" supply (US Department of Commerce, 2019; Dou and Xu, 2023). The Carnegie Endowment writes, for example, that "the US and NATO face serious risks of mineral shortages [...] especially if US-China tensions escalate" (Carnegie, 2024). As a result, organizations like the USGS are building tools to identify risks to mineral access so that firms can preemptively adjust accordingly (USGS, 2020). Anecdotally, new technologies that limit reliance on foreign sources have emerged in response to risks to mineral supply (Vespignani and Smyth, 2024), including techniques to increase the efficiency of extraction, prospecting, refining and processing,

Figure 1: Foreign Political Risk and Mineral Innovation

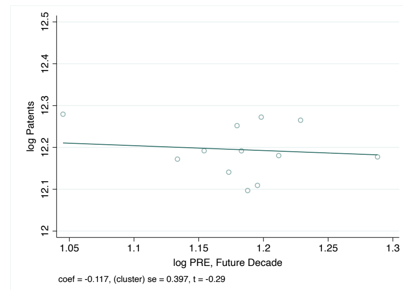
(a) Patents (Annual)



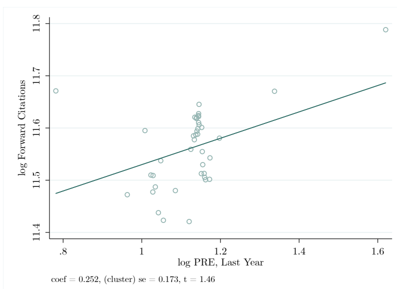
(b) Patents (Decadal)



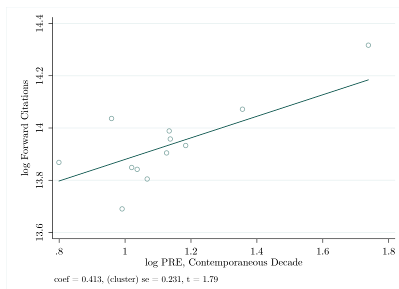
(c) Patents (Pre-Trend)



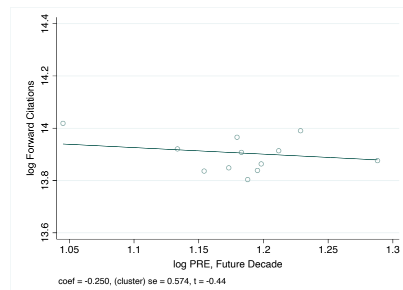
(d) Citations (Annual)



(e) Citations (Decadal)



(f) Citations (Pre-Trend)



Notes: In the first row, the outcome is log patents per mineral and in the second row it is log citation-weighted patents per mineral. In panels (a) and (d), the unit of observation is a mineral-year and in (b-c) and (e-f), it is a decade-year. In all regressions, we weight observations by mineral-level patents during the pre-period and standard errors are clustered at the mineral level. The coefficient and standard error for the fitted line are displayed below each sub-figure.

and recycling. For example, recent touch-screen technology aims to limit US dependence on indium from China (Akhavan, 2021).

Figure A.5 displays the global deposit shares for three critical industrial minerals: copper, aluminum, and zinc, all of which are among the most important industrial metals.[9] Aluminum, for example, accounted for 40% of global metal production in 2021, and China represented over 50% of aluminum output (VisualCapitalist, 2022). Figure A.6 displays the trend in political risk for each of these three metals alongside the (log of the) number of patents that mention each mineral. In all three cases, risk exposure fluctuates substantially over the sample period, and patenting related to each mineral seems to follow the trend in political risk in all three cases.

To systematically investigate whether exposure to political risk affects the direction

[9]Table A.2 presents the full list of minerals included in the USGS sample.

of innovation across minerals, we estimate the following regression equation, versions of which we return to throughout the analysis:

$$y_{it} = \beta \cdot \log\text{PRE}^{\text{Minerals}}_{i,t-1} + \alpha_i + \delta_t + \epsilon_{it} \tag{4.1}$$

where i indexes minerals and t indexes either years (capturing short-run changes in risk and innovation) or decades (capturing longer-run changes in risk and innovation). y_{it} measures patenting related to mineral i in year t and $\text{PRE}^{\text{Minerals}}_{i,t}$ is defined as $\sum_c \text{PoliticalRisk}_{ct} \cdot (\text{DepositShare}_{ic})^2$.[10] The coefficient of interest is β, which captures the relationship between political risk exposure and technology development.

Estimates of β are presented in Figure 1, which displays a series of partial correlation plots. In Figure 1a, the outcome variable is (log of) mineral-specific patents and we estimate a positive and significant ($p < 0.01$) effect of political risk exposure. The coefficient estimate implies that a one standard deviation rise in risk exposure increases innovation by roughly 27%. Figure 1b repeats the same specification except both innovation and political risk exposure are aggregated to the decade level, in order to understand how innovation reacts to longer-run changes in political turmoil around the world. The coefficient estimate is about 50% larger, perhaps driven by the fact that technology development takes time to react as well as the fact that innovation may be more responsive to persistent (versus transitory) changes in political risk exposure. This larger response at longer time horizons will be a feature of all of our results, across samples and sectors.

Turning to dynamics, Figure 1c reports the relationship between political risk in the *future* decade and innovation. We estimate a flat and statistically insignificant relationship, suggesting that the results are not driven by pre-existing trends. Mineral-level trends in innovation are unrelated to future trends in political risk exposure.

Finally, Figure 1d-1f repeat the same three specifications, except in all cases the outcome measure is log of *citation-weighted* patents instead of the raw patent count. In all cases, the results are very similar, indicating that the findings are not driven by unimpactful patented technologies. Together, these findings are a first indication that technology development reacts dramatically to supply threats.

[10] In our main analysis, we assign each patent to a mineral if the mineral name is mentioned in the title or abstract. In Figure A.7, we show that the results are similar if we also require that the mineral name be a stand-alone word or if we drop all minerals with common names that may be prone to mis-classification.

5 Foreign Political Risk and US Innovation

In this section, we investigate how exposure to foreign political risk affects the direction of innovation across all US sectors.

5.1 Empirical Strategy

Our main estimating equation is:

$$y_{it} = \beta \cdot \log\text{PRE}^{\text{US}}_{i,t-1} + \alpha_i + \delta_t + X'\Gamma + \epsilon_{it} \tag{5.1}$$

where i indexes sectors, defined in our baseline specification as six-digit NAICS industries, t indexes years. We include sector α_i and year δ_t fixed effects in all specifications to capture any average differences in political risk or innovation at the sector level sectors and any aggregate trends over time, respectively. X' is a vector of industry-by-time covariates, which we vary across specifications to probe the robustness of our estimates and provide evidence about key mechanisms. Standard errors are clustered by sector.

The coefficient of interest is β, which captures the effect of import-embodied exposure to political risk on US innovation. Our identifying assumption is that foreign fluctuations in import-weighted risk are plausibly exogenous with respect to the future direction of US innovation. Consistent with this assumption, we find no evidence that *future* changes in our measure of import risk are associated with innovation (i.e., no pre-existing trends).

Finally, while Equation 5.1 only includes a single lag of import risk, it seems plausible that the technological response could accumulate over several years and could grow over time. To investigate this, we also report results from an analogous set of specifications in which the unit of observation is instead the sector-by-*decade* pair. These estimates capture how innovation responds to changes in political risk exposure over the longer-run.

5.2 Main Results

Our baseline estimates of Equation 5.1 are reported in Table 1. In Panel A, we use the measure of political risk in Equation 3.2 and control directly for the contemporaneous unweighted concentration of imports in the sector (which is equivalent to a Herfindahl–Hirschman index of imports). In Panel B, we use the measure of political risk that fixes the import share weights at their pre-2000 level, thereby ruling out any potential

Table 1: Foreign Political Risk and US Innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:	log Patents	Patents	log Fwd Citations	log Patent Value	log Patent Importance	log New Firms	log Patents per Firm
	Panel A: Risk Measure Using Contemporaneous Import Shares						
log PRE, First Lag	0.326	0.323	0.229	0.334	0.311	0.047	0.257
	(0.163)	(0.141)	(0.083)	(0.158)	(0.140)	(0.126)	(0.128)
log HHI, First Lag	-0.061	-0.063	-0.090	0.002	-0.139	0.033	-0.087
	(0.153)	(0.129)	(0.101)	(0.172)	(0.143)	(0.143)	(0.093)
Mean Dep. Var.	2.31	173	3.74	4.02	2.27	4.19	-2.89
Observations	13926	15432	12092	12788	11144	13822	13916
	Panel B: Risk Measure Using Pre-Period Import Shares						
log PRE, First Lag	0.336	0.433	0.277	0.246	0.208	0.299	0.035
	(0.152)	(0.147)	(0.138)	(0.147)	(0.126)	(0.120)	(0.152)
Mean Dep. Var.	2.29	171	3.73	3.99	2.26	4.18	-2.90
Observations	13718	15213	12037	12654	11170	13615	13708
NAICS 6-digit FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is a 6-digit NAICS industry by year. In Panel A, the political risk exposure measure uses contemporaneous import shares as weights, and we control for the log sum of squared import shares (HHI). In Panel B, the political risk exposure measure uses pre-period import shares as weights. The dependent variable is log patent applications in column 1, patent applications in column 2, log forward citations within five years in column 3, log patent market values (Kogan, Papanikolaou, Seru, and Stoffman, 2017) in column 4, log patent importance (Kelly, Papanikolaou, Seru, and Taddy, 2021) in column 5, log number of new patenting firms in column 6, and log patents per firm in column 7. In column 2, we run PPML while in other columns we run OLS. We weight observations by 6-digit NAICS level patent applications during 1990-1999. Standard errors, reported in parentheses, are clustered at the 6-digit NAICS level.

bias from import patterns responding to political risk exposure.[11]

In column 1, the outcome is the log of the number of patents in the sector-year, and we find that $\beta > 0$. This coefficient estimate implies that a one standard deviation increase in our political risk measure raises patenting activity by approximately 22%. We find no evidence (in this or subsequent specifications) of an association between the concentration of imports (i.e., the un-weighted sum of squared import shares) and innovation. Thus, if innovation is concentrated in few countries but those countries are not risky by our measure, the direction of innovation does not seem to change. In column 2, we repeat the same specification except that we use a Poisson pseudo-maximum likelihood estimator

[11] We find very similar results using alternative parametrizations of PRE_{it}, including versions where we use the import share as the weight (rather than our preferred concentration measure using squared shares), as well as versions where we use the *level* of imports or level of imports squared as the weights (see Appendix Figure A.8 and A.9).

and use the count of patents as the dependent variable. The estimates are very similar.

The next three columns explore two strategies for scaling each patent by its potential importance. In column 3, we weight each patent by the number of citations it receives in the five years following its publication; in column 4, we focus on the set of patents issued to public firms and measure the market value of each patent as captured by the abnormal stock market return to the patenting firm following patent filing (as in Kogan, Papanikolaou, Seru, and Stoffman, 2017); and in column 5, we use methods developed by Kelly, Papanikolaou, Seru, and Taddy (2021) to measure the importance of each patent based on its similarity to subsequent relative to previous work. In all cases, we find positive and large effects of political risk on innovation, indicating that the re-direction of technology is not driven by insubstantial or irrelevant technologies.

In columns 6-7, we investigate whether the results are driven by the expansion of innovative activity at existing firms versus firms innovating for the first time. In column 6, the outcome variable is the log of firms entering innovation activity in the sector, and in column 7 it is the log of patents per firm. We find positive effects on both margins; the former is larger in magnitude (and significant) in Panel A while the latter is larger in magnitude (and significant) in Panel B. In the language of the model, these estimates suggest that the re-direction of innovation is driven both by new firms becoming insurance innovators (extensive margin) as well as higher incentives for innovation by existing innovators (intensive margin).

In Figure 2a, we display the results graphically after aggregating over time to the decade level. The graph reports a partial correlation plot of β from a version of Equation 5.1 in which t indexes decades instead of years. We estimate a value for β that is larger than the analogous specification in Table 1, potentially capturing the fact that technology development can take several years to respond to a change in political risk, as well as the fact that innovation may be more responsive to longer-run (persistent) changes in risk.

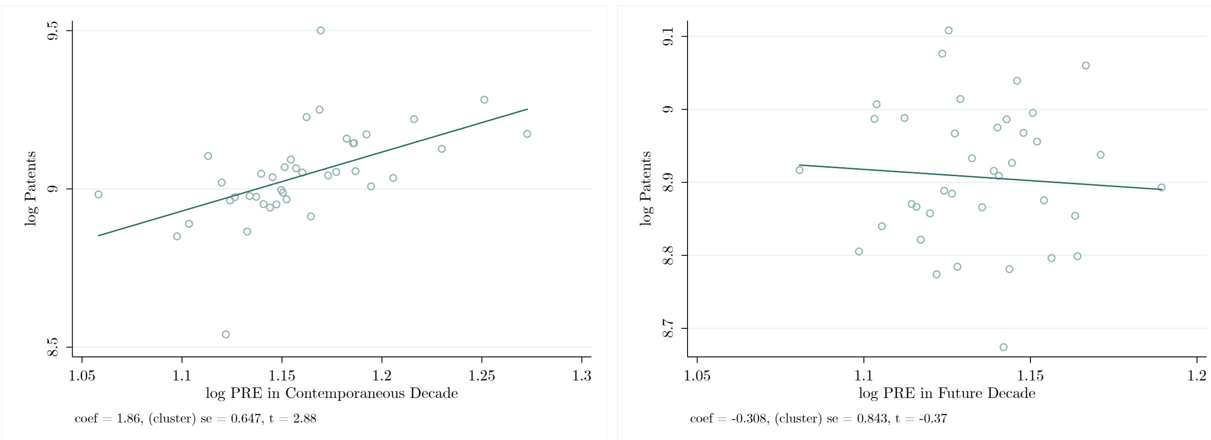
Turning to dynamics, Figure 2b is identical to Figure 2a, except we include political risk from the *subsequent* decade on the right-hand side of the regression. The best-fit line is completely flat and the corresponding coefficient estimate is statistically insignificant. This finding of an absence of "pre-trends" suggests that innovation responds to political risk and not the other way around, validating our identification assumption.

Finally, we show that the findings are similar using R&D investment as a separate measure of innovation. Figure A.10a shows that there is a strong, positive relationship between sector-year patenting (as we measure it) and sector-year R&D investment as

Figure 2: Foreign Political Risk and US Innovation: Decennial Estimates and Pre-Trends

(a) PRE in Contemporaneous Decade

(b) PRE in Future Decade (pre-trend)

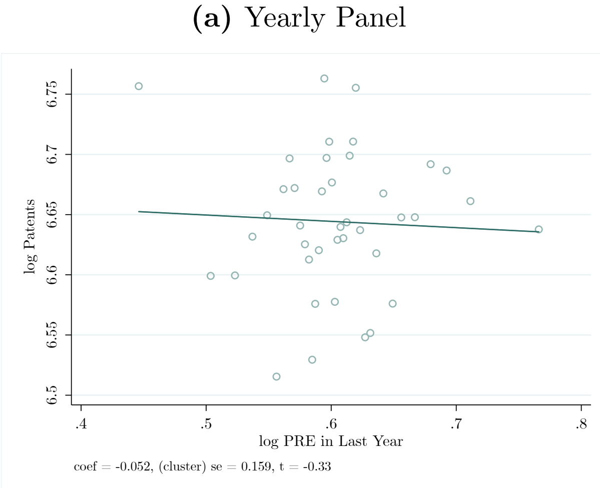


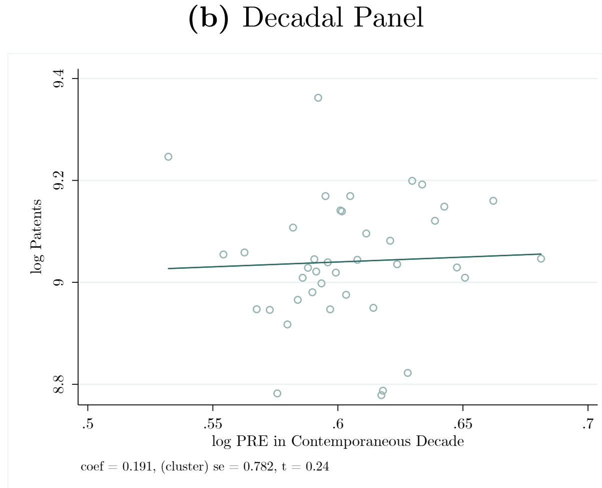
Notes: Panel (a) shows the effect of political risk exposure in the contemporaneous decade on total patent applications in the US. Panel (b) shows the effect of political risk exposure in the subsequent decade on total patent applications in the US. We control for 6-digit NAICS and decade fixed effects, and weight observations by 6-digit NAICS level patent applications during 1990-1999. In both panels, we use the political risk exposure measure weighted by pre-period import shares. The coefficient and standard error for the fitted line are displayed below each sub-figure. Standard errors are clustered by NAICS sector.

measured in Compustat. This helps validate our patent data measurement strategy, which involves linking patent classes to production sectors. Then, we show that there are similar positive effects of political import risk on R&D investment. Figure A.10b reports the estimate from an identical specification to Figure 2a, except the outcome is log of R&D spending instead of log of patenting. The coefficient estimate is positive and statistically significant.

Falsification Test. One potential concern is that our main results capture the effect of other forms of economic exposure to foreign countries rather than the causal effect of import supply risk. If the exposure of imports to political risk were spuriously correlated with the exposure of *exports* to political risk, for example, the main findings may capture innovation driven by changes in potential foreign market access. To rule this out, we estimate a version of our Equation 5.1 in which we define a placebo measure of PRE_{it}^{Export} in which time-varying foreign political risk is weighted by fixed pre-period US *exports* instead of imports. Consistent with a causal interpretation of our main results, we find no statistically or economically significant relationship between export-weighted political risk and innovation at either yearly (Figure 3a) or decadal (Figure 3b) frequencies.

Figure 3: Falsification Test: Export-Weighted Political Risk Exposure





Notes: Panel (a) shows the effect of export-weighted foreign political risk using the sector-year panel and Panel (b) shows the same using the sector-decade panel. In both cases, the outcome variable is the log of the total patent count. The coefficient and standard error for the fitted line are displayed below each sub-figure.

Foreign economic shocks. A remaining question is whether our baseline results are driven by political risk *per se* or the economic consequences of political turmoil, which could directly reduce foreign productivity. While economic downturns could be one mechanism through which political risk threatens input supply, we next assess whether this seems to be an important mechanism driving our results. First, we control directly for the lag of log imports in the sector and find that the estimates are very similar (Appendix Table A.3). These findings indicate that the main results are not driven by realized changes in total sector-level imports. Second, we control directly for (log of) import-weighted exposure to foreign countries' per-capita GDP and GDP growth. Again, our estimates are similar (Appendix Table A.4). While both sets of estimates amount to the inclusion of "bad controls," since foreign imports and economic changes could be caused by changes in foreign political risk, they indicate that the effect of political risk on innovation is not solely a consequence of changes in contemporaneous foreign economic performance.

5.3 Mechanisms and Heterogeneity

Our main results document a positive relationship on average between foreign political risk exposure and sector-level innovation. This section investigates which firms, sectors, and innovators drive the main result, and investigates underlying mechanisms.

Firm-Level Heterogeneity. Our theoretical framework (Section 2) motivated our main analysis at the sector-level since the relationship between firm-level exposure to foreign input risk and innovation can be non-monotonic and would fail to capture how foreign politics affects the direction of innovation. However, the model does have clear predictions for which firms in each sector should be most responsive to foreign political risk. In particular, the effect should be driven by middle-productivity firms ("insurance innovators"), who innovate to insure themselves against potential future input loss, and/or high innovation productivity firms, who innovate in response to anticipated changes in domestic demand (this latter force is only present in a model with general equilibrium price effects; see Section A.5). We proxy each firm's innovation intensity using their total patenting during the first decade of the sample period, and estimate the following specification separately for firms with different levels of innovation intensity:

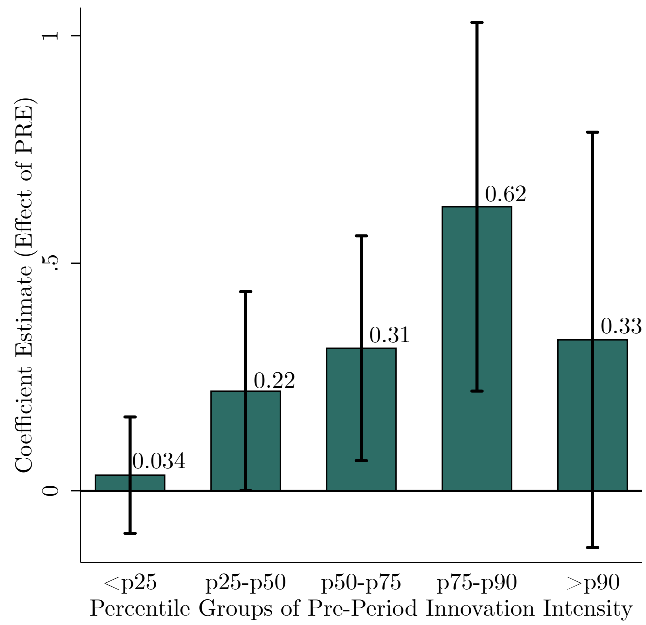
$$y_{jt} = \beta^p \cdot \log\text{PRE}_{i(j),t-1} + \alpha_{i(j)} + \delta_t + X'\Gamma + \epsilon_{jt}, \quad j \in p \tag{5.2}$$

where now j indexes firms in the patent data and $p \in P$ are a series of quantiles of baseline innovation intensity. We also control for firm age, to make sure this does not bias our measure of firm-level innovation intensity from a single time period (though, in practice, this control makes little difference).

The estimates are reported in Figure 4. Consistent with our theoretical framework, we find the largest effect of political risk on innovation for firms with intermediate innovation intensity. We detect no effect for the lowest innovation-intensity firms and a weaker response for the highest innovation-intensity firms. Through the lens of the model, these findings suggest an important role for "insurance innovation," though we cannot rule out that anticipated domestic price effects are also an important mechanism.

Which Inventors Drive the Results? So far, our findings have treated all inventions equally and not distinguished between the type of inventor developing the technology. However, the interpretation of the findings could be very different if the results are driven by (for example) greater government technology licensing in response to foreign threats versus individual firms responding to market incentives due to concerns about supply risk. To investigate this question, we first compile data on the assignee of each patent and categorize each assignee as either a firm, a university, or the government. In Appendix Figure A.11, we report the effect of foreign political risk separately on the (log of the) number of patents assigned to each group. We find a positive effect on both patents assigned to

Figure 4: Foreign Political Risk and US Innovation: Firm-Level Heterogeneity



Notes: This figure shows the effect of foreign political risk on US firms' innovation. We partition all US firms into five groups based on their total patenting during the pre-2000 decade and run equation 5.2 separately on these five groups. Standard errors are clustered at 6-digit NAICS level. The coefficient and 95% CI for each group is plotted.

firms and patents assigned to universities, and we find no effect on patents assigned to the government. Since the vast majority of patents have firms as their assignees, nearly all of our main results can be accounted for by firms' patenting (Figure A.11b).

This finding does not necessarily imply that innovation *funded* by the government is unimportant since not all technologies that benefit from government support are acquired by the government itself. To develop a broader measure of government-backed technology, we identify all patented technologies with a "government interest statement," meaning that technology was supported by US government research funding. We estimate a positive effect of foreign political risk on government-interest patents (Table A.5, Panel A), but these effects are smaller than our estimates for the full sample and for patenting that is not supported by government funding (Table A.5, Panel B). That said, government innovation and investment may underlie a large share of private-sector technology development in ways that we are unable to measure here. Thus, these results do not imply that government innovation is irrelevant, but rather that market forces play a major role.

Which Sectors Drive the Results? We next investigate the pattern of results across sectors. First, we separate sectors by their NAICS 2-digit category and separately estimate effects for agriculture, energy/mining, and the three classes of manufacturing. The results are displayed in Figure A.12. We find positive effects for all sectors with the exception of agriculture. However, we find the largest effects for energy and mining, as well as "heavier" manufacturing industries (those classified in 2-digit NAICS sector 33).

Next, we investigate whether the findings are driven by sectors that the US Government International Trade Association (under the Department of Commerce) has deemed "critical" for the functioning of US supply chains. While we find slightly larger effects for critical sectors, we also estimate a positive response among non-critical sectors, and the difference between the two is not statistically significant (Figure A.12b). The large and significant effect among sectors not explicitly prioritized by the government further indicates that a large part of our results are driven not by explicit government support.

Input Risk vs. Foreign Competition. Our discussion so far has focused on the impact of supply risk in the areas where firms innovate, and the model highlighted firm-level input risk as an important mechanism. However, as we described in an extension of the baseline model (Section 2.2), political risk can also affect foreign competition in the product market and this could be another mechanism. While distinguishing between these channels is not the main focus of this paper, it is nevertheless interesting to explore which of these channels may be driving the effect of political risk on innovation.

In Appendix C.1, we investigate the foreign competition mechanism directly by exploiting firm-level data from Compustat and methods introduced by Bloom, Schankerman, and Van Reenen (2013). We separately measure foreign political risk in the NAICS code of the good(s) that the firm sells, capturing its effect on foreign competition (i.e., in each firm's "product market"), and in the NAICS code implied by the CPC classes in which the firm patents (i.e., in each firm's "technology market").

We use Equation 5.2 to separately estimate the effect of firm-level product market and technology market foreign political risk exposure on firm level innovation. We find a large effect of political risk in the technology market and no effect of political risk in the product market (Figure A.13). The latter effect is small in magnitude, statistically indistinguishable from zero, and negative. The results are similar if we estimate both effects in the same or separate regressions. Subject to the obvious caveat that measurement of spillovers is challenging, this finding suggests that pure product market competition is unlikely to be a major driver of our main results.

We next investigate potential spillovers effects across industries. New technology development need not be concentrated only in the sector that receives the shock. First, shocks to upstream sectors may encourage firms to innovate to accommodate the use of new or different inputs in production. This would be further evidence in favor of the input risk mechanism in highlighted by the model, since shocks to upstream sectors affect the availability of productive inputs but do not directly affect foreign product market competition. Second, shocks to "substitute" sectors in the supply chain may also encourage innovation (e.g., greater conflict in rubber-growing areas could encourage the development of rubber substitutes). This is not captured by our model but could nevertheless be an interesting spillover mechanism.

In Appendix C.2, we use the US input-output tables from the Bureau of Economic Analysis (BEA) to parameterize each of these potential spillover channels. We find positive effects of political risk shocks to upstream sectors on innovation, consistent with access to key inputs being an important mechanism (columns 1 and 3). We also find a positive effect of innovation after political risk shocks to substitute sectors (columns 2 and 4). That said, these estimates should be interpreted with caution since we have at best imperfect proxies for the linkages across sectors that could mediate spillover effects.

6 Global Estimates and the Role of Geopolitical Alliances

So far, we have focused on changes in political risk exposure across sectors in the US. In this section, we extend the analysis to innovation around the world and, using this global sample, investigate the role of political alliances and geopolitics in shaping our results.

6.1 Empirical Strategy

Our main estimating equation in this section extends Equation 5.1 to include many countries. There are three reasons to conduct this global analysis. First, it is interesting to know if our US results can be generalized. Second, the use of identifying variation not only across sectors and time periods but also across countries allows for the inclusion of additional sets of fixed effects that fully absorb potential threats to a causal interpretation from the first part of the analysis. Finally, the inclusion of many countries in the sample makes it possible to investigate several dimensions of heterogeneity that shed light on the types of risk shocks and trading relationships driving the results.

The main estimating equation in this section is:

$$y_{cit} = \beta \cdot \log\text{PRE}_{cit-1}^{\text{Global}} + \alpha_{ci} + \delta_{ct} + \eta_{it} + X'\Gamma + \epsilon_{cit} \tag{6.1}$$

where c indexes the country of the inventor, i indexes sectors, t indexes years, and $\text{PRE}_{cit}^{\text{Global}}$ is defined in Equation 3.3. Our coefficient of interest is β, which captures the effect of country-sector specific exposure to foreign political risk on innovation. Compared to the previous analysis, here we exploit the fact that a given sector is differentially exposed to political risk across countries in a given year due to heterogeneous baseline reliance, within a sector, of each country on each exporter.

This specification includes all possible two-way fixed effects, including country-sector fixed effects (α_{ci}), country-year fixed effects (δ_{ct}) and sector-year fixed effects (η_{it}). Country-sector fixed effects fully absorb the extent to which particular country-sector pairs are systematically more innovative than others (or more exposed to political risk). Country-year fixed effects capture any country-specific trends, including the fact that countries may become more or less innovative over time (e.g., the rise of China) and that countries may become more or less exposed to political risk over time. Finally, sector-year fixed effects capture any sector-specific trends, including the fact that innovation (or political risk) in certain sectors may be increasing (or declining) globally in tandem over time (e.g., the global rise in semiconductor research *and* average political risk over the past decades). Moreover, sector-year fixed effects also mitigate the possibility political risk itself can be caused by foreign innovation that increases (decreases) the value of a particular industry.

6.2 Baseline Results

Our baseline estimates of Equation 6.1 are reported in Table 2.[12] Foreign political risk is positively associated with patenting activity (columns 1-2). Moreover, this specification rules out the possibility that the US-only results could be driven by any omitted technology-specific (or sector-specific) trends by including a complete set of sector-by-year fixed effects. The estimate is similar and, if anything, slightly larger in magnitude when we weight each patent by the number of citations it received in the five years following publication (column 3) or by its "importance" (see Kelly, Papanikolaou, Seru, and Taddy, 2021), as determined by its textual similarity to subsequent innovation (column 4). The

[12]These estimates are analogous to Panel B of Table 1, except that we exclude the outcome related to firm values since the vast majority of patents with stock market value are by US firms.

Table 2: Foreign Political Risk and Global Innovation

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	log Patents	Patents	log Fwd Citations	log Patent Importance	log New Firms	log Patents per Firm
log PRE, First Lag	0.084	0.069	0.133	0.132	0.036	0.067
	(0.034)	(0.039)	(0.048)	(0.032)	(0.019)	(0.028)
Mean Dep. Var.	-0.93	1.88	-0.043	-0.90	1.73	-3.15
Observations	243549	2499030	185958	173810	207171	240949
NAICS 6-digit × Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
NAICS 6-digit × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is a 6-digit NAICS industry in a country in a year. Political risk exposure is constructed using pre-period import shares for the weights. The dependent variable is log patents in column 1, total patents in column 2, log forward citations in column 3, log patent importance (Kelly, Papanikolaou, Seru, and Taddy, 2021) in column 4, log number of newly patenting firms in column 5, and log patents per firm in column 6. We weight observations by 6-digit NAICS × country-level patent applications during 1990-1999. In column 2, we run PPML while in other columns we run OLS. Standard errors are clustered at the country-sector level.

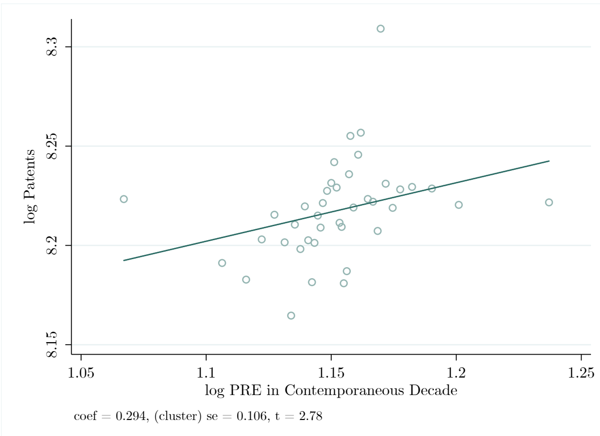
results are driven both by the expansion of R&D activity in existing innovating firms, as well as firms entering innovation (columns 5 and 6). Thus, our baseline findings are similar when estimated across all countries.

We next aggregate the data to the decade level and estimate the same specification as above, except t now indexes decades instead of years. A binned partial correlation plot of β is reported in Figure 5a. We estimate a positive effect that is about three times as large as the yearly estimate, consistent with our results from the US-only analysis. Moreover, when we instead include the leading value of political risk exposure instead of the contemporaneous value, we estimate a coefficient that is very close to zero, negative, and statistically insignificant (Figure 5b). This null placebo result suggests once again that our main estimate is not driven by a pre-existing trend in the relationship between political risk and innovation. As in the US-only results, we document in the Appendix that the findings are not sensitive to alternative parametrizations of the political risk measure (see Appendix Figures A.14 and A.15), and that results are similar after controlling directly for lags of realized imports (see Appendix Table A.7).

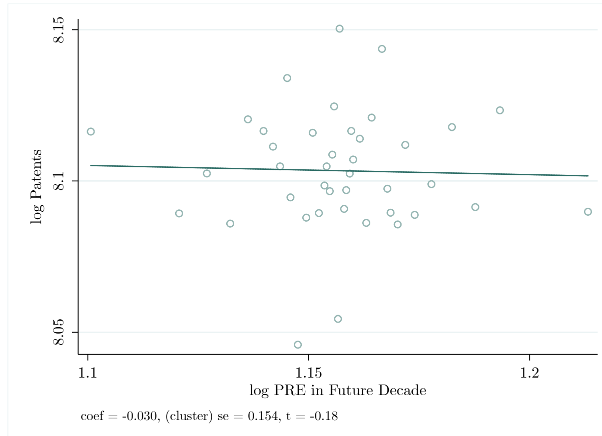
Heterogeneity by Market-Level Innovation Intensity. We next investigate which markets exhibit the largest innovative response to foreign political risk. One possibility is that country-sector pairs that are relatively less "innovation-intensive" at baseline are

Figure 5: Foreign Political Risk and Global Innovation: Decennial Estimates and Pre-Trends

(a) PRE in Contemporaneous Decade



(b) PRE in Future Decade (pre-trend)



Notes: Panel (a) shows the effect of foreign political risk in the contemporaneous decade on total patent applications. Panel (b) shows the effect of foreign political risk in the future decade on total patent applications. We control for 6-digit NAICS × country, country × decade, and 6-digit NAICS × decade fixed effects. We weight observations by 6-digit NAICS × country level patent applications during 1990-1999. In all panels, we use the foreign political risk measure which is weighted by pre-period import shares. The coefficient and standard error for the fitted line are displayed below each sub-figure.

less able to respond to foreign political risk via a ramp-up in technology development.[13] However, it need not be the case that the most innovation-intensive markets are also the ones that have the highest *elasticity* with respect to foreign political risk exposure.

We split the sample between country-sector pairs with above-75th versus below-75th percentile patent stocks at the start of the sample period.[14] We find a small and insignificant effect of foreign political risk on patenting for markets with low initial patent stocks (Table 3, column 1) and a large, positive effect for markets with high initial patent stocks (column 2). The pattern is similar when we use citation-weighted patenting as the outcome (columns 3-4). These findings indicate that "adaptation-via-innovation" is not a strategy available to all countries. While markets that already do substantial innovation may be able to weather foreign political risk exposure through innovation, this process does not take place in markets with little innovation to begin with.

[13]This is consistent with a parameterization of the model in which most firms are laggards and innovation-intensity captures the number of potential innovators, or in which general equilibrium price effects lead classical innovators to innovate more in response to political risk.

[14]We construct the patent stock as the discounted (at 5%) sum of previous patent applications.

Table 3: Global Estimates: Heterogeneity by Innovation Intensity

	(1)	(2)	(3)	(4)
	log Patents		log Fwd Citations	
Dependent Variable:	Low Innov. Markets	High Innov. Markets	Low Innov. Markets	High Innov. Markets
log PRE, First Lag	-0.006	0.085	0.002	0.106
	(0.052)	(0.035)	(0.089)	(0.048)
Mean Dep. Var.	-3.12	0.28	-2.56	0.93
Observations	86317	157232	61075	135835
NAICS 6-digit × Country FE	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes
NAICS 6-digit × Year FE	Yes	Yes	Yes	Yes

Notes: The unit of observation is a 6-digit NAICS industry in a country in a year. The political risk exposure measure uses pre-period import shares as weights. The dependent variable is log patent applications in column 1-2, and log forward citations within 5 years in column 3-4. We weight observations by 6-digit NAICS × country level patent applications during 1990-1999. In column 1 and 3, the sample is restricted in country-industry pairs whose pre-period patenting is in the bottom three quartiles. In column 2 and 4, the sample is restricted to country-industry pairs whose pre-period patenting is in the highest quartile. Standard errors, clustered at the country-sector level, are reported in parentheses.

6.3 The Role of Geopolitical Alliances

So far, we have treated political import risks emanating from all foreign countries as equal. However, this may not be the case. Firms and governments may be particularly responsive to political turmoil in geopolitical adversaries. The recent technology "decoupling" between the US and China is a recent and prominent example of on-shoring technology development couched in a narrative of geopolitical competition (e.g., Inkster, 2021). This could be driven by the fact that political risk in adversaries comes with expectations of additional breakdown of trade relations. For example, as highlighted by the recent geoeconomics literature (Clayton, Maggiori, and Schreger, 2023), policy interventions to restrict trade either by the home or foreign government may disproportionately emerge between political foes. Moreover, unchecked political leaders may direct their expropriation toward geopolitical foes, while leaving their friends largely unaffected. Given this, our model predicts that firms have greater innovation incentives when adverse political shocks arise in an adversary, due to a higher likelihood of losing access to foreign inputs.

To investigate this possibility, we construct separate measures of political risk in ally countries and political risk in non-ally countries by partitioning total foreign risk (Equation 3.3) into the sum only over foreign allies or non-allies, respectively. We then estimate

Table 4: Foreign Political Risk in Allies vs Non-Allies

Dependent Variable: log Patents	(1)	(2)	(3)	(4)	(5)	(6)
	Annual Specification			Decadal Specification		
	CoW	UN	ATOP	CoW	UN	ATOP
log PRE$^{\text{Non-Ally}}$, First Lag	0.033	0.018	0.018	0.035	0.063	0.024
	(0.013)	(0.009)	(0.008)	(0.012)	(0.021)	(0.009)
log PRE$^{\text{Ally}}$, First Lag	-0.025	-0.006	-0.011	0.008	-0.001	-0.020
	(0.019)	(0.002)	(0.028)	(0.030)	(0.002)	(0.047)
Mean Dep. Var.	-0.70	-0.86	-0.82	-0.03	0.12	0.12
Observations	112853	161721	201083	19826	37778	37988
NAICS 6-digit × Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
NAICS 6-digit × Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is a 6-digit NAICS industry-country-year in column 1-3, and a 6-digit NAICS industry-country-decade in column 4-6. The data on political ties between countries comes from Correlates of War (CoW) in columns 1 and 4, from UN voting-derived ideal point data (Bailey, Strezhnev, and Voeten, 2017) in columns 2 and 5, and from the Alliance Treaty Obligations and Provisions Project (ATOP) in columns 3 and 6. We use the political risk exposure measure with pre-period import shares in all columns. The dependent variable is log patent applications. We weight observations by 6-digit NAICS by country level patent applications during 1990-1999. Standard errors are clustered at the 6-digit NAICS by country level.

the following regression model:

$$y_{cit} = \beta^A \log \text{PRE}^{\text{Ally}}_{ci,t-1} + \beta^E \log \text{PRE}^{\text{Non-Ally}}_{ci,t-1} + \alpha_{ci} + \delta_{ct} + \eta_{it} + \epsilon_{cit} \tag{6.2}$$

which is simply an augmented version of Equation 6.1. β^A and β^E capture the effect of political risk in geopolitical allies and adversaries, respectively.[15]

Estimates of Equation 6.2 are reported in Table 4. As our main measure of country-pair specific alliances, we use data from the Correlates of War (COW) project on all military, defense, or strategic alliances between pairs of countries (column 1). We find a positive and significant effect of political risk from non-ally countries and an insignificant effect of political risk in ally countries. β^E and β^A are also statistically distinguishable from each other ($p = 0.012$). The decadal version of the same result tells a very similar story (column 4). Estimates of β_A and β_E for our full set of outcome variables, and for both

[15]We define allies in the CoW and ATOP data sets as pairs of countries that have at least one formal alliance or agreement following each measure, and we define allies in the UN data as countries with above-median UN voting-implied ideal point similarity, following Bailey, Strezhnev, and Voeten (2017). We define the remaining country pairs as non-allies. Since the CoW data end in 2012, the decennial specification using CoW data only includes two decades: the 1990s and the 2000s.

the annual and decadal aggregations, are reported in Figure A.16. Across specifications, we find that political risk in non-allied countries is positively associated with domestic innovation, while political risk in allied countries is not.

We also explore whether the results are similar using two alternative potential measures of political ties. First, we develop a fully independent measure of political connections that uses data on UN voting behavior to measure the similarity in international political preferences across countries (see Bailey, Strezhnev, and Voeten, 2017). Second, we use an alternative measure of strategic alliance signing compiled by the Alliance Treaty Obligations and Provisions Project (ATOP). Both measurement strategies tell a similar story: the re-direction of innovation in response to foreign political risk is strongly driven by political risk emanating from political adversaries (Table 4, columns 2-3, 5-6).

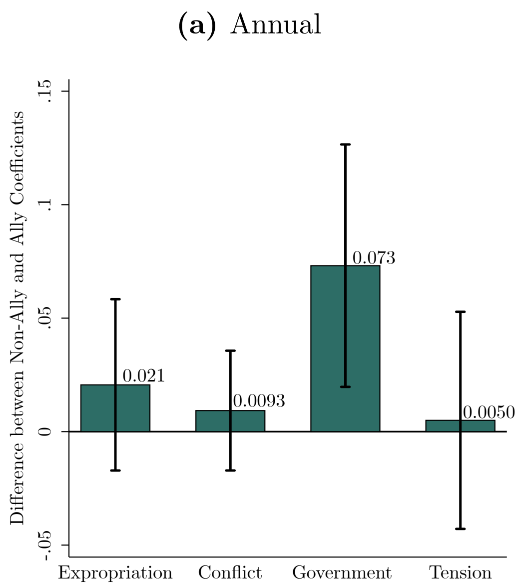
Sources of Political Risk. We next investigate which types of risk account for the stronger response of innovation to political activity in adversary countries. Certain types of political turmoil—including domestic or international armed conflict—may disrupt supply regardless of whether the country is an ally or an enemy. Other sources of political risk, however, may disproportionately affect trade relationships with enemy countries. For example, lower democratic accountability may reduce checks on the government and lead to more extreme political behavior, but even governments that face few domestic constraints may want to preserve their geopolitical relationships and maintain economic ties with their friends. The same argument could be made for risk due to investment expropriation, military involvement in politics, or corruption: these sources of risk depend directly on government decision making and as a result, governments could choose to not disrupt the economic activity of friendly nations.

We divide the components of the political risk index into four groups: economic expropriation (socioeconomic conditions and investment risk), violent conflict (internal and external conflict), government institutions (government stability, corruption, military in politics, law and order, democratic accountability, and bureaucracy quality), and domestic tension (religious and ethnic tension). We run the following regression:

$$y_{cit} = \beta_x^A \log \text{PRE}_{cit-1}^{x,\text{Ally}} + \beta_x^E \log\ \text{PRE}_{cit-1}^{x,\text{Non-Ally}} + \alpha_{ci,x} + \delta_{ct,x} + \eta_{it,x} + \epsilon_{cit,x} \tag{6.3}$$

for each of the four risk types (indexed by x), where (the log of) patents is the outcome variable. We estimate this specification at both annual and decadal frequencies. Figure 6 reports the difference between β_x^E and β_x^A for each of the four risk categories.

Figure 6: Sources of Political Risk from Allies vs Non-Allies and Global Innovation



Notes: This figure shows the effect of different types of political risk exposure from allies and non-allies, at both annual and decennial frequencies. The bars plot the difference between our estimates of β_x^E and β_x^A for each of the four types of political risk. In all specifications, the political risk exposure measure is weighted by pre-period import shares. 95% confidence intervals are reported and standard errors are clustered at the country-sector pair level.

We find that the difference in the innovation response to risk in allied versus enemy countries is driven by risk due to changing government institutions (e.g., democratic accountability, military in politics). We also find a smaller effect for expropriation risk. We find no significant differences for risks due to internal or external wars, or for risk due to ethnic or religious tension. This is intuitive, since the consequences of these sources of supply risk are unlikely to be mediated by international political relationships. The effects of changing government institutions, however, *are* likely mediated by geopolitical ties: military governments or corrupt heads of state may pose no economic risks to their friends abroad. And these are precisely the sources of risk that seem to drive a wedge between the response of innovation to political turmoil in allies versus adversaries.

Endogenous Trade Restrictions as a Mechanism. One explanation for the findings in Table 4 is that firms anticipate that a rise in political turmoil in geopolitical adversaries is more likely to spur breakdowns in trade relations. The model highlights how anticipated changes in policy amplify firms' incentives to innovate in response to foreign political risk.[16] Trade restrictions could be driven by policy changes made by their own government or by the foreign government. This would be consistent with the findings that sources of political risk related to government decision making explain our baseline results.

To investigate trade restrictions directly, we combine data on all documented restrictions to trade relations since 2008 in the Global Trade Alert (GTA) database, which is to our knowledge the most complete compilation of the myriad policy levers governments have used to restrict trade. For each country pair and year, we construct an indicator that equals one if a trade-restricting policy was put in place. We then estimate:

$$\mathbb{I}(\text{Restrict})_{ckt} = \beta^R \log \text{PR}_{kt} \cdot \text{Non-Ally}_{ck} + \beta^I \log \text{PR}_{ct} \cdot \text{Non-Ally}_{ck} + \alpha_{ck} + \delta_{kt} + \eta_{ct} + \epsilon_{ckt} \quad (6.4)$$

where c is the policy-imposing country, k is the partner country, and t is the year. $\mathbb{I}(\text{Restrict})_{ckt}$ is an indicator that equals one if country c imposes a trade restricting policy that affects its trade with country k in year t. Non-Ally_{ck} is an indicator that equals one if c and k were never in an alliance during the sample period, and PR_{kt} and PR_{ct} measure political risk in the policy-receiving and policy-imposing countries, respectively.

The coefficients of interest are β^R and β^I. β^R captures whether countries are disproportionately likely to impose trade restrictions on a foreign country that becomes more politically risky if that country is an enemy. β^I captures whether countries are disproportionately likely to impose trade restrictions on a foreign country when they themselves become more politically risky if that country is an enemy.

Estimates of Equation 6.4 are reported in Table 5. We find strong evidence that $\beta^R > 0$ *and* $\beta^I > 0$, both when they are estimated from separate regressions (columns 1-2) and when they are estimated in the same regression (column 3). The results are similar if we focus attention on "extreme" restrictions of trade, defined as policies affecting more than 20 product categories (columns 4–6).[17] While just one potential mechanism, the fact that rising political risk is accompanied by expanding restrictions to trade among geopolitical foes could help explain why technology development is so much more responsive to political risk arising in foreign suppliers who are adversaries compared to allies.

[16] This hypothesis is consistent with Liu, Liu, Makarin, and Wen (2025), which shows that Chinese firms increased R&D in response to export restrictions imposed by the US government in 2007.

[17] This follows the Global Trade Alert Handbook, which notes that the number of products covered is a commonly used indicator of trade policy severity (Evenett and Fritz, 2022).

Table 5: Political Risk and Trade-Restricting Policies

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Restricting Trade Policy that Affects...					
	at least 1 Product			Over 20 Products		
log $PR_{kt} \cdot \text{Non-Ally}_{ck}$	0.058		0.050	0.031		0.027
	(0.012)		(0.016)	(0.008)		(0.010)
log $PR_{ct} \cdot \text{Non-Ally}_{ck}$		0.097	0.076		0.096	0.050
		(0.014)	(0.017)		(0.008)	(0.010)
Mean Dep. Var.	0.163	0.203	0.258	0.037	0.050	0.060
Observations	439545	439545	273002	439545	439545	273002
Imposer × Receiver FE	Yes	Yes	Yes	Yes	Yes	Yes
Imposer × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Receiver × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is an imposing country-receiving country pair in a year. The dependent variable is an indicator that equals one if the imposing country imposes a restricting trade policy on the receiving country in column 1-3, and an indicator that equals one if the imposing country imposes a restricting trade policy that affects over 20 product categories on the receiving country in column 4-6. All possible two-way fixed effects are included in all specifications. Standard errors, clustered at country pair level, are reported in parentheses.

7 Innovation Reshapes the Consequences of Political Risk

Finally, we investigate how endogenous technological change mediates the relationship between political risk shocks and patterns of cross-country trade. If innovation endogenously reduces import reliance on risky countries, then it may exacerbate the impact of political risk shocks on trade. While heightened political risk abroad has a direct negative effect on Foreign's exports, the model predicts that the technological response at Home will exacerbate this effect by eroding Foreign's initial comparative advantage. As Home firms respond to rising political risk abroad by innovating in a sector, they increase their own productivity and reduce their reliance on imports. Even if Foreign fully emerges from its political risk episode and even if that risk never materializes, it will export less to Home than in a world where innovation at Home did not respond. In this way, the results that we have documented on the re-direction of innovation could exacerbate and extend the economic consequences of political turmoil for the country that experiences it.

7.1 Empirical Strategy

The ideal experiment to investigate this hypothesis would be to compare the impact of political risk on exports in a world where innovation *does* and a world in which it *does* *not* respond. However, there is no clear way to shut directed innovation down entirely or to make this comparison. Thus, we exploit the finding from Section 6.2 (Table 3) that the elasticity of innovation to foreign political risk is substantially larger in markets with high levels of baseline innovation. The model predicts that the negative response of trade flows to political risk should scale with the elasticity of innovation to political risk in the importing market. Therefore, we compare the effect of political risk shocks in country-sector pairs that initially export to *low-innovation* (low-elasticity) markets to that of similar political risk shocks occurring in country-sector pairs that initially export to *high-innovation* (high-elasticity) markets. Our hypothesis is that the marginal (negative) effect of political risk on exports is larger for country-sector pairs initially exporting to high-innovation markets, where innovation responds more forcefully.

Our main estimating equation for this part of the analysis is:

$$\log \text{Exports}_{cit} = \phi \log \text{PR}_{ct} \cdot \log \text{IE}_{ci} + \alpha_{ic} + \delta_{ct} + \eta_{it} + \epsilon_{cit} \tag{7.1}$$

where as above, c indexes countries, i indexes sectors, and t indexes years. PR_{ct} is the political risk measure for country c in year t and IE_{ci} is the foreign innovation exposure of sector i in country c, computed as:

$$\text{IE}_{ci} = \sum_{k \neq c} \text{Exports}_{i,c \to k,t_0} \cdot \text{InnovationStock}_{ikt_0} \tag{7.2}$$

where the $\text{Exports}_{i,c \to k,t_0}$ is the total value of exports from country c and sector i to country k in a fixed cross-section before 2000.[18] The innovation stock is calculated as the average discounted sum of patents or citation-weighted patents in country k and sector i during the period 1995-1999, following the same method as Section 6.2. All possible two-way fixed effects are included in the baseline specification, absorbing all country and sector-specific trends, as well as baseline differences in all observable and unobservable characteristics between country-sector pairs.

Our hypothesis is that $\phi < 0$. That is, in response to political risk shocks, innovation-intensive import markets reduce their reliance on risky foreign countries and, hence, exports from riskier countries decline disproportionately in sectors that are more exposed to foreign innovators. The key potential concern when interpreting β is that the initial char-

[18]The results are very similar if we instead use the export share instead of the export level to construct IE_{ci}. Estimates using this alternative measurement strategy are summarized by Figure A.17.

Table 6: Political Risk and Trade: The Effect of Innovation Exposure

	(1)	(2)	(3)	(4)
Dependent Variable:	log Exports			
log PR × log IE	-0.048	-0.044		
	(0.003)	(0.003)		
Δ log PR × log IE			-0.017	-0.015
			(0.003)	(0.003)
Mean Dep. Var.	7.72	7.74	7.88	7.90
Observations	1250460	1246192	1178815	1175245
NAICS 6-digit × Exporter FE	Yes	Yes	Yes	Yes
NAICS 6-digit × Year FE	Yes	Yes	Yes	Yes
Exporter × Year FE	Yes	Yes	Yes	Yes

Notes: The unit of observation is a 6-digit NAICS industry-year-exporter triplet. The dependent variable is log exports. In column 1 and 3, we use pre-period patent stock to calculate innovation exposure and in column 2 and 4, we use pre-period citation-weighted patent stock to calculate innovation exposure. All possible two-way fixed effects are included in all specifications. Standard errors, clustered at 6-digit NAICS-exporter level, are reported in parentheses.

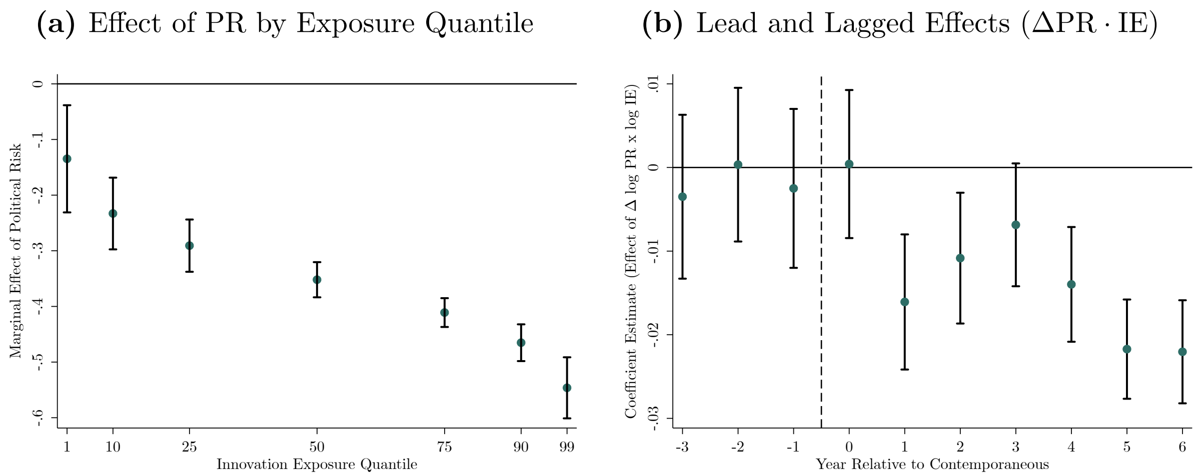
acteristics of country-sector export markets could be associated with subsequent trends in exports for reasons unrelated to innovation, biasing the results. We will return to this issue after presenting the baseline results.

7.2 Results

Estimates of Equation 7.1 are reported in Table 6. In columns 1 and 2 we use pre-period patent stock and citation-weighted patent stock (respectively) to calculate innovation exposure. We find strong evidence that $\phi < 0$. A given increase in political risk leads to a 32% greater decline in exports for a sector with top-quartile export-market innovation exposure compared to a sector with bottom-quartile export-market innovation exposure. In column 3-4 of Table 6, we replace log PR with Δlog PR, to better capture the consequences of a *shock* to political risk. ϕ remains negative ($p < 0.01$). Thus, exports from markets that experience political risk shocks decline substantially more to innovative-intensive countries, potentially driven by the fact that endogenous technological change facilitates production on-shoring. Stated differently, foreign innovation exacerbates the negative effects of domestic political turmoil on export performance.

We next estimate a related specification where we remove the country-year fixed effects and include PR_{ct} in the regression, in order to compare the direct impact of political risk on exports to the additional effect induced by export-market innovation exposure. Intuitively,

Figure 7: Political Risk and Trade: The Effect of Innovation Exposure



Notes: Panel (a) shows the marginal effect of political risk on exports, evaluated at different quantiles of innovation exposure. Standard errors are clustered at the 6-digit NAICS $\times$ country level and the graph reports both coefficients and 95% confidence intervals. Panel (b) reports a series of leads and lags of the effect of $\Delta PR \cdot IE$ in estimates of Equation 7.1. Standard errors are clustered at 6-digit NAICS $\times$ country level and 95% confidence intervals are reported.

we find a negative direct effect of political risk, along with the negative amplifying effect of innovation exposure. Figure 7a displays the results graphically, plotting the implied marginal effect of political risk for several quantiles of export-market innovation exposure. For example, the elasticity of exports to political risk is roughly -0.35 at the median value of innovation exposure. However, it is -0.23 at the tenth percentile of innovation exposure and nearly -0.5 at the ninetieth percentile of innovation exposure. The variation in elasticity spanned by heterogeneity in innovation exposure is slightly larger than the marginal effect of political risk at median innovation exposure. Thus, innovation plays a major role in reshaping the direct effect of political risk on patterns of trade.

Finally, we explore the dynamic effect of political risk and innovation exposure on exports. Figure 7b plots several leading and lagged values of the interaction $\Delta \log \mathrm{PR}_{ct} \cdot \log \mathrm{IE}_{ci}$. We find no evidence of pre-existing trends: all leads are close to zero and statistically insignificant. Instead, in the years following a shock, exports decline substantially and significantly more in markets with higher innovation exposure. This effect persists for several years and does not appear to decrease over time, indicating that foreign innovation exacerbates the medium-run negative consequences of political risk shocks.

Addressing Threats to Interpretation. As noted above, the main challenge when interpreting these estimates is that a country-sector's exposure to innovation in foreign markets may be correlated with other features of its export markets. For this to bias our estimates, that feature would also have to affect *trends* in that sector's exports and, in particular, how exports respond to political risk. The absence of pre-trends in Figure 7b is reassuring in this regard. Nevertheless, causal identification is more challenging in this part of the analysis since we are interested in estimating the (heterogeneous) consequences of *domestic* changes in political risk, rather than the consequences of foreign changes in political risk that were our focus in previous sections. Therefore, we urge a more cautious reading of these findings, but nevertheless provide a battery of results consistent with a causal interpretation of the estimates.

First, we construct a series of controls that attempt to account for features of export markets other than their innovation intensity, and include interactions of political risk with these in estimates of Equation 7.1. In particular, we construct variables of the form:

$$X_{ci} = \sum_{k \neq c} \text{Exports}_{i,c \to k,t_0} \cdot Z_{kt_0}$$

where Z_{kt_0} are baseline characteristics of export markets. We then include the X_{ic} interacted with $\log \text{PR}_{ct}$ as controls. To be as flexible as possible, we download all country-level characteristics from the World Bank World Development Indicators (WDI) database and compute the average of each for each country over the period 1990-2000. In a first test, we select the indicators by hand that seem most relevant (including GDP, per-capita GDP, GDP growth, population, proxies for educational attainment, etc.). In a second, we use post-double LASSO to select the characteristics most predictive of export responses to political risk shocks (see Appendix B.5 for details). Appendix Table A.8 reports the results. Many of these covariates could be considered "bad controls" (i.e., they could be outcomes of differences in innovation intensity). Nevertheless, our baseline estimates of ϕ remain negative after including these broad sets of controls.[19] Thus, the findings do not seem driven by any obvious characteristic of export markets that may spuriously drive changes in trade flows following political risk shocks.

Second, we exploit finer variation in exports within a given sector to export markets

[19]The difference in coefficient is largely due to the different sample when conditioning on the availability of all relevant WDI characteristics.

of varying innovation intensity. That is, we estimate:

$$\log \text{Exports}_{ckit} = \phi \log\ \text{PR}_{ct} \cdot \log\ \text{IE}_{cki} + \alpha_{cki} + \delta_{ckt} + \gamma_{kit} + \eta_{cit} + \epsilon_{ckit} \tag{7.3}$$

where now the unit of observation is the origin-destination-sector-year quadruplet and the outcome is exports from country c to country k in sector i at time t. The coefficient of interest is the interaction term between the same political risk measure and innovation intensity at the *sector-origin-destination* level. Specifically, we calculate $\text{IE}_{cki} = \text{ExportShare}_{i,c\to k,t_0} \cdot \text{InnovationStock}_{ikt_0}$. This specification accommodates all *three-way* fixed effects, including sector-origin-year fixed effects, fully absorbing market-specific trends that could bias the estimates in Table 6. This specification also includes sector-destination-year fixed effects, fully absorbing all characteristics of destination markets (including innovation intensity). This specification exploits only variation *within* country-sector-year triplets and *across* destination markets of varying innovation intensity.

Estimates from this specification are reported in Table A.9. We find that $\phi < 0$, again consistent with foreign-directed innovation exacerbating the negative effect of political risk on exports and reshaping comparative advantage in response to political risk shocks. The results are also qualitatively similar if we include each of the three-way fixed effects independently rather than all at once (see columns 2-5 in Appendix Table A.9).

Together, these estimates suggest that directed innovation mediates the effect of political risk on exports and patterns of trade. From the perspective of an importer, innovation leads to lower reliance on politically risky foreign markets. From the perspective of an exporter experiencing political turmoil, foreign innovation exacerbates and extends export declines, perhaps worsening the economic consequences of political risk.

8 Conclusion

Rising political tension and overseas political risk threaten access to critical economic inputs. We study how innovation responds to these political risks, potentially reshaping their economic consequences. We formalize how foreign political risk generates a domestic incentive for innovative activity and how this leads to a reduction in reliance on foreign inputs, even when adverse political shocks do not actually take place. Combining data on political risk, innovation, and trade around the world, we present three main sets of empirical findings. First, when sectors are more exposed to foreign political risk, innovation in those sectors increases. This relationship holds both across critical minerals and across all sectors, in the US and around the world. Second, when political risk emanates from a geopolitical adversary, there is a greater response of innovation to mitigate potential risks. This result is consistent with our finding that geopolitical adversaries are more likely to impose restrictive trade policies in response to a rise in political risk in either country. Finally, when a country-sector pair exports to more innovation-intensive markets, increases in domestic political risk lead to a larger reduction in exports.

Taken together, our analysis shows that innovation responds endogenously to changes in foreign political risk. This could allow countries to adapt to foreign shocks by reducing their reliance on risky foreign markets. The opposite side of the same coin, however, is that directed technological change further weakens the export performance of countries undergoing political turmoil. This could exacerbate the negative economic effects of political risk shocks for the countries that experience them and increase global inequality.

These findings are potentially relevant for a nascent literature in geoeconomics studying the optimal policy to harm a foreign adversary (e.g., Clayton, Maggiori, and Schreger, 2023, 2024, 2025, for a review). Our findings suggest that even the specter of government intervention can reduce reliance on foreign imports: the mere risk of a loss of access in the future through policy restrictions may spur an innovative response that reduces the need for such intervention *ex post*. This raises interesting questions regarding the complementarity between government intervention and endogenous technology investment. The recent development of reasoning models in China (such as DeepSeek) that require substantially less computing power exemplifies the response of innovation to the risk of potential future restrictions on chip imports driven by political competition. Thus, not only can policy spur domestic innovation but it can also shape innovation incentives overseas—perhaps even catalyzing the very technological advancements that it seeks to curtail. Integrating such interactions between innovation and policy into models of geopolitics would be an interesting avenue for future research.

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Online Appendix

Foreign Political Risk and Technological Change

by Joel P. Flynn, Antoine Levy, Jacob Moscona, and Mai Wo

A Model Analysis, Extensions, and Omitted Proofs

A.1 Equilibrium Innovation Incentives and Aggregate Outcomes

We study the equilibrium outcomes of the model, where all firms optimally decide whether to import or produce domestically and optimally choose their level of innovation. By solving out for all equilibrium conditions except for the firms' optimal innovation level, we obtain the following result that characterizes firms innovation choices and the aggregate consequences of those choices:

Proposition 3 (Equilibrium Properties)**.** *In any equilibrium, the following are true:*

1. *Each firm $i \in [0,1]$ has marginal costs given by*

$$\mathcal{M}^i_{k,t}(s) = \min\left\{P_{k,F,t}(s), \frac{1}{A^i_{k,t}}\right\}, \quad s \in \{0,\tau\} \tag{A.1}$$

where state ($s=0$) $s=\tau$ corresponds to the political shock (not) taking place.

2. *Each firm $i \in [0,1]$ has an innovation level $A^i_{k,1}$ that solves the following problem:*

$$A_1(A^i_{k,0}) = \arg \max_{A^i_{k,1} \geq A^i_{k,0}} \bar{\Pi}\mathbb{E}\left[\mathcal{M}^i_{k,1}(s)^{1-\eta}\right] - C\left(A^i_{k,1}, A^i_{k,0}\right) \tag{A.2}$$

where $\bar{\Pi}$ is an exogenous constant that we report in the proof of the result.

3. *Letting an equilibrium cumulative distribution function of $A^i_{k,1}$ be G, we have that the aggregate production of the sector is given by:*

$$Y_{k,1} = \left(\alpha_{k,1} X_{k,F,1}^{\frac{\eta-1}{\eta}} + (1-\alpha_{k,1})\mathbb{E}_G\left[\left(A^i_{k,1}L^i_{k,1}\right)^{\frac{\eta-1}{\eta}} \mid A^i_{k,1} \geq P^{-1}_{k,F,1}\right]\right)^{\frac{\eta}{\eta-1}} \tag{A.3}$$

where $\alpha_{k,1} = G(P^{-1}_{k,F,1}) \in [0,1]$, and $X_{k,F,1}$ denotes the imports of firms that import in sector k.

Proof. By standard arguments, the final demand of good k and the demand for variety i of good k are given by:

$$Y_{k,t} = Y_t\left(\frac{P_{k,t}}{P_t}\right)^{-\eta}, \quad Y^i_{k,t} = Y_{k,t}\left(\frac{P^i_{k,t}}{P_{k,t}}\right)^{-\eta} \tag{A.4}$$

We also have that the cost of the foreign input, the output of sector k, and final output are given by:

$$P_{k,F,t} = \frac{1}{(1-\tau_{k,t})A_{k,F}}, \quad P_{k,t} = \left(\int_{[0,1]} {P^i_{k,t}}^{1-\eta}\,\mathrm{d}i\right)^{\frac{1}{1-\eta}}, \quad P_t = \left(\int_{[0,1]} P_{k,t}^{1-\eta}\,\mathrm{d}k\right)^{\frac{1}{1-\eta}} \tag{A.5}$$

where we normalize the price of aggregate output $P_t = 1$. If a firm sources from abroad or produces domestically, then its marginal costs of production are given by, respectively:

$$\mathcal{M}^i_{k,F,t} = P_{k,F,t}, \quad \mathcal{M}^i_{k,D,t} = \frac{1}{A^i_{k,t}} \tag{A.6}$$

In equilibrium, a firm must choose its least marginal cost production technology at each date and in each state and so its marginal costs will be given by:

$$\mathcal{M}^i_{k,t} = \min\{\mathcal{M}^i_{k,F,t}, \mathcal{M}^i_{k,D,t}\} \tag{A.7}$$

Given the firm faces an isoelastic demand curve, it is optimal for the firm to charge the following price $P^i_{k,t}$ and produce the following quantity $Y^i_{k,t}$:

$$P^i_{k,t} = \frac{\eta}{\eta-1}\mathcal{M}^i_{k,t}, \quad Y^i_{k,t} = \left(\frac{\eta-1}{\eta}\right)^{\eta} Y_{k,t}P^{\eta}_{k,t}(\mathcal{M}^i_{k,t})^{-\eta} \tag{A.8}$$

Thus, the firm's profits are given by:

$$\Pi_{k,t}(\mathcal{M}^i_{k,t}) = \frac{1}{\eta-1}\left(\frac{\eta-1}{\eta}\right)^{\eta} Y_t(\mathcal{M}^i_{k,t})^{1-\eta} \tag{A.9}$$

Equilibrium then boils down to characterizing firms' innovation decisions. To economize on notation, we drop the k subscript and write $\mathcal{M}^i_{k,t} = \mathcal{M}^i(s)$, where $s = \tau$ corresponds to the political shock happening in F and $s = 0$ corresponds to the political shock not taking place. We have that the date zero innovation decision A^i_1 solves:

$$A_1(A^i_0) = \arg\max_{A^i_1 \geq A^i_0} \bar{\Pi}\mathbb{E}\left[\ \mathcal{M}^i(s)^{1-\eta}\right] - C\left(A^i_1, A^i_0\right) \tag{A.10}$$

where $\bar{\Pi} = \frac{1}{\eta-1}\left(\frac{\eta-1}{\eta}\right)^{\eta} Y_1$ is invariant to outcomes in sector k. The final part of the result follows immediately by substituting into the sector-level production function. $\square$

This result clarifies the equilibrium innovation incentives of firms stem from the desire to reduce the expected marginal costs of production. In turn, these marginal costs depend on whether the firm is sufficiently productive for it to produce domestically rather than importing: there are only gains to innovating if the firm will actually rely on its own technology to produce. In this context, the importance of political risk is that it induces variation across states of the world in whether firms will import from abroad or prefer to "on-shore" and produce domestically. Firms internalize this risk when making their optimal innovation decisions. The final part of this result shows that this structure of optimal production and innovation generates an endogenous CES production technology at the sector level, where the weight on imports $\alpha_{k,1}$ is decreasing in the distribution of firms' innovation decisions G (in the sense of first-order stochastic dominance). Thus, while individual firms face lumpy re-shoring decisions, this generates emergent smooth substitution patterns at the sector level. In turn, these sector level patterns will be the relevant ones for determining production and import patterns.

A.2 Equilibrium Segmentation

Firms endogenously segment into three groups: firms that never produce using the domestic technology, firms that produce using the domestic technology only when the foreign political shock occurs, and firms that always produce using the domestic technology. We call firms in the first group *laggards*, as they never engage in innovation. We call firms in the second group *insurance innovators*, as they innovate to mitigate the risk of facing high input prices when adverse political shocks hit, while retaining the option of using imports if they do not. We call firms in the final group *classical innovators*, as these firms are so productive they never rely on the foreign input and their innovation decisions are affected only by the standard market size effect.

Proposition 4 (Segmentation into Innovation Types). *In equilibrium, only two segmentation patterns are possible:*

1. *Two Types: There exists a unique $\bar{A} > 0$ such that low productivity ($A_0^i < \bar{A}$) firms ("laggards") always import while high productivity ($A_0^i \geq \bar{A}$) firms ("classical innovators") always use the domestic technology.*
2. *Three Types: There exist unique $\underline{A} > 0$ and $\overline{A} > \underline{A}$ such that low productivity ($A_0^i \leq \underline{A}$) firms always import, medium productivity ($A_0^i \in (\underline{A}, \overline{A})$) firms ("insurance innovators") use the domestic technology only when the political shock happens, and high productivity ($A_0^i \geq \overline{A}$) firms always use the domestic technology.*

Proof. To avoid repetition, we derive this result in the setting of the extended model with nested CES developed in Appendix A.5. Our baseline model corresponds to $\epsilon = \eta$. Hereafter, we refer to laggards as N, insurance innovators as S, and classical innovators as A. Let $\Pi^c(A_1^i, A_0^i)$, $c = \{N, S, A\}$ denote the net profit under each of the three cases, given (A_1^i, A_0^i). Let $\bar{\Pi}^c(A_0^i)$ denote the corresponding optimal net profit in each case. We begin by proving the following lemma:

Lemma 1 (Properties of Profits). *In any equilibrium, i.e., for any sector-level vector of prices across states $(P(0), P(\tau))$, the following statements are true:*

1. *$\bar{\Pi}^S$ crosses $\bar{\Pi}^N$ once and from below at a unique value $\underline{A} > 0$.*
2. *$\bar{\Pi}^A$ crosses $\bar{\Pi}^N$ once and from below at a unique value $\tilde{A} > 0$.*
3. *$\bar{\Pi}^A$ crosses $\bar{\Pi}^S$ once and from below at a unique value $\overline{A} > 0$.*

Proof. We break the proof of this result into three steps.

Step I: Optimal Investment. We begin by characterizing the optimal level of investment in each of three cases. First, in case (N), firm's marginal costs are given by $\mathcal{M}^i(s) = \mathcal{M}_F(s) = \frac{1}{(1-\tau(s))A_F}$. Thus, we have that firms' expected profits are given by:

$$\Pi^N(A_1^i, A_0^i) = \bar{\Pi}\mathbb{E}[P(s)^{\eta-\epsilon}\mathcal{M}_F(s)^{1-\eta}] - C(A_1^i, A_0^i) \tag{A.11}$$

and it is immediate that $A_1^i = A_0^i$ is optimal. We denote the profit value in this case by:

$$\bar{\Pi}^N(A_0^i) = \pi^N(A_0^i, A_0^i) = \bar{\Pi}\mathbb{E}[P(s)^{\eta-\epsilon}\mathcal{M}_F(s)^{1-\eta}] \tag{A.12}$$

which is constant as a function of A_0^i.

Second, in case (S), firms' marginal costs are given by $\mathcal{M}^i(\tau) = \frac{1}{A_1^i}$ and $\mathcal{M}^i(0) = \frac{1}{A_F}$. Thus, firms' expected profits are given by:

$$\Pi^S(A_1^i, A_0^i) = \bar{\Pi}\left[pP(\tau)^{\eta-\epsilon}(A_1^i)^{\eta-1} + (1-p)P(0)^{\eta-\epsilon}A_F^{\eta-1}\right] - \kappa\left[\left(\frac{A_1^i}{A_0^i}\right)^{\delta} - 1\right] \tag{A.13}$$

The first-order condition for optimal investment sets:

$$(\eta-1)\bar{\Pi}[pP(\tau)^{\eta-\epsilon}](A_1^i)^{\eta-2} = \kappa\delta(A_1^i)^{\delta-1}(A_0^i)^{-\delta} \tag{A.14}$$

This condition admits a unique solution given by

$$A_1^i = \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}[pP(\tau)^{\eta-\epsilon}](A_0^i)^{\delta}\right)^{\frac{1}{1+\delta-\eta}} \tag{A.15}$$

Since $\delta+1 > \eta$, the second-order condition is satisfied, ensuring that A_1^i above attains the maximum. Moreover, $A_1^i > A_0^i$ iff $A_0^i > \hat{A}^S = \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}[pP(\tau)^{\eta-\epsilon}]\right)^{\frac{-1}{\eta-1}}$. All Case (S) firms with $A_0^i \leq \hat{A}^S$ do not innovate. All Case (S) firms with $A_0^i > \hat{A}^S$ innovate. Formally

$$A_1^i = A^S(A_0^i) = \begin{cases} A_0^i & , A_0^i \leq \hat{A}^S, \\ \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}[pP(\tau)^{\eta-\epsilon}](A_0^i)^{\delta}\right)^{\frac{1}{1+\delta-\eta}} & , A_0^i > \hat{A}^S. \end{cases} \tag{A.16}$$

which is a continuous and strictly increasing function.

Finally, in case (A), firms' marginal costs are given by $\mathcal{M}^i(s) = \frac{1}{A_i^1}$. Thus, we have that firms' expected profits are:

$$\Pi^A(A_1^i, A_0^i) = \bar{\Pi}[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}](A_1^i)^{\eta-1} - \kappa\left[\left(\frac{A_1^i}{A_0^i}\right)^{\delta} - 1\right] \tag{A.17}$$

In this case, taking the first order condition for optimal investment and rearranging, we obtain that:

$$A_1^i = \left((\eta - 1)\bar{\Pi}\frac{1}{\kappa\delta}[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}](A_0^i)^\delta \right)^{\frac{1}{1+\delta-\eta}} \tag{A.18}$$

Similarly, we define $\hat{A}^A = \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}]\right)^{\frac{-1}{\eta-1}}$. Similarly to case (S), we have that:

$$A_1^i = A^A(A_0^i) = \begin{cases} A_0^i & , A_0^i \leq \hat{A}^A, \\ \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}](A_0^i)^\delta\right)^{\frac{1}{1+\delta-\eta}} & , A_0^i > \hat{A}^A. \end{cases} \tag{A.19}$$

which is a continuous and strictly increasing function. Also, we have $\hat{A}^A < \hat{A}^S$.

Step II: Properties of Profits. We now determine various properties of the profits from investing optimally (as per Step I). In Case (N), we have already found that $\bar{\Pi}^N(A_0^i)$ is constant.

In Case(S), we can similarly define the payoff from investing optimally as:

$$\bar{\Pi}^S(A_0^i) = \max_{A_1^i \geq A_0^i} \Pi^S(A_1^i, A_0^i) \tag{A.20}$$

We now establish the monotonicity and convexity properties of $\bar{\Pi}^S(A_0^i)$. We have shown that $A_1^i = A_0^i$ if and only if $A_0^i \leq \hat{A}^S$. Thus, for all $A_0^i \leq \hat{A}^S$, we have that $\bar{\Pi}^S(A_0^i) = \Pi^S(A_0^i, A_0^i) = \bar{\Pi}[pP(\tau)^{\eta-\epsilon}(A_0^i)^{\eta-1} + (1-p)P(0)^{\eta-\epsilon}A_F^{\eta-1}]$, which is a strictly increasing function. For all $A_0^i > \hat{A}^S$, we have that $\bar{\Pi}^S(A_0^i) = \Pi^S(A^S(A_0^i), A_0^i)$. Differentiating this function, we obtain:

$$\begin{aligned} \bar{\Pi}^{S\prime}(A_0^i) &= \Pi_1^S(A^S(A_0^i), A_0^i)A^{S\prime}(A_0^i) + \Pi_0^S(A^S(A_0^i), A_0^i) = \Pi_0^S(A^S(A_0^i), A_0^i) \\ &= \kappa\delta A^S(A_0^i)^\delta \left(A_0^i\right)^{-\delta-1} = \kappa\delta\left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}[pP(\tau)^{\eta-\epsilon}]\left(A_0^i\right)^\delta\right)^{\frac{\delta}{1+\delta-\eta}}\left(A_0^i\right)^{-\delta-1} \\ &= \kappa\delta\left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}[pP(\tau)^{\eta-\epsilon}]\right)^{\frac{\delta}{1+\delta-\eta}}\left(A_0^i\right)^{\frac{(\eta-1)\delta}{1+\delta-\eta}-1} \end{aligned} \tag{A.21}$$

Thus, for $A_0^i > \hat{A}^S$, we have that $\bar{\Pi}^S$ is a strictly increasing function. Moreover, for $A_0^i > \hat{A}^S$, it is a strictly convex function if and only if $\eta > 1 + \frac{\delta}{1+\delta}$, which is implied by our assumption that $\eta \geq 2$.

In Case (A), can follow the same steps and write:

$$\bar{\Pi}^A(A_0^i) = \max_{A_1^i \geq A_0^i} \Pi^A(A_1^i, A_0^i) \tag{A.22}$$

We have shown that $A_1^i = A_0^i$ if and only if $A_0^i \leq \hat{A}^A$. Thus, for all $A_0^i \leq \hat{A}^A$, we have that $\bar{\Pi}^A(A_0^i) = \bar{\Pi}[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}](A_0^i)^{\eta-1}$, which is strictly increasing in A_0^i. For all $A_0^i > \hat{A}^A$, we have that $\bar{\Pi}^A(A_0^i) = \Pi^A(A^A(A_0^i), A_0^i)$. Differentiating this function yields:

$$\begin{aligned}
\bar{\Pi}^{A\prime}(A_0^i) &= \Pi_1^A(A^A(A_0^i), A_0^i)A^{A\prime}(A_0^i) + \Pi_0^A(A^A(A_0^i), A_0^i) = \Pi_0^A(A^A(A_0^i), A_0^i) \\
&= \kappa\delta A^A(A_0^i)^\delta \left(A_0^i\right)^{-\delta-1} \\
&= \kappa\delta\left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}]\left(A_0^i\right)^\delta\right)^{\frac{\delta}{1+\delta-\eta}}\left(A_0^i\right)^{-\delta-1} \\
&= \kappa\delta\left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}]\right)^{\frac{\delta}{1+\delta-\eta}}\left(A_0^i\right)^{\frac{(\eta-1)\delta}{1+\delta-\eta}-1}
\end{aligned} \tag{A.23}$$

which is again both strictly positive and strictly increasing if $\eta \geq 2$. Thus, for $A_0^i > \hat{A}^A$, $\bar{\Pi}^A$ is a strictly increasing and strictly convex function.

Finally, we observe that the original problem of the firm is equivalent to selecting the optimal case from cases (N), (S), and (A):

$$\begin{aligned}
\Pi^*(A_0^i) = \max_{A_1^i \geq A_0^i} \bar{\Pi}\Bigg[&pP(\tau)^{\eta-\epsilon}(\max\{A_1^i, (1-\tau)A_F\})^{\eta-1} \\
&+ (1-p)P(0)^{\eta-\epsilon}(\max\{A_1^i, A_F\})^{\eta-1}\Bigg] \\
&- \kappa\left[\left(\frac{A_1^i}{A_0^i}\right)^\delta - 1\right] \\
= \max\{&\bar{\Pi}^N(A_0^i), \bar{\Pi}^S(A_0^i), \bar{\Pi}^A(A_0^i)\}
\end{aligned} \tag{A.24}$$

Formally, if $A_1^i \geq A_F$, observe that $\Pi^*(A_0^i) = \bar{\Pi}^A(A_0^i)$. If $A_1^i \in ((1-\tau)A_F, A_F)$, then $\Pi^*(A_0^i) = \bar{\Pi}^S(A_0^i)$. And if $A_1^i \leq (1-\tau)A_F$, then $\Pi^*(A_0^i) = \bar{\Pi}^N$. Thus, as we have solved for firms' optimal investments in each case, it now suffices to check how firms endogenously segment into cases (N), (S), and (A).

Step III: Patterns of Segmentation. We now use these profits to determine into which of the three cases firms optimally sort. We have shown that $\bar{\Pi}^N$ is constant and that $\bar{\Pi}^S$ and $\bar{\Pi}^A$ are strictly increasing. Thus, if $\bar{\Pi}^S$ and $\bar{\Pi}^A$ cross $\bar{\Pi}^N$, then they do so at most once. To show that they do indeed cross at most once, it suffices to show that there exist values of A_0^i such that $\bar{\Pi}^S(A_0^i) < \bar{\Pi}^N$ and $\bar{\Pi}^A(A_0^i) < \bar{\Pi}^N$.

To this end, in case (S) consider the point such that $A^S(A_0^i) = (1-\tau)A_F$. If $A_0^i \leq \hat{A}^S$, then $A^S(A_0^i) = A_0^i = (1-\tau)A_F \leq \hat{A}^S$. In this case, we have that the firm is indifferent between using domestic technology and importing in the bad state and pays zero innovation costs, and so $\bar{\Pi}^S(A_0^i) = \bar{\Pi}^N$, which implies that $\bar{\Pi}^S(A_0^i)$ cross at the point $A_0^i = (1-\tau)A_F$. If $A_0^i > \hat{A}^S$, then the firm is indifferent between both technologies in the bad state but expends a strictly positive innovation cost, implying that $\bar{\Pi}^S(A_0^i) < \bar{\Pi}^N$. Thus, in either case, we have that $\bar{\Pi}^S$ and $\bar{\Pi}^N$ cross exactly once at some value $\underline{A} > 0$:

$$\underline{A} = \bar{\Pi}^{S^{-1}}\left(\bar{\Pi}^N\right) \tag{A.25}$$

Moreover, we have also established that $\underline{A} \geq A^{S^{-1}}((1-\tau)A_F)$, which is strict if and only if $(1-\tau)A_F > \hat{A}^S$.

We can follow the same steps for case (A). Consider the point such that $A^A(A_0^i) = (1-\tau)A_F$. If $A_0^i \leq \hat{A}^A$, then $A^A(A_0^i) = A_0^i = (1-\tau)A_F \leq \hat{A}^A$. As in case (S), such a firm is indifferent between using the domestic technology and importing in the bad state but now also strictly prefers to use the foreign good in the good state. Thus, $\bar{\Pi}^A(A_0^i) < \bar{\Pi}^N$. If $A_0^i > \hat{A}^A$, then again the firm is indifferent in the bad state but prefers to use the foreign good in the good state and moreover expends strictly positive innovation costs. Thus, in both cases $\bar{\Pi}^A(A_0^i) < \bar{\Pi}^N$ and so there exists a unique value $\tilde{A} > 0$ such that:

$$\tilde{A} = \bar{\Pi}^{A^{-1}}\left(\bar{\Pi}^N\right) \tag{A.26}$$

Finally, to understand the preference between case (S) and case (A), we need to understand where $\bar{\Pi}^S$ and $\bar{\Pi}^A$ cross. In what follows, we show that there is a unique value $\overline{A} > 0$ such that $\bar{\Pi}^S(\overline{A}) = \bar{\Pi}^A(\overline{A})$. We split this analysis into three cases based on the relationship between A_F, $\hat{A}^A$, and $\hat{A}^S$ (which are exhaustive by the fact that $\hat{A}^A < \hat{A}^S$):

1. $A_F \leq \hat{A}^A < \hat{A}^S$: As $A_1^i \geq A_0^i$, if $A_0^i > A_F$, then it is immediate that $\bar{\Pi}^A(A_0^i) > \bar{\Pi}^S(A_0^i)$, as it is always optimal to use the domestic technology in either state. Similarly, if $A_0^i < A_F$, as $A_F \leq \hat{A}^A < \hat{A}^S$, in both cases (A) and (S), firms set $A_1^i = A_0^i$. Thus, we have that $A_1^i < A_F$ and it is optimal to use the foreign technology in the good state, implying that $\bar{\Pi}^S(A_0^i) > \bar{\Pi}^A(A_0^i)$. Thus, $\bar{\Pi}^S$ and $\bar{\Pi}^A$ cross once and only once at the value of $A_0^i = A_F$ and $\bar{\Pi}^A$ crosses $\bar{\Pi}^S$ from below.
2. $\hat{A}^A < \hat{A}^S < A_F$: We further segment this analysis into four subcases and compare the values of $\bar{\Pi}^S$ and $\bar{\Pi}^A$.
    (a) $A_0^i > A_F$: We have that

    $$\bar{\Pi}^A(A_0^i) = \Pi^A(A^A(A_0^i), A_0^i) > \Pi^A(A^S(A_0^i), A_0^i) > \Pi^S(A^S(A_0^i), A_0^i) = \bar{\Pi}^S(A_0^i) \tag{A.27}$$

    where the first equality is by definition, the second inequality is by the fact that $A^A(A_0^i) \neq A^S(A_0^i)$ (as $A_0^i > \hat{A}^A, \hat{A}^S$), the third inequality is by the fact that $A^S(A_0^i) > A_0^i > A_F$ which means using the domestic technology in both states is optimal, and the final inequality is by definition.
    (b) $A_0^i < \hat{A}^A$: Here we have that $A^A(A_0^i) = A_0^i$ and $A^S(A_0^i) = A_0^i$. As $A_0^i < A_F$, we have that it is optimal to use the foreign technology in the good state and so $\bar{\Pi}^S(A_0^i) > \bar{\Pi}^A(A_0^i)$.
    (c) $A_0^i \in [\hat{A}^A, \hat{A}^S]$: Suppose that $\bar{\Pi}^A$ and $\bar{\Pi}^S$ cross on $A_0^i \in [\hat{A}^A, \hat{A}^S]$ and let $\overline{A}$ be the smallest such value that $\bar{\Pi}^A(\overline{A}) = \bar{\Pi}^S(\overline{A})$. By the fundamental theorem of

calculus, we can write:

$$\begin{aligned} \bar{\Pi}^A(A_0^i) &= \bar{\Pi}^A(\overline{A}) + \int_{\overline{A}}^{A_0^i} \bar{\Pi}^{A'}(z)\,\mathrm{d}z \\ \bar{\Pi}^S(A_0^i) &= \bar{\Pi}^S(\overline{A}) + \int_{\overline{A}}^{A_0^i} \bar{\Pi}^{S'}(z)\,\mathrm{d}z \end{aligned} \tag{A.28}$$

which implies that:

$$\bar{\Pi}^A(A_0^i) - \bar{\Pi}^S(A_0^i) = \int_{\overline{A}}^{A_0^i} \left(\bar{\Pi}^{A'}(z) - \bar{\Pi}^{S'}(z)\right) \mathrm{d}z \tag{A.29}$$

Thus, $\bar{\Pi}^A - \bar{\Pi}^S$ is increasing whenever $\bar{\Pi}^{A'}(z) - \bar{\Pi}^{S'}(z) > 0$ and decreasing whenever $\bar{\Pi}^{A'}(z) - \bar{\Pi}^{S'}(z) < 0$. We now show that there exists exactly one value of $\breve{A} > 0$ such that (i) $\bar{\Pi}^{A'}(\breve{A}) - \bar{\Pi}^{S'}(\breve{A}) = 0$, (ii) $\bar{\Pi}^{A'}(z) - \bar{\Pi}^{S'}(z) > 0$ for all $z > \breve{A}$, and (iii) $\bar{\Pi}^{A'}(z) - \bar{\Pi}^{S'}(z) < 0$ for all $z < \breve{A}$. To this end, recall from Step II that for $A_0^i > \hat{A}^A$ and $A_0^i < \hat{A}^S$, respectively:

$$\begin{aligned} \bar{\Pi}^{A'}(A_i^0) &= \kappa\delta \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}\right]\right)^{\frac{\delta}{1+\delta-\eta}} \left(A_0^i\right)^{\frac{(\eta-1)\delta}{1+\delta-\eta}-1} \\ \bar{\Pi}^{S'}(A_i^0) &= \bar{\Pi}(\eta-1)\left[pP(\tau)^{\eta-\epsilon}\right]\left(A_1^i\right)^{\eta-2} \end{aligned} \tag{A.30}$$

and we define:

$$\begin{aligned} C^A &= \kappa\delta \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}\right]\right)^{\frac{\delta}{1+\delta-\eta}} \\ \tilde{C}^S &= \bar{\Pi}(\eta-1)\left[pP(\tau)^{\eta-\epsilon}\right] \\ \Gamma &= \frac{(\eta-1)\delta}{1+\delta-\eta} - 1 \end{aligned} \tag{A.31}$$

Thus, we have that any value of $\breve{A}$ must solve:

$$C^A \breve{A}^\Gamma = \tilde{C}^S \breve{A}^{\eta-2} \implies \breve{A} = \left(\frac{\tilde{C}^S}{C^A}\right)^{\frac{1}{\Gamma-(\eta-2)}} \tag{A.32}$$

We now need to check if $\bar{\Pi}^{A''}(\check{A}) - \bar{\Pi}^{S''}(\check{A}) > 0$. We calculate that:

$$\begin{aligned}
\bar{\Pi}^{A''}(\check{A}) - \bar{\Pi}^{S''}(\check{A}) &= \Gamma C^A \check{A}^{\Gamma-1} - (\eta-2)\tilde{C}^S \check{A}^{(\eta-2)-1} \\
&= \Gamma C^A \left(\frac{\tilde{C}^S}{C^A}\right)^{\frac{\Gamma-1}{\Gamma-(\eta-2)}} - (\eta-2)\tilde{C}^S \left(\frac{\tilde{C}^S}{C^A}\right)^{\frac{(\eta-2)-1}{\Gamma-(\eta-2)}} \\
&= \Gamma C^{A\,1-\frac{\Gamma-1}{\Gamma-(\eta-2)}} \tilde{C}^{S\,\frac{\Gamma-1}{\Gamma-(\eta-2)}} - (\eta-2) C^{A\,-\frac{(\eta-2)-1}{\Gamma-(\eta-2)}} \tilde{C}^{S\,1+\frac{(\eta-2)-1}{\Gamma-(\eta-2)}} \\
&= \Gamma C^{A\,-\frac{(\eta-2)-1}{\Gamma-(\eta-2)}} \tilde{C}^{S\,\frac{\Gamma-1}{\Gamma-(\eta-2)}} - (\eta-2) C^{A\,-\frac{(\eta-2)-1}{\Gamma-(\eta-2)}} \tilde{C}^{S\,\frac{\Gamma-1}{\Gamma-(\eta-2)}} \\
&= (\Gamma-(\eta-2)) C^{A\,-\frac{(\eta-2)-1}{\Gamma-(\eta-2)}} \tilde{C}^{S\,\frac{\Gamma-1}{\Gamma-(\eta-2)}}
\end{aligned} \tag{A.33}$$

which is greater than zero if and only if $\Gamma > \eta - 2$. We now calculate that:

$$\begin{aligned}
\Gamma - (\eta-2) &= \frac{(\eta-1)\delta}{1+\delta-\eta} - 1 - (\eta-2) = \frac{(\eta-1)\delta}{1+\delta-\eta} - \eta + 1 \\
&= \frac{\eta\delta - \delta - \eta - \eta\delta + \eta^2 + 1 + \delta - \eta}{1+\delta-\eta} = \frac{\eta^2 + 1 - 2\eta}{1+\delta-\eta}
\end{aligned} \tag{A.34}$$

As $\eta > 2$, we have that $\eta^2 > 2\eta$ and so $\Gamma > \eta - 2$.
We have therefore shown that $\bar{\Pi}^A - \bar{\Pi}^S$ is either (i) strictly increasing over $[\hat{A}^A, \hat{A}^S]$ or (ii) strictly decreasing up to some $\check{A}$ and then strictly increasing. We know that $\bar{\Pi}^A(\hat{A}^A) < \bar{\Pi}^S(\hat{A}^A)$ by the same argument as step (b). Thus, $\bar{\Pi}^A - \bar{\Pi}^S$ crosses zero at most once over $[\hat{A}^A, \hat{A}^S]$.

(d) $A_0^i \in (\hat{A}^S, A_F]$: Suppose that $\bar{\Pi}^A$ and $\bar{\Pi}^S$ cross on $A_0^i \in (\hat{A}^S, A_F]$ and let $\overline{A}$ be the smallest such value that $\bar{\Pi}^A(\overline{A}) = \bar{\Pi}^S(\overline{A})$. By the fundamental theorem of calculus, as in step (c), we may write:

$$\bar{\Pi}^A(A_0^i) - \bar{\Pi}^S(A_0^i) = \int_{\overline{A}}^{A_0^i} \left(\bar{\Pi}^{A\prime}(z) - \bar{\Pi}^{S\prime}(z)\right) \mathrm{d}z \tag{A.35}$$

We now use from Step II of the proof that for $A_0^i > \hat{A}^A$ and $A_0^i > \hat{A}^S$:

$$\begin{aligned}
\bar{\Pi}^{A\prime}(A_i^0) &= \kappa\delta \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}\right]\right)^{\frac{\delta}{1+\delta-\eta}} \left(A_0^i\right)^{\frac{(\eta-1)\delta}{1+\delta-\eta}-1} \\
\bar{\Pi}^{S\prime}(A_i^0) &= \kappa\delta \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon}\right]\right)^{\frac{\delta}{1+\delta-\eta}} \left(A_0^i\right)^{\frac{(\eta-1)\delta}{1+\delta-\eta}-1}
\end{aligned} \tag{A.36}$$

We now let:

$$C^S = \kappa\delta\left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon}\right]\right)^{\frac{\delta}{1+\delta-\eta}} \tag{A.37}$$

and therefore have that (recalling C^A and Γ from part (c)):

$$\bar{\Pi}^A(A_0^i) - \bar{\Pi}^S(A_0^i) = (C^A - C^S)\int_{\underline{A}}^{A_0^i} z^\Gamma \,\mathrm{d}z \tag{A.38}$$

As $C^A > C^S$, this is a strictly increasing function. This implies the following: (i) There is at most one crossing point of $\overline{\Pi}^A$ and $\overline{\Pi}^S$ on $(\hat{A}^S, A_F]$, (ii) If $\overline{\Pi}^A(\hat{A}^S) > \overline{\Pi}^S(\hat{A}^S)$, then there is no crossing point of $\overline{\Pi}^A$ and $\overline{\Pi}^S$ on $(\hat{A}^S, A_F]$, and (iii) If $\overline{\Pi}^A(\hat{A}^S) < \overline{\Pi}^S(\hat{A}^S)$, as $\overline{\Pi}^A$ and $\overline{\Pi}^S$ are continuous and $\overline{\Pi}^A(A_F) \geq \overline{\Pi}^S(A_F)$ (by the arguments of part (a)), then there is exactly one crossing point of $\overline{\Pi}^A$ and $\overline{\Pi}^S$ on $(\hat{A}^S, A_F]$. Thus, if $\overline{\Pi}^A$ and $\overline{\Pi}^S$ have not crossed by $\hat{A}^S$, they must cross exactly once on $(\hat{A}^S, A_F]$. Moreover, if $\overline{\Pi}^A(\hat{A}^S) > \overline{\Pi}^S(\hat{A}^S)$, then $\overline{\Pi}^A$ and $\overline{\Pi}^S$ do not cross on $(\hat{A}^S, A_F]$.

Putting all of this together, we have shown that there exists a unique value of $\overline{A} \in [\hat{A}^A, A_F]$ such that $\bar{\Pi}^A(\overline{A}) = \bar{\Pi}(\overline{A})$ and $\bar{\Pi}^A$ crosses $\bar{\Pi}^S$ from below.

3. $\hat{A}^A < A_F \leq \hat{A}^S$: If $A_0^i > A_F$, we have already shown that $\bar{\Pi}^A(A_0^i) > \bar{\Pi}^S(A_0^i)$. If $A_0^i \leq \hat{A}^A < A_F$, we have already shown that $\bar{\Pi}^S(A_0^i) > \bar{\Pi}^A(A_0^i)$. Thus, as $\bar{\Pi}^A$ and $\bar{\Pi}^S$ are continuous, they must cross at least once on the interval $[\hat{A}^A, A_F]$. The arguments from 2(c) apply here, establishing that there exists a unique value of $\overline{A} \in [\hat{A}^A, A_F]$ such that $\bar{\Pi}^A(\overline{A}) = \bar{\Pi}^S(\overline{A})$ and $\bar{\Pi}^A$ crosses $\bar{\Pi}^S$ from below.

□

Given Lemma 1, Proposition 4 follows immediately. □

We now use these arguments to prove Propositions 1 and 2 from the main text, where $\eta = \epsilon$.

A.3 Proof of Proposition 1

Proof. We first study changes in τ. We immediately observe that $\bar{\Pi}^A$ is invariant to τ, $\bar{\Pi}^S$ is invariant to τ, and $\bar{\Pi}^N$ is decreasing in τ. Thus, increases in τ weakly increase investment for all firms. We now study how changes in p affect investment. Observe that:

$$\begin{aligned}
\frac{\partial}{\partial p}\bar{\Pi}^N(A_0^i) &= \bar{\Pi}\left[((1-\tau)A_F)^{\eta-1} - A_F^{\eta-1}\right] \\
\frac{\partial}{\partial p}\bar{\Pi}^S(A_0^i) &= \bar{\Pi}\left[(A_1^i)^{\eta-1} - A_F^{\eta-1}\right] \\
\frac{\partial}{\partial p}\bar{\Pi}^A(A_0^i) &= \bar{\Pi}\left[(A_1^i)^{\eta-1} - (A_1^i)^{\eta-1}\right] = 0
\end{aligned} \tag{A.39}$$

Thus, we have that $\frac{\partial}{\partial p}\bar{\Pi}^S(A_0^i) - \frac{\partial}{\partial p}\bar{\Pi}^N(A_0^i) = \bar{\Pi}\left[(A_1^i)^{\eta-1} - ((1-\tau)A_F)^{\eta-1}\right]$. This implies that no firm switches from S to N while type N firms may switch to S. Moreover, for type S firms, investment increases. We also have that $\frac{\partial}{\partial p}\bar{\Pi}^A(A_0^i) - \frac{\partial}{\partial p}\bar{\Pi}^S(A_0^i) = \bar{\Pi}\left[A_F^{\eta-1} - (A_1^i)^{\eta-1}\right]$. If $A_1^i \leq A_F$ (as it is for type S firms), this is positive, implying that firms may switch from S to A but not A to S. The previous arguments establish that increases in p or τ may only strictly increase investment for all $i \in \mathcal{I}$. □

A.4 Proof of Proposition 2

Proof. From Equation A.4, we have that $Y_{k,t}^i = Y_t(P_{k,t}^i)^{-\eta}$. Moreover, when a firm imports from Foreign, we have that $X_{k,F,t}^i = Y_t(P_{k,t}^i)^{-\eta}$. We also know that firms optimally set prices such that $P_{k,t}^i = \frac{\eta}{\eta-1}\mathcal{M}_{k,t}^i$. We further know when a firm imports in state s that its marginal costs are given by $\mathcal{M}_{k,t}^i = P_{k,t}(s) = \frac{1}{(1-\tau(s))A_{k,F}}$. Thus, the quantity and value of imports in state s for a firm that imports from foreign are given by, respectively:

$$\begin{aligned}
X_t(s) \equiv X_{k,F,t}^i &= Y_t\left(\frac{\eta-1}{\eta}\right)^{\eta}((1-\tau(s))A_F)^{\eta} \\
X_t^V(s) \equiv P_{k,F,t}X_{k,F,t}^i &= Y_t\left(\frac{\eta-1}{\eta}\right)^{\eta}((1-\tau(s))A_F)^{\eta-1}
\end{aligned} \tag{A.40}$$

From Proposition 4, we have that the equilibrium segmentation of firms can be summarized by the fraction of laggards $\alpha_{L,t}$ and the fraction of insurance innovators $\alpha_{I,t}$. In state $s=\tau$, the importing firms are the laggards. In state $s=0$, the importing firms are the laggards and the insurance innovators. Thus, in each state, the aggregate quantities and values of imports are given by, respectively:

$$\begin{aligned}
\mathrm{QI}_t(\tau) &= X_t(\tau)\alpha_{L,t}, \quad \mathrm{QI}_t(0) = X_t(0)(\alpha_{L,t}+\alpha_{I,t}) \\
\mathrm{VI}_t(\tau) &= X_t^V(\tau)\alpha_{L,t}, \quad \mathrm{VI}_t(0) = X_t^V(0)(\alpha_{L,t}+\alpha_{I,t})
\end{aligned} \tag{A.41}$$

Consider now an increase in political risk from (p,τ) to (p',τ'), *i.e.*, $p' \geq p$ and $\tau' \geq \tau$. Observe that $X_t(\tau), X_t(0), X_t^V(\tau), X_t^V(0)$ are invariant to p, $X_t(0), X_t^V(0)$ are invariant to τ, and $X_t(\tau), X_t^V(\tau)$ are decreasing in τ (as $\eta > 1$). Thus, we have that:

$$(X_t(\tau)', X_t(0)', X_t^V(\tau)', X_t^V(0)') \leq (X_t(\tau), X_t(0), X_t^V(\tau), X_t^V(0)) \tag{A.42}$$

Moreover, by Proposition 1, we have that $\alpha'_{L,t} \leq \alpha_{L,t}$ and $\alpha'_{L,t} + \alpha'_{I,t} \leq \alpha_{L,t} + \alpha_{I,t}$. Combining these last two facts, we obtain the conclusion that:

$$(\mathrm{QI}_t(\tau)', \mathrm{QI}_t(0)', \mathrm{VI}_t(\tau)', \mathrm{VI}_t(0)') \leq (\mathrm{QI}_t(\tau), \mathrm{QI}_t(0), \mathrm{VI}_t(\tau), \mathrm{VI}_t(0)) \tag{A.43}$$

which completes the proof. □

A.5 Extended Model with a Nested CES Production Structure

Our main analysis featured an elasticity of substitution that was equal within and across sectors. This made our analysis tractable as there were no general equilibrium price effects on firms' innovation decisions. In this appendix, we extend our model to allow for the realistic feature that sectors may have different substitutability than firms within sectors.

The Nested CES Structure. The rest of the model is as in Section 2. Each sector is a CES aggregate across firms with $\eta > 2$, as before.

$$Y_k = \left(\int_{[0,1]} {Y_k^i}^{\frac{\eta-1}{\eta}} \, \mathrm{d}i \right)^{\frac{\eta}{\eta-1}} \tag{A.44}$$

The output of various sectors k is aggregated to the final good according to a CES aggregator with an elasticity of substitution $\epsilon > 0$:

$$Y = \left(\int_{[0,1]} Y_k^{\frac{\epsilon-1}{\epsilon}} \, \mathrm{d}k \right)^{\frac{\epsilon}{\epsilon-1}} \tag{A.45}$$

Observe that this collapses to the model considered in the main text when $\epsilon = \eta$.

Equilibrium. We study the equilibrium outcomes of the model, where all firms optimally decide whether to import or produce domestically and optimally choose their level of innovation. To this end, the final demand of good k and the demand for variety i of good k are given by:

$$Y_{k,t} = Y_t \left(\frac{P_{k,t}}{P_t} \right)^{-\epsilon}, \quad Y_{k,t}^i = Y_{k,t} \left(\frac{P_{k,t}^i}{P_{k,t}} \right)^{-\eta} \tag{A.46}$$

We also have that the cost of the foreign input, the output of sector k, and final output are given by:

$$P_{k,F,t} = \frac{1}{(1-\tau_{k,t})A_{k,F}}, \quad P_{k,t} = \left(\int_{[0,1]} {P_{k,t}^i}^{1-\eta} \, \mathrm{d}i \right)^{\frac{1}{1-\eta}}, \quad P_t = \left(\int_{[0,1]} P_{k,t}^{1-\epsilon} \, \mathrm{d}k \right)^{\frac{1}{1-\epsilon}} \tag{A.47}$$

where we normalize the price of aggregate output $P_t = 1$. Equilibrium then boils down to understanding firms' optimal choices of production technique in each period and each state and understanding their initial innovation decision. If a firm sources from abroad or domestically, then its marginal costs of production are given by, respectively:

$$\mathcal{M}^i_{k,F,t} = P_{k,F,t}, \quad \mathcal{M}^i_{k,D,t} = \frac{1}{A^i_{k,t}} \tag{A.48}$$

In equilibrium, a firm must choose its least marginal cost production technology at each date and in each state and so its marginal costs will be given by:

$$\mathcal{M}^i_{k,t} = \min\{\mathcal{M}^i_{k,F,t}, \mathcal{M}^i_{k,D,t}\} \tag{A.49}$$

Given the firm faces an isoelastic demand curve, it is optimal for the firm to charge the following price $P^i_{k,t}$ and produce the following quantity $Y^i_{k,t}$:

$$P^i_{k,t} = \frac{\eta}{\eta - 1}\mathcal{M}^i_{k,t}, \quad Y^i_{k,t} = \left(\frac{\eta-1}{\eta}\right)^{\eta} Y_{k,t} P^{\eta}_{k,t} \left(\mathcal{M}^i{}_{k,t}\right)^{-\eta} \tag{A.50}$$

Thus, the firms' profits are given by:

$$\Pi_{k,t}\left(\mathcal{M}^i_{k,t}\right) = \frac{1}{\eta-1}\left(\frac{\eta-1}{\eta}\right)^{\eta} Y_t P^{\eta-\epsilon}_{k,t}\left(\mathcal{M}^i_{k,t}\right)^{1-\eta} \tag{A.51}$$

Finally, each firm's innovation decision must solve:

$$\max_{A^i_{k,1} \geq A^i_{k,0}} \mathbb{E}\left[\Pi_{k,t}\left(\mathcal{M}^i_{k,t}\right)\right] - C\left(A^i_{k,1}, A^i_{k,0}\right) \tag{A.52}$$

An equilibrium can then be formally defined as follows:

Definition 1. *An equilibrium is a collection of random variables:*

$$\left\{Y_t, \{Y_{k,t}, P_{k,t}, P_{k,F,t}\}_{k\in[0,1]}, \{Y^i_{k,t}, P^i_{k,t}, A^i_{k,1}, \mathcal{M}^i_{k,t}, \mathcal{M}^i_{k,F,t}, \mathcal{M}^i_{k,D,t}\}_{i\in[0,1]}\right\}_{t\in\{0,1\}} \tag{A.53}$$

such that Equations A.46-A.52 hold.

Proposition 4 holds as written in this setting. However, equilibrium comparative statics are also affected by the endogenous price of output in the sector. Depending on the relationship between η and ϵ, this can lead to ambiguous effects of political risk on innovation that operate through general equilibrium effects, while all partial equilibrium effects are as in the main analysis (which corresponds to the case of $\eta = \epsilon$).

Numerical Illustration of the Extended Model. We simulate the behavior of firms and sector-level innovation and imports in response to changes in the likelihood and magnitude of political risk, in an illustrative, calibrated version of the extended model described above. We simulate the period-0 distribution of firm productivity from an

Table B.1: Calibration summary

Symbol	Parameter	Value
ε	elasticity of substitution across sectors	2
η	elasticity of substitution across firms	3
κ	scale of innovation cost	10^{-4}
δ	shape of innovation cost	14
τ	foreign political shock	0.5
p	probability of foreign political shock	0.5
A_F	foreign productivity	5
w	domestic wage	1
w_F	foreign wage	1

Note: Parameters used for simulations of the extended model

exponential distribution with scale 1. Table B.1 summarizes the rest of the calibrated parameters for the simulation.

After simulating firms' optimal innovation decisions, we iterate until convergence in the sectoral price index, taking into account the recursive feedback loop between firms' innovation choice, firm-level prices and sourcing decisions, and sector-level expected market size in each state. Figure A.18 plots the firm's shadow value functions of picking each potential status (*laggard*, *insurance innovator*, or *classical innovator*), and their equilibrium choices.

We next simulate the effects of an increase in τ. Figure A.19 demonstrates that going from a small to a large-sized potential political shock induces two types of responses. First, classical innovators respond by innovating more, since they face a larger potential market size in the state when the political shock is realized (a classical market-sized effect). Second, the larger political shock allows for the emergence of an intermediate range of insurance innovators, who now find it beneficial to innovate in case the political shock materializes. In the terminology of proposition 4, moving from a small to a large political shock leads to a change from pattern 1 to pattern 2 of innovation type segmentation.

By contrast, Figure A.20 evidences that the effects of an increase in p, the *probability* of the political shock, are distinct. In particular, while the segmentation into innovation types is the same (pattern 2), moving from a small to a higher probability of a political shock occurring abroad increases the amount of innovation performed by insurance innovators, since the state in which their innovation is made worthwhile by the realization of the foreign shock is more likely.

Finally, Figure A.21 illustrates how, in response to a rise in the probability of the political shock, both the share of innovators in the industry and their total innovation effort increases, and more so (i.e. with a steeper slope) in highly innovative markets (those with low innovation costs, as defined either by having low levels of the innovation cost function κ, or lower convexity of the innovation cost function δ). This larger response of innovation to political shocks in more innovative markets is consistent with the arguments of Propositions 1 and 2.

A.6 Model with Foreign Competition

In this Appendix, we examine an alternative model that incorporates foreign competition. The main results on how rising political risk affects sector-level innovation and imports (Propositions 1 and 2) continue to hold in this framework.

As in the baseline model, there is a continuum of goods sectors in Home, indexed by $k \in [0,1]$, and each sector contains a continuum of varieties indexed by $i \in [0,1]$. A representative final goods firm produces consumption goods according to the constant elasticity of substitution (CES) aggregator:

$$Y_t = \left(\int_{[0,1]} \int_{[0,1]} {Y_{k,t}^i}^{\frac{\eta-1}{\eta}} \, \mathrm{d}i \, \mathrm{d}k \right)^{\frac{\eta}{\eta-1}} \tag{A.54}$$

where $\eta \geq 2$ is the elasticity of substitution across sectors and varieties. Each variety of good can either be produced by Home or Foreign. A continuum of competitive foreign producers produce according to the technology:

$$X_{k,F,t}^i = A_{k,F,t} L_{k,F,t}^i \tag{A.55}$$

where $A_{k,F,t}$ is the foreign productivity of labor and $L_{k,F,t}^i$ is the foreign labor input in production in sector k and variety i. A monopolistic domestic producer produces according to the technology:

$$X_{k,t}^i = A_{k,t}^i L_{k,t}^i \tag{A.56}$$

where $A_{k,t}^i$ is the domestic productivity of labor and $L_{k,t}^i$ is the domestic labor input in production in sector k and variety i. Both foreign and domestic labor is supplied at wages w and w^F that we henceforth normalize to 1. Given this market structure, the foreign producers will set a price $P_{k,F,t}^i = 1/A_{k,F,t}$. Moreover, if the domestic producer sets a price $P_{k,t}^i$, then the household will buy from the domestic producer if and only if $P_{k,t}^i < P_{k,F,t}^i$. The innovation cost and political risk specifications are the same as the baseline model.

We study the equilibrium outcomes of the model, where all domestic firms optimally decide whether to produce facing the competition of foreign firms and optimally choose their level of innovation. In order to avoid the case of limit pricing and maintain a simple model, we adopt the following stage-game assumption.

Assumption 1 (Monopoly Pricing)**.** *In a given variety i, the domestic monopolist and foreign competitors enter a two-stage price-bidding game. In the first stage, each firm pays a fee of $\epsilon > 0$. In the second stage, all firms that paid the fee announce their prices.*

Under Assumption 1, only the more productive firm pays the entry fee and proceeds to the second stage, as less productive firms would never recover the fee. Hence, whenever a domestic firm enters in variety i, it operates under monopoly pricing. In what follows, we take the $\epsilon \to 0$ limit. Solving for all equilibrium conditions except the optimal innovation decision yields the following result:

Proposition 5 (Equilibrium Properties)**.** *In any equilibrium, the following are true:*

1. *The price of each variety $i \in [0, 1]$ in sector k is given by*

$$P^i_{k,t} = \begin{cases} P_{k,F,t}, & A^i_{k,t} \in [0, \dfrac{1}{P_{k,F,t}}] \\ \dfrac{\eta}{\eta-1}\dfrac{1}{A^i_{k,t}}, & A^i_{k,t} \in (\dfrac{1}{P_{k,F,t}}, \infty) \end{cases} \tag{A.57}$$

   where varieties with $A^i_{k,t} \leq \frac{1}{P_{k,F,t}}$ are produced by foreign firms, while those with $A^i_{k,t} > \frac{1}{P_{k,F,t}}$ are produced by domestic firms.
2. *Each domestic firm $i \in [0, 1]$ earns the following contemporaneous profits*

$$\pi_{k,t}(A^i_{k,t}) = \begin{cases} 0, & A^i_{k,t} \in [0, \dfrac{1}{P_{k,F,t}}] \\ \dfrac{1}{\eta-1}\left(\dfrac{\eta-1}{\eta}\right)^{\eta} Y_t (A^i_{k,t})^{\eta-1}, & A^i_{k,t} \in (\dfrac{1}{P_{k,F,t}}, \infty) \end{cases} \tag{A.58}$$

3. *Each firm $i \in [0, 1]$ has an innovation level $A^i_{k,1}$ that solves the following problem:*

$$A_1(A^i_{k,0}) = \arg \max_{A^i_{k,1} \geq A^i_{k,0}} \mathbb{E}\left[\pi_{k,1}(A^i_{k,1})\right] - C\left(A^i_{k,1}, A^i_{k,0}\right) \tag{A.59}$$

4. *Letting an equilibrium cumulative distribution function of $A^i_{k,1}$ be G, we have that the aggregate production of the sector is given by:*

$$Y_{k,1} = \left(\alpha_{k,1} X_{k,F,1}^{\frac{\eta-1}{\eta}} + (1-\alpha_{k,1})\mathbb{E}_G\left[\left(A^i_{k,1} L^i_{k,1}\right)^{\frac{\eta-1}{\eta}} \mid A^i_{k,1} > P^{-1}_{k,F,1}\right]\right)^{\frac{\eta}{\eta-1}} \tag{A.60}$$

   where $\alpha_{k,1} = G(P^{-1}_{k,F,1}) \in [0, 1]$, and $X_{k,F,1}$ are the variety imports of the sector.

Proof. By standard arguments, the final demand of good k and the demand for variety i of good k are given by:

$$Y_{k,t} = Y_t \left(\frac{P_{k,t}}{P_t}\right)^{-\eta}, \quad Y^i_{k,t} = Y_{k,t}\left(\frac{P^i_{k,t}}{P_{k,t}}\right)^{-\eta} \tag{A.61}$$

We also have that the price of the foreign varieties, the output of sector k, and final output are given by:

$$P_{k,F,t} = \frac{1}{(1-\tau_{k,t})A_{k,F}}, \quad P_{k,t} = \left(\int_{[0,1]} {P^i_{k,t}}^{1-\eta}\, \mathrm{d}i\right)^{\frac{1}{1-\eta}}, \quad P_t = \left(\int_{[0,1]} P^{1-\eta}_{k,t}\, \mathrm{d}k\right)^{\frac{1}{1-\eta}} \tag{A.62}$$

where we normalize the price of aggregate output $P_t = 1$. Each variety i can be either produced domestically or imported from abroad. There are two possible cases depending on the productivity level of domestic firms:

1. *Low productivity.* If $A^i_{k,t} \in [0, \frac{1}{P_{k,F,t}(s)}]$, the marginal cost of domestic production, $\frac{1}{A^i_{k,t}}$ exceeds the foreign price, $P_{k,F,t}$. In this case, the domestic firm does not produce and earns zero profit. The variety is supplied by foreign producers at price $P_{k,F,t}$.
2. *High productivity.* If $A^i_{k,t} \in \left(\frac{1}{P_{k,F,t}}, \infty\right)$, the domestic firm will enter and produce. Under Assumption 1, the domestic firm therefore sets monopoly price $P^i_{k,D,t} = \frac{\eta}{\eta-1}\frac{1}{A^i_{k,t}}$, and $Y^i_{k,t} = \left(\frac{\eta-1}{\eta}\right)^{\eta} Y_t(A^i_{k,t})^{\eta}$. The corresponding profit is

$$\pi_{k,t}\left(A^i_{k,t}\right) = \frac{1}{\eta-1}\left(\frac{\eta-1}{\eta}\right)^{\eta} Y_t(A^i_{k,t})^{\eta-1} \tag{A.63}$$

Equilibrium then boils down to characterizing firms' innovation decisions. We have that the date zero innovation decision $A^i_{k,1}$ solves:

$$A_1(A^i_{k,0}) = \arg\max_{A^i_{k,1} \geq A^i_{k,0}} \mathbb{E}\left[\pi_{k,1}(A^i_{k,1})\right] - C\left(A^i_{k,1}, A^i_{k,0}\right) \tag{A.64}$$

where the expectation is taken with respect to the foreign price $P_{k,F,1}$. The final part of the result follows immediately by susbtituting into the sector-level production function. □

This result clarifies that equilibrium innovation incentives arise from firms' desire to lower their expected marginal costs of production. These marginal costs, in turn, depend on whether a firm is sufficiently productive to profitably produce domestically rather than being displaced by foreign competitors: innovation is valuable only if it allows the firm to outcompete the foreign price. In this context, political risk matters because it generates uncertainty across states of the world regarding whether domestic firms will be dominated by foreign producers or will instead produce domestically. Firms internalize this risk when choosing their optimal level of innovation. The final part of the result shows that this interaction between optimal production and innovation decisions gives rise to an endogenous CES production structure at the sector level. The effective weight on imports, $\alpha_{k,1}$, decreases with the distribution of firms' innovation decisions G (in the sense of first-order stochastic dominance). Consequently, while individual firms face discrete, "lumpy" production choices, the aggregation of these micro decisions produces smooth substitution patterns at the sector level. These sector-level substitution patterns are, in turn, the key determinants of aggregate production and import behavior.

Varieties endogenously segment into three groups: those that never produce domestically and rely exclusively on foreign supply; those that produce domestically only in response to adverse foreign political shocks; and those that always produce domestically. As in the baseline model, we refer to these groups as (N), (S), and (A). We then establish the following counterpart to the main results presented in the main text.

Proposition 6 (Innovation and Imports Response to Political Risk)**.** *If political risk increases in Foreign, then*

1. *Innovation at the sector level increases. This increase is driven by firms with intermediate initial productivity, $\mathcal{I} = \{i \in [0,1] : A_0^i \in (A_*, A^*)\}$ where $0 \leq A_* \leq A^*$.*
2. *The value and quantity of imports from Foreign decrease, both when the political shock happens and when it does not.*

Proof. To simplify notation, we omit the sector subscript k and denote the sectoral price index and foreign price by $P(s)$ and $P_F(s)$, respectively, where $s = \tau$ indicates that a political shock occurs and $s = 0$ otherwise. We begin by proving the following Lemma:

Lemma 2. *Suppose $\delta > \eta - 1$. In any equilibrium, only two innovation patterns are possible:*

1. *Two Types: There exists a unique $\tilde{A} > 0$ such that low productivity ($A_0^i \leq \tilde{A}$) firms do not innovate, while high productivity ($A_0^i > \tilde{A}$) firms innovate, with $A_1^i = A^A(A_0^i)$.*
2. *Three Types: There exist unique $\underline{A} > 0$ and $\bar{A} > \underline{A}$ such that low productivity ($A_0^i \leq \underline{A}$) firms do not innovate, medium productivity ($A_0^i \in (\underline{A}, \bar{A}]$) firms innovate, with $A_1^i = A^S(A_0^i)$, and high productivity ($A_0^i > \bar{A}$) firms innovate more, with $A_1^i = A^A(A_0^i)$.*

where $A^S(A_0^i) = \left(\frac{p}{\kappa\delta}\left(\frac{\eta-1}{\eta}\right)^\eta Y_1(A_0^i)^\delta\right)^{\frac{1}{1+\delta-\eta}}$, *and* $A^A(A_0^i) = \left(\frac{1}{\kappa\delta}\left(\frac{\eta-1}{\eta}\right)^\eta Y_1(A_0^i)^\delta\right)^{\frac{1}{1+\delta-\eta}}$.

Proof. We break the proof of this result into two steps.

Step I: Optimal Investment. We begin by characterizing the optimal level of investment in each of three cases. First, in case (N), we have that firms' expected profits are given by:

$$\Pi^N(A_1^i, A_0^i) = -C(A_1^i, A_0^i) \tag{A.65}$$

and it is immediate that $A_1^i = A_0^i$ is optimal. And the profit value in this case is $\bar{\Pi}^N(A_0^i) = 0$, which is constant as a function of A_0^i.

Second, in case (S), the firm's expected profit is given by:

$$\Pi^S(A_1^i, A_0^i) = p\pi(A_1^i; \tau) - C(A_1^i, A_0^i) \tag{A.66}$$

The first-order derivative of Π^S with respect to A_1^i is

$$\Pi_1^S = \left.\begin{cases} 0, & A_1^i \in [0, \dfrac{1}{P_F(\tau)}) \\ p\left(\dfrac{\eta-1}{\eta}\right)^{\eta} Y_1 (A_1^i)^{\eta-2}, & A_1^i \in (\dfrac{1}{P_F(\tau)}, \infty) \end{cases}\right\} - \kappa\delta (A_0^i)^{-\delta}(A_1^i)^{\delta-1} \tag{A.67}$$

When $A_1^i < \frac{1}{P_F(\tau)}$, it collapses to the (N) case. When $A_1^i > \frac{1}{P_F(\tau)}$, the unique zero satisfies

$$A^S(A_0^i) = \left(\frac{p}{\kappa\delta}\left(\frac{\eta-1}{\eta}\right)^{\eta} Y_1 \left(A_0^i\right)^{\delta}\right)^{\frac{1}{1+\delta-\eta}} \tag{A.68}$$

Given $\delta > \eta - 1$, the second-order condition is also satisfied at this point. Moreover, we obtain that $A^S(A_0^i) > A_0^i$ iff $A_0^i > \hat{A}^S = \left(\frac{p}{\kappa\delta}\left(\frac{\eta-1}{\eta}\right)^{\eta} Y_1\right)^{\frac{-1}{\eta-1}}$, and that $A^S(A_0^i) > \frac{1}{P_F(\tau)}$ iff $A_0^i > \tilde{A}^S = \left(\frac{p}{\kappa\delta}\left(\frac{\eta-1}{\eta}\right)^{\eta} Y_1 (P_F(\tau))^{1+\delta-\eta}\right)^{\frac{-1}{\delta}}$. All Case (S) firms with $A_0^i \leq \max\{\hat{A}^S, \tilde{A}^S\}$ do not innovate. All Case (S) firms with $A_0^i > \max\{\hat{A}^S, \tilde{A}^S\}$ innovate. Formally

$$A_1^i = \begin{cases} A_0^i, & A_0^i \leq \max\{\hat{A}^S, \tilde{A}^S\}, \\ \left(\frac{p}{\kappa\delta}\left(\frac{\eta-1}{\eta}\right)^{\eta} Y_1 \left(A_0^i\right)^{\delta}\right)^{\frac{1}{1+\delta-\eta}}, & A_0^i > \max\{\hat{A}^S, \tilde{A}^S\}. \end{cases} \tag{A.69}$$

which is a strictly increasing function.

Finally, in case (A), the firm's expected profit is:

$$\Pi^A(A_1^i, A_0^i) = p\pi(A_1^i;\tau) + (1-p)\pi(A_1^i;0) - \kappa\left[\left(\frac{A_1^i}{A_0^i}\right)^{\delta} - 1\right] \tag{A.70}$$

The first-order derivative of Π^A with respect to A_1^i is given by

$$\Pi_1^A = \left.\begin{cases} 0, & A_1^i \in [0, \dfrac{1}{P_F(\tau)}) \\ p\left(\dfrac{\eta-1}{\eta}\right)^{\eta} Y_1 (A_1^i)^{\eta-2}, & A_1^i \in (\dfrac{1}{P_F(\tau)}, \dfrac{1}{P_F(0)}) \\ \left(\dfrac{\eta-1}{\eta}\right)^{\eta} Y_1 (A_1^i)^{\eta-2}, & A_1^i \in (\dfrac{1}{P_F(0)}, \infty) \end{cases}\right\} - \kappa\delta (A_0^i)^{-\delta}(A_1^i)^{\delta-1} \tag{A.71}$$

When $A_1^i < \frac{1}{P_F(0)}$, it collapses to either (N) or (S) case. When $A_1^i > \frac{1}{P_F(0)}$, the unique zero satisfies

$$A^A(A_0^i) = \left(\frac{1}{\kappa\delta}\left(\frac{\eta-1}{\eta}\right)^{\eta} Y_1 \left(A_0^i\right)^{\delta}\right)^{\frac{1}{1+\delta-\eta}} \tag{A.72}$$

Given $\delta > \eta - 1$, the second-order condition is also satisfied at this point. Moreover, we obtain that $A^A(A_0^i) > A_0^i$ iff $A_0^i > \hat{A}^A = \left(\frac{1}{\kappa\delta}\left(\frac{\eta-1}{\eta}\right)^\eta Y_1\right)^{\frac{-1}{\eta-1}}$, and that $A^A(A_0^i) > \frac{1}{P_F(0)}$ iff $A_0^i > \tilde{A}^A = \left(\frac{1}{\kappa\delta}\left(\frac{\eta-1}{\eta}\right)^\eta Y_1(P_F(0))^{1+\delta-\eta}\right)^{\frac{-1}{\delta}}$. All Case (A) firms with $A_0^i \le \max\{\hat{A}^A, \tilde{A}^A\}$ do not innovate. All Case (A) firms with $A_0^i > \max\{\hat{A}^A, \tilde{A}^A\}$ innovate. Formally

$$A_1^i = \begin{cases} A_0^i, & A_0^i \le \max\{\hat{A}^A, \tilde{A}^A\}, \\ \left(\frac{1}{\kappa\delta}\left(\frac{\eta-1}{\eta}\right)^\eta Y_1(A_0^i)^\delta\right)^{\frac{1}{1+\delta-\eta}}, & A_0^i > \max\{\hat{A}^A, \tilde{A}^A\}. \end{cases} \tag{A.73}$$

which is a strictly increasing function. Also, we have $\hat{A}^A < \hat{A}^S$.

Step II: Patterns of Segmentation. We now determine into which of the three cases firms optimally sort. We split this analysis into scenarios based on the relationship between $\hat{A}^S$, $\tilde{A}^S$, $\hat{A}^A$, $\tilde{A}^A$, and $\frac{1}{P_F(\tau)}$, $\frac{1}{P_F(0)}$.

1. $\hat{A}^S \le \frac{1}{P_F(\tau)}$. Since $\hat{A}^A < \hat{A}^S \le \frac{1}{P_F(\tau)} < \frac{1}{P_F(0)}$, by the definition of $\tilde{A}^A$, we have $\tilde{A}^A > \hat{A}^A$. Otherwise, $A^A(\tilde{A}^A) \le A^A(\hat{A}^A) = \hat{A}^A < \frac{1}{P_F(0)}$, a contradiction. Similarly, since $\hat{A}^S \le \frac{1}{P_F(\tau)}$, we have $\tilde{A}^S \ge \hat{A}^S$. Since $A^S(A_0^i) - A_0^i$ is strictly increasing for $A_0^i \ge \hat{A}^S$, then given $\tilde{A}^S \ge \hat{A}^S$, we have $A^S(\tilde{A}^S) - \tilde{A}^S \ge A^S(\hat{A}^S) - \hat{A}^S = 0$. Further, if $\tilde{A}^S > \frac{1}{P_F(\tau)}$, then $A^S(\tilde{A}^S) \ge \tilde{A}^S > \frac{1}{P_F(\tau)}$, which is contradictory to the definition of $\tilde{A}^S$. Thus $\hat{A}^A < \hat{A}^S \le \tilde{A}^S \le \frac{1}{P_F(\tau)} < \frac{1}{P_F(0)}$. Then depending on the magnitude of $\tilde{A}^A$, there are two sub-cases:
   (a) $\tilde{A}^A \le \tilde{A}^S$. Firms with initial productivity $A_0^i \le \tilde{A}^A$ neither innovate nor produce, whereas firms with $A_0^i > \tilde{A}^A$ choose to innovate, attaining $A_1^i = A^A(A_0^i)$, and produce in both states.
   (b) $\tilde{A}^A > \tilde{A}^S$. Firms with low initial productivity ($A_0^i \le \tilde{A}^S$) neither innovate nor produce. Firms with medium initial productivity ($A_0^i \in (\tilde{A}^S, \tilde{A}^A]$) choose to innovate, achieving $A_1^i = A^S(A_0^i)$, but produce only when a political shock occurs. Firms with high initial productivity ($A_0^i > \tilde{A}^A$) also innovate, with $A_1^i = A^A(A_0^i)$, and produce in both states of the world.
2. $\hat{A}^S \in (\frac{1}{P_F(\tau)}, \frac{1}{P_F(0)}]$. Since $\hat{A}^A < \hat{A}^S \le \frac{1}{P_F(0)}$, similar as in scenario 1, we have $\tilde{A}^A > \hat{A}^A$. Since $\hat{A}^S > \frac{1}{P_F(\tau)}$, we have $\tilde{A}^S < \hat{A}^S$. Otherwise if $\tilde{A}^S \ge \hat{A}^S$, then $A^S(\tilde{A}^S) \ge A^S(\hat{A}^S) = \hat{A}^S > \frac{1}{P_F(\tau)}$, a contradiction. Then we only need to compare $\hat{A}^S$ and $\tilde{A}^A$.
   (a) $\tilde{A}^A \le \hat{A}^S$. Firms with initial productivity $A_0^i \le \tilde{A}^A$ do not innovate. Among them, those with $A_0^i \le \frac{1}{P_F(\tau)}$ never produce, while those with $A_0^i \in (\frac{1}{P_F(\tau)}, \tilde{A}^A]$ produce only when a political shock occurs. Firms with $A_0^i > \tilde{A}^A$ choose to innovate and produce in both states of the world, with $A_1^i = A^A(A_0^i)$.

(b) $\tilde{A}^A > \hat{A}^S$. Firms with low initial productivity ($A_0^i \leq \hat{A}^S$) do not innovate. Firms with medium initial productivity ($A_0^i \in (\hat{A}^S, \tilde{A}^A]$) choose to innovate, achieving $A_1^i = A^S(A_0^i)$, but produce only when a political shock occurs. Firms with high initial productivity ($A_0^i > \tilde{A}^A$) also innovate, with $A_1^i = A^A(A_0^i)$, and produce in both states of the world.

3. $\hat{A}^S > \frac{1}{P_F(0)}$. This scenario can further split into two sub-cases.

(a) $\hat{A}^A \leq \frac{1}{P_F(0)}$. Similar as in scenario 1, we have $\hat{A}^A \leq \tilde{A}^A \leq \frac{1}{P_F(0)}$. For low-productivity firms ($A_0^i \leq \tilde{A}^A$), no innovation occurs. Whether they produce in the bad state depends on whether $A_0^i > \frac{1}{P_F(\tau)}$. Firms with $A_0^i > \tilde{A}^A$ choose to innovate, achieving $A_1^i = A^A(A_0^i)$, and always produce.

(b) $\hat{A}^A > \frac{1}{P_F(0)}$. In this sub-case, we have $\hat{A}^A > \tilde{A}^A$. For low-productivity firms ($A_0^i \leq \hat{A}^A$), no innovation occurs. Among them, firms with $A_0^i \leq \frac{1}{P_F(\tau)}$ never produce; those with $A_0^i \in (\frac{1}{P_F(\tau)}, \frac{1}{P_F(0)}]$ produce only in the bad state; and those with $A_0^i \in (\frac{1}{P_F(0)}, \hat{A}^A]$ always produce. Firms with $A_0^i > \hat{A}^A$ choose to innovate, achieving $A_1^i = A^A(A_0^i)$, and always produce.

Combining all the cases discussed above gives Lemma 2. □

As shown in the proof of Lemma 2, innovation in case (S) increases with p and is invariant to τ, whereas innovation in case (A) is invariant to both p and τ. The cut-off $\hat{A}^S$ decreases with p and remains invariant to τ, while $\tilde{A}^S$ decreases with both p and τ. In contrast, the cut-offs $\hat{A}^A$ and $\tilde{A}^A$ are invariant to both p and τ. Consequently, as p or τ increase, the range of firms classified under case (S) expands downward—that is, some firms previously in case (N) become (S) firms and start innovating—and previous (S) firms undertake a higher level of innovation. This establishes the first claim in Proposition 6.

When a variety is imported from Foreign, we have that $X_{k,F,t}^i = Y_t(P_{k,F,t})^{-\eta}$. We also know that the foreign price is given by $P_{k,F,t}(s) = \frac{1}{(1-\tau(s))A_{k,F}}$. Thus, the quantity and value of imports in state s for a variety that is imported from foreign are given by:

$$\begin{aligned} X_t(s) &\equiv X_{k,F,t}^i = Y_t((1-\tau(s))A_F)^{\eta} \\ X_t^V(s) &\equiv P_{k,F,t}X_{k,F,t}^i = Y_t((1-\tau(s))A_F)^{\eta-1} \end{aligned} \tag{A.74}$$

In the bad state, the upper bound of domestic productivity for importing is determined by $\tilde{A}^A$, $\tilde{A}^S$, or $\frac{1}{P_F(\tau)}$. Each of these thresholds is either invariant or decreasing in p and τ. Hence, as p or τ increase, fewer firms engage in importing during the bad state, and those that do import smaller quantities and values. In the good state, the upper bound of domestic productivity for importing is given by $\tilde{A}^A$, $\hat{A}^S$, or $\frac{1}{P_F(0)}$, all of which are likewise (weakly) decreasing in p and τ. Accordingly, import quantities and values also decline with higher values of (p, τ). This completes the proof of Proposition 6.

□

Proposition 6 demonstrates that, in the alternative model setup with foreign competition, the effects of political risk on sector-level innovation and imports remain the same as in the baseline model. The framework can be readily extended to accommodate a more general substitution pattern, as discussed in Appendix A.5, which would introduce a standard market-size effect into firms' innovation decisions. Moreover, the model can be further generalized to incorporate production networks, whereby upstream sector prices enter the marginal costs of downstream firms, generating an additional general equilibrium effect. Nonetheless, the partial-equilibrium incentive for firms to innovate in order to out-compete foreign rivals under higher political risk continues to hold.

B Additional Data

B.1 Trade Flows

We use BACI data, a pre-processed version of UN Comtrade data curated by CEPII (Centre d'Études Prospectives et d'Informations Internationales), to measure bilateral trade flows. This dataset provides detailed trade information for over 200 countries at the 6-digit HS (Harmonized System) level, during 1995-2022. To link the 6-digit HS codes to 6-digit NAICS industry codes, we utilize the concordance provided by Pierce and Schott (2012). For U.S. trade data, we extend the coverage back to 1989 utilizing data provided by Peter Schott (`https://sompks4.github.io/sub_data.html`). The trade data include information on origin and destination countries, 6-digit NAICS codes, trade values, and quantities.

B.2 Minerals

We obtain deposit data for 122 minerals from the USGS (United States Geological Survey, `https://mrdata.usgs.gov/pp1802/`). This dataset includes information on the mineral type and geographic location of each deposit. We then calculate the number of deposits each country holds for each mineral. For each mineral, we evaluate the importance of each country based on its share of the total number of deposits.[20] Using these shares, we calculate the political risk for each mineral by computing the weighted average of the political risks of the countries involved:

$$\text{PRE}_{mt} = \sum_{c} \text{PoliticalRisk}_{ct} \cdot (\text{DepositShare}_{cm})^2 \tag{B.1}$$

where m indexes minerals and c indexes countries.

To measure innovation related to each mineral, we examine all patents in PatentsView and count a patent as related to a mineral if the name of the mineral appears in either the title or the abstract. Then we run the following regression:

$$y_{mt} = \beta \cdot \log\text{PRE}_{m,t-1} + \alpha_m + \delta_t + \epsilon_{mt} \tag{B.2}$$

[20] The ideal approach would be to use the reserves of each deposit; however, since this dataset does not include such information, we use the number of deposits as a proxy instead.

where y_{mt} is the log patent applications or forward citations within 5 years related to each mineral, and α_m, δ_t are mineral and year fixed effects. Standard errors are clusterd at the mineral level. We also run the regression at the mineral-decade level, where we use the political risk for each mineral in the contemporaneous decade, and control for decade fixed effects.

B.3 Geopolitical Friendship

To assess geopolitical "friendship" between pairs of countries, we primarily use the Formal Alliance (v4.1) dataset provided by the Correlates of War (COW) project (Gibler, 2008). This dataset identifies formal alliances involving at least two states, classified into defense pacts, neutrality or non-aggression treaties, and entente agreements. It includes information on the type of alliance, member states, and relevant dates of activity, during 1816-2012. We define a country pair as "friends" in a given year if there is at least one of the aforementioned alliance types between them. All other country pairs are classified as "enemies."

Since the Formal Alliance (v4.1) dataset concludes in 2012, we supplement it with two auxiliary datasets. The first is the Ideal Points dataset, constructed based on countries' voting behavior in the UN General Assembly, as provided by Bailey, Strezhnev, and Voeten (2017). This dataset quantifies a uni-dimensional index (ideal points) to reflect countries' foreign policy preferences and measures the similarity of international political preferences between countries as the absolute distance between their ideal points. Then, for each country, we define "friends" as those with above-median similarity and "enemies" as those with below-median similarity.

The second additional dataset is the Alliance Treaty Obligations and Provisions (ATOP) project (v5.1) (see Leeds, Ritter, Mitchell, and Long, 2002), which provides information on the content of military alliance agreements signed by all countries worldwide between 1815 and 2018. Consistent with our baseline approach, we define a country pair as "friends" in a given year if there is at least one of the four alliance types—defense pacts, neutrality or non-aggression treaties, or entente agreements—between them. All other country pairs are classified as "enemies."

Given the geopolitical friendship measure, we construct separate measures of political risk in ally countries and political risk in non-ally countries as follow:

$$\begin{aligned} \mathrm{PRE}_{cit}^{\mathrm{ALLY}} &= \sum_{k\neq c, k\in \mathrm{friend}_{ct}} \mathrm{PoliticalRisk}_{kt} \cdot (\mathrm{ImportShare}_{k\to c, it_0})^2 \\ \mathrm{PRE}_{cit}^{\text{NON-ALLY}} &= \sum_{k\neq c, k\notin \mathrm{friend}_{ct}} \mathrm{PoliticalRisk}_{kt} \cdot (\mathrm{ImportShare}_{k\to c, it_0})^2 \end{aligned} \tag{B.3}$$

B.4 Global Trade Alert

To measure policy interventions that restrict trade, we utilize data from the Global Trade Alert (GTA) database, which has tracked various types of trade interventions implemented by governments since 2008. This dataset includes detailed information on each trade intervention, such as the imposing and affected countries, the announcement, implementation, and end dates, the policy instruments used, the affected products, and whether the intervention is restrictive or not. In the absence of a direct measure of the severity of each intervention, we use the number of affected products as a proxy, as recommended by the GTA itself.

B.5 Country Characteristics

In Section 7, we construct a series of controls that attempt to account for features of a country-sector's typical export markets other than their innovation intensity, and include these in estimates of Equation 7.1. In particular, we construct exposure variables of the form:

$$X_{ci} = \sum_{k \neq c} \text{Exports}_{i,c \to k,t_0} \cdot Z_{kt_0}$$

where Z_{kt_0} are characteristics of export markets during 1990-2000. We then include the interaction of $\log X_{ci}$ and $\log \text{PR}_{ct}$ as controls.

We obtain country characteristics from the World Development Indicators (WDI) database. The dataset includes 1,496 indices, but incorporating all of them as controls would make our regression computationally infeasible. Therefore, we select key characteristics that are likely to influence both country-level innovation and imports. These selected variables are: total imports, GDP, GDP growth rate, GDP per capita, population, population growth, life expectancy, education (measured by secondary education completion rates), inflation (measured by GDP deflator and CPI), interest rate, foreign reserves, foreign aid, external debt, and the governance index (WGI).

First, we include all these controls in columns 1-2 in Table A.8. Next, we apply the post-double LASSO method to select the most relevant controls. The resulting selected controls are: total imports, GDP, population growth, education, interest rate, and foreign aid.

C Additional Results

C.1 Incentives in Technology vs. Product Markets

To separately esitmate the effect of political risk in "technology space" vs. "product space," we return to the firm-level data from Compustat and extend methods introduced by Bloom, Schankerman, and Van Reenen (2013). For each firm, we identify the NAICS code(s) of the good(s) that the firm sells. We also use all patents assigned to each firm to identify the cooperative patent class (CPC) codes for each patent, which we then link to the NAICS codes using the methodology outlined in Goldschlag, Lybbert, and Zolas (2020). We then identify the modal NAICS code for each firm's patenting activity. Next, for each firm and decade, we estimate the effect of both political risk in the sector in which that firm *patents*, alongside the effect of political risk in the sector in which that firm *sells* its output. We estimate versions of the following specification:

$$y_{jit} = \gamma \log \text{PRE}_{jit}^{\text{Tech}} + \phi \log \text{PRE}_{jit}^{\text{Goods}} + \alpha_i + \delta_t + \epsilon_{jit} \tag{C.1}$$

where now j indexes firms, γ captures the effect of political risk in its technology space on firm-level patenting, and ϕ captures the effect of political risk in its product space on firm-level patenting.

Estimates of Equation C.1 are reported in Figure A.13. We find strong evidence that the findings are driven by firm-level political risk in the technology space ($\gamma > 0$, $\phi = 0$). The same pattern holds when the outcome is citation-weighted patenting. The result is also very similar if we estimate the effect of technology-space and goods-space political risk in separate regressions, rather than the same regression as in Equation C.1.

C.2 Cross-Sector Spillovers

Our primary analysis examines how sector-specific political risk affects innovation within that sector. However, cross-sector spillovers may arise through supply-chain linkages. Foreign political risk in upstream industries can influence innovation downstream. Heightened foreign political risk may also affect innovation in closely related, substitutable sectors.

To measure each of these forces, we use the US input-output tables from the Bureau of Economic Analysis (BEA). We separately measure political risk in upstream and substitute sectors in the following way:

$$\begin{aligned} \text{PRE}_{it}^{\text{UP}} &= \sum_k \text{PoliticalRisk}_{kt} \cdot \Big(\sum_{u \neq i} \text{ImportShare}_{k \to c, ut_0} \cdot \frac{\text{Input}_{u \to i}}{\text{Output}_i}\Big)^2 \\ \text{PRE}_{it}^{\text{SUB}} &= \sum_k \text{PoliticalRisk}_{kt} \cdot \Big(\sum_{s \neq i} \text{ImportShare}_{k \to c, st_0} \cdot \text{Similarity}_{si}\Big)^2 \end{aligned} \tag{C.2}$$

where the import share is the share of an upstream sector u or substitutable sector s imports that are from country k in a fixed pre-period before 2000. To measure political risk in upstream sectors for a given sector i, we weight the import share of each upstream sector u by i's input share ($\frac{\text{Input}_{u \to i}}{\text{Output}_i}$) from it. To measure political risk in substitute sectors, we use a weighting scheme based on the extent to which sectors s and i serve as inputs to other common sectors:

$$\text{Similarity}_{si} = \text{Cos}(\{\text{InputShare}_{s \to k}\}_{k \neq s,i}, \{\text{InputShare}_{i \to k}\}_{k \neq s,i}) \tag{C.3}$$

There are a variety of reasons to be skeptical of these measures. First, input-output tables are imprecise measures of true supply chain linkages across sectors. Second, at our level of aggregation, the input-output matrix remains strongly diagonal, suggesting many of these mechanisms are already captured by the own-sector analysis and thus hard to distinguish empirically. Finally, in the case of substitute-sector spillovers, our measure is at best an imprecise proxy for which sectors could replace others in the supply chain.

With these caveats in mind, estimates of Equation 5.1 in which each of these measures is included on the right-hand side are reported in Appendix Table A.6. Our findings suggest that, if anything, there is some evidence of positive spillovers across sectors.

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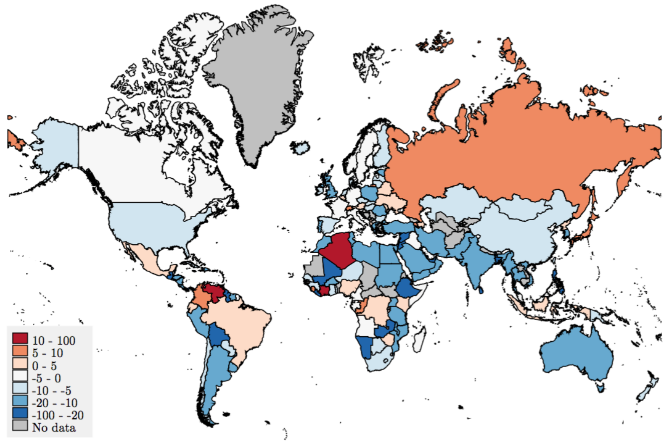
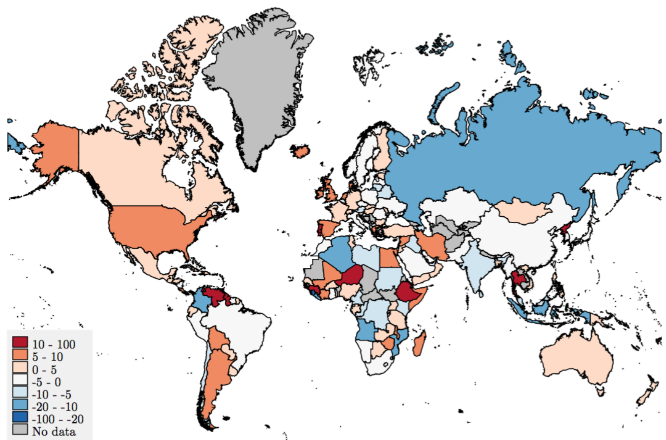
D Supplementary Tables and Figures

Figure A.1: Country-Level Changes in Political Risk by Decade

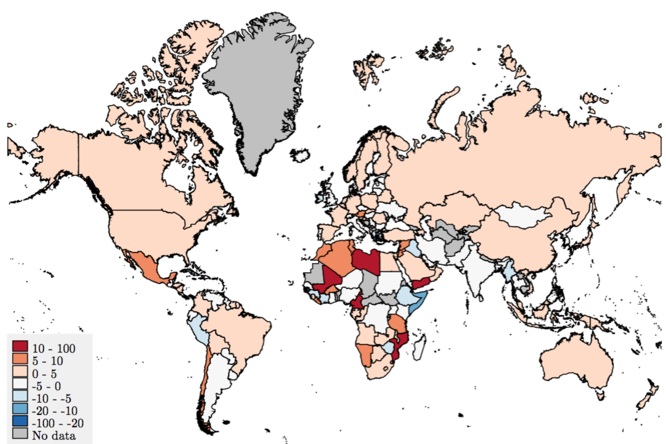
(a) 1990-2000



(b) 2000-2010



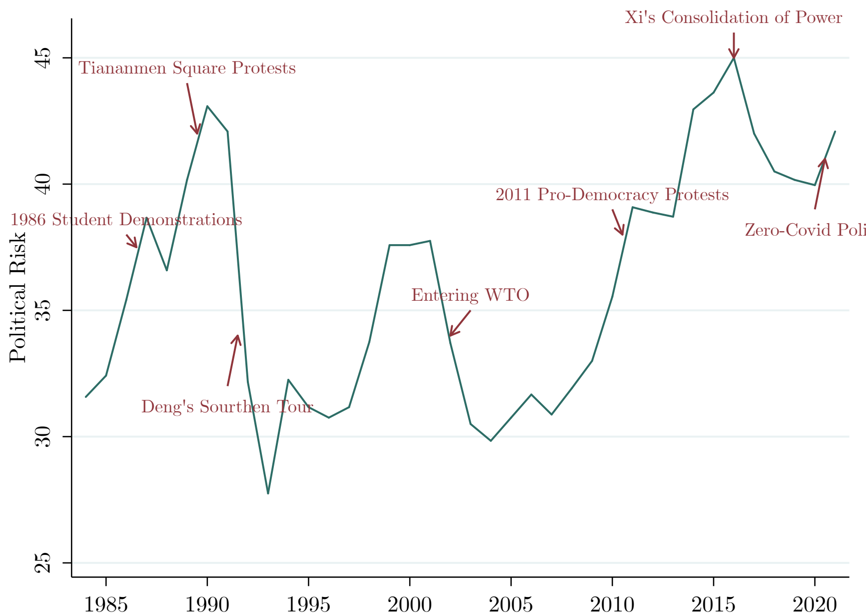
(c) 2010-2020



Notes: This figure maps country-level changes in political risk during the 1990s (a), the 2000s (b), and 2010s (c). The color schemes are the same across three sub-figures, where red shading corresponds to rising political risk and blue shading corresponds to declining political risk.

Figure A.2: Time Trends of Political Risk: China and Russia

(a) China

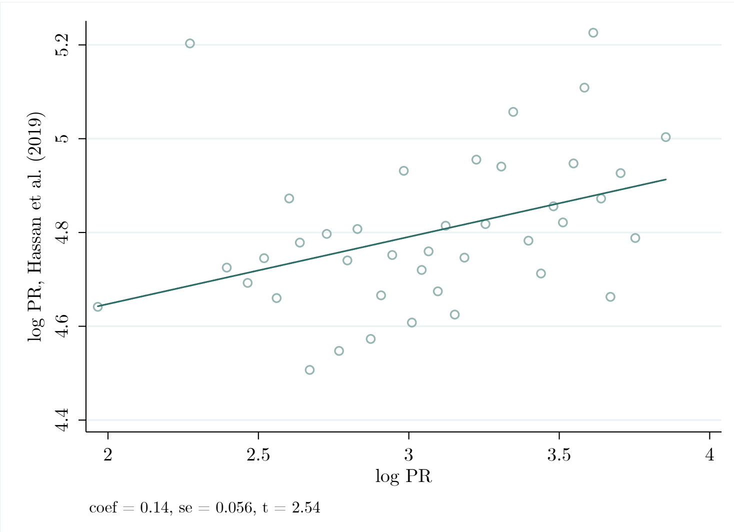


(b) Russia

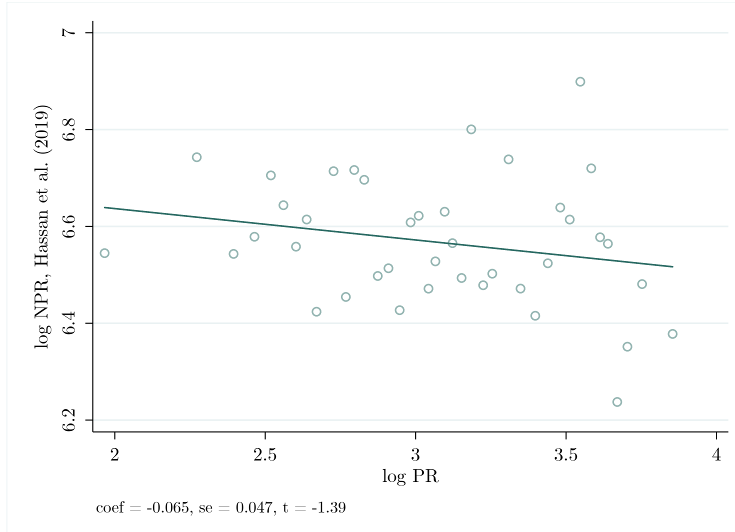
Notes: This figure shows the time trend of political risk, as measured by the International Country Risk Guide (ICRG), for China (a) and Russia (b). A series of major political events are labeled in each sub-figure.

Figure A.3: Validation of Main Political Risk Measure: Correlation with Alternative Measures

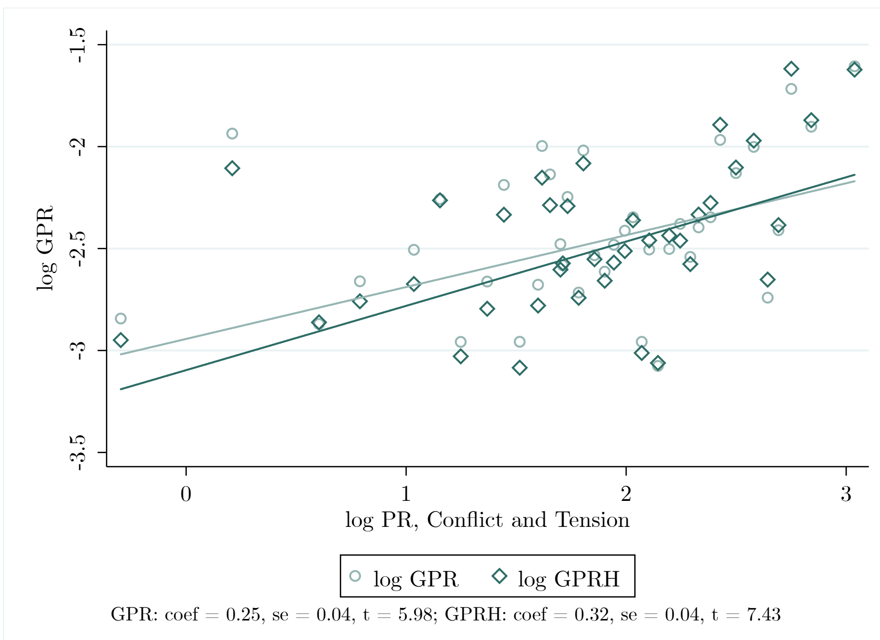
(a) Hassan et al. (2019) Political Risk



(b) Hassan et al. (2019) Non-Political Risk



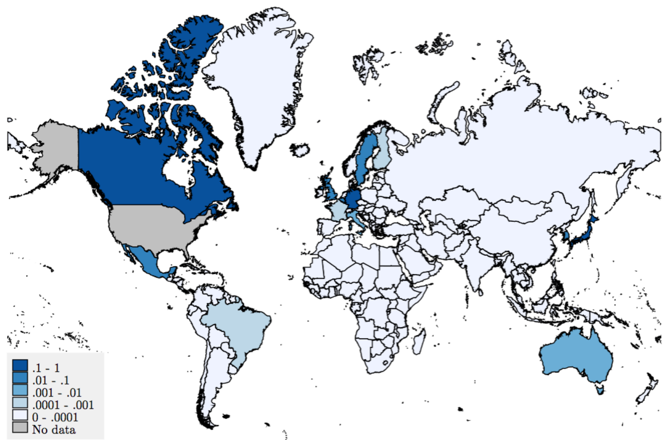
(c) Caldara and Iacoviello (2022) Geopolitical Risk



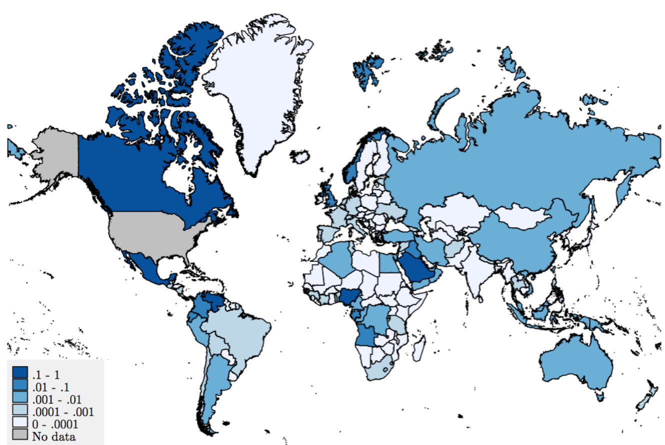
Notes: The unit of observation in all panels is the country-year. Panel (a) plots the correlation between the ICRG political risk index and the political-risk index of Hassan, Hollander, Van Lent, and Tahoun (2019), after aggregating their firm-level measure to the country-year level. Panel (b) plots the correlation between the ICRG political risk index and the non-political-risk index of Hassan, Hollander, Van Lent, and Tahoun (2019), aggregated in the same way. Panel (c) shows the correlation between the Caldara and Iacoviello (2022) Geopolitical Risk (GPR) index and our political risk measure, where we restrict the ICRG index to its Conflict and Tension components to match the GPR definition. We show the relationship both with the baseline GPR index, which uses a broad set of newspapers to construct the measure, as well as with the "historical" GPRH measure, which restricts attention to the three newspapers with the longest-running coverage. Estimated coefficients and standard errors are reported beneath each sub-figure.

Figure A.4: Pre-period US Import Shares in Automobiles, Oil and Gas, and Semiconductors

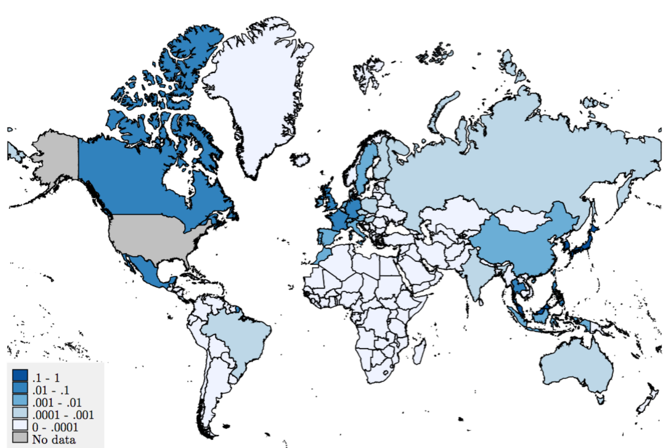
(a) Automobiles



(b) Oil and Gas



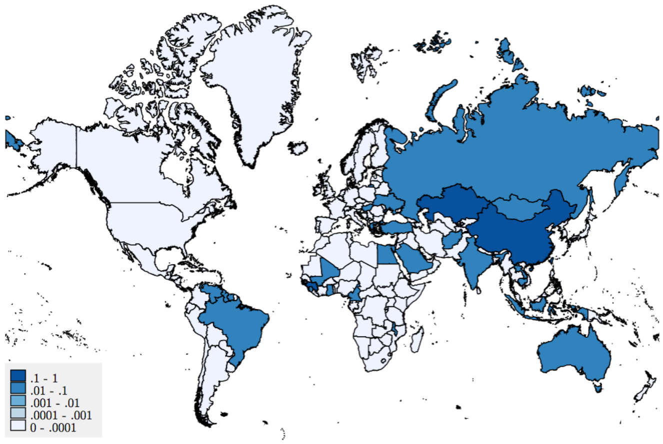
(c) Semiconductors



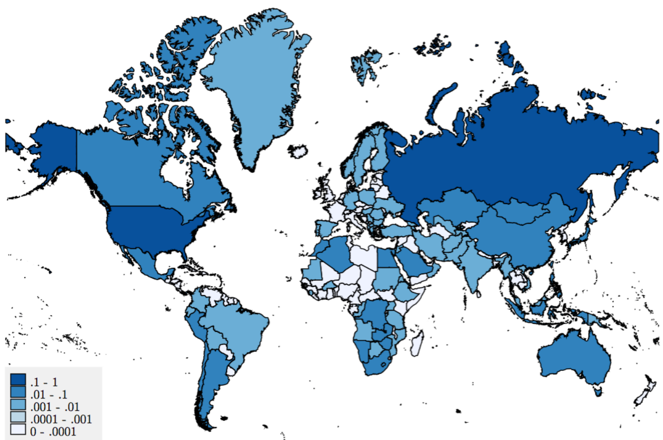
Notes: This figure shows US import shares during the 1990s from every country in three industries: (a) automobiles, (b) oil and gas extraction, and (c) semiconductors. The color schemes are the same across three subfigures, where darker shades of blue correspond to higher import shares.

Figure A.5: Deposit Shares in Aluminum, Copper, and Zinc

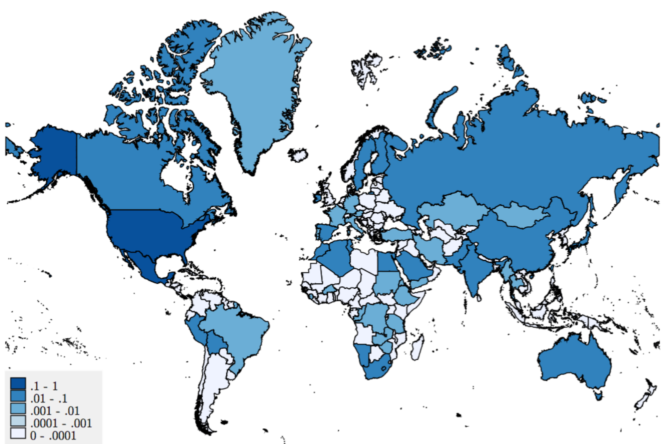
(a) Aluminum



(b) Copper



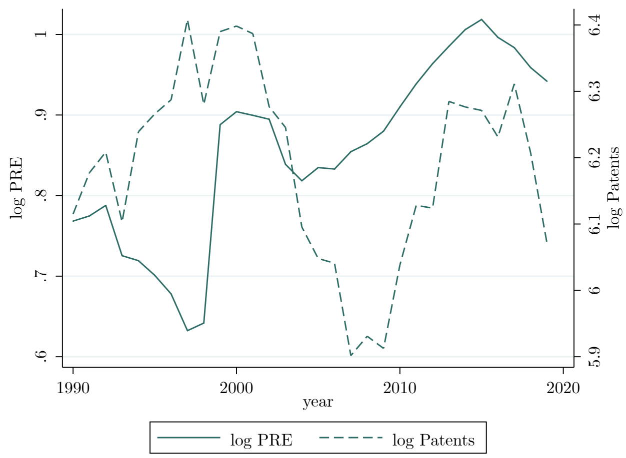
(c) Zinc



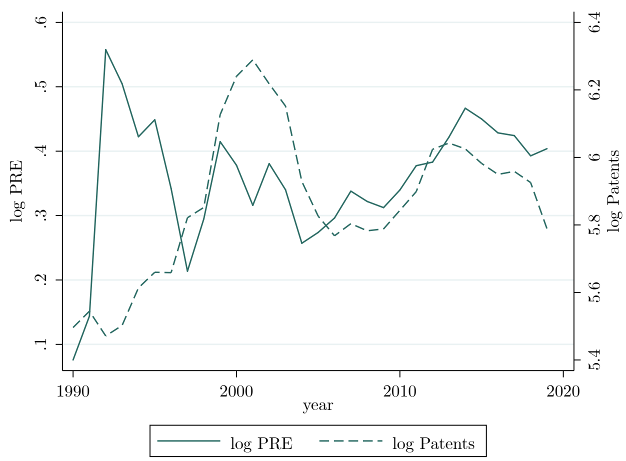
Notes: This figure shows the global deposit shares obtained from the US Geological Survey (USGS) for three minerals: aluminum (a), copper (b), and zinc (c). The color schemes are the same across three subfigures where darker shades of blue correspond to higher deposit shares.

Figure A.6: Foreign Political Risk and Innovation: Aluminum, Copper, and Zinc

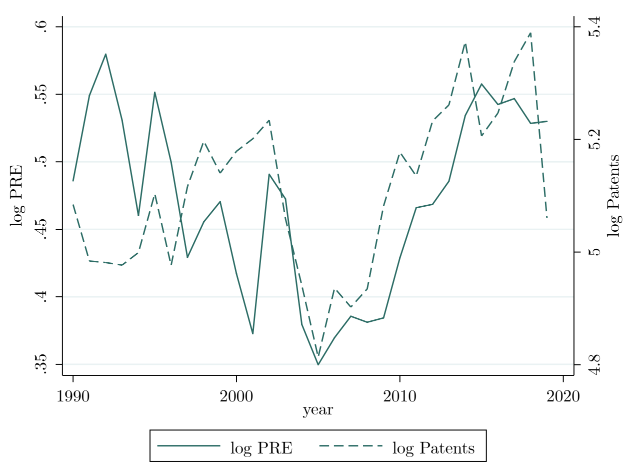
(a) Aluminum



(b) Copper



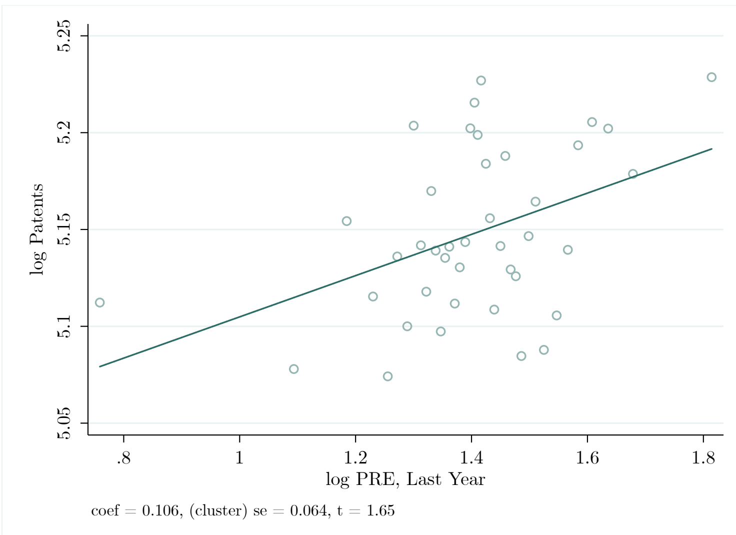
(c) Zinc



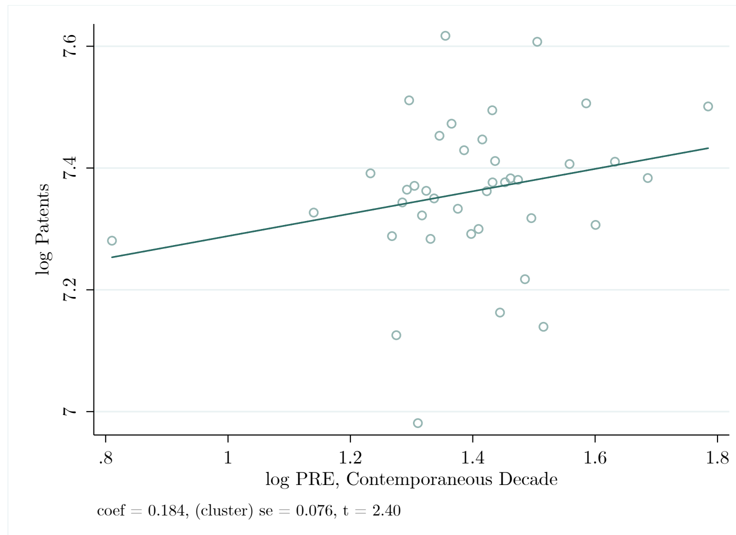
Notes: This figure shows the relationship between log political risk and log patents related to three minerals: aluminum (a), copper (b), and zinc (c). In all three subfigures, log of political risk is plotted on the left y-axis using a solid line and the log number of patent applications is plotted on the right y-axis using a dashed line.

Figure A.7: Foreign Political Risk and Mineral Innovation: Robustness

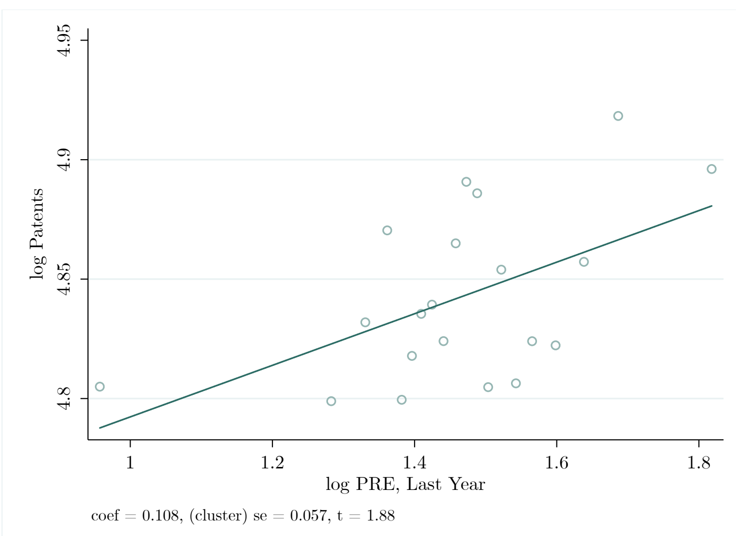
(a) Patents (Annual), Stand-Alone Mineral Words



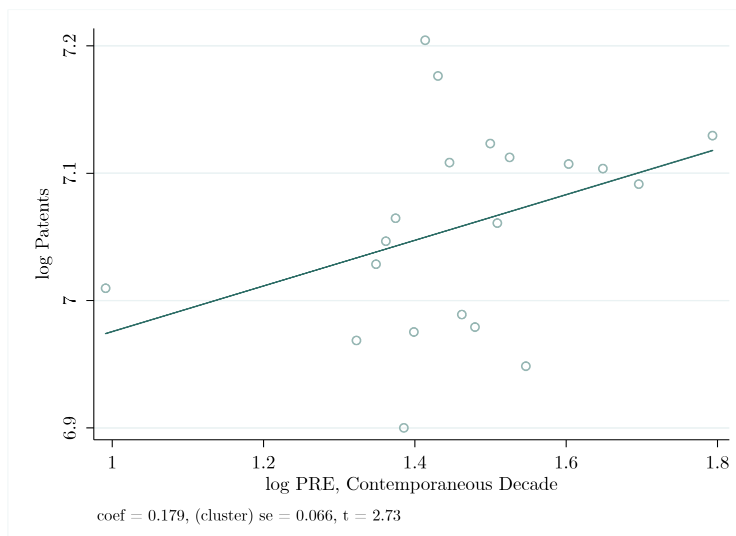
(b) Patents (Decadal), Stand-Alone Mineral Words



(c) Patents (Annual), Drop Common Names



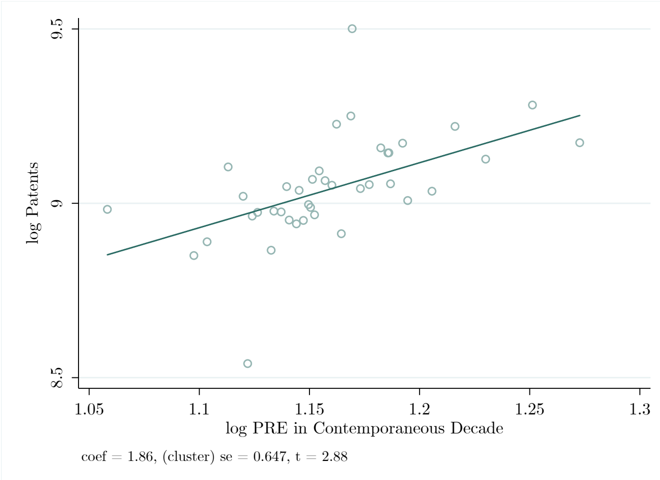
(d) Patents (Decadal), Drop Common Names



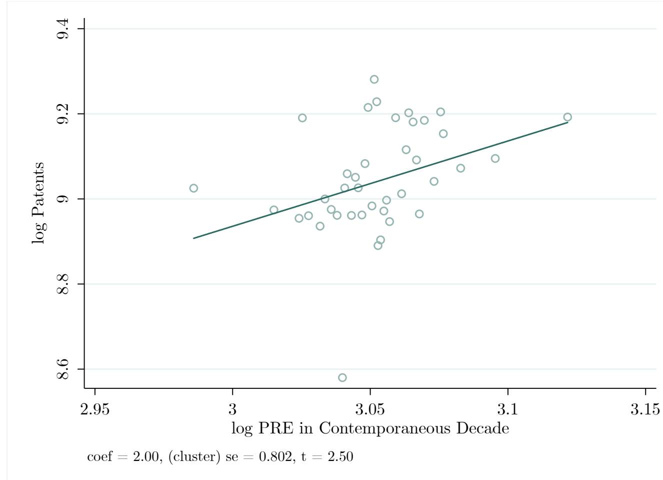
Notes: All panels report the relationship between mineral-level political risk exposure and mineral-specific patenting. In the first row, we require that the mineral name be a stand-alone word when classifying patents, and in the second row we drop all minerals with common names that may be prone to mis-classification: amber, gem, iron, lead, mica, and tin. In panels (a) and (c), the unit of observation is a mineral-year and in panels (b) and (d) it is a mineral-decade. In all regressions, we weight observations by mineral-level patents during the pre-period and standard errors are clustered at the mineral level. The coefficient and standard error for the fitted line are displayed below each sub-figure.

Figure A.8: Foreign Political Risk and US Innovation (Patents), Alternative Specifications

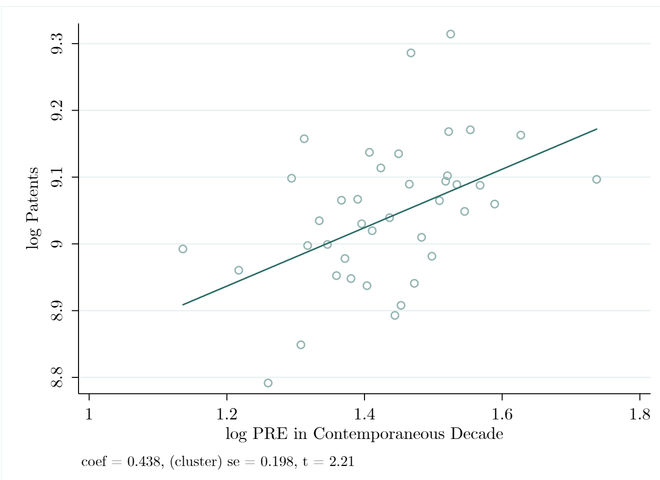
(a) Pre-period Squared Import Shares



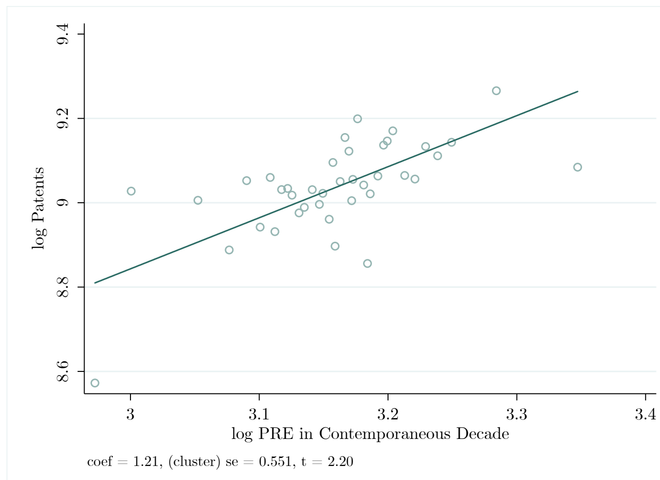
(b) Pre-period Import Shares



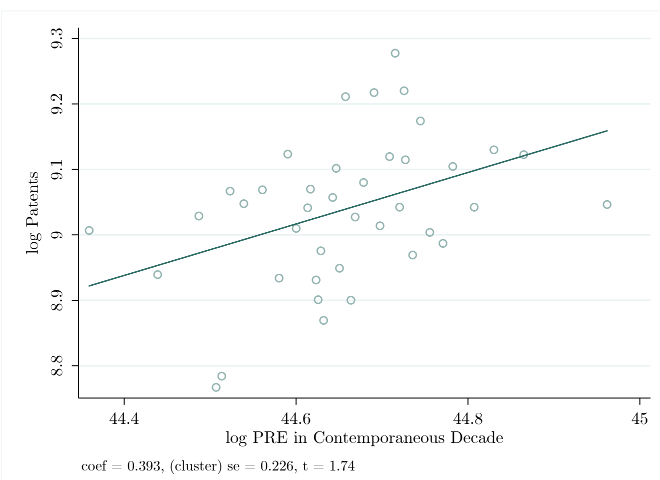
(c) Contemporaneous Squared Import Shares



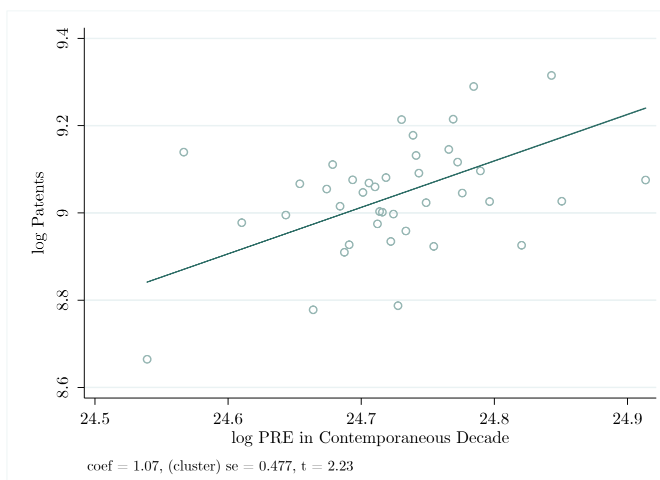
(d) Contemporaneous Import Shares



(e) Contemporaneous Squared Import Levels



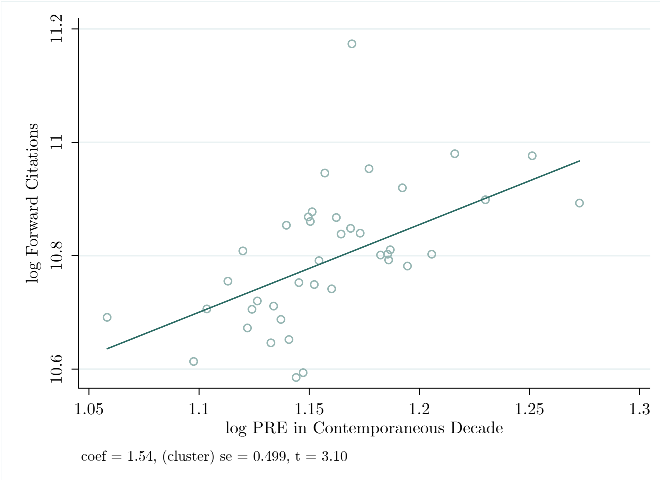
(f) Contemporaneous Import Levels



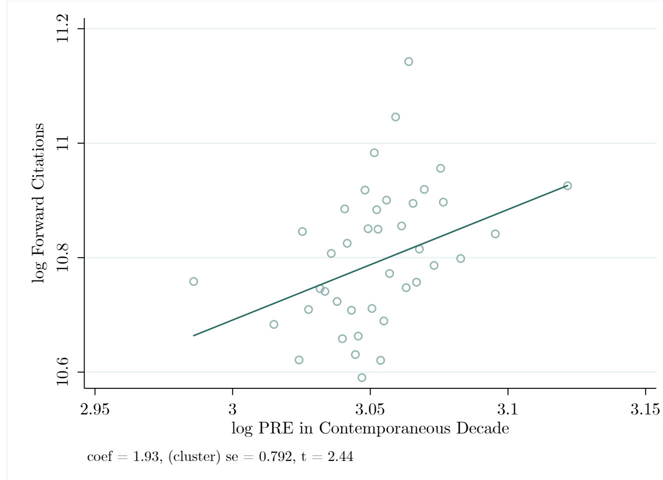
Notes: This figure shows the effect of political risk exposure in the contemporaneous decade on total patent applications in the US, using different parameterizations of the political risk variable. Panel (a) replicates Figure 2a, using the political risk exposure measure which is weighted by pre-period squared import shares. Panel (b) uses the political risk exposure measure which is weighted by pre-period import shares (without squaring). Panel (c) uses the political risk exposure measure which is weighted by contemporaneous squared import shares, and controls for the sum of squared import shares (HHI). Panel (d) uses the political risk exposure measure which is weighted by contemporaneous import shares (without squaring). Panel (e) uses the political risk exposure measure which is weighted by contemporaneous squared total imports. Panel (f) uses the political risk exposure measure which is weighted by contemporaneous imports (without squaring). In all six panels, we control for 6-digit NAICS and decade fixed effects, and weight observations by 6-digit NAICS industry patent applications during 1990-1999. The coefficient and standard errors, clustered by sector, for the fitted line are displayed below each sub-figure.

Figure A.9: Foreign Political Risk and US Innovation (Forward Citations), Alternative Specifications

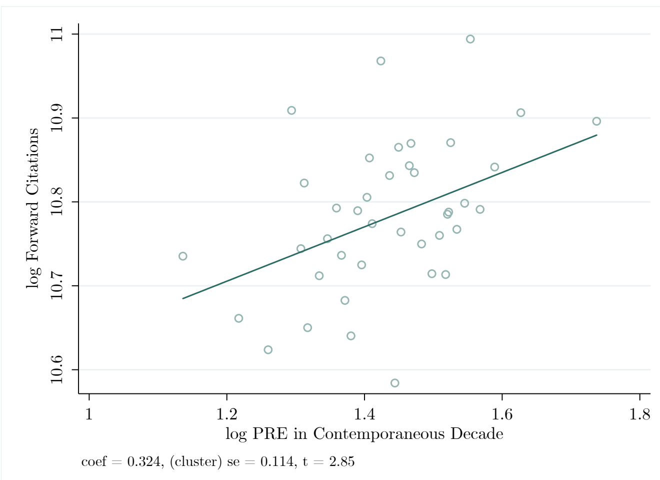
(a) Pre-period Squared Import Shares



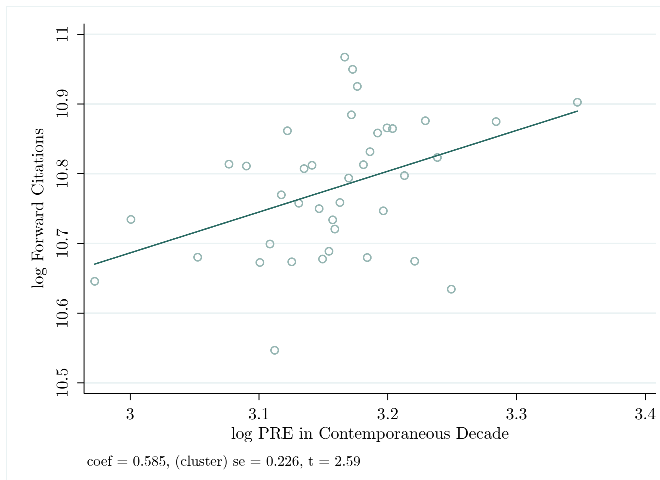
(b) Pre-period Import Shares



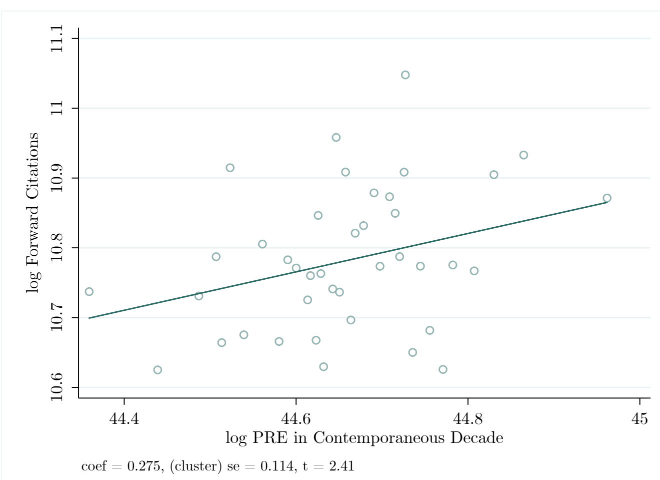
(c) Contemporaneous Squared Import Shares



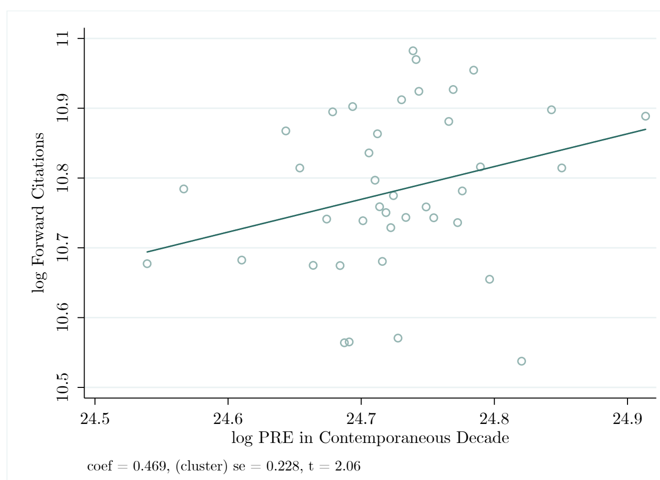
(d) Contemporaneous Import Shares



(e) Contemporaneous Squared Imports



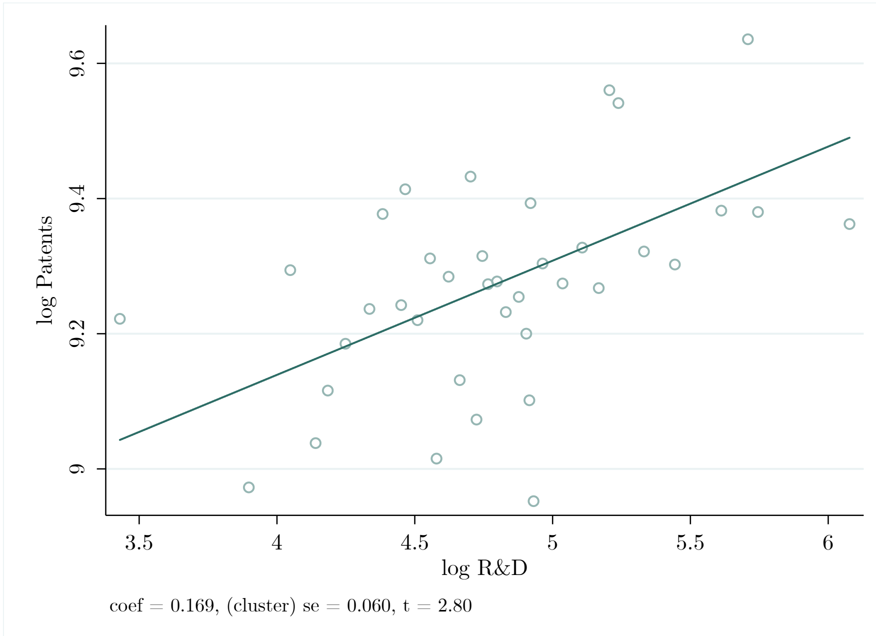
(f) Contemporaneous Imports



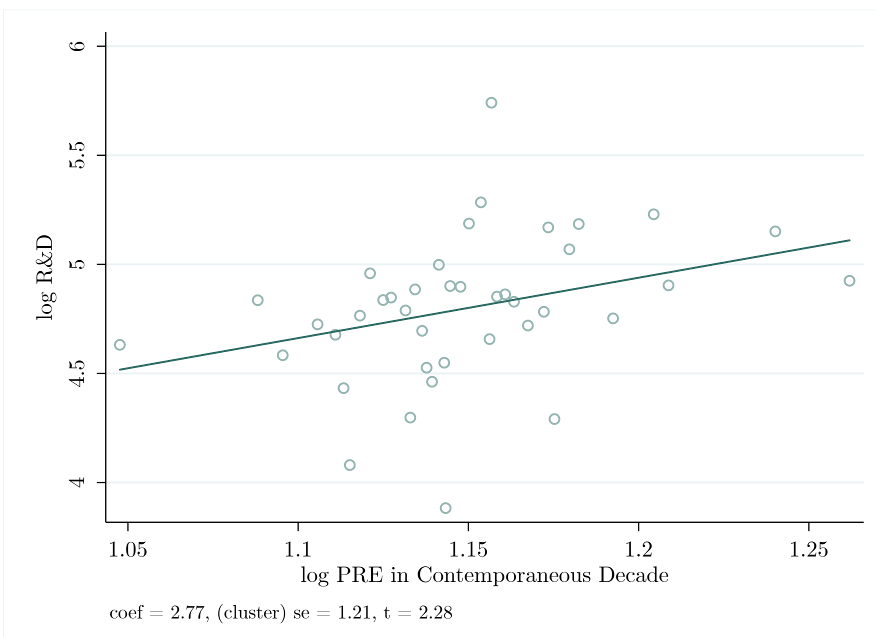
Notes: This figure shows the effect of political risk exposure in the contemporaneous decade on total forward citations within 5 years in the US, using different parameterizations of the political risk variable. Panel (a) replicates Figure 2a, using the political risk exposure measure which is weighted by pre-period squared import shares. Panel (b) uses the political risk exposure measure which is weighted by pre-period import shares (without squaring). Panel (c) uses the political risk exposure measure which is weighted by contemporaneous squared import shares, and controls for the sum of squared import shares (HHI). Panel (d) uses the political risk exposure measure which is weighted by contemporaneous import shares (without squaring). Panel (e) uses the political risk exposure measure which is weighted by contemporaneous squared total imports. Panel (f) uses the political risk exposure measure which is weighted by contemporaneous imports (without squaring). In all six panels, we control for 6-digit NAICS and decade fixed effects, and weight observations by 6-digit NAICS industry patent applications during 1990-1999. The coefficient and standard errors, clustered by sector, for the fitted line are displayed below each sub-figure.

Figure A.10: Foreign Political Risk and US R&D

(a) Correlation Between Sector-Level Patenting and R&D Investment

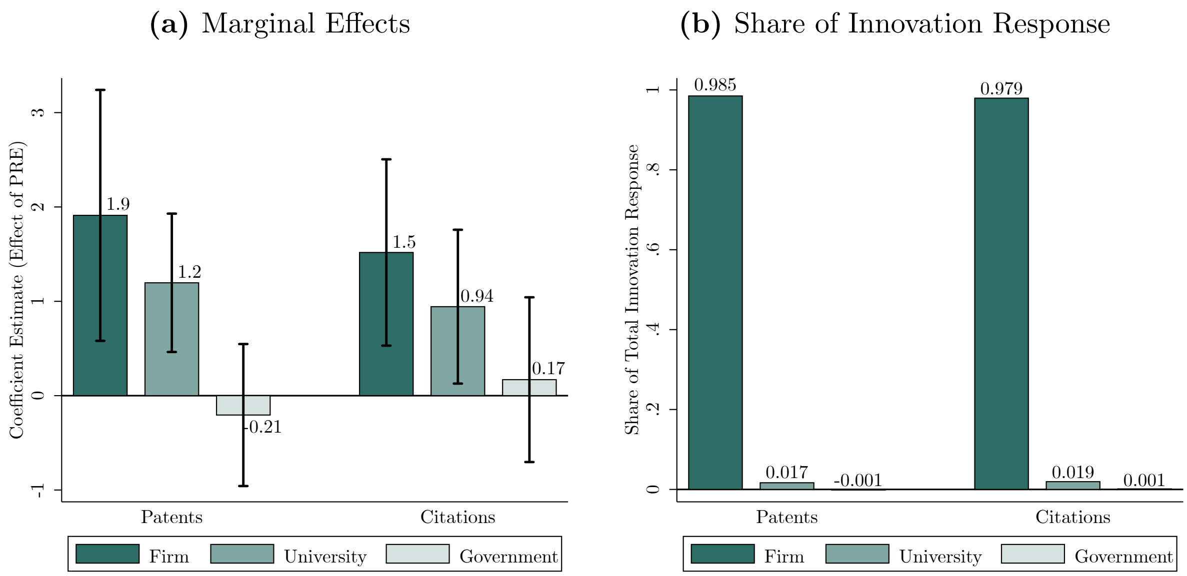


(b) Political Risk Exposure and R&D Investment



Notes: Panel (a) shows the correlation between sector-level R&D expenditure from Compustat and patent applications. Panel (b) shows the effect of political risk exposure in the contemporaneous decade on R&D expenditure. In both panels, we control for 6-digit NAICS and decade fixed effects, and weight observations by 6-digit NAICS level patent applications during 1990-1999. The coefficient and standard error for the fitted line are displayed below each sub-figure. Standard errors are clustered by sector.

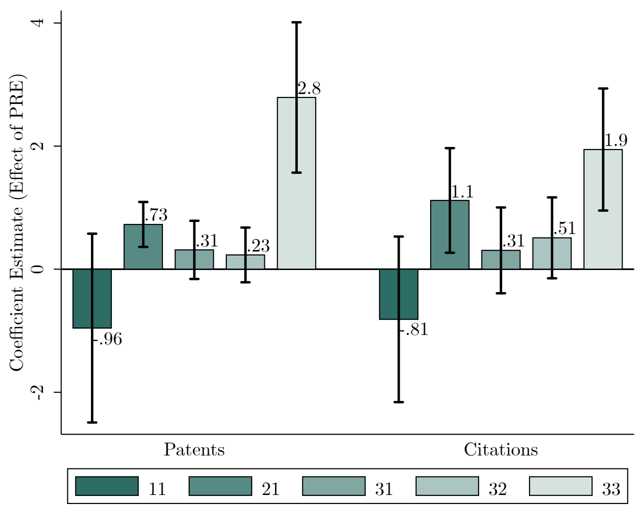
Figure A.11: Foreign Political Risk and US Innovation, by Inventor Type



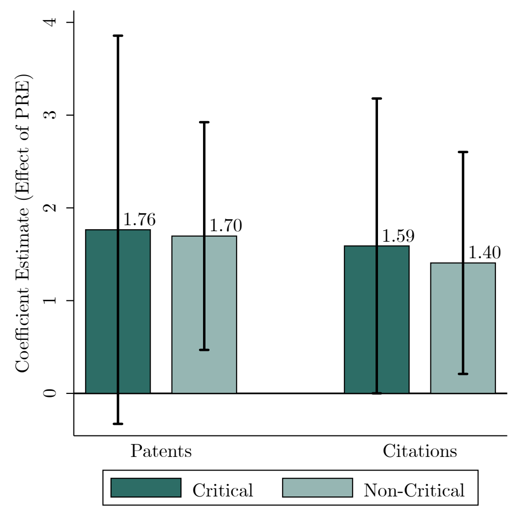
Notes: Panel (a) shows the effect of political risk exposure on patent applications by firms, universities, and governments, respectively. We regress log patent applications from each type of inventor on the political risk exposure measure. We control for 6-digit NAICS and decade fixed effects, and weight observations by 6-digit NAICS level patent applications during 1990-1999. Standard errors are clustered at 6-digit NAICS level, and 95% confidence intervals are reported. In panel (b), we calculate the share of the total innovation response by firms, universities, and governments, implied by estimates from (a), taking into account that innovation sizes of these three inventor types are different.

Figure A.12: Foreign Political Risk and US Innovation, Sector Heterogeneity

(a) 2-digit NAICS Sectors



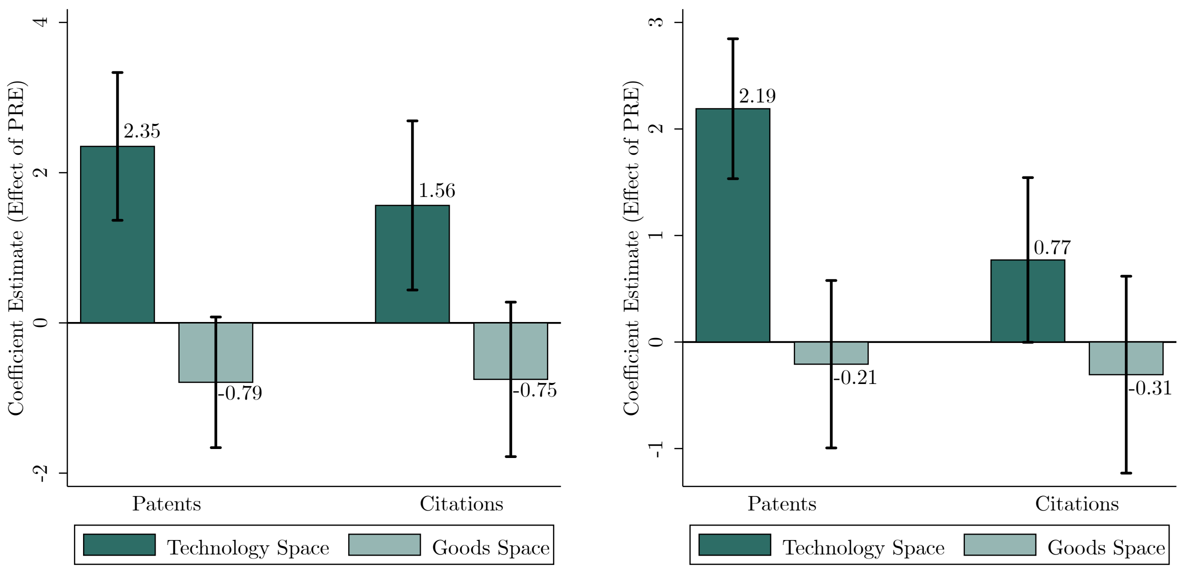
(b) Critical vs Non-Critical Sectors



Notes: Panel (a) shows the effect of political risk exposure in the contemporaneous decade on total patent applications and forward citations within 5 years in US, across five 2-digit NAICS sectors. Standard errors are clustered at 6-digit NAICS level and 95% confidence intervals are reported. Panel (b) shows the effect of political risk exposure in the contemporaneous decade on total patent applications/ forward citations within 5 years in US, across critical vs non-critical sectors. The list of critical sectors are provided by the US International Trade Administration (ITA). Specifically, we run the following regression: $\log \text{patents}_{it} = \beta_C \log \text{PRE}_{it} \times 1[i \in C] + \beta_{NC} \log \text{PRE}_{it} \times 1[i \in NC] + \delta_i + \delta_{Ct} + \epsilon_{it}$, where C stands for critical sector, NC stands for non-critical sector, and t stands for decade. The standard errors are clustered at 6-digit NAICS level and 95% confidence intervals are reported. In both panels, we use the political risk exposure measure which is weighted by pre-period import shares.

Figure A.13: Foreign Political Risk and US Innovation, Technology vs Goods Space

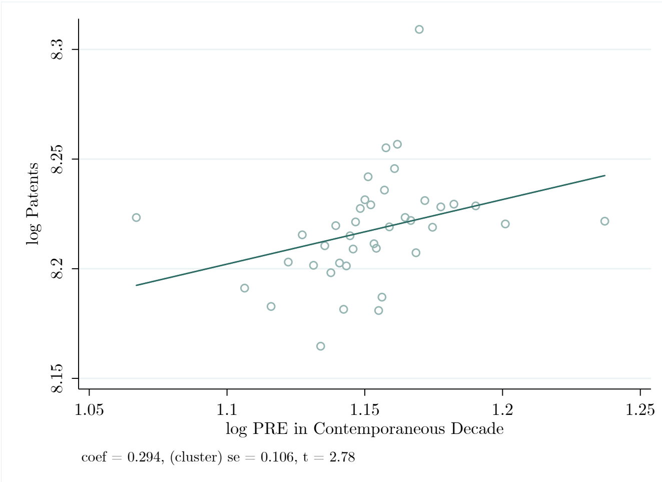
(a) Pooled Regression **(b)** Separate Regression



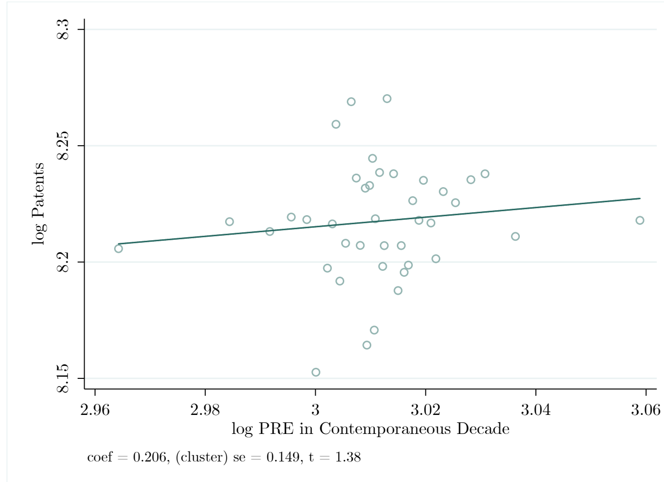
Notes: This figure estimates the effect of political risk exposure in each firm's "goods space" versus "technology space" on patenting. In Panel (a), the goods space effect and technology space effect are estimated from the same regression, whereas in Panel (b) they are estimated from separate regressions. In the left columns of both panels, the outcome is log of the number of patent applications for the firm-decade and in the right columns of both panels the outcome is the log number of forward citations within 5 years for patents filed by the firm in the corresponding decade. Standard errors are clustered by firm and 95% confidence intervals are reported.

Figure A.14: Foreign Political Risk and Global Innovation (Patents), Alternative Specifications

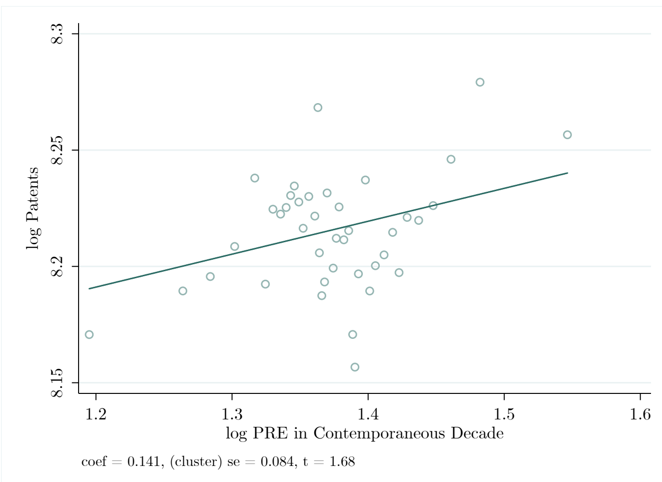
(a) Pre-period Squared Import Shares



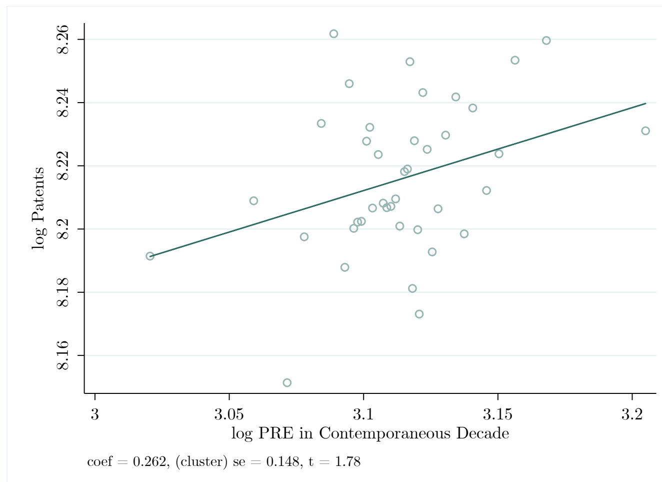
(b) Pre-period Import Shares



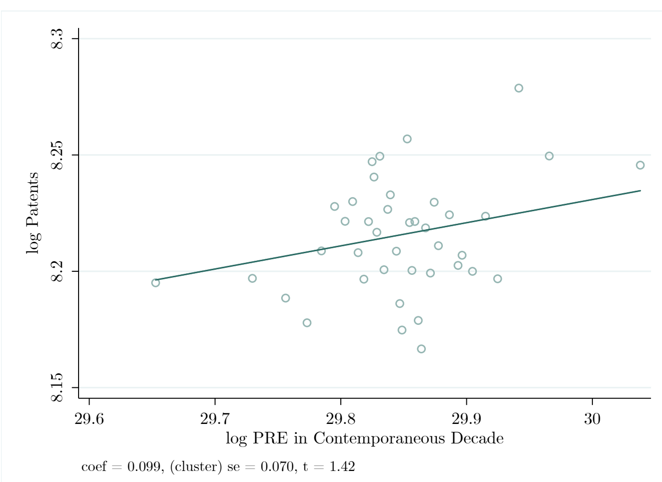
(c) Contemporaneous Squared Import Shares



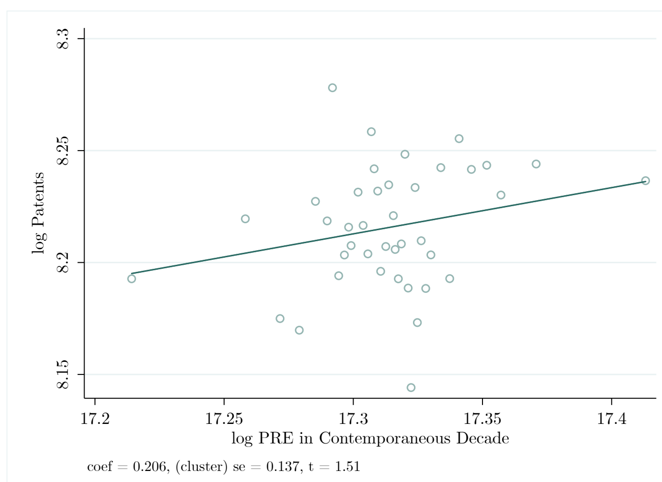
(d) Contemporaneous Import Shares



(e) Contemporaneous Squared Import Levels



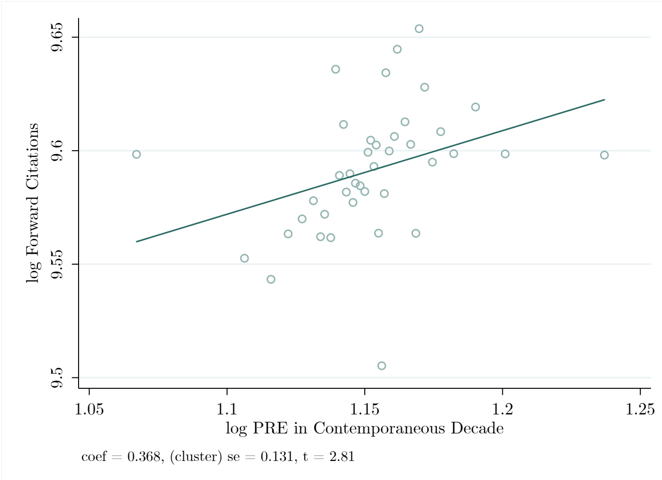
(f) Contemporaneous Import Levels



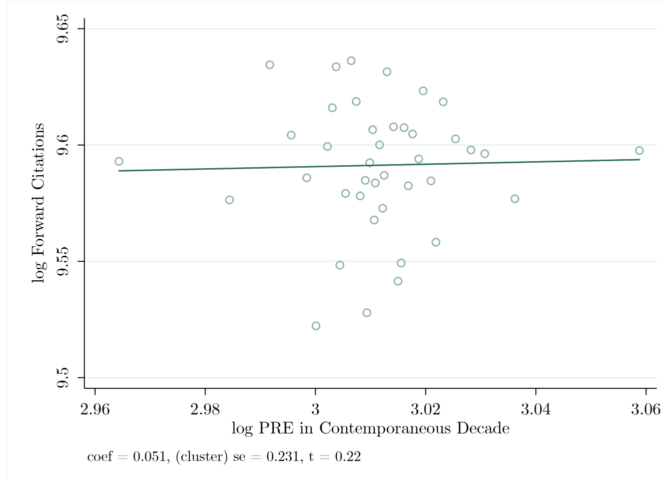
Notes: This figure shows the effect of political risk exposure in the contemporaneous decade on total patents. Panel (a) replicates Figure 5a. Panel (b) uses the political risk exposure measure which is weighted by pre-period import shares without squaring. Panel (c) uses the political risk exposure measure which is weighted by contemporaneous squared import shares. Panel (d) uses the political risk exposure measure which is weighted by contemporaneous import shares without squaring. Panel (e) uses the political risk exposure measure which is weighted by squared contemporaneous imports. Panel (f) uses the political risk exposure measure which is weighted by contemporaneous imports without squaring. In all six panels, we control for 6-digit NAICS × country, 6-digit NAICS × decade and country × decade fixed effects and weight observations by 6-digit NAICS × country level patent applications during 1990-1999. The coefficient and standard error, clustered by country×sector, for the fitted line are displayed below each sub-figure.

Figure A.15: Foreign Political Risk and Global Innovation (Forward Citations), Alternative Specifications

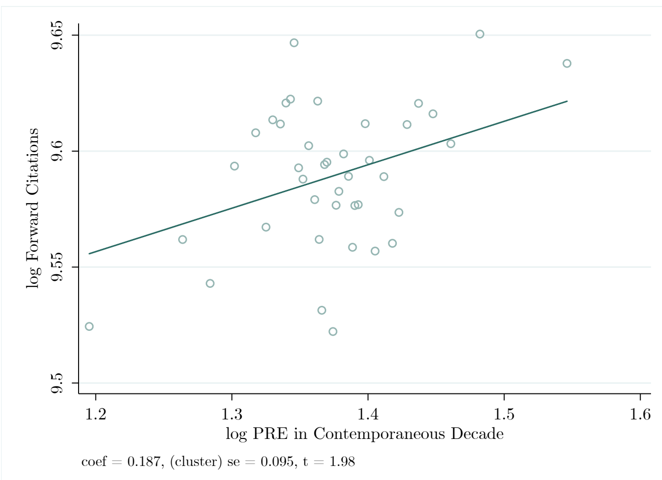
(a) Pre-period Squred Import Shares



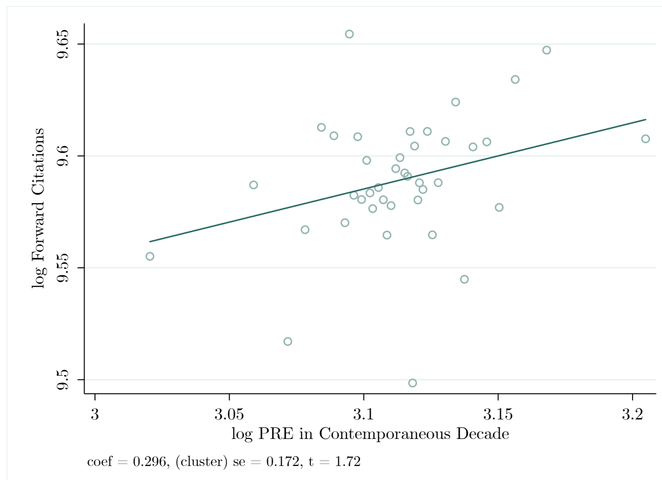
(b) Pre-period Import Shares



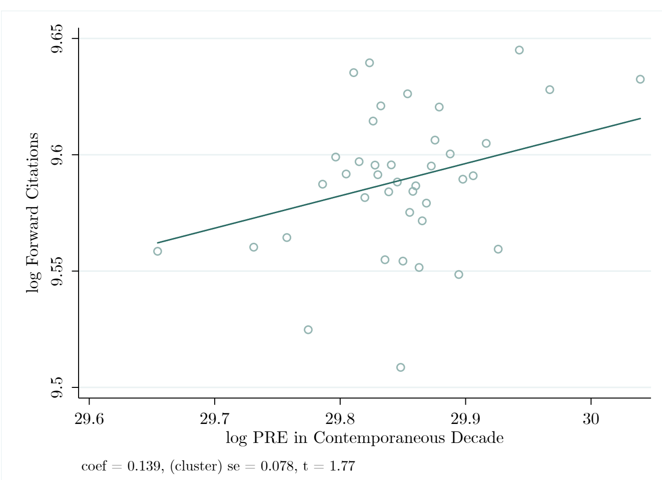
(c) Contemporaneous Squared Import Shares



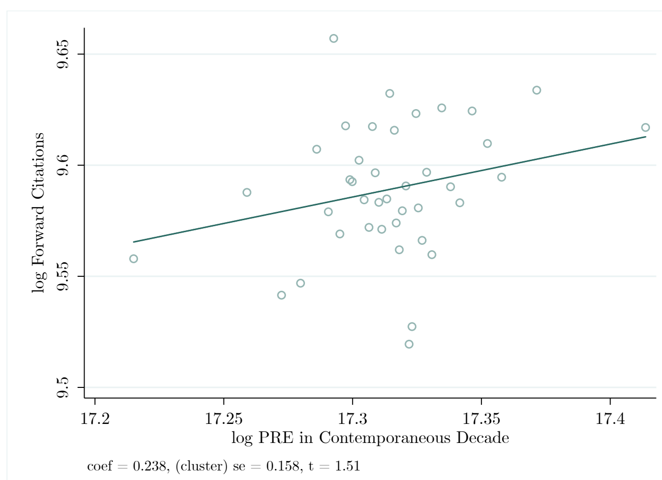
(d) Contemporaneous Import Shares



(e) Contemporaneous Squared Imports



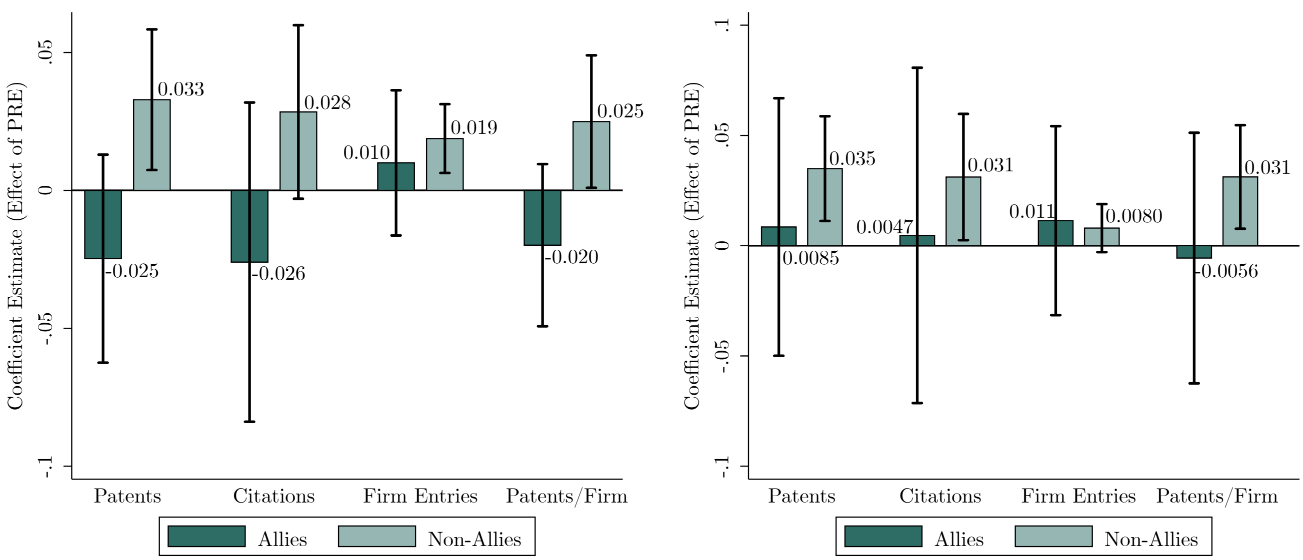
(f) Contemporaneous Imports



Notes: This figure shows the effect of political risk exposure in the contemporaneous decade on total forward citations within 5 years. Panel (a) uses the political risk exposure measure which is weighted by pre-period squared import shares. Panel (b) uses the political risk exposure measure which is weighted by pre-period import shares without squaring. Panel (c) uses the political risk exposure measure which is weighted by contemporaneous squared import shares. Panel (d) uses the political risk exposure measure which is weighted by contemporaneous import shares without squaring. Panel (e) uses the political risk exposure measure which is weighted by contemporaneous squared imports. Panel (f) uses the political risk exposure measure which is weighted by contemporaneous imports without squaring. In all six panels, we control for 6-digit NAICS × country, 6-digit NAICS × decade and country × decade fixed effects and weight observations by 6-digit NAICS × country level patent applications during 1990-1999. The coefficient and standard error, clustered by country×sector, for the fitted line are displayed below each sub-figure.

Figure A.16: Foreign Political Risk from Allies vs Non-Allies and Global Innovation

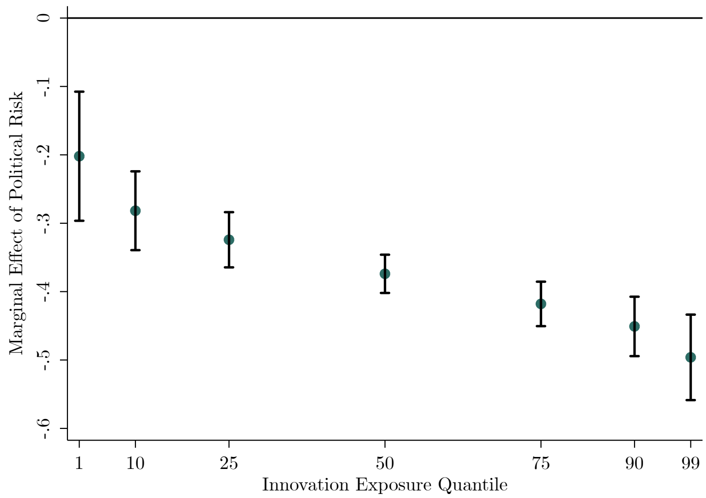
(a) Annual **(b)** Decennial



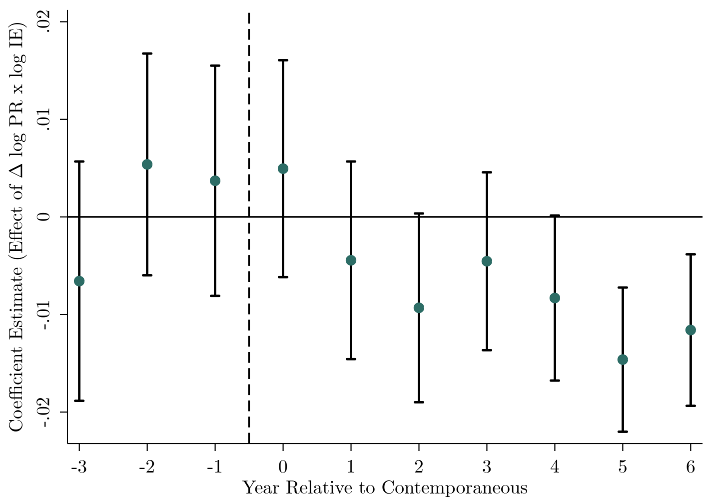
Notes: This figure shows the effect of political risk exposure from allies and non-allies on global innovation, at both annual and decennial frequencies. For the annual frequency (a), we run the following regression: $y_{cit} = \beta^A \log \text{PRE}^{\text{Ally}}_{cit-1} + \beta^E \log \text{PRE}^{\text{Non-Ally}}_{cit-1} + \alpha_{ci} + \delta_{ct} + \eta_{it} + X'\Gamma + \epsilon_{cit}$, and standard errors are clustered at 6-digit NAICS $\times$ country level. For the decennial frequency (b), we run the following regression: $y_{cit} = \beta^A \log \text{PRE}^{\text{ALLY}}_{cit} + \beta^E \log \text{PRE}^{\text{NON-ALLY}}_{cit} + \alpha_{ci} + \delta_{ct} + \eta_{it} + X'\Gamma + \epsilon_{cit}$, and standard errors are clustered at 6-digit NAICS $\times$ country level. The outcome variable for each set of bars is listed at the bottom of each graph, and β^A and β^E are reported in dark and light green respectively. In all specifications, observations are weighted by 6-digit NAICS $\times$ country level patent applications during 1990-1999 and we use the political risk exposure measure which is weighted by pre-period import shares.

Figure A.17: Political Risk and Exports: Effect of Innovation Exposure (Export Share Weighted)

(a) Effect of PR by Exposure Quantile

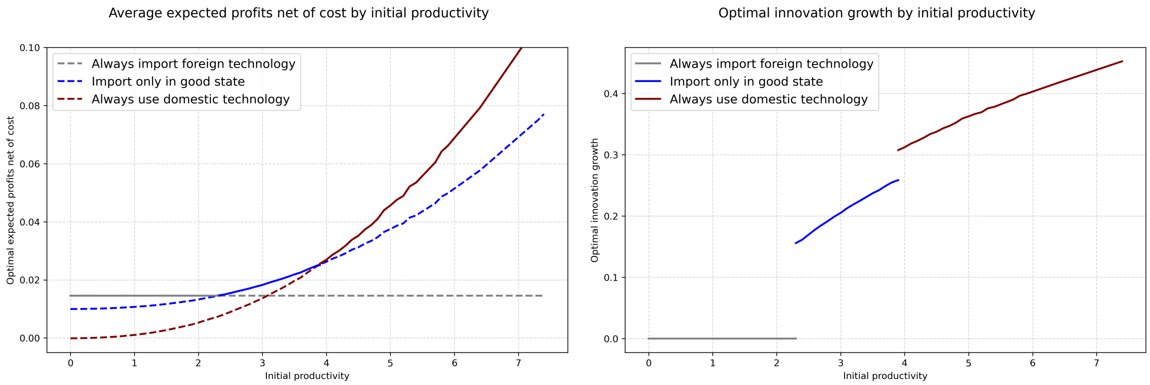


(b) Effect of ΔPR $\cdot$ IE, Leads and Lags



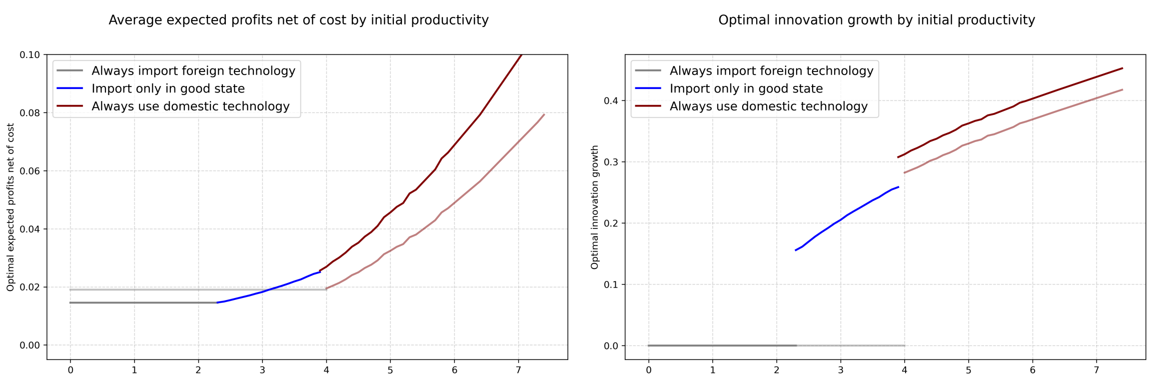
Notes: The unit of observation in both panels is an exporter-sector-year. Panel (a) shows the marginal effect of political risk on exports, evaluated at different quantiles of innovation exposure. Specifically, we run the following regression: $\log \text{Exports}_{cit} = \gamma \log \text{PR}_{ct} + \beta \log \text{PR}_{ct} \cdot \log \text{IE}_{ci} + \alpha_{ic} + \eta_{it} + X'\Gamma + \epsilon_{cit}$ and plot the total marginal effect of $\log \text{PR}_{ct}$ at different quantiles (reported on the x-axis) of $\log \text{IE}_{ci}$. Standard error is clustered at 6-digit NAICS $\times$ country level and 95% confidence intervals are reported. In Panel (b), we run the following regression: $\log \text{Export}_{cit} = \sum_{\tau=-3}^{6} \beta_\tau \log \text{IE}_{ci} \times \Delta \log \text{PR}_{c,t-\tau} + \alpha_{ic} + \delta_{ct} + \eta_{it} + \epsilon_{cit}$ and then report the point estimates and 95% confidence intervals for the β_τ. The standard errors are clustered at 6-digit NAICS $\times$ country level. In both panels, we use innovation exposure measure that is weighted by pre-period export shares.

Figure A.18: Firm decisions along the initial productivity distribution (baseline)



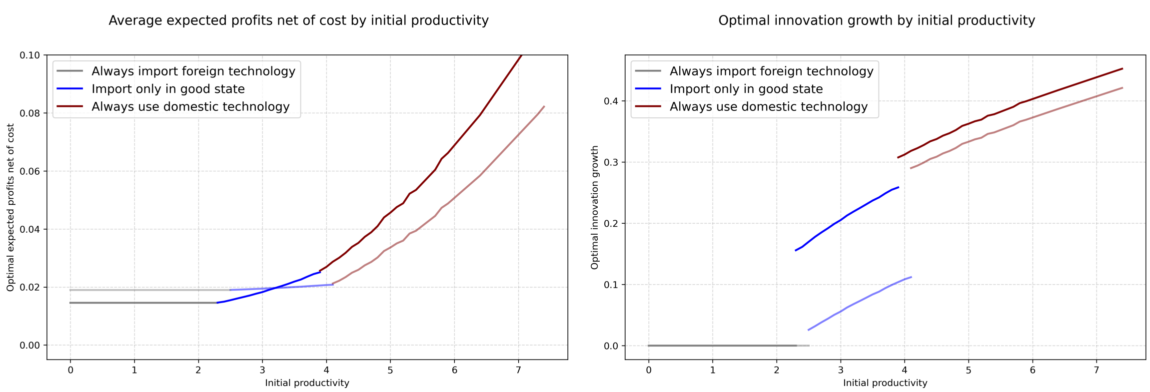
Note: The left panel plots the shadow expected profits net of costs at different bins of endowed period-0 productivity. The solid segments represent the optimal expected profits (net of costs) in equilibrium. Each bin represents $\frac{1}{10}$. The right panel plots the average step-up in firm productivity stemming from innovation between period 0 and period 1 across bins of endowed period-0 productivity.

Figure A.19: Effects of an increase in τ



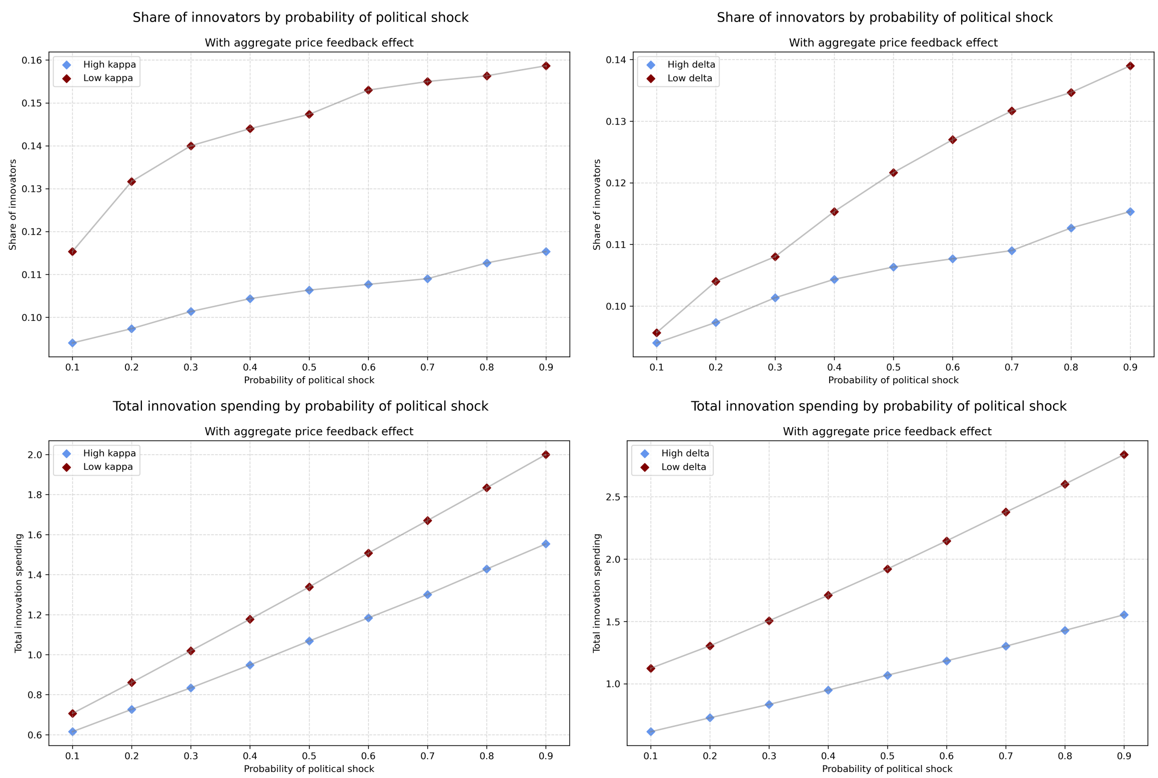
Note: The left panel plots the shadow expected profits net of costs at different bins of endowed period-0 productivity. The darker lines correspond to the larger political shock τ ($\tau = 0.5$), compared to a small political shock ($\tau = 0.10$ -lighter lines). Each bin represents $\frac{1}{10}$. The right panel plots the average step-up in firm productivity stemming from innovation between period 0 and period 1 across bins of endowed period-0 productivity, for the large (dark lines) or small (light lines) political shock τ.

Figure A.20: Effects of an increase in p



Note: The left panel plots the shadow expected profits net of costs at different bins of endowed period-0 productivity. The darker lines correspond to the larger probability of a political shock p ($p = 0.5$), compared to a smaller probability of shock ($p = 0.10$ -lighter lines). Each bin represents $\frac{1}{10}$.The right panel plots the average step-up in firm productivity stemming from innovation between period 0 and period 1 across bins of endowed period-0 productivity, for the large (dark lines) or small (light lines) political shock probability p.

Figure A.21: Effects of an increase in p on aggregate innovation



Note: The top panels plot the share of innovators, while the bottom panels plot the total innovation spending in the sector. The panels in the left column compare high and low-κ domestic innovation cost levels, while the right column compares high and low-δ domestic innovation cost elasticities. The figure plots the sector-level innovation response to changes in the probability of the political shock occurring, taking into account the general equilibrium feedback response of the sectoral price level.

Table A.1: Foreign Political Risk and Firm Performance

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	log Investment		log Profits	log Sales	log Employ.
log PRE, First Lag	-0.337	-0.242	-0.235	-0.330	-0.228
	(0.138)	(0.132)	(0.131)	(0.133)	(0.127)
Mean Dep. Var.	4.03	4.25	6.12	7.30	1.82
Observations	10743	10063	10670	10734	10751
NAICS 6-digit FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is a 6-digit NAICS industry by year. For each industry-year, we compute the average of firm-level variables using Compustat data to construct each dependent variable. The dependent variables is log capital expenditure in column 1, log PPE (plant, property, equipment) investment plus depreciation in column 2, log gross profits in column 3, log sales in column 4, and log employment column 5. Standard errors, clustered at the 6-digit NAICS level, are reported in parentheses.

Table A.2: Mineral List

Aluminum	Alunite	Amber	Andalusite	Anhydrite
Antimony	Arsenic	Asbestos	Attapulgite	Barite
Barium	Bauxite	Bentonite	Beryllium	Boron
Bromine	Cadmium	Calcite	Calcium Carbonate	Cesium
Chromium	Clay	Coal	Cobalt	Columbium
Copper	Corundum	Cryolite	Diamond	Diatomite
Dolomite	Emerald	Feldspar	Feldspathic Sand	Fluorine
Fluorite	Garnet	Gem Amethyst	Gem Beryl	Gem Topaz
Gold	Graphite	Gypsum	Halite	Halloysite
Hectorite	Iodine	Iron	Jade	Kaolin
Kunzite	Lapis Lazuli	Limestone	Lithium	Magnesia
Magnesite	Magnesium	Magnetite	Manganese	Mercury
Mica	Molybdenum	Muscovite	Nepheline Syenite	Nickel
Nitrate	Olivine	Opal	Palladium	Perlite
PGE	Phlogopite	Phosphate	Phosphorus	Platinum
Potash	Potassium	Pumice	Pyrophyllite	Rare Earth
Rhodochrosite	Rubidium	Ruby	Saponite	Sapphire
Scandium	Selenium	Sepiolite	Silica	Silica Sand
Sillimanite	Silver	Soda Ash	Sodium	Sodium Carbonate
Sodium Sulfate	Spinel	Strontium	Sulfur	Sylvite
Talc	Tantalum	Tellurium	Thorium	Tin
Titanium	Tourmaline	Tungsten	Uranium	Vanadium
Vermiculite	Wollastonite	Zeolite	Zinc	Zircon
Zirconium				

Table A.3: Foreign Political Risk and US Innovation: Controlling for Lagged Imports

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:	log Patents	Patents	log Fwd Citations	log Patent Value	log Patent Importance	log New Firms	log Patents per Firm
Panel A: Risk Measure Using Contemporaneous Imports							
log PRE, First Lag	0.299	0.275	0.207	0.310	0.287	0.044	0.231
	(0.147)	(0.126)	(0.083)	(0.147)	(0.126)	(0.125)	(0.092)
log HHI, First Lag	-0.034	-0.030	-0.076	0.023	-0.131	0.037	-0.060
	(0.165)	(0.140)	(0.103)	(0.183)	(0.151)	(0.141)	(0.098)
log Imports, First Lag	0.130	0.135	0.111	0.112	0.118	0.016	0.129
	(0.062)	(0.044)	(0.037)	(0.072)	(0.057)	(0.042)	(0.068)
Mean Dep. Var.	2.31	173	3.74	4.02	2.27	4.19	-2.89
Observations	13926	15432	12092	12788	11144	13822	13916
Panel B: Risk Measure Using Pre-Period Imports							
log PRE, First Lag	0.390	0.462	0.312	0.301	0.268	0.306	0.082
	(0.154)	(0.152)	(0.141)	(0.150)	(0.123)	(0.122)	(0.156)
log Imports, First Lag	0.136	0.156	0.121	0.122	0.132	0.016	0.134
	(0.094)	(0.073)	(0.044)	(0.111)	(0.079)	(0.044)	(0.087)
Mean Dep. Var.	2.31	174	3.75	4.02	2.29	4.19	-2.89
Observations	13571	14942	11902	12518	11041	13471	13561
NAICS 6-digit FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is a 6-digit NAICS industry by year. In Panel A, we use the political risk exposure measure which is weighted by contemporaneous import shares, and control for the log sum of squared import shares (HHI) and log imports. In Panel B, we use the political risk exposure measure which is weighted by pre-period import shares, and control for log imports. The dependent variable is log patent applications in column 1, patent applications in column 2, log forward citations in five years in column 3, log patent market value in column 4 (Kogan, Papanikolaou, Seru, and Stoffman, 2017), log patent importance (Kelly, Papanikolaou, Seru, and Taddy, 2021) in column 5, log number of new patenting firms in column 6, and log patents per firm in column 7. In column 2 we run PPML while in other columns we run OLS. We weight observations by 6-digit NAICS level patent applications during 1990-1999. Standard errors, reported in parentheses, are clustered at the 6-digit NAICS level.

Table A.4: Foreign Political Risk and US Innovation: Controlling for Exporters' GDP and Growth

Dependent Variable:	(1) log Patents	(2) Patents	(3) log Fwd Citations	(4) log Patent Value	(5) log Patent Importance	(6) log New Firms	(7) log Patents per Firm
log PRE, First Lag	0.299	0.493	0.293	0.178	0.144	0.338	-0.037
	(0.141)	(0.154)	(0.137)	(0.145)	(0.124)	(0.127)	(0.152)
log GDPExposure, First Lag	-0.148	-0.195	0.062	0.032	-0.131	0.157	-0.242
	(0.224)	(0.226)	(0.183)	(0.306)	(0.214)	(0.165)	(0.167)
log GrowthExposure, First Lag	-0.020	0.001	0.001	-0.020	-0.016	0.005	-0.024
	(0.013)	(0.015)	(0.012)	(0.018)	(0.010)	(0.013)	(0.012)
Mean Dep. Var.	2.34	175	3.77	4.04	2.28	4.21	-2.88
Observations	11648	12922	10433	11023	9644	11569	11640
NAICS 6-digit FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is a 6-digit NAICS industry by year. In all columns, we control for import share weighted foreign GDP and growth rate, measured as $\text{GDPExposure}_{it} = \sum_c \text{GDP}_{ct} \cdot (\text{ImportShare}_{ict_0})^2$, and $\text{GrowthExposure}_{it} = \sum_c \text{growth rate}_{ct} \cdot (\text{ImportShare}_{ict_0})^2$. The dependent variable is log patent applications in column 1, patent applications in column 2, log forward citations in five years in column 3, log patent market values in column 4 (Kogan, Papanikolaou, Seru, and Stoffman, 2017), log patent importance (Kelly, Papanikolaou, Seru, and Taddy, 2021) in column 5, log number of new patenting firms in column 6, and log patents per firm in column 7. In column 2 we run PPML while in other columns we run OLS. We weight observations by 6-digit NAICS level patent applications during 1990-1999. Standard errors, reported in parentheses, are clustered at the 6-digit NAICS level.

Table A.5: Foreign Political Risk and US Innovation with and without Government Interest

Dependent Variable:	(1) log Patents	(2) Patents	(3) log Fwd Citations	(4) log Patent Value	(5) log Patent Importance
			Panel A: with Government Interest		
log PRE, First Lag	0.174	0.097	0.095	0.169	0.159
	(0.100)	(0.135)	(0.114)	(0.225)	(0.118)
Mean Dep. Var.	-0.71	7.85	0.70	0.59	-0.59
Observations	11251	15213	9513	7759	8833
			Panel B: without Government Interest		
log PRE, First Lag	0.350	0.451	0.281	0.248	0.210
	(0.159)	(0.152)	(0.141)	(0.147)	(0.129)
Mean Dep. Var.	2.25	164	3.69	3.98	2.22
Observations	13713	15213	12031	12644	11164
NAICS 6-digit FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is a 6-digit NAICS industry by year. We use the political risk exposure measure which is weighted by pre-period import shares. To construct each outcome variable, we focus exclusively on patents with "government interest" in Panel A, and those without "government interest" in Panel B. The dependent variable is log patent applications in column 1, patent application numbers in column 2, log forward citations in 5 years in column 3, log patent market values (Kogan, Papanikolaou, Seru, and Stoffman, 2017) column 4, and log patent importance (Kelly, Papanikolaou, Seru, and Taddy, 2021) in column 5. We weight observations by 6-digit NAICS level patent applications during 1990-1999. In column 2 we run PPML while in other columns we run OLS. Standard errors are clustered at the 6-digit NAICS level.

Table A.6: Foreign Political Risk and US Innovation: Cross Sector Spillovers

	(1)	(2)	(3)	(4)
Dependent Variable:	log Patents		log Fwd Citations	
log PRE^{UP}, First Lag	0.792		0.422	
	(0.339)		(0.238)	
log PRE^{SUB}, First Lag		1.845		0.909
		(0.757)		(0.488)
Mean Dep. Var.	2.26	2.25	3.33	3.32
Observations	15071	14972	14712	14614
NAICS 6-digit FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: The unit of observation is a 6-digit NAICS industry by year. We include on the right-hand side of each regression proxies for upstream and substitute-sector exposure to political risk exposure, all constructed using the input-output matrix. Additional details behind each measures are described in Section C.2. The dependent variable is log patent applications in column 1-2, and log forward citations within 5 years in column 3-4. We weight observations by 6-digit NAICS level patent applications during 1990-1999 and standard errors, clustered at the 6-digit NAICS level, are reported in parentheses.

Table A.7: Foreign Political Risk and Global Innovation: Controlling for Lagged Imports

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	log Patents	Patents	log Fwd Citations	log Patent Importance	log New Firms	log Patents per Firm
log PRE, First Lag	0.081	0.071	0.134	0.131	0.033	0.066
	(0.033)	(0.039)	(0.049)	(0.032)	(0.019)	(0.028)
log Imports, First Lag	0.068	0.044	0.076	0.056	0.041	0.039
	(0.020)	(0.017)	(0.030)	(0.022)	(0.013)	(0.013)
Mean Dep. Var.	-0.92	1.99	-0.034	-0.90	1.73	-3.15
Observations	242247	2359652	184974	172805	206293	239667
NAICS 6-digit × Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
NAICS 6-digit × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is a 6-digit NAICS industry in a country in a year. We use the political risk exposure measure which is weighted by pre-period import shares and control for log import shares. The dependent variable is log patent applications in column 1, patent applications in column 2, log forward citations in 5 years in column 3, log patent importance (Kelly, Papanikolaou, Seru, and Taddy, 2021) in column 4, log number of new patenting firms in column 5, and log patents per firm in column 6. We weight observations by 6-digit NAICS × country level patent applications during 1990-1999. In column 2 we run PPML while in other columns we run OLS. Standard errors are clustered at the 6-digit NAICS × country level.

Table A.8: Political Risk and Exports: The Effect of Innovation Exposure (Additional Controls)

	(1)	(2)	(3)	(4)
Dependent Variable:	log Exports			
log PR × log IE	-0.014	-0.013	-0.011	-0.011
	(0.004)	(0.004)	(0.004)	(0.004)
Mean Dep. Var.	9.24	9.24	9.11	9.11
Observations	826660	826086	860985	860030
Controls	All	All	LASSO	LASSO
NAICS 6-digit × Exporter FE	Yes	Yes	Yes	Yes
NAICS 6-digit × Year FE	Yes	Yes	Yes	Yes
Exporter × Year FE	Yes	Yes	Yes	Yes

Notes: The unit of observation is a 6-digit NAICS industry by year by exporter. The dependent variable is log exports. In column 1 and 3, we use pre-period patent stock to calculate innovation exposure. In column 2 and 4, we use pre-period citation-weighted patent stock to calculate innovation exposure. The export market characteristics include GDP, GDP per capita, GDP growth, population, population growth, import levels, secondary education completion rates, life expectancy, the GDP deflator, CPI, interest rates, external debt, foreign aid, foreign reserves, and Worldwide Governance Indicators (WGI). In column 3-4, we employ the post-double LASSO approach to select control variables. Standard errors are clustered at 6-digit NAICS × exporter level.

Table A.9: Political Risk and Exports: the Effect of Innovation Exposure (Bilateral Variation)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	log Exports					
log PR × log IE	-0.034	-0.031	-0.033	-0.053	-0.045	-0.238
	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)	(0.033)
Mean Dep. Var.	5.01	5.01	5.01	5.01	5.01	5.01
Observations	17619120	17619120	17619120	17619120	17619120	17619120
NAICS 6-digit × Exporter FE	Yes	-	Yes	-	Yes	-
NAICS 6-digit × Importer FE	Yes	Yes	-	-	Yes	-
NAICS 6-digit × Year FE	Yes	-	-	Yes	Yes	-
Exporter × Year FE	Yes	-	Yes	Yes	-	-
Importer × Year FE	Yes	Yes	-	Yes	-	-
Exporter × Importer FE	Yes	Yes	Yes	-	-	-
NAICS 6-digit × Exporter × Year FE	No	Yes	No	No	No	Yes
NAICS 6-digit × Importer × Year FE	No	No	Yes	No	No	Yes
NAICS 6-digit × Exporter × Importer FE	No	No	No	Yes	No	Yes
Exporter × Importer × Year FE	No	No	No	No	Yes	Yes

Notes: The unit of observation is a 6-digit NAICS industry by year by exporter by importer. The dependent variable is log exports. Standard errors are three-way clustered at 6-digit NAICS, exporter and importer level. The set of two and three-way fixed effects included in each specification are listed below each column.