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. We develop a model of innovation in which foreign political shocks can disrupt the supply of traded inputs, predicting that greater sector-level political risk exposure abroad leads to increased domestic innovation efforts and endogenously lower reliance on foreign inputs. We combine data on sector-level technology development with time-varying measures of sector-level exposure to foreign political risk and report three sets of empirical findings. First, sectors with higher exposure to foreign political risk exhibit significantly greater innovative activity, both in the US and globally. Second, the response of innovation is particularly strong when the risk emanates from geopolitical adversaries, consistent with the finding that policy barriers to trade are more likely to emerge between geopolitical foes in response to a rise in political risk in either country. Third, country-sector pairs that export to more innovation-intensive destinations see a greater reduction in exports following a rise in domestic political risk. This finding suggests that endogenous technological change limits reliance on risky foreign markets and thus amplifies the negative effects of political turmoil on export performance.

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1 Introduction

In 2022, the Creating Helpful Incentives to Produce Semiconductors (CHIPS) and Science Act passed the US Congress with bipartisan support and facilitated a surge in investment in semiconductor research and development (R&D). A central motivation for the legislation was a perceived increase in the likelihood that the US could lose access to foreign semiconductors. Commerce Secretary Gina Raimondo described the Act "as foremost a national security initiative [...] Today, more than 90 percent of the most technologically advanced chips, which are critical for the U.S. military and the economy, are produced in Taiwan. That has prompted concerns about the supply's vulnerability, given China's aggression toward Taiwan and the potential for a military invasion of the island."[1]

While the CHIPS act represents a government-led approach to mitigating foreign supply risk, many examples arise in the private sector. The rise of 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 timing was no coincidence: "In light of Russia's de facto annexation of Ukraine's Crimea region and the formal severing of military ties, 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."[2] A range of examples highlight how innovation can react dynamically to foreign political threats, shifting the direction of domestic technology and reshaping the economic consequences of political conflict.

In this paper, we empirically investigate how innovation, both in the US and around the world, reacts to foreign political risk embodied in import reliance. Does technology development systematically shift toward more risk-exposed industries, or do the examples above represent extreme cases and convenient justifications for investment? If so, what mechanisms underlie the redirection of innovation? And what are the impacts of directed technological change on adaptation to foreign political conflict?

We begin our analysis with a model to develop hypotheses for how foreign political risk affects domestic innovation and resulting patterns of 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 in using the domestic input, and can invest in innovation to increase their productivity at a cost. The price of inputs from Foreign is

[1] See: https://www.nytimes.com/2023/02/28/business/economy/chips-act-childcare.html.
[2] See: https://www.businessinsider.com/elon-musk-spacex-russia-ukraine-ula-2014-3.

subject to political risk: with some likelihood, political risk abroad will lead to production disruptions or restrictive trade policies of some intensity, increasing import costs.

The model predicts that an increase in the likelihood or intensity of foreign political shocks (e.g., conflict, expropriation) drives greater domestic innovation and reduced reliance on foreign inputs. Critically, 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 punishing trade restrictions (e.g., sanctions) are more likely to emerge between geopolitical enemies following a rise in political tension in either country, the response should be larger for political risk 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 only to general 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.

To investigate these questions empirically, we combine data on global innovation and political risk. Our main measure of innovation is the universe of patents filed in the US, compiled from PatentsView. This allows us to measure technology investment by topic or sector over time, along with a wealth of detailed information about the inventors and citation patterns. As an alternative proxy for technology development, we compile data on all R&D investment by US public firms from Compustat. To measure time-varying political risk, we use information from 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.

Before turning to our main empirical results, we begin with an analysis of political risk and innovation in an important sector where risk-exposure is geographically determined: minerals. Supply risk and innovation related to minerals have received substantial attention both because of the central importance of many minerals to a broad set of 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 the political risk in each country-year by that country's mineral-specific deposit share, as measured by the US Geological Survey (USGS).

We find that increases in exposure to political risk for a given mineral are followed 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 seemingly persistent changes in supply risk. This is a first indication that, in one sector, increases in political risk are met with increased innovative activity to mitigate their adverse consequences.

To understand 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 are concentrated in each foreign country, using fixed pre-period data on sector-level import shares from the UN Comtrade Database. We then build on methods from Goldschlag et al. (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.[3] We estimate the dynamic relationship between foreign political risk and domestic innovation, fully absorbing both sector and time fixed effects.

We first show that foreign political risk in a sector is strongly positively associated with subsequent innovation. This effect is similar when we focus on highly-cited patents or (for a subset of the sample) when we weight each patent by its private value as captured by changes in the patenting firm's stock market value around the date of patent granting (see Kogan et al., 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 politically risky. 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. 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 sectors based on whether they are defined by the US International Trade Association as "critical" for functioning US supply chains and do not find evidence of stronger effects for critical sectors.[4] Thus, consistent with private incentives playing a key role, the

[3] Our measure of patenting activity by NAICS 6-digit sector is strongly positively correlated with our measure of R&D investment, validating the method we use to link patenting by technology class to NAICS production sectors.

[4] Separating the effect by broader sector groupings, we find the largest effects for hard manufacturing

results do not seem driven only by public sector patenting or innovation in areas explicitly prioritized by the government. We next use firm-level data from Compustat to identify the technology-space of each firm (based on the areas in which it patents) and the goods-space of each firm (based on the main sector of its output) and separately estimate the effect of political risk shocks to both. 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 expected competition in the goods market. Finally, we find suggestive evidence of positive innovation spillovers along the supply chain—especially resulting from political risk shocks to downstream sectors—suggesting that, if anything, our baseline estimates may understate the technological response to foreign political risk.

We then further 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 to both investigate the role of geopolitical relationships in mediating the response to political risk and 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. 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 highly-cited patents, and we again find evidence both of new firms entering innovation and of increased patenting by existing innovators. We validate that there are no pre-trends between innovation and political risk exposure: innovation rises following increases in risk exposure, but not before.

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

and energy/mining, and no evidence of an effect for agriculture.

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. Next, we show direct evidence of the mechanism highlighted by the model: 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 innovation response to foreign political risk documented in our main results re-shapes the economic consequences of political shocks. We first show that our main result is driven almost entirely by markets with a high innovation stock at baseline. This suggests that only certain countries may be able to weather foreign political risk shocks via innovation and production onshoring. Then, we show that following a domestic political risk shock, exports decrease disproportionately and persistently in sectors that were initially exported to more innovation-intensive markets, where innovation is more elastic to foreign political risk. The results are robust to controlling for a broad set of additional export-market characteristics, and are 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 countries 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 re-shapes revealed comparative advantage.

Related Literature. This paper is at the intersection of several bodies of work. A growing literature investigates the causes and consequences of input supply risk (Baldwin et al., 2023; Moll et al., 2023). Most work at this intersection is theoretical and studies the role of policy (e.g., Grossman et al., 2023; Becko and O'Connor, 2024; Kooi, 2024; Liu et al., 2024). Rather than focusing on optimal government responses, we study how innovation reacts endogenously to foreign risk, reshaping its economic impact. Another strand of literature has shown that trade reacts to international conflict, concentrating among geopolitical allies and fragmenting as a result of geopolitical tension (e.g., Schiller, 1955; Morrow et al., 1998; Gopinath et al., 2024; Blanga-Gubbay and Rubínová, 2023;

Aiyar et al., 2023). Our results suggest that directed technological change could be an important mechanism linking political conflict to economic disintegration.

Scholars since at least Hirschman (1945) have studied the economic underpinnings of international conflict and geopolitical power. Much recent work in this area, again often focused on optimal government policymaking, has analyzed how economic ties between countries affect their political relationship (Martin et al., 2008; Clayton et al., 2023, 2024; Kleinman et al., 2024). We focus on the opposite relationship: how foreign political risk affects innovation and, in turn, international patterns of production and trade. Relatedly, Berger et al. (2013) study how international politics can affect comparative advantage by showing that US CIA interventions increase US exports to affected markets. We show that endogenous technological change, absent any explicit foreign intervention, is an additional mechanism through which international relations affect patterns of trade.

Finally, this paper extends existing work that studies the direction of technology (e.g., Acemoglu, 2002), including empirical analyses of cotton supply during the US Civil War (Hanlon, 2015), medicine (e.g., Acemoglu and Linn, 2004; Finkelstein, 2004), agriculture (e.g., Moscona and Sastry, 2023; Moscona, 2021), and energy-saving technology (e.g., Popp, 2002; Jaffe et al., 2003; Newell et al., 2010; Acemoglu et al., 2023; Dugoua and Gerarden, 2023). Our results suggest that potential scarcity—in our case, driven by expected political turmoil—is can be a major driver of technological change (Acemoglu, 2010). Our findings highlight how international political ties affect the direction of innovation and how innovation, in turn, mediates the consequences of political risk. Thus, we build on a relatively small body of work investigating how politics can shape the direction of innovation (Acemoglu and Johnson, 2023; Beraja et al., 2023a,b). The last part of our analysis highlights how this innovation can have negative international business-stealing externalities: induced innovation in one country can exacerbate the consequences of negative shocks in others by eroding their initial productivity advantage.

The rest of the paper proceeds as follows. Section 2 introduces our theoretical model. Section 3 describes our main data sources and measurement approach. Section 4 studies political risk and innovation in minerals. Section 5 studies political risk and innovation in all sectors in the US. Section 6 studies how political alliances mediate the relationship between political risk and innovation globally. Section 7 studies how innovation in response to political risk affects patterns of trade. Section 8 concludes.

2 Model

We begin by analyzing a model to formulate hypotheses for how innovation and trade are affected by foreign political risk that influences the domestic cost of importing inputs.

2.1 Set-Up

Production Technology. There are two time periods $t \in \{0,1\}$ and there are two countries, Home (H) and Foreign (F). In Home, there is a continuum of goods sectors, indexed by $k \in [0,1]$, each inhabited by a continuum of monopolistically competitive firms indexed by the variety $i \in [0,1]$ they produce. Each variety producer can use either domestic labor L, or an input sourced from abroad ("Foreign"), to produce output:

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

where $A^i_{k,t}$ is the productivity of using domestic labor L^i_t to produce variety i of good k at Home in period t, $X^i_{k,F,t}$ is the amount of inputs sourced from Foreign, and foreign intermediate inputs and domestic labor are perfect substitutes in production within a variety. 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 $\eta > 2$.[5] 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 wages w and w^F that we henceforth normalize to 1.[6]

[5]In Appendix A.4, we extend the model to allow for different elasticities of substitution across and within sectors, and we simulate this model in Appendix A.5. We do this to allow for and study the empirically reasonable idea that different firms' products within a sector are more substitutable than the outputs of different sectors. Our characterization of the equilibrium segmentation of firms into laggards, insurance innovators and classical innovators (Proposition 1) holds as written. However, competing effects on sectoral prices affect the innovation incentives of classical innovators, making the effect of foreign political risk on innovation and imports an empirical question.

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

Innovation Decisions. Domestic goods 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 compactly-supported cumulative distribution function. They can use final output 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 in equilibrium.

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 date zero 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 probability p and, if it does, then the productivity of sector k goes down. Conversely, in the absence of a political shock, there is no effect on productivity.[7] Modelling 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 the potential effects of policy without taking a stand on the fine details of what policies induce these distortions. That said, as we shortly detail, this model accommodates an interpretation as a reduced-form model of geoeconomics and retaliatory trade restrictions in which Home imposes tariffs on Foreign with some probability in response to political shocks occurring in Foreign (see Clayton et al., 2023, 2024; Becko and O'Connor, 2024, for detailed theoretical analyses of why Home might impose such tariffs and how they might be most effectively designed).

2.2 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

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

end, the final demand of good k and the demand for variety i of good k are given by:

$$Y_{k,t} = Y_t \left(\frac{P_{k,t}}{P_t}\right)^{-\eta}, \quad Y_{k,t}^i = Y_{k,t} \left(\frac{P_{k,t}^i}{P_{k,t}}\right)^{-\eta} \tag{2.6}$$

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

$$P_{k,F,t} = \frac{1}{(1-\tau_{k,t})A_{k,F}}, \quad P_{k,t} = \left(\int_{[0,1]} P_{k,t}^{i\ 1-\eta}\,\mathrm{d}i\right)^{\frac{1}{1-\eta}}, \quad P_t = \left(\int_{[0,1]} P_{k,t}^{1-\eta}\,\mathrm{d}k\right)^{\frac{1}{1-\eta}} \tag{2.7}$$

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

$$\mathcal{M}_{k,F,t}^i = P_{k,F,t}, \quad \mathcal{M}_{k,D,t}^i = \frac{1}{A_{k,t}^i} \tag{2.8}$$

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:

$$\mathcal{M}_{k,t}^i = \min\{\mathcal{M}_{k,F,t}^i, \mathcal{M}_{k,D,t}^i\} \tag{2.9}$$

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

$$P_{k,t}^i = \frac{\eta}{\eta-1}\mathcal{M}_{k,t}^i, \quad Y_{k,t}^i = \left(\frac{\eta-1}{\eta}\right)^{\eta} Y_{k,t} P_{k,t}^{\eta} \left(\mathcal{M}_{k,t}^i\right)^{-\eta} \tag{2.10}$$

Thus, the firms' profits are given by:

$$\Pi_{k,t}\left(\mathcal{M}_{k,t}^i\right) = \frac{1}{\eta-1}\left(\frac{\eta-1}{\eta}\right)^{\eta} Y_t \left(\mathcal{M}_{k,t}^i\right)^{1-\eta} \tag{2.11}$$

Equilibrium then boils down to characterizing firms' innovation decisions. To economize on notation, we drop the k and 1 subscripts and write $\mathcal{M}_{k,t}^i = \mathcal{M}^i(s)$, 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_1^i solves:

$$A_1(A_0^i) = \arg\max_{A_1^i \geq A_0^i} \bar{\Pi}\, \mathbb{E}\left[\mathcal{M}^i(s)^{1-\eta}\right] - C\left(A_1^i, A_0^i\right) \tag{2.12}$$

where $\bar{\Pi} = \frac{1}{\eta-1}\left(\frac{\eta-1}{\eta}\right)^{\eta} Y_1$ is invariant to outcomes in sector k.

2.3 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 for Foreign.

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 1 (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 firms ($A_0^i \geq \overline{A}$) always use the domestic technology.*

Proof. See Appendix A.1. □

How Innovation Responds to Political Risk. Having understood how firms innovate, we now study how innovation at the firm and sector levels responds to changes in foreign political risk. To do this, we consider shocks to political risk that potentially vary the likelihood of a political shock p and the intensity τ of the political shock. 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_1^i in any given sector k is greater after the change than before in the 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.

Corollary 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* $0 \leq A_* \leq A^*$.

Proof. See Appendix A.2. □

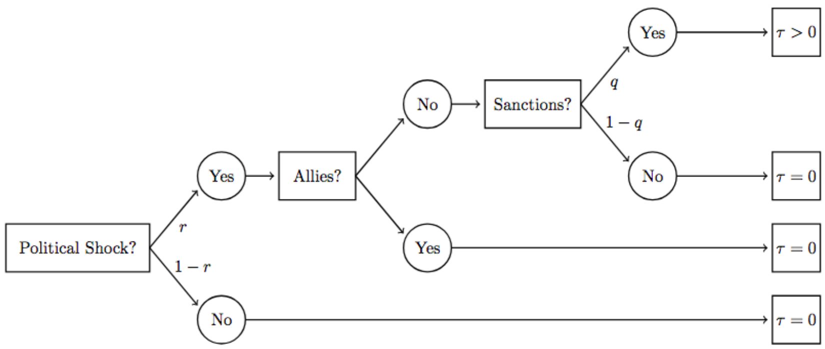
Thus, increased foreign political risk leads to an endogenous sector-level increase in innovation at Home. However, underlying this aggregate response are complicated firm-level responses that are not linearly or monotonically related to variation in foreign exposure across firms. This motivates our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

To unpack this result, consider how changes in political risk affect innovation incentives for each type of firm. For laggards, changes in the likelihood of a political shock p and the intensity of a political shock τ both reduce the expected profits from always importing the good, potentially increasing their innovation by turning them into insurance innovators. For insurance innovators, changes in τ do not affect profits or innovation incentives since they do not import the foreign good when the political shock takes place. On the other hand, increases in p makes it more likely that they will rely on their own technology and thereby increase their incentives to innovate *ex ante*. For classical innovators, neither shocks to p or τ affect innovation since firms in this group do not import so foreign changes in political risk have no effect on profits.[8] Thus, only firms with intermediate exposure to political shocks increase innovation when political risk rises.

How Geopolitical Ties Can Shape the Innovative Response. To this point, we have treated political risk as an exogenous change in the probability or severity of input supply disruption that would have the same effect regardless of the relationship between

[8] In Appendix A.4 and simulations in 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. However, this response is ambiguous in sign due to competing price effects, further complicating firm-level response dynamics.

Figure 1: Timeline of the Extended Model



Home and Foreign. Many shifts in political turmoil, including heightened conflict risk or threat of religious tension, may take this form. That said, an important mechanism linking political risk to loss of foreign supply could be government policy changes in response to underlying changes in political behavior. And this policy response could be very different depending on the relationship between Home and Foreign. For example, the US may only sanction its enemies but not its allies. Putin may threaten to cut off access to rocket engines for the US but not for his friends. Moreover, a theoretical literature in geoeconomics studies how countries use directed sanctions on political adversaries in order to advance domestic interests (Clayton et al., 2023, 2024; Becko and O'Connor, 2024).

Our framework accommodates an interpretation as a model of how the private sector innovative response is shaped by retaliatory trade policy of this form (see Figure 1). To see this, suppose an adverse political event in Foreign happens with probability r and does not happen with the complementary probability. Foreign may either be a geopolitical ally or non-ally of Home. If Foreign is a non-ally, then Home responds with trade sanctions with probability q. If Home responds with trade sanctions, then they impose an *ad valorem* tariff of τ on imports from Foreign. We assume that Home does not impose trade sanctions on allies in response to political shocks. This model is nested in our baseline framework with $p = q \times r$ for non-allies and $p = 0 \times r = 0$ for allies. Corollary 1 immediately implies that there will be a positive innovation response to increases in political risk emanating from geopolitical adversaries but not from allies. This arises because increases in baseline political risk r in non-allies lead to a greater likelihood of trade-restricting policies, further reducing Foreign input supply, while allies are not subjected to these policies.

How Imports Respond to Political Risk. A further implication of Corollary 1 is that when Foreign becomes politically riskier, domestic innovation will erode productivity advantages held abroad and domestic imports from abroad will decrease:

Corollary 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.*

Proof. See Appendix A.3. □

Moreover, when innovation is more elastic to changes in political risk, the arguments of Corollary 2 demonstrate that both the value and quantity of imports will be more elastic to changes in political risk (as shown in numerical simulations in Appendix A.5).

Summary of Predictions. Taken together, while there may be complicated effects of different types of political risk shocks on different types of firms, the model makes four clear predictions at the sector level for any composite change in political risk that increases the intensity and/or likelihood of future political shocks: (i) innovation will increase, (ii) this increase in innovation will be driven by political risk emanating from non-allies (if governments respond to political risk by restricting trade with 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.

In our empirical analysis, we will test these predictions and study the mechanisms underlying them. We first exploit changes in political risk exposure across minerals and US sectors and find that innovation increases substantially in response to increased political risk (i). Next, turning to a global sample and exploiting variation in geopolitical ties across country pairs, we again find a positive effect of foreign political risk on innovation but show that the effect is specific to risk emanating from geopolitical adversaries (ii). Consistent with the model, we find direct evidence that governments enact trade-restricting policies disproportionately in response to political risk shocks in non-allies. Finally, to study the impact of endogenous innovation in foreign input supply, we identify country-sector-level shifters of the elasticity of innovation to political risk and show that export declines following political risk shocks are driven by these high-elasticity markets (iii and iv).

3 Data and measurement

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

3.1 Data

Our key goals are to measure exposure to political risk and innovation 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 exposure to sources of political, economic, and financial 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 data, and has been used widely in policy documents, in reports by international organizations (e.g., the IMF), and in academic research in economics and political science.[9] 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.

To measure innovation, we compile data on all patents filed in the US using PatentsView (`https://patentsview.org/`), 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 methods described in Goldschlag et al. (2020). We also link each public firm listed in the patent record to data from Kogan et al. (2017) in order to measure the "value" of each patent as proxied by the excess stock market return of the patenting firm around the filing date. We use these data to measure both US innovation, using the sample of US-based inventors, as well as innovation in other countries, using the full sample of inventors linked to their countries of origin.[10] As a second measure of investment in innovation, we compile data on all research and development (R&D) investments made by publicly traded firms using Compustat and aggregate these data to the sector level.[11]

We rely on a range of additional data sources, mentioned briefly here and described in greater detail in the Appendix B. In order 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. To measure trade flows between countries at the NAICS six-digit level, we use the UN Comtrade database. We also build

[9]See, for example: Casanova et al. (2024), Catalán et al. (2024), Filippou et al. (2018), Kanga (2024), Keefer and Knack (2002), Kim (2025), Montes de Oca Leon et al. (2024), etc.

[10]In order to focus on a comparable sample of technologies (e.g., same inclusion criteria, quality threshold, etc.) we focus throughout the analysis only on patents issued in the US.

[11]Compustat reports firm-level R&D investment for all publicly traded firms.

several strategies used to measure geopolitical "friendship" across pairs of countries. These include data on military and strategic alliances from the Correlates of War (COW) project; data on UN voting, which we use to build a voting similarity measure based on methods developed by Bailey et al. (2017); and a database of all signed international alliance agreements from The Alliance Treaty Obligations and Provisions Project (ATOP). 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.

3.2 Measuring Political Risk Exposure

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

$$\text{PIR}_{it} = \sum_c \text{PoliticalRisk}_{ct} \cdot \text{Exposure}_{ic} \tag{3.1}$$

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, 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, we define:

$$\text{PIR}^{Min}_{it} = \sum_c \text{PoliticalRisk}_{ct} \cdot (\text{DepositShare}_{ic})^2 \tag{3.2}$$

where DepositShare_{ic} is the share of global deposits of mineral i that are located in country c according to data from the USGS. Intuitively, values of PIR^{Min}_{it} are higher when the deposits of mineral i are more concentrated in countries with high values of $\text{PoliticalRisk}_{ct}$.

When we focus on innovation across the entire US economy, i indexes NAICS 6-digit sectors and we define political import risk in sector i and time t as:

$$\text{PIR}^{Sect}_{it} = \sum_c \text{PoliticalRisk}_{ct} \cdot (\text{ImportShare}_{ict})^2 \tag{3.3}$$

where ImportShare_{ict} is the share of total imports to the US of sector i coming from country c in year t.[12] Values of PIR_{it}^{Sect} are higher if US imports in sector i are concentrated in countries with higher levels of political risk. This baseline 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 import relationship or because of a shift in imports toward a country that is politically risky.

That said, 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 proxy sector-level political risk fixing the import weights at their average prior to the year 2000 ($\text{ImportShare}_{ict_0}$):

$$\text{PIR}_{it}^{Init} = \sum_{c} \text{PoliticalRisk}_{ct} \cdot (\text{ImportShare}_{ict_0})^2 \tag{3.4}$$

This measure only exploits changes over time in the distribution of political risk across foreign countries for identification.

Figures A.1 and A.2 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.2 displays US import reliance on each country for three sectors (automobiles, oil and gas, and semiconductors) during the pre-period. 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.

[12] Our use of the squared import share in the baseline political risk 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 et al. (2024). Nevertheless, we show throughout the analysis that our results are similar if we use the level of exposure shares rather than the square.

In Section 6, we extend our analysis to a global sample, exploiting variation in political risk not only across sectors and time but also across countries. In this part of the analysis, we measure political import risk across countries, sectors, and years as:

$$\text{PIR}_{cit}^{Global} = \sum_{k \neq c} \text{PoliticalRisk}_{kt} \cdot (\text{ImportShare}_{k \to c, it_0})^2 \quad (3.5)$$

Now, variation in $\text{PIR}_{cit}^{Global}$ derives both from differential changes in country-specific political risk and differences in each country's pre-period, sector-specific import reliance.

4 Case Study: Political Risk and Innovation in Minerals

Before turning to our main results, we first analyze the effect of political risk on innovation in minerals. Minerals play a critical role in many industries and are central to technologies deployed in defense, agriculture, renewable energy, and information technology. Lithium, for example, is a key component in rechargeable batteries for electronics—including phones, computers, and electric vehicles. Aluminum and copper are essential to a range of electronics, including many with military and defense applications.

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). Growing concern about the concentration of copper and aluminum deposits in China has led to price spikes (Bloomberg News, 2024; Bastin, 2024) and calls for new strategies to "de-risk" supply (US Department of Commerce, 2019; Shiquan and Deyi, 2023). The Carnegie Endowment writes, for example, that "the US and NATO face serious risks of mineral shortages [...] especially if US-China tensions escalate."[13] As a result, organizations like the USGS are building tools to identify risks to mineral access so that firms can preemptively adjust accordingly.[14] Anecdotally, new technologies have also emerged in response to risks to mineral supply (Vespignani and Smyth, 2024), including techniques to increase the efficiency of extraction, prospecting, refining and processing, and recycling.

Figure A.3 uses data from the United States Geological Survey (USGS) to display the global deposit shares for three critical industrial minerals: copper, aluminum, and zinc,

[13]See https://carnegieendowment.org/research/2024/02/the-us-military-and-nato-face-serious-risks-of-mineral-shortages?lang=en

[14]See: https://www.usgs.gov/news/national-news-release/new-methodology-identifies-mineral-commodities-whose-supply-disruption.

all of which are among the most important industrial metals. Aluminum, for example, accounted for 40% of global metal production in 2021, and China represented over 50% of aluminum output.[15] Figure A.4 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 in all three cases patenting related to each mineral seems to follow the trend in political risk.

To systematically investigate whether exposure to political risk affects the direction of innovation across minerals, we estimate the following regression equation, versions of which we return to throughout the analysis:

$$y_{it} = \beta \cdot \log\text{PIR}^{Min}_{i,t-1} + \alpha_i + \delta_t + X'\Gamma + \epsilon_{it} \tag{4.1}$$

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} is a measure of patenting related to mineral i in year t. The coefficient of interest is β, which captures the relationship between political risk exposure and technology development.

Estimates of β are presented in Figure 2, which displays a series of partial correlation plots. In Figure 2a, 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 2b 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.

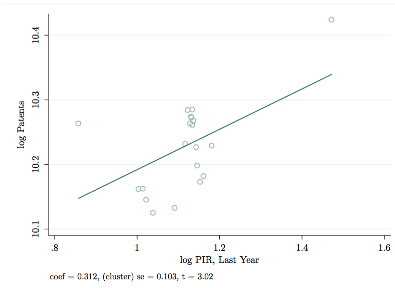
Turning to dynamics, Figure 2c reports the relationship between political risk in the *future* decade and innovation. We estimate a flat and statistically insignificant relationship, suggesting that the results are not driven by pre-existing trends. Mineral-level trends in innovation are unrelated to future trends in political risk exposure.

Finally, Figure 2d-2f 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

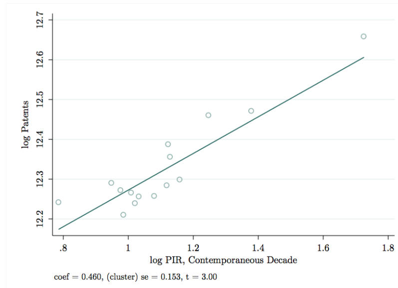
[15] See: https://www.visualcapitalist.com/all-the-metals-we-mined-in-2021-visualized/

Figure 2: Foreign Political Risk and Mineral Innovation

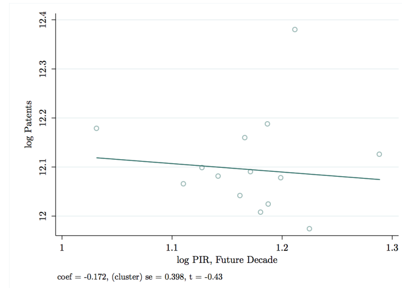
(a) Patents (Annual)



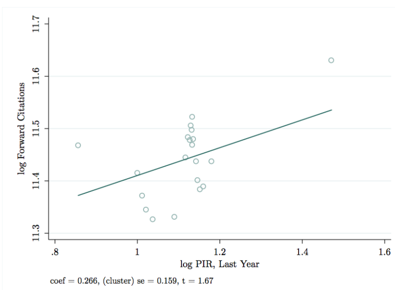
(b) Patents (Decadal)



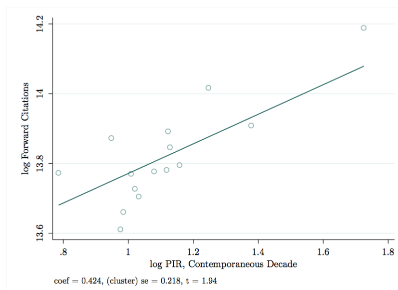
(c) Patents (Pre-Trend)



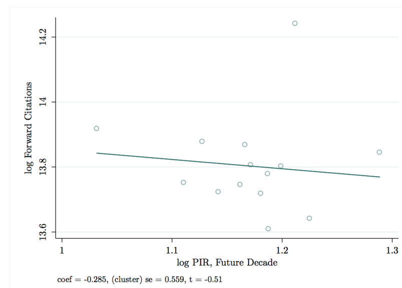
(d) Citations (Annual)



(e) Citations (Decadal)



(f) Citations (Pre-Trend)



Notes: In the first row the outcome is log of patents per mineral and in the second row it is log of citation-weighted patents per mineral. In (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.

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.

5 Foreign Political Risk and US Innovation

In this section, we investigate how exposure to foreign political risk affects the direction of innovation systematically across sectors in the US. Our main result is that foreign political risk exposure leads to a large increase in innovation.

5.1 Empirical Strategy

Our main estimating equation is:

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

where i indexes sectors, defined in our baseline specification as NAICS six-digit industries, t indexes years. α_i and δ_t are sector and year fixed effects respectively, which we include in all specifications and capture any average differences in political risk or innovation across sectors, as well as any aggregate trends over time. 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 over the longer-run to changes in political risk exposure.

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 3.3 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 potential bias from import patterns responding to political risk exposure.

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,

Table 1: Foreign Political Risk and US Innovation

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

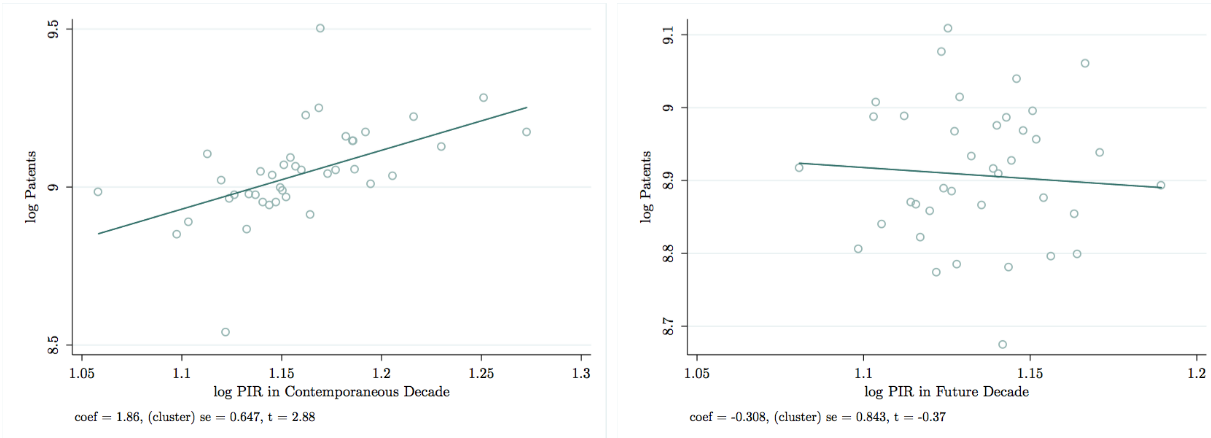
Notes: The unit of observation is a 6-digit NAICS industry by year. In Panel A, we use the imported political risk measure which is weighted by contemporaneous import shares, and control for the log sum of squared import shares (HHI). In Panel B, we use the imported political risk measure which is weighted by pre-period import shares. 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, log number of new patenting firms in column 5, and log patents per firm in column 6. 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 are clustered at the 6-digit NAICS level.

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

The next two 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, a commonly used (albeit imperfect) proxy for the quality of a patent; 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 (see Kogan et al., 2017). In both

Figure 3: Foreign Political Risk and US Innovation: Decennial Estimates and Pre-Trends

(a) PIR in Contemporaneous Decade **(b)** PIR in Future Decade (pre-trend)



Notes: Panel (a) shows the effect of imported political risk in the contemporaneous decade on total patent applications in US. Panel (b) shows the effect of imported political risk in the future decade on total patent applications in 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 imported 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.

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 5-6, we investigate whether the results are driven by the expansion of innovative activity by existing firms versus new firms innovating for the first time. In column 5, the outcome variable is the log of firms entering innovation activity in the sector, and in column 6 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).

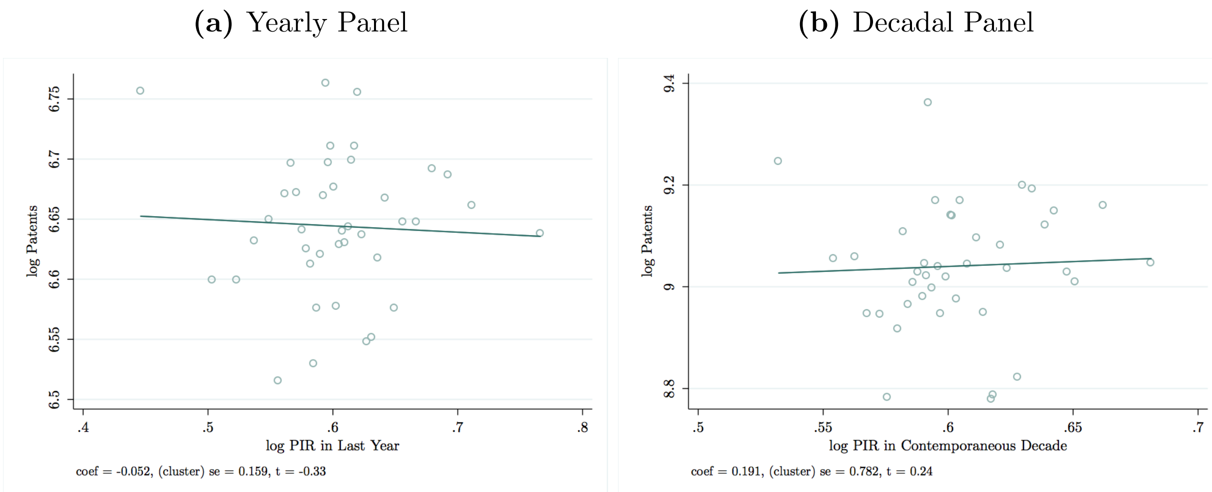
In Figure 3a, we display the results graphically after aggregating over time to the decade level. The graph reports a partial correlation plot of β from a version of Equation 5.1 in which t indexes decades instead of years. We estimate a value for β that is larger than the analogous specification in 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. Separating the effect of aggregate political risk into its components defined by the ICRG, we estimate the largest effect for risk due to government instability, followed by risk due to ethnic tensions, investment expropriation and contract viability, and religious tensions. We find no evidence of an effect of several sub-components, including military in politics, corruption, and democratic accountability. While our model does not make a distinction between different sources of political risk, exploring this heterogeneity with more detailed data could be an interesting avenue for future work.

Finally, Figure 3b is identical to Figure 3a, except we include political risk from the *future* (rather than contemporaneous) decade on the right-hand side of the regression. The best-fit line is completely flat and the corresponding coefficient estimate 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.

Falsification Test. We next present a falsification test designed to verify whether our main result is truly driven by foreign threats to import supply. Since import and export shares are correlated across countries and industries, 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 supriously 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 PIR_{it}^{Export} in which time-varying foreign risk 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 4a) or decadal (Figure 4b) frequencies.

Sensitivity and Robustness. First, and most importantly, we show that we find similar results using R&D investment as a separate measure of technology development. Figure A.7a shows that there is a strong, positive relationship between sector-year patenting (as we measure it) and sector-year R&D investment as measured by 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

Figure 4: 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.

import risk on R&D investment. Figure A.7b reports the estimate from an identical specification to Figure 3a, except the outcome is log of R&D spending instead of log of patenting. The coefficient estimate is positive and statistically significant.

We next probe the sensitivity of our baseline estimates in a range of ways, presented briefly here and in more detail in the Appendix. First, we find very similar results using alternative parametrizations of PIR_{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.5 and A.6). Second, we show that the estimates are also very similar if we control directly for the lag of log imports in the sector (see Appendix Table A.1). These findings indicate that the main results are not driven by changes in total sector-level imports.

5.3 Mechanisms and Heterogeneity

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 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.8, we report the effect of political import risk separately on the (log of the) number of patents assigned to each group. We find a positive effect on both patents assigned to firms and patents assigned to universities (though the latter is smaller in magnitude), and we find no effect on patents assigned to the government.[16] Since the vast majority of patents have firms as their assignees, while we estimate a positive marginal effect for universities nearly all of our main result can be accounted for by patenting by firms (Figure A.8b).

Which Sectors Drive the Results? We next investigate the pattern of results across sectors. First, we simply 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.9. We find positive effects for all sectors with the exception of agriculture, where the point estimate is negative but statistically insignificant. However, we find the largest effects for energy and mining, as well as "heavier" manufacturing industries (those classified in NAICS 2-digit 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). The results are displayed in Figure A.9b. 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 but by incentives faced by private firms across all industries.

Incentives in Technology *vs.* Goods Markets. Our model and discussion so far has focused on the impact of supply risk in the areas where firms innovate. However, foreign political risk can also affect competition in the goods market. In Appendix C.1,

[16] This does not necessarily imply that innovation funded by the government or the that resulted from government policy is unimportant. Not all technologies that benefit from government support are acquired by the government itself. That said, these results rule out a narrower potential mechanism, in which the findings are driven by technologies that will ultimately be used only by the government or some government agency. The finding below that the results are not driven by industries that the US International Trade Administration deems "critical sectors" lends further support to the idea that the findings are not attributable to explicit government priorities or policies (Figure A.9b).

we investigate this possibility by exploiting firm-level data from Compustat and separately estimating the effect of political risk in the NAICS code of the good(s) that the firm sells ("goods space") and the NAICS code implied by the CPC classes in which the firm patents ("technology space"). We estimate a large effect of firm-level political risk in "technology space" and no effect of political risk in "goods space" (Figure A.10). This finding is consistent with our model of innovation based on risks to input supply, and inconsistent with innovation driven by goods market competition or prices.

Cross-Sector Spillovers. So far, we have focused on how political risk in a given sector affects innovation in that sector. However, new technology development need not be concentrated only in the sector that receives the shock. While this is outside the scope of our model, shocks to upstream or downstream sectors could spur innovation—the former because they encourage firms to develop their own inputs and the latter because they increase potential domestic market size for firms' output. 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).

In Appendix C.2, we use the US input-output tables from the Bureau of Economic Analysis (BEA) to directly parameterize each of these potential spillover effect channels. There is some evidence of positive spillovers along each margin, suggesting that our baseline results may underestimate the effect of foreign political risk on innovation. The effect of shocks to downstream sectors seems larger than the effect of shocks to upstream sectors, consistent with an important role for increased domestic demand. 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:

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

where c indexes countries, i indexes sectors, t indexes years, and $\mathrm{PIR}_{cit}^{Global}$ is defined in Equation 3.5. 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).

6.2 Baseline Results

Our baseline estimates of Equation 6.1 are reported in Table 2.[17] Foreign political risk is strongly positively associated with patenting activity (column 1). 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). The results are driven both by the expansion of R&D activity in

[17] 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 where we can extract stock market value are by US firms.

Table 2: Foreign Political Risk and Global Innovation

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

Notes: The unit of observation is a 6-digit NAICS industry in a country in a year. PIR is constructed using pre-period import shares for the weights. The dependent variable is log patents in columns 1, total patents in column 2, log forward citations in column 3, log number of new patenting firms in column 4, and log patents per firm in column 5. 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.

innovating firms, as well as new firms entering R&D (columns 4 and 5).

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.[18]

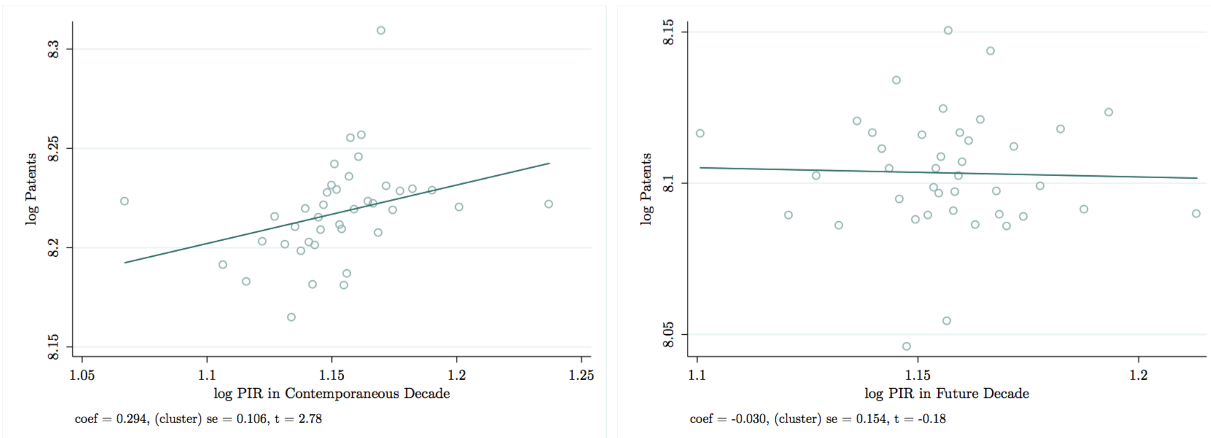
6.3 The Role of Geopolitical Alliances

So far, we have treated political import risk emanating from all foreign countries as equal. However, this may not be the case. Anecdotally, firms and governments seem particularly responsive to political turmoil in geopolitical adversaries. The recent technology

[18] 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 Figure A.11 and A.12), and that results are similar after controlling directly for lags of realized imports (see Appendix Table A.3).

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

(a) PIR in Contemporaneous Decade **(b)** PIR in Future Decade (pre-trend)



Notes: Panel (a) shows the effect of imported political risk in the contemporaneous decade on total patent applications. Panel (b) shows the effect of imported political risk in the future decade on total patent applications. We control for 6-digit NAICS $\times$ country, country $\times$ decade, and 6-digit NAICS $\times$ decade fixed effects. We weight observations by 6-digit NAICS $\times$ country level patent applications during 1990-1999. In all panels, we use the imported 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.

"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, as highlighted by the model. This could be driven by policy interventions to restrict trade either by the home or foreign government, or by greater explicit expropriation risk. Given this, our model predicts that when adverse political shocks arise in a geopolitical adversary, firms have greater innovation incentives 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 constructing separate measures of foreign political risk (Equation 3.5) in which, for each country c, we sum only over foreign allies or non-allies, respectively. We then estimate the following regression model:

$$y_{cit} = \beta^A \log \mathrm{PIR}^{\mathrm{ALLY}}_{ci,t-1} + \beta^E \log \mathrm{PIR}^{\mathrm{NON\text{-}ALLY}}_{ci,t-1} + \alpha_{ci} + \delta_{ct} + \eta_{it} + X'\Gamma + \epsilon_{cit} \tag{6.2}$$

Table 3: 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 PIR$^{\text{ALLY}}$, 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)
log PIR$^{\text{NON-ALLY}}$, 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)
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 × 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 in column 1-3, and a 6-digit NAICS industry in a country in a decade in column 4-6. The data on political ties between countries comes from Correlates of War (CoW) in column 1 and 4, from UN Ideal Point in column 2 and 5, and from the Alliance Treaty Obligations and Provisions Project (ATOP) in column 3 and 6. We use the imported political risk measure which is weighted by pre-period import shares. The dependent variable is log patent applications. We weight observations by 6-digit NAICS × country level patent applications during 1990-1999. Standard errors are clustered at the 6-digit NAICS × country level.

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 enemies, respectively.[19]

Estimates of Equation 6.2 are reported in Table 3. 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 the annual and decadal aggregations, are reported in Figure A.13. 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.

[19]Since the Correlates of War data end in 2012, the decennial specification using CoW data only includes two decades in this part of the analysis: the 1990s and the 2000s.

We also explore whether the results are similar using alternative potential measures of political ties between countries. As a completely independent measure of political connections that is not based on formal alliances, we use data on UN voting behavior to measure the similarity in international political preferences across countries and, for each country, and define their "allies" as those with above-median similarity in UN voting (see Bailey et al., 2017). We also use an alternative measure of strategic alliance signing compiled by the Alliance Treaty Obligations and Provisions Project (ATOP) to identify which countries are aligned with each other. 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 3, columns 2-3, 5-6).

6.4 Endogenous Trade Restrictions: Allies vs. Enemies

One explanation for this pattern, as noted above, is that firms may anticipate that a rise in political turmoil in geopolitical adversaries is more likely to spur further breakdown of trade relations. The model highlights how anticipated changes in policy would amplify firms' incentives to innovate in response to foreign political risk. Trade restrictions could be driven by policy changes made by their own government (e.g., sanctions) or by the foreign government.

To investigate this potential mechanism, 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 the following regression specification:

$$\mathbb{I}(\text{Restrict})_{ckt} = \beta^R \log \text{PR}_{kt} \cdot \text{Enemy}_{ck} + \beta^I \log \text{PR}_{ct} \cdot \text{Enemy}_{ck} + \alpha_{ck} + \delta_{kt} + \eta_{ct} + \epsilon_{ckt} \quad (6.3)$$

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. Enemy_{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 (by our measure) if that country is an enemy. β^I captures whether coun-

Table 4: 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 $\text{PR}_{kt} \cdot \text{Enemy}_{ck}$	0.058		0.050	0.031		0.027
	(0.012)		(0.016)	(0.008)		(0.010)
log $\text{PR}_{ct} \cdot \text{Enemy}_{ck}$		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 whether the imposing country imposes a restricting trade policy on the receiving country in column 1-3, and whether the imposing country imposes a restricting trade policy that affects over 20 products on the receiving country in column 4-6. Standard errors are clustered at country pair level.

tries 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 6.3 are reported in Table 4. 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).[20] 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 enemies compared to allies.

7 Innovation Reshapes the Consequences of Political Risk

This section presents a final set of findings investigating how the technological response to political risk shocks mediates their longer-term consequences by re-shaping patterns of trade. We first show that, consistent with our model, innovation is more responsive to

[20]This follows the Global Trade Alert Handbook, which notes that the number of products covered is a commonly used indicator of trade policy severity; see GTA website.

foreign political risk shocks in markets with a larger existing stock of innovation. Then, we argue that innovation reduces reliance on risky foreign markets, shielding innovation-intensive countries but exacerbating the negative export consequences of political risk shocks for the countries that experience them. Following domestic political risk shocks, countries experience larger and persistent declines in exports to high-innovation markets that were most likely to have "innovated away" their foreign import demand.

7.1 Preliminaries: Heterogeneity by Innovation Intensity

First, we 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 less able to respond to foreign political risk via a ramp-up in technology development. This is consistent with a version of the model in which most firms are laggards and innovation-intensity captures the number of potential innovators, or in which price effects lead classical innovators to innovate more in response to political risk. Empirically, 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 risk.

To investigate this question, we return to estimates of Equation 6.1 but split the sample between country-sector pairs with above-75th percentile versus below-75th percentile patent stocks at the start of the sample period.[21] We find that the results are almost entirely driven by markets that are more innovation-intensive. Table 5 reports the results. We estimate large, positive effects focusing on the markets with a high patent stock at the start of the period, and an insignificant effect for the rest of the sample when (log of) the total patent count is the dependent variable (column 1) that becomes essentially zero when the (log of) the citation-weighted patent count is the dependent variable (column 3). 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 and on-shoring technology, this process does not take place in markets with little innovation to begin with.

7.2 Political Risk Shocks, Innovation, and Patterns of Trade

Next, we investigate how endogenous technological change mediates the relationship between political risk shocks and patterns of trade across countries. If innovation endogenously reduces import reliance on risky countries, then it may exacerbate the impact of

[21] We construct the patent stock as the discounted sum of previous patent applications, with an annual depreciation rate of 5%.

Table 5: 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 PIR, 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. We use the imported political risk measure which is weighted by pre-period import shares. The dependent variable is log patent applications in column 1-2, and log forward citations in 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 patents is inside the lowest three quartiles. In column 2 and 4, the sample is restricted in country-industry pairs whose pre-period patents is inside the highest quartile. Standard errors are clustered at the sector × country level.

political risk shocks on trade. Although heightened political risk in a country A (e.g., greater internal conflict risk, expropriation risk, etc.) is likely associated with worse economic outcomes, the technological response of other countries may exacerbate the damage to A by eroding its initial comparative advantage. If A initially exports in sector X but then experiences an episode of political risk, other countries will innovate in X (as we have shown), increase their own productivity in X, and potentially reduce their reliance on A. Even if A fully emerges from its political risk episode, it will export less in X than in a world where innovation in the rest of the world 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.

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 7.1 (Table 5) 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 response of trade flows to political risk should scale with the elasticity of innovation to political risk. 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 actually responds and erodes their initial comparative advantage away.

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

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

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:

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

where the $\text{Exports}_{i,c\rightarrow k,t_0}$ is the total value of exports from country c and sector i to country k in a fixed cross-section before 2000.[22] 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 above. 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 $\beta < 0$. 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 characteristics 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.

[22] 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.14.

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

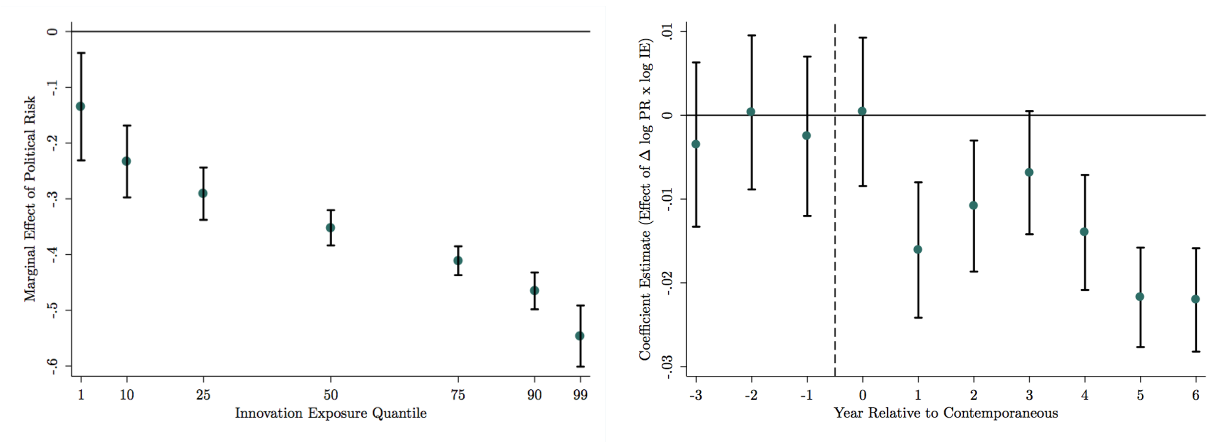
Notes: The unit of observation is a 6-digit NAICS industry by year by exporter. The dependent variable is log exports. In column 1 and 3, we use pre-period patent stock to calculate innovation exposure. In column 2 and 4, we use pre-period citation-weighted patent stock to calculate innovation exposure. Standard errors are clustered at 6-digit NAICS × exporter level.

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 to calculate innovation exposure respectively. We find strong evidence that $\beta < 0$. A given increase in political risk leads to a 32% greater decline in exports for a sector with top-quartile innovation exposure compared to a sector with bottom-quartile 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. β remains negative and significant ($p < 0.01$). Thus, exports from risky markets decline substantially more to innovative-intensive countries, potentially driven by the fact that endogenous technological change facilitates production on-shoring. This exacerbates the negative effect of domestic political turmoil on exports.

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 innovation exposure. Intuitively, we find a negative direct effect of political risk, along with the negative amplifying effect of innovation exposure. Figure 6a displays the results graphically, plotting the implied marginal effect of political risk for several quantiles of innovation exposure. The variation driven by heterogeneity in innovation exposure is slightly larger than the direct marginal effect of political risk at median innovation exposure. Thus, innovation plays a major role

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

(a) Effect of PR by Exposure Quantile **(b)** Lead and Lagged Effects (ΔPR $\cdot$ IE)



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 effefct of $\Delta PR \cdot IE$. Standard errors are clustered at 6-digit NAICS $\times$ country level and 95% confidence intervals are reported.

in re-shaping 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 6b plots several leading and lagged values of the interaction $\Delta \log \text{PR}_{ct} \cdot \log \text{IE}_{ci}$. Importantly, we find no evidence of pre-existing trends: all leads are close to zero and statistically significant. Instead, in the years following a political risk 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 technology development 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 the sector or 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 6b 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.4 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 β remain negative after including these broad sets of controls.[23] Thus, the findings do not seem driven by an observable 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 of varying innovation intensity. That is, we estimate:

$$\log \text{Exports}_{ckit} = \beta \log \text{PR}_{ct} \cdot \log \text{IE}_{cki} + \alpha_{cki} + \delta_{ckt} + \gamma_{kit} + \eta_{cit} + \epsilon_{ckit} \tag{7.2}$$

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

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

intensity at the *sector-origin-destination* level.[24] This specification includes all *three-way* fixed effects, including sector-origin-year fixed effects, fully absorbing market-specific trends that might have biased the baseline estimates. This specification also includes sector-destination-year fixed effects, fully absorbing all characteristics of destination markets (including innovation intensity). Instead, here we only exploit whether, following a political risk shock, exports from a particular country-sector pair decline disproportionately to markets that are relatively more innovation-intensive compared to markets that are relatively less innovation-intensive.

Estimates from this specification are reported in Table A.5. We find that $\beta < 0$, again consistent with foreign directed innovation exacerbating the negative effect of political risk on exports and re-shaping 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.5).

8 Conclusion

Policy makers and private sector leaders have warned that rising political tensions and overseas political risk could harm access to critical economic inputs. We study how innovation responds to these political risks, potentially re-shaping their economic consequences. We formalize how anticipated 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. 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 towards markets where innovation is more responsive to foreign political risk, 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 and shapes its consequences by mitigating domestic exposure to foreign risks. The opposite side of the same coin, however, is that directed technological change further weakens the export performance of countries undergoing political turmoil,

[24] Specifically, we calculate $\text{IE}_{cki} = \text{ExportShare}_{i,c\to k,t_0} \cdot \text{InnovationStock}_{ikt_0}$.

exacerbating and extending its negative economic consequences.

These findings are potentially relevant for a nascent literature in geoeconomics studying the optimal policy to harm a foreign adversary (see e.g., Clayton et al., 2024; Becko and O'Connor, 2024). Our analysis establishes that private economic actors themselves act to alleviate foreign political risk and weaken import dependence on risky countries, especially if they are adversaries. Even the specter of government intervention can effectively reduce reliance on foreign imports: the mere risk of a loss of access in the future through policy restrictions may spur a private sector innovative response that reduces the need for such intervention *ex post*. This raises interesting questions regarding the complementarity between government intervention and private sector responses and brings with it potentially important time-inconsistency issues. Integration of the role of private innovation and its interaction with government policy into the theoretical analysis of geopolitics would be an interesting avenue for future research.

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A Omitted Proofs and Model Extensions

A.1 Proof of Proposition 1

To avoid repetition, we derive this result in the setting of the extended model with nested CES developed in Appendix A.4. Our baseline model corresponds to $\epsilon = \eta$. 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), firms' 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:

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

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

$$\bar{\Pi}^N(A_0^i) = \Pi^N(A_0^i, A_0^i) = \bar{\Pi}\mathbb{E}\left[P(s)^{\eta-\epsilon}\mathcal{M}_F(s)^{1-\eta}\right] \tag{A.2}$$

which is constant as a function of A_0^i.

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

$$\Pi^S(A_1^i, A_0^i) = \bar{\Pi}\left[pP(\tau)^{\eta-\epsilon}\left(A_1^i\right)^{\eta-1} + (1-p)P(0)^{\eta-\epsilon}A_F^{\eta-1}\right] - \kappa\left[\left(\frac{A_1^i}{A_0^i}\right)^{\delta} - 1\right] \tag{A.3}$$

The first order condition for optimal investment sets:

$$(\eta-1)\bar{\Pi}\left[pP(\tau)^{\eta-\epsilon}\right]\left(A_1^i\right)^{\eta-2} = \kappa\delta\left(A_1^i\right)^{\delta-1}\left(A_0^i\right)^{-\delta} \tag{A.4}$$

which gives us that optimal investment is given by:

$$A_1^i = \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon}\right]\left(A_0^i\right)^{\delta}\right)^{\frac{1}{1+\delta-\eta}} \tag{A.5}$$

We moreover have that $A_1^i > A_0^i$ if and only if $A_0^i > \hat{A}^S = \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon}\right]\right)^{\frac{-1}{\eta-1}}$. All Case (S) firms with $A_i^0 \leq \hat{A}^S$ do not innovate. All Case (S) firms with $A_i^0 > \hat{A}^S$ innovate. That is:

$$A_1^i = A^S(A_0^i) = \begin{cases} A_0^i & , A_0^i \leq \hat{A}^S, \\ \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon}\right]\left(A_0^i\right)^{\delta}\right)^{\frac{1}{1+\delta-\eta}} & , A_0^i > \hat{A}^S. \end{cases} \tag{A.6}$$

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:

$$\Pi^A(A_1^i, A_0^i) = \bar{\Pi}\left[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}\right]\left(A_1^i\right)^{\eta-1} - \kappa\left[\left(\frac{A_1^i}{A_0^i}\right)^{\delta} - 1\right] \tag{A.7}$$

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

$$A_1^i = \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}\right]\left(A_0^i\right)^{\delta}\right)^{\frac{1}{1+\delta-\eta}} \tag{A.8}$$

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

$$A_1^i = A^A(A_0^i) = \begin{cases} A_0^i & , A_0^i \leq \hat{A}^A, \\ \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}\right]\left(A_0^i\right)^{\delta}\right)^{\frac{1}{1+\delta-\eta}} & , A_0^i > \hat{A}^A. \end{cases} \tag{A.9}$$

which is a continuous and strictly increasing function.

Step II: Properties of Profits. We now determine various properties of the profits from investing optimally from 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:

$$\bar{\Pi}^S(A_0^i) = \max_{A_1^i \geq A_0^i} \Pi^S(A_1^i, A_0^i) \tag{A.10}$$

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 $\bar{\Pi}^S(A_0^i) = \Pi^S(A_0^i, A_0^i) = \bar{\Pi}\left[pP(\tau)^{\eta-\epsilon}\left(A_0^i\right)^{\eta-1} + (1-p)P(0)^{\eta-\epsilon}A_F^{\eta-1}\right]$, 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:

$$\begin{aligned}
\bar{\Pi}^{S\prime}(A_0^i) &= \Pi_1^S(A^S(A_0^i), A_0^i)A^{S\prime}(A_0^i) + \Pi_0^S(A^S(A_0^i), A_0^i) = \Pi_0^S(A^S(A_0^i), A_0^i) \\
&= \kappa\delta A^S(A_0^i)^\delta \left(A_0^i\right)^{-\delta-1} = \kappa\delta\left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon}\right]\left(A_0^i\right)^\delta\right)^{\frac{\delta}{1+\delta-\eta}}\left(A_0^i\right)^{-\delta-1} \\
&= \kappa\delta\left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon}\right]\right)^{\frac{\delta}{1+\delta-\eta}}\left(A_0^i\right)^{\frac{(\eta-1)\delta}{1+\delta-\eta}-1}
\end{aligned} \tag{A.11}$$

which is both strictly positive and strictly increasing. Thus, 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 $\eta \geq 1 + \frac{\delta}{1+\delta}$, which is implied by our assumption that $\eta > 2$.

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

$$\bar{\Pi}^A(A_0^i) = \max_{A_1^i \geq A_0^i} \Pi^A(A_1^i, A_0^i) \tag{A.12}$$

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 $\bar{\Pi}^A(A_0^i) = \bar{\Pi}\left[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}\right]\left(A_0^i\right)^{\eta-1}$, 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:

$$
\begin{aligned}
\bar{\Pi}^{A\prime}(A_0^i) &= \Pi_1^A(A^A(A_0^i), A_0^i)A^{A\prime}(A_0^i) + \Pi_0^A(A^A(A_0^i), A_0^i) = \Pi_0^A(A^A(A_0^i), A_0^i) \\
&= \kappa\delta A^A(A_0^i)^\delta \left(A_0^i\right)^{-\delta-1} \\
&= \kappa\delta \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}\right]\left(A_0^i\right)^\delta\right)^{\frac{\delta}{1+\delta-\eta}} \left(A_0^i\right)^{-\delta-1} \\
&= \kappa\delta \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}\right]\right)^{\frac{\delta}{1+\delta-\eta}} \left(A_0^i\right)^{\frac{(\eta-1)\delta}{1+\delta-\eta}-1}
\end{aligned}
\tag{A.13}
$$

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

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

$$
\begin{aligned}
\Pi^*(A_0^i) = \max_{A_1^i \geq A_0^i} \bar{\Pi} &\Bigg[pP(\tau)^{\eta-\epsilon}\left(\max\{A_1^i, (1-\tau)A_F\}\right)^{\eta-1} \\
&+ (1-p)P(0)^{\eta-\epsilon}\left(\max\{A_1^i, A_F\}\right)^{\eta-1}\Bigg] \\
&- \kappa\left[\left(\frac{A_1^i}{A_0^i}\right)^\delta - 1\right] \\
= \max\{&\bar{\Pi}^N, \bar{\Pi}^S(A_i^0), \bar{\Pi}^A(A_i^0)\}
\end{aligned}
\tag{A.14}
$$

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 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 $\underline{A} > 0$:

$$\underline{A} = \bar{\Pi}^{S^{-1}}\left(\bar{\Pi}^N\right) \tag{A.15}$$

Moreover, we have also established that $\underline{A} \leq A^{S^{-1}}((1-\tau)A_F)$, 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 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:

$$\tilde{A} = \bar{\Pi}^{A^{-1}}\left(\bar{\Pi}^N\right) \tag{A.16}$$

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

$$\bar{\Pi}^A(A_0^i) = \Pi^A(A^A(A_0^i), A_0^i) > \Pi^A(A^S(A_0^i), A_0^i) > \Pi^S(A^S(A_0^i), A_0^i) = \bar{\Pi}^S(A_0^i) \tag{A.17}$$

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:

$$\begin{aligned} \bar{\Pi}^A(A_0^i) &= \bar{\Pi}^A(\overline{A}) + \int_{\overline{A}}^{A_0^i} \bar{\Pi}^{A\prime}(z)\,\mathrm{d}z \\ \bar{\Pi}^S(A_0^i) &= \bar{\Pi}^S(\overline{A}) + \int_{\overline{A}}^{A_0^i} \bar{\Pi}^{S\prime}(z)\,\mathrm{d}z \end{aligned} \tag{A.18}$$

which implies that:

$$\bar{\Pi}^A(A_0^i) - \bar{\Pi}^S(A_0^i) = \int_{\overline{A}}^{A_0^i} \left(\bar{\Pi}^{A\prime}(z) - \bar{\Pi}^{S\prime}(z)\right) \mathrm{d}z \tag{A.19}$$

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

$$\begin{aligned} \bar{\Pi}^{A\prime}(A_i^0) &= \kappa\delta \left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}\right]\right)^{\frac{\delta}{1+\delta-\eta}} \left(A_0^i\right)^{\frac{(\eta-1)\delta}{1+\delta-\eta}-1} \\ \bar{\Pi}^{S\prime}(A_i^0) &= \bar{\Pi}(\eta-1)\left[pP(\tau)^{\eta-\epsilon}\right]\left(A_1^i\right)^{\eta-2} \end{aligned} \tag{A.20}$$

and we define:

$$\begin{aligned}
C^A &= \kappa\delta\left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon}+(1-p)P(0)^{\eta-\epsilon}\right]\right)^{\frac{\delta}{1+\delta-\eta}} \\
\tilde{C}^S &= \bar{\Pi}(\eta-1)\left[pP(\tau)^{\eta-\epsilon}\right] \\
\Gamma &= \frac{(\eta-1)\delta}{1+\delta-\eta}-1
\end{aligned} \tag{A.21}$$

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

$$C^A\check{A}^{\Gamma}=\tilde{C}^S\check{A}^{\eta-2} \implies \check{A}=\left(\frac{\tilde{C}^S}{C^A}\right)^{\frac{1}{\Gamma-(\eta-2)}} \tag{A.22}$$

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

$$\begin{aligned}
\bar{\Pi}^{A''}(\check{A})-\bar{\Pi}^{S''}(\check{A}) &= \Gamma C^A\check{A}^{\Gamma-1}-(\eta-2)\tilde{C}^S\check{A}^{(\eta-2)-1} \\
&= \Gamma C^A\left(\frac{\tilde{C}^S}{C^A}\right)^{\frac{\Gamma-1}{\Gamma-(\eta-2)}}-(\eta-2)\tilde{C}^S\left(\frac{\tilde{C}^S}{C^A}\right)^{\frac{(\eta-2)-1}{\Gamma-(\eta-2)}} \\
&= \Gamma {C^A}^{1-\frac{\Gamma-1}{\Gamma-(\eta-2)}}{\tilde{C}^S}{}^{\frac{\Gamma-1}{\Gamma-(\eta-2)}}-(\eta-2){C^A}^{-\frac{(\eta-2)-1}{\Gamma-(\eta-2)}}{\tilde{C}^S}{}^{1+\frac{(\eta-2)-1}{\Gamma-(\eta-2)}} \\
&= \Gamma {C^A}^{-\frac{(\eta-2)-1}{\Gamma-(\eta-2)}}{\tilde{C}^S}{}^{\frac{\Gamma-1}{\Gamma-(\eta-2)}}-(\eta-2){C^A}^{-\frac{(\eta-2)-1}{\Gamma-(\eta-2)}}{\tilde{C}^S}{}^{\frac{\Gamma-1}{\Gamma-(\eta-2)}} \\
&= (\Gamma-(\eta-2)){C^A}^{-\frac{(\eta-2)-1}{\Gamma-(\eta-2)}}{\tilde{C}^S}{}^{\frac{\Gamma-1}{\Gamma-(\eta-2)}}
\end{aligned} \tag{A.23}$$

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

$$\begin{aligned}
\Gamma-(\eta-2) &= \frac{(\eta-1)\delta}{1+\delta-\eta}-1-(\eta-2)=\frac{(\eta-1)\delta}{1+\delta-\eta}-\eta+1 \\
&= \frac{\eta\delta-\delta-\eta-\eta\delta+\eta^2+1+\delta-\eta}{1+\delta-\eta}=\frac{\eta^2+1-2\eta}{1+\delta-\eta}
\end{aligned} \tag{A.24}$$

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:

$$\bar{\Pi}^A(A_0^i) - \bar{\Pi}^S(A_0^i) = \int_{\overline{A}}^{A_0^i} \left(\bar{\Pi}^{A\prime}(z) - \bar{\Pi}^{S\prime}(z)\right) \mathrm{d}z \tag{A.25}$$

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

$$\begin{aligned} \bar{\Pi}^{A\prime}(A_i^0) &= \kappa\delta\left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon} + (1-p)P(0)^{\eta-\epsilon}\right]\right)^{\frac{\delta}{1+\delta-\eta}} \left(A_0^i\right)^{\frac{(\eta-1)\delta}{1+\delta-\eta}-1} \\ \bar{\Pi}^{S\prime}(A_i^0) &= \kappa\delta\left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon}\right]\right)^{\frac{\delta}{1+\delta-\eta}} \left(A_0^i\right)^{\frac{(\eta-1)\delta}{1+\delta-\eta}-1} \end{aligned} \tag{A.26}$$

We now let:

$$C^S = \kappa\delta\left((\eta-1)\bar{\Pi}\frac{1}{\kappa\delta}\left[pP(\tau)^{\eta-\epsilon}\right]\right)^{\frac{\delta}{1+\delta-\eta}} \tag{A.27}$$

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

$$\bar{\Pi}^A(A_0^i) - \bar{\Pi}^S(A_0^i) = (C^A - C^S)\int_{\overline{A}}^{A_0^i} z^{\Gamma}\,\mathrm{d}z \tag{A.28}$$

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 1 is straightforward. □

A.2 Proof of Corollary 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:

$$\begin{aligned}
\frac{\partial}{\partial p}\bar{\Pi}^N(A_0^i) &= \bar{\Pi}\left[P(\tau)^{\eta-\epsilon}((1-\tau)A_F)^{\eta-1} - P(0)^{\eta-\epsilon}A_F^{\eta-1}\right] \\
\frac{\partial}{\partial p}\bar{\Pi}^S(A_0^i) &= \bar{\Pi}\left[P(\tau)^{\eta-\epsilon}(A_1^i)^{\eta-1} - P(0)^{\eta-\epsilon}A_F^{\eta-1}\right] \\
\frac{\partial}{\partial p}\bar{\Pi}^A(A_0^i) &= \bar{\Pi}\left[P(\tau)^{\eta-\epsilon}(A_1^i)^{\eta-1} - P(0)^{\eta-\epsilon}(A_1^i)^{\eta-1}\right]
\end{aligned} \tag{A.29}$$

Thus, we have that $\frac{\partial}{\partial p}\bar{\Pi}^S(A_0^i) - \frac{\partial}{\partial p}\bar{\Pi}^N(A_0^i) = \bar{\Pi}P(\tau)^{\eta-\epsilon}\left[(A_1^i)^{\eta-1} - ((1-\tau)A_F)^{\eta-1}\right]$. 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 $\frac{\partial}{\partial p}\bar{\Pi}^A(A_0^i) - \frac{\partial}{\partial p}\bar{\Pi}^S(A_0^i) = \bar{\Pi}P(0)^{\eta-\epsilon}\left[A_F^{\eta-1} - (A_1^i)^{\eta-1}\right]$. 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.3 Proof of Corollary 2

Proof. From Equation 2.6, we have that $Y_{k,t}^i = Y_t P_t^\eta (P_{k,t}^i)^{-\eta}$. Moreover, when a firm imports from Foreign, we have that $X_{k,F,t}^i = Y_t P_t^\eta (P_{k,t}^i)^{-\eta}$. 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 $\mathcal{M}_{k,t}^i = P_{k,t}(s) = \frac{1}{(1-\tau(s))A_F}$. Thus, both the quantity and value of imports in state s for a firm that imports from foreign are given by, respectively:

$$\begin{aligned}
X_t(s) \equiv X_{k,F,t}^i &= Y_t P_t^\eta \left(\frac{\eta}{\eta-1}\right)^\eta ((1-\tau(s))A_F)^\eta \\
X_t^V(s) \equiv P_{k,F,t}X_{k,F,t}^i &= Y_t P_t^\eta \left(\frac{\eta}{\eta-1}\right)^\eta ((1-\tau(s))A_F)^{\eta-1}
\end{aligned} \tag{A.30}$$

From Proposition 1, 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:

$$\begin{aligned} \mathrm{QI}_t(\tau) &= X_t(\tau)\alpha_{L,t}, \quad \mathrm{QI}_t(0) = X_t(0)(\alpha_{L,t} + \alpha_{I,t}) \\ \mathrm{VI}_t(\tau) &= X_t^V(\tau)\alpha_{L,t}, \quad \mathrm{VI}_t(0) = X_t^V(0)(\alpha_{L,t} + \alpha_{I,t}) \end{aligned} \tag{A.31}$$

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:

$$(X_t(\tau)', X_t(0)', X_t^V(\tau)', X_t^V(0)') \leq (X_t(\tau), X_t(0), X_t^V(\tau), X_t^V(0)) \tag{A.32}$$

Moreover, by Corollary 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:

$$(\mathrm{QI}_t(\tau)', \mathrm{QI}_t(0)', \mathrm{VI}_t(\tau)', \mathrm{VI}_t(0)') \leq (\mathrm{QI}_t(\tau), \mathrm{QI}_t(0), \mathrm{VI}_t(\tau), \mathrm{VI}_t(0)) \tag{A.33}$$

which completes the proof. □

A.4 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 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.

$$Y_k = \left(\int_{[0,1]} Y_k^{i\,\frac{\eta-1}{\eta}} \, \mathrm{d}i \right)^{\frac{\eta}{\eta-1}} \tag{A.34}$$

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

$$Y = \left(\int_{[0,1]} Y_k^{\frac{\epsilon-1}{\epsilon}} \, \mathrm{d}k \right)^{\frac{\epsilon}{\epsilon-1}} \tag{A.35}$$

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:

$$Y_{k,t} = Y_t \left(\frac{P_{k,t}}{P_t} \right)^{-\epsilon}, \quad Y_{k,t}^i = Y_{k,t} \left(\frac{P_{k,t}^i}{P_{k,t}} \right)^{-\eta} \tag{A.36}$$

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

$$P_{k,F,t} = \frac{1}{(1-\tau_{k,t})A_{k,F}}, \quad P_{k,t} = \left(\int_{[0,1]} {P_{k,t}^i}^{1-\eta} \, \mathrm{d}i \right)^{\frac{1}{1-\eta}}, \quad P_t = \left(\int_{[0,1]} P_{k,t}^{1-\epsilon} \, \mathrm{d}k \right)^{\frac{1}{1-\epsilon}} \tag{A.37}$$

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:

$$\mathcal{M}_{k,F,t}^i = P_{k,F,t}, \quad \mathcal{M}_{k,D,t}^i = \frac{1}{A_{k,t}^i} \tag{A.38}$$

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:

$$\mathcal{M}_{k,t}^i = \min\{\mathcal{M}_{k,F,t}^i, \mathcal{M}_{k,D,t}^i\} \tag{A.39}$$

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 $Y^i_{k,t}$:

$$P^i_{k,t} = \frac{\eta}{\eta - 1}\mathcal{M}^i_{k,t}, \quad Y^i_{k,t} = \left(\frac{\eta - 1}{\eta}\right)^{\eta} Y_{k,t} P^{\eta}_{k,t} \left(\mathcal{M}^i{}_{k,t}\right)^{-\eta} \tag{A.40}$$

Thus, the firms' profits are given by:

$$\Pi_{k,t}\left(\mathcal{M}^i_{k,t}\right) = \frac{1}{\eta - 1}\left(\frac{\eta - 1}{\eta}\right)^{\eta} Y_t P^{\eta-\epsilon}_{k,t} \left(\mathcal{M}^i_{k,t}\right)^{1-\eta} \tag{A.41}$$

Finally, each firm's innovation decision must solve:

$$\max_{A^i_{k,1} \geq A^i_{k,0}} \mathbb{E}\left[\Pi_{k,t}\left(\mathcal{M}^i_{k,t}\right)\right] - C\left(A^i_{k,1}, A^i_{k,0}\right) \tag{A.42}$$

An equilibrium can then be formally defined as follows:

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

$$\left\{Y_t, \{Y_{k,t}, P_{k,t}, P_{k,F,t}\}_{k\in[0,1]}, \left\{Y^i_{k,t}, P^i_{k,t}, A^i_{k,1}, \mathcal{M}^i_{k,t}, \mathcal{M}^i_{k,F,t}, \mathcal{M}^i_{k,D,t}\right\}_{i\in[0,1]}\right\}_{t\in\{0,1\}} \tag{A.43}$$

such that Equations 2.6-A.42 hold.

Proposition 1 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 $\eta = \epsilon$).

A.5 Numerical simulations 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 a calibrated version of the extended model described above. We simulate the period-0 distribution of firm productivity from an 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 B.1 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 B.2 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 1, moving from a small to a large political shock leads to a change from pattern 1 to pattern 2 of innovation type segmentation.

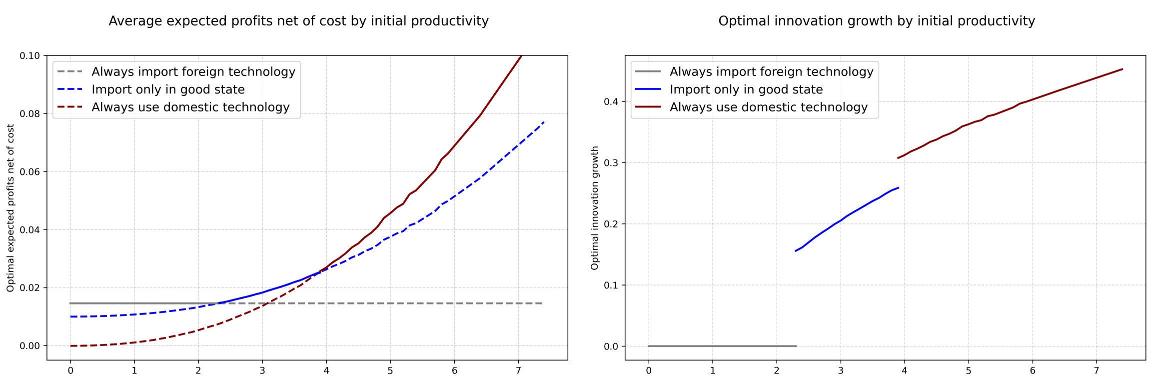
By contrast, Figure B.3 evidences that the effects of an increase in p, the *probability* of the political shock, are distinct. In particular, while the segmentation into innovation types is the same (pattern 2), moving from a small to a higher probability of a political shock occurring abroad increases 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 B.4 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 proposition 1 and corollary 2.

Table B.1: Calibration summary (baseline)

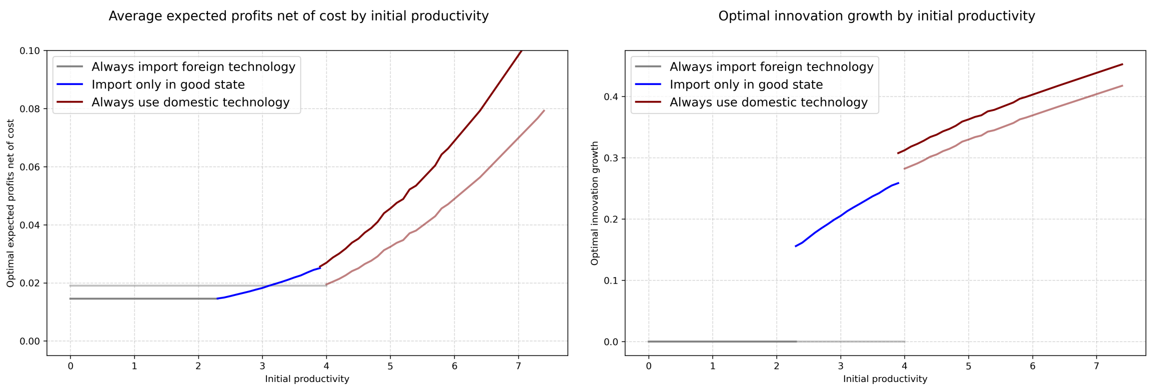
Symbol	Parameter	Value
ε	elasticity of substitution across sectors	2
η	elasticity of substitution across firms	3
κ	scale of innovation cost	10^{-4}
δ	shape of innovation cost	14
τ	foreign political shock	0.5
p	probability of foreign political shock	0.5
A_F	foreign productivity	5
w	domestic wage	1
w_F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

Figure B.1: Firm decisions along the initial productivity distribution (baseline)



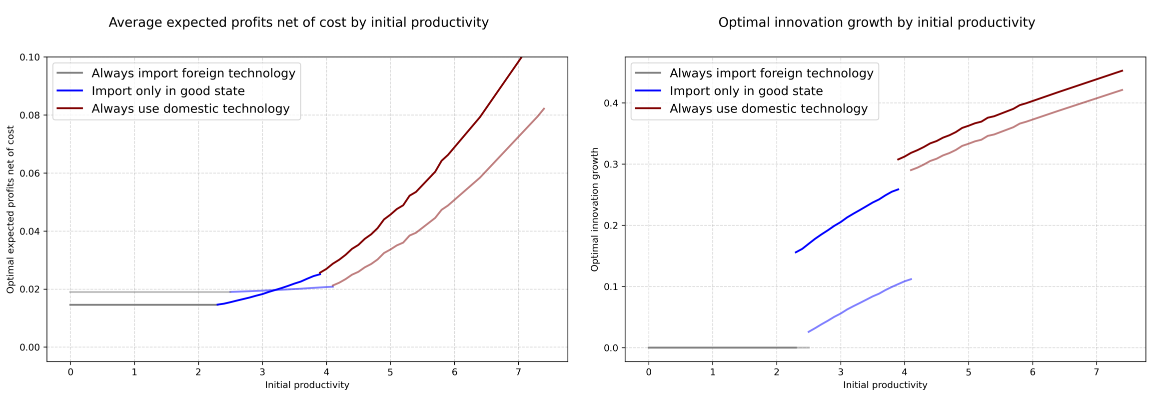
Note: The left panel plots the shadow expected profits net of costs at different bins of endowed period-0 productivity. The solid segments represent the optimal expected profits (net of costs) in equilibrium. Each bin represents $\frac{1}{10}$. The right panel plots the average step-up in firm productivity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

Figure B.2: Effects of an increase in τ



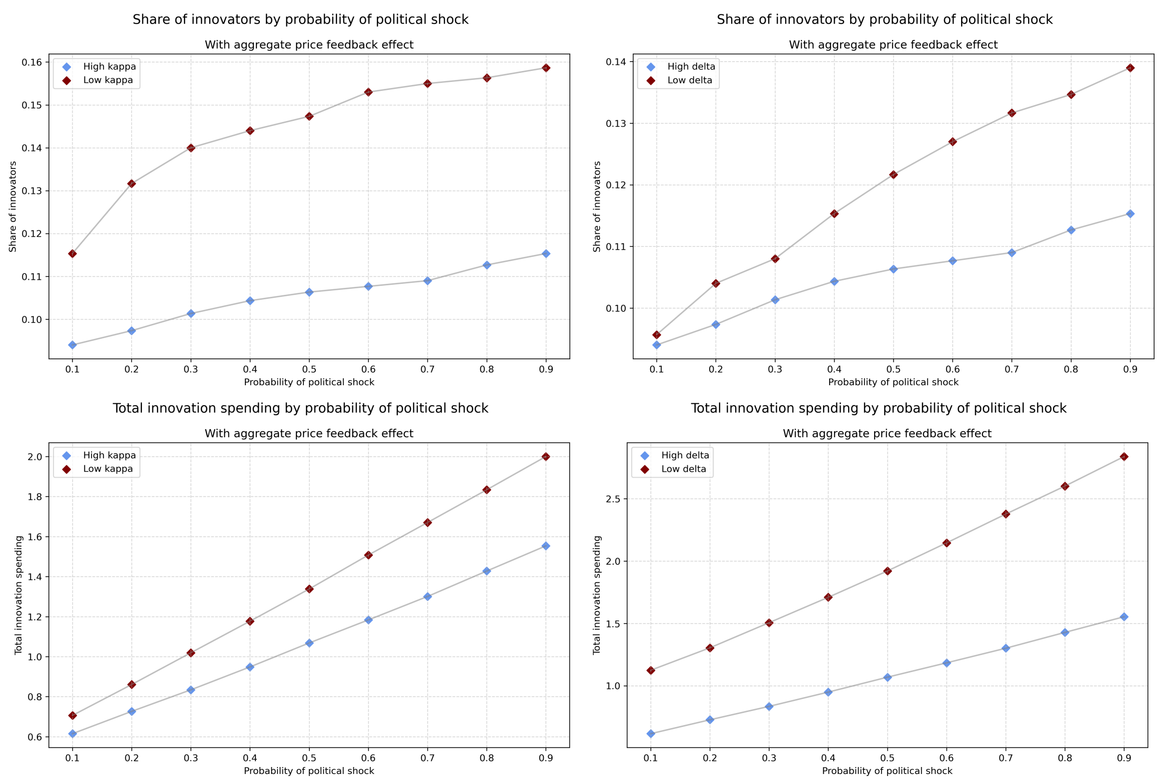
Note: The left panel plots the shadow expected profits net of costs at different bins of endowed period-0 productivity. The darker lines correspond to the larger political shock τ ($\tau = 0.5$), compared to a small political shock ($\tau = 0.10$ -lighter lines). Each bin represents $\frac{1}{10}$. The 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 B.3: 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 B.4: 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.

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.[25] Using these shares, we calculate the political risk for each mineral by computing the weighted average of the political risks of the countries involved:

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

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:

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

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

[25] 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.

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 et al. (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 et al. (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:

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

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 7.2, 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_{ic} 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.4. 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. Goods Markets

To separately esitmate the effect of political risk in "technology space" vs. "goods space," we return to the firm-level data from Compustat. 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 et al. (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:

$$y_{jit} = \gamma \log \text{PIR}_{jit}^{\text{TECH}} + \phi \log \text{PIR}_{jit}^{\text{GOODS}} + \alpha_i + \delta_t + \epsilon_{jit} \tag{C.1}$$

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 goods space on firm level patenting.

Estimates of Equation C.1 are reported in Figure A.10. 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 main analysis focuses on how political risk in a given sector affects innovation in that sector. However, there could be potentially important cross-sector spillover effects. In this section, we ask whether political risk shocks affect innovation in upstream, downstream, or substitute sectors. While this is outside the scope of our model, shocks to upstream or downstream sectors could spur innovation—the former because they may encourage firms to develop their own inputs and the latter because they could increase potential domestic market size for firms' output. Shocks to "substitute" sectors in the supply chain may also encourage innovation.

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, downstream, and substitute sectors in the following way:

$$
\begin{aligned}
\text{PIR}_{it}^{\text{UP}} &= \sum_k \text{PoliticalRisk}_{kt} \cdot (\sum_{u \neq i} \text{ImportShare}_{k \to c, ut_0} \cdot \frac{\text{Input}_{u \to i}}{\text{Output}_i})^2 \\
\text{PIR}_{it}^{\text{DOWN}} &= \sum_k \text{PoliticalRisk}_{kt} \cdot (\sum_{d \neq i} \text{ImportShare}_{k \to c, dt_0} \cdot \frac{\text{Input}_{i \to d}}{\text{Output}_i})^2 \qquad \text{(C.2)} \\
\text{PIR}_{it}^{\text{SUB}} &= \sum_k \text{PoliticalRisk}_{kt} \cdot (\sum_{s \neq i} \text{ImportShare}_{k \to c, st_0} \cdot \text{Similarity}_{si})^2
\end{aligned}
$$

where the import share is the share of an upstream sector u, downstream sector d, 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 build on Equation 3.4 by weighting the import share of each upstream sector u by i's input share ($\frac{\text{Input}_{u \to i}}{\text{Output}_i}$) from it. Similarly, to measure political risk in downstream sectors for sector i, we weight the import share of each downstream sector d by sector i's output share ($\frac{\text{Input}_{i \to d}}{\text{Output}_i}$) to 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:

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

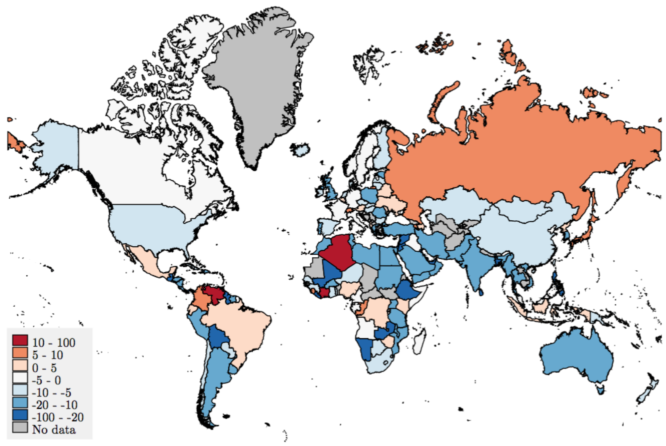
There are a variety of reasons to be skeptical of these measures. First, input-output tables are imprecise measures of true supply chain linkages across sectors. Second, at our level of aggregation, the input-output matrix remains strongly diagonal, suggesting many of these mechanisms are already captured 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.2. Our findings suggest that, if anything, there is some evidence of positive spillovers across sectors. The effect of shocks to downstream sectors seems larger than the effect of shocks to upstream sectors, consistent with an important role for increased domestic output demand.

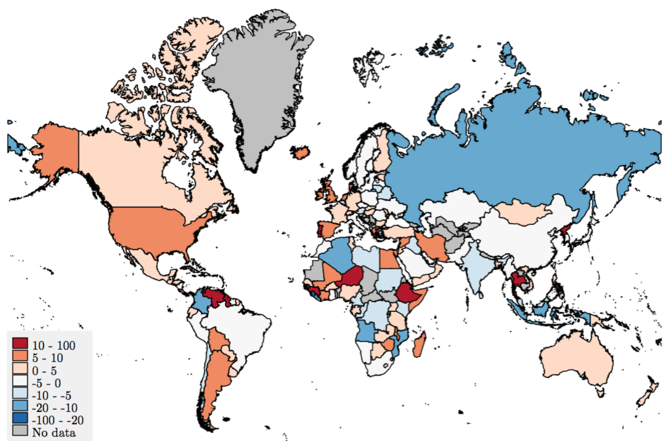
D Omitted Tables and Figures

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

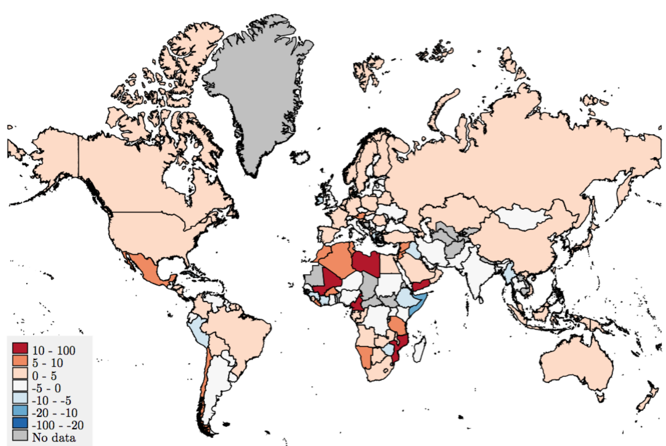
(a) 1990-2000



(b) 2000-2010



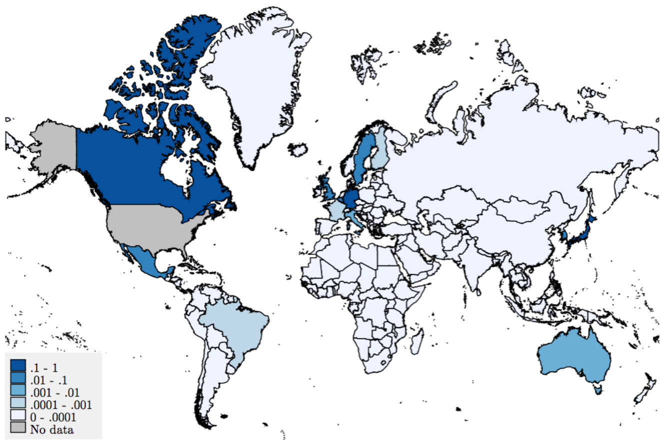
(c) 2010-2020



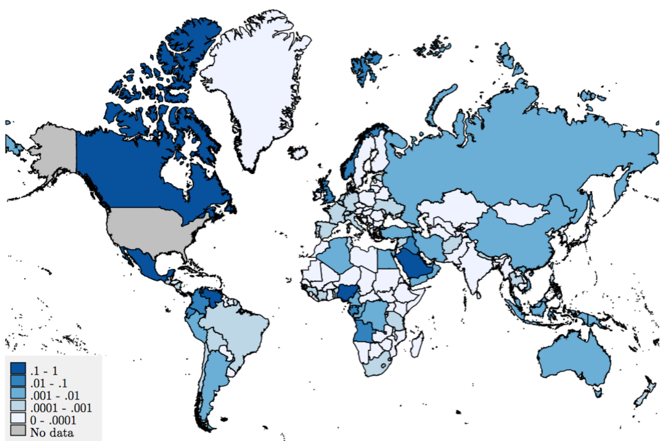
Notes: This figure shows the global change of political risk during 1990-2000, 2000-2010, and 2010-2020. The color schemes are the same across three subfigures.

Figure A.2: Pre-period US Import Shares in Automobiles, Oil and Gas, and Semiconductor

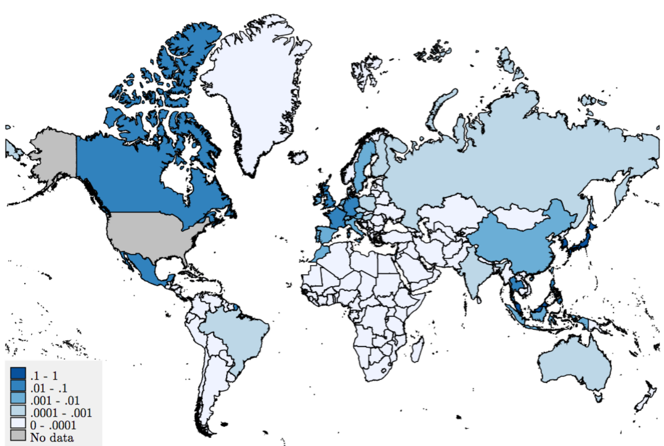
(a) Automobile



(b) Oil and Gas



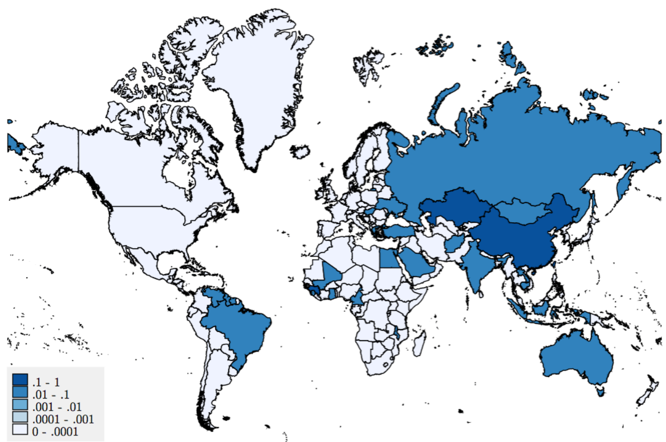
(c) Semiconductor



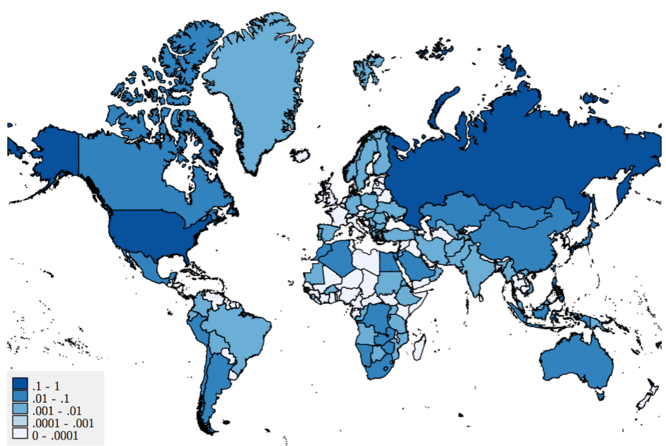
Notes: This figure shows US import shares from every country in three industries: automobile, oil and gas extraction, and semiconductor. The color schemes are the same across three subfigures.

Figure A.3: Deposit Shares in Aluminum, Copper, and Zinc

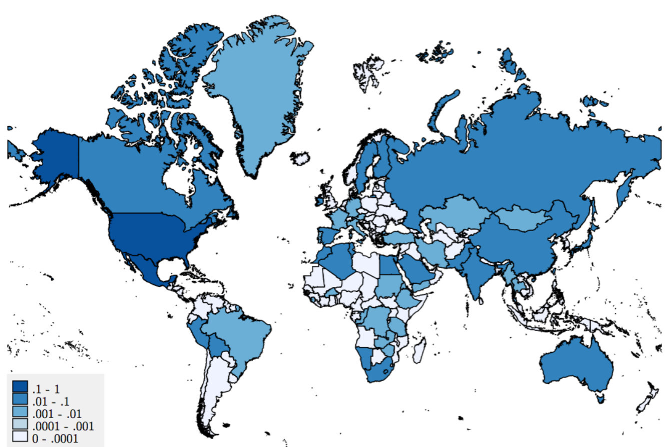
(a) Aluminum



(b) Copper



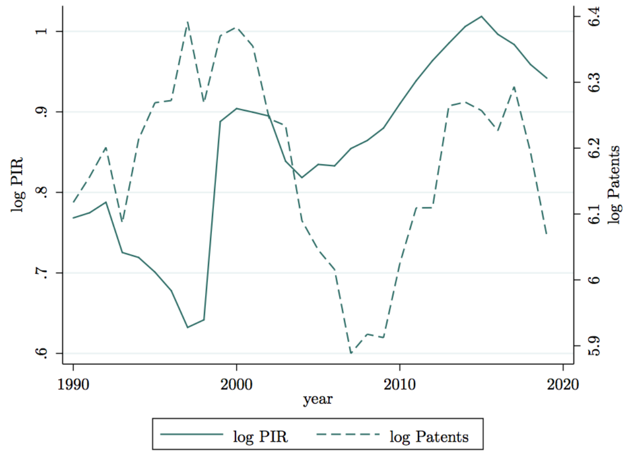
(c) Zinc



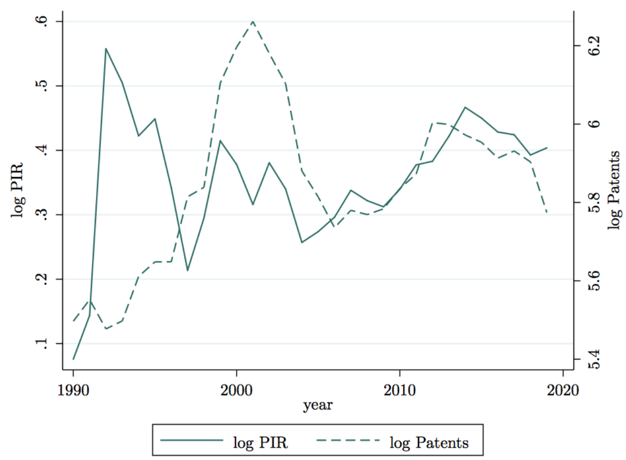
Notes: This figure shows the global deposit shares obtained from the US Geological Survey (USGS) for three minerals: aluminum, copper, and zinc. The color schemes are the same across three subfigures.

Figure A.4: Foreign Political Risk and Innovation: Aluminum, Copper, and Zinc

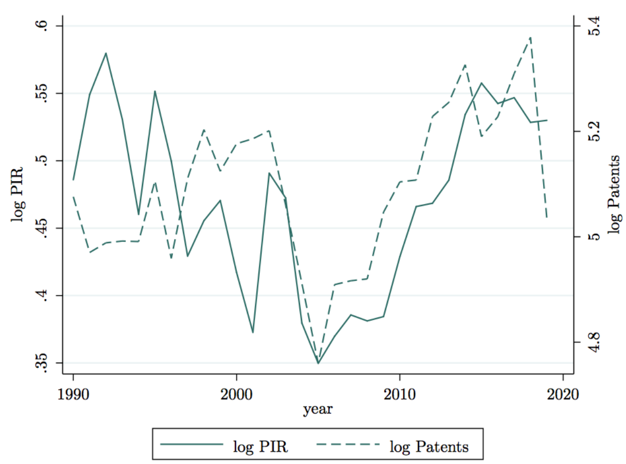
(a) Aluminum



(b) Copper



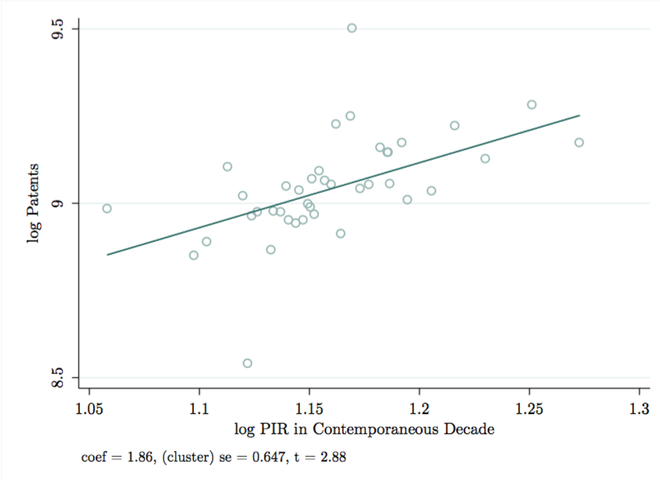
(c) Zinc



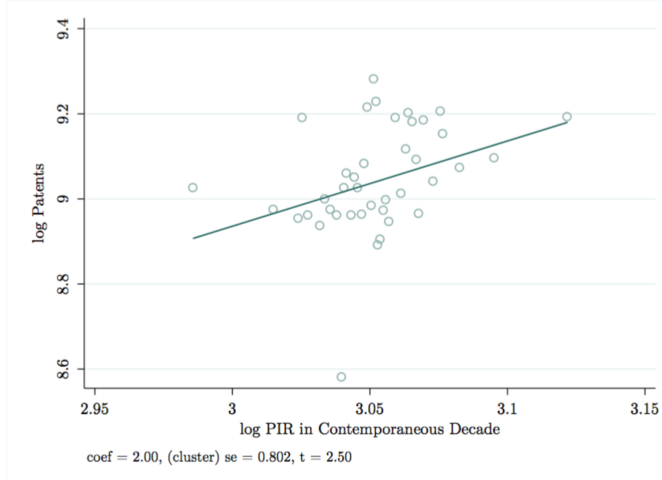
Notes: This figure shows the relationship between log political risk and log patents related to three minerals: aluminum, copper, and zinc. In all three sub-figures, log of political risk is plotted on the left y-axis using a solid line and the log number of patent applications is plotted on the right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

Figure A.5: Foreign Political Risk and US Innovation (Patents), Alternative Specifications

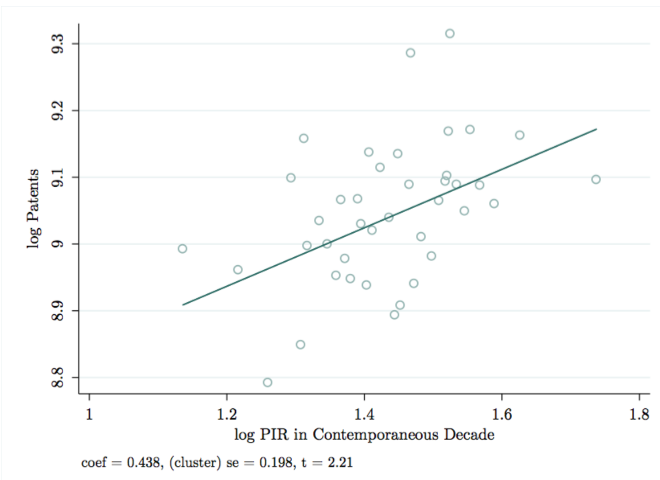
(a) Pre-period Import Shares



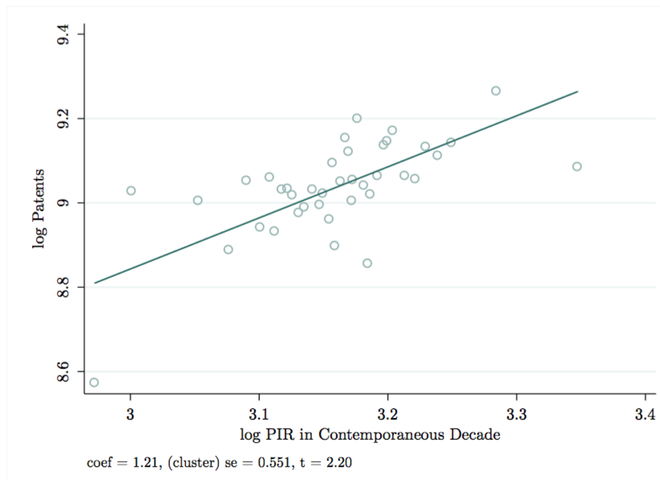
(b) Pre-period Import Shares, no Square



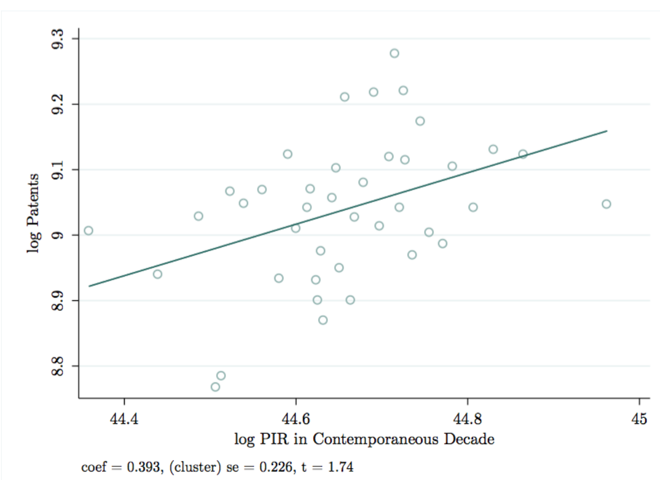
(c) Contemporaneous Import Shares



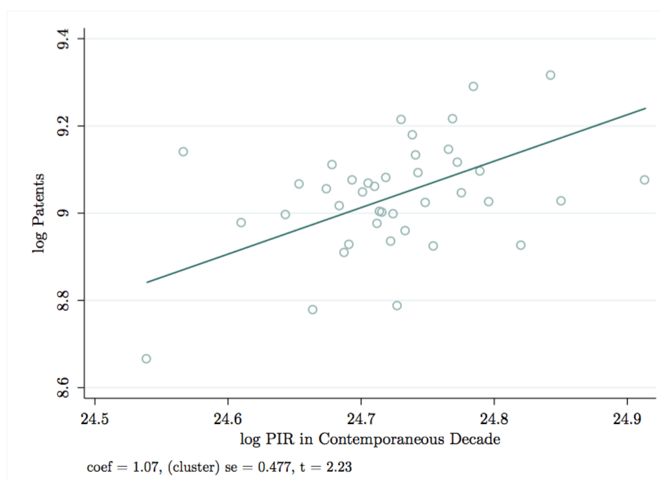
(d) Contemporaneous Import Shares, no Square



(e) Contemporaneous Import Levels



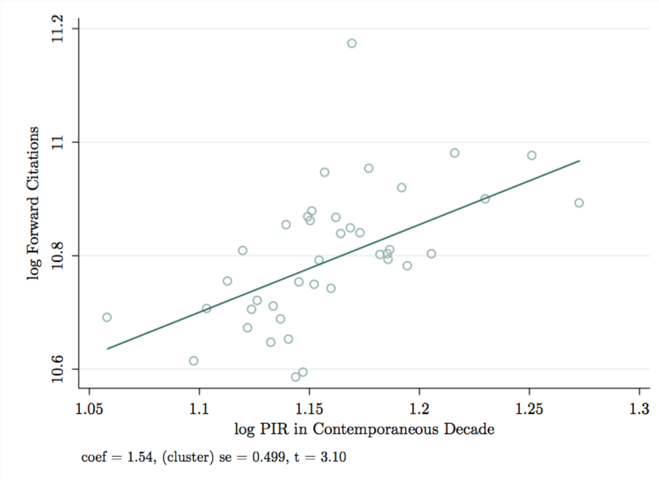
(f) Contemporaneous Import Levels, no Square



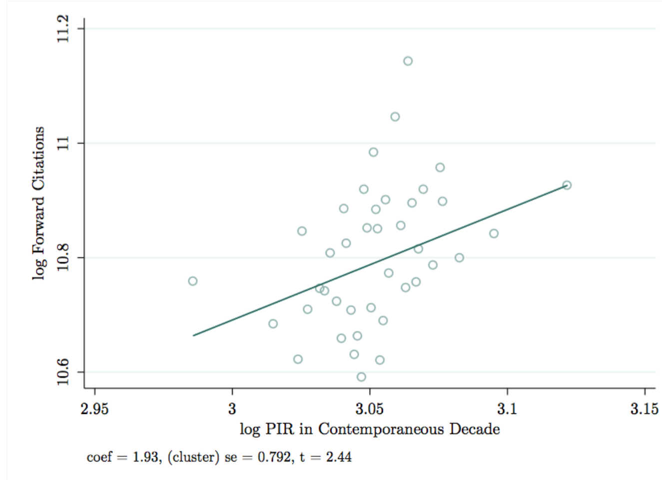
Notes: This figure shows the effect of political import risk in the contemporaneous decade on total patent applications in the US, applying different specifications. Panel (a) replicates Figure 3a, using the political import risk measure which is weighted by pre-period import shares. Panel (b) uses the political import risk measure which is weighted by pre-period import shares without squaring. Panel (c) uses the political import risk measure which is weighted by contemporaneous import shares, and controls for the sum of squared import shares (HHI). Panel (d) uses the political import risk measure which is weighted by contemporaneous import shares without squaring. Panel (e) uses the political import risk measure which is weighted by contemporaneous imports, and controls for the sum of squared imports. Panel (f) uses the political import risk measure which is weighted by contemporaneous imports without squaring, and controls for the sum of imports. 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 error for the fitted line are displayed below each sub-figure.

Figure A.6: Foreign Political Risk and US Innovation (Forward Citations), Alternative Specifications

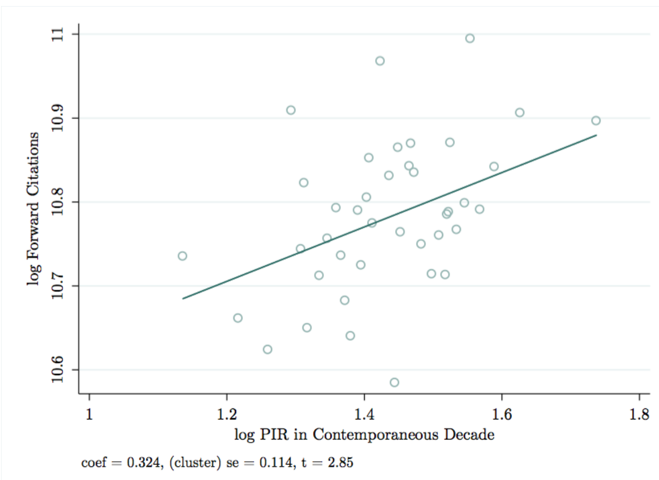
(a) Pre-period Import Shares



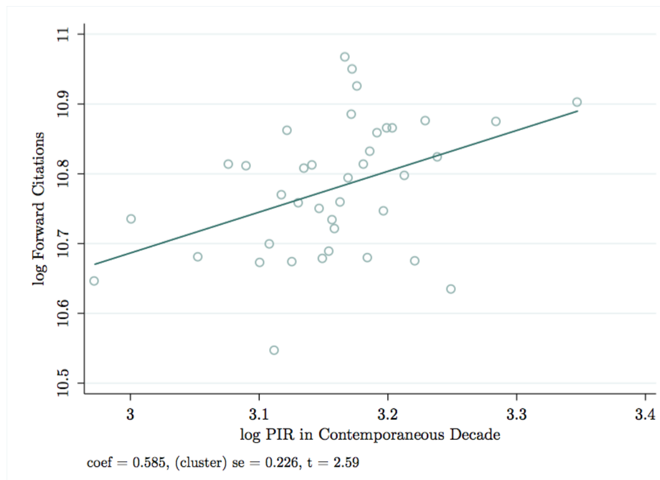
(b) Pre-period Import Shares, no Square



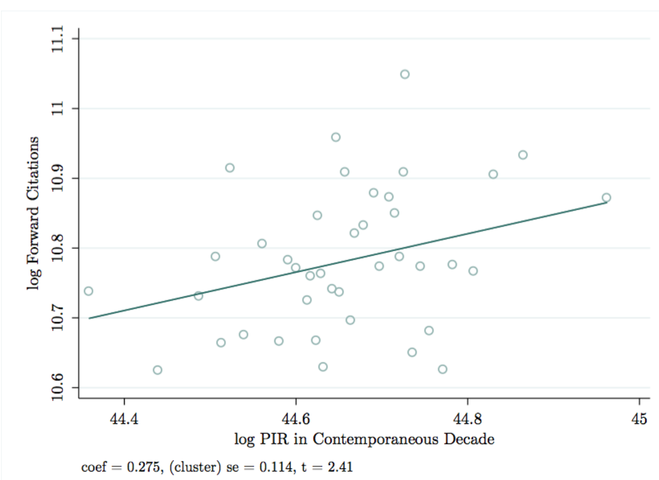
(c) Contemporaneous Import Shares



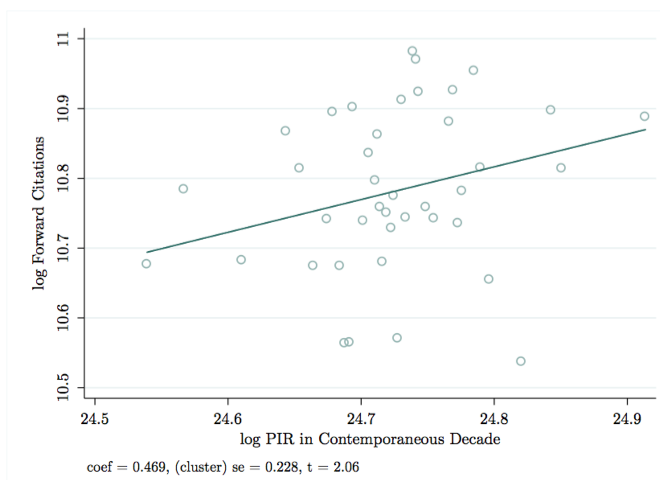
(d) Contemporaneous Import Shares, no Square



(e) Contemporaneous Imports



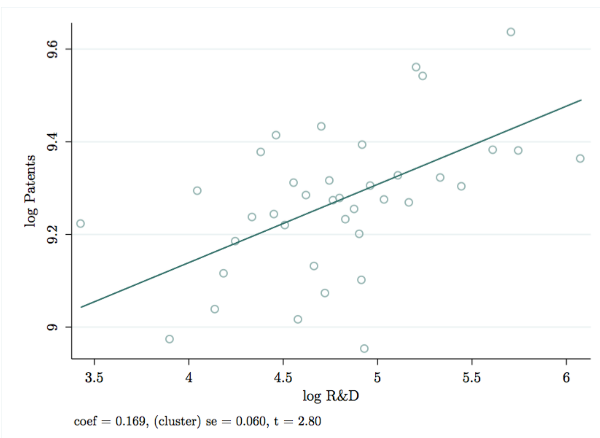
(f) Contemporaneous Imports, no Square



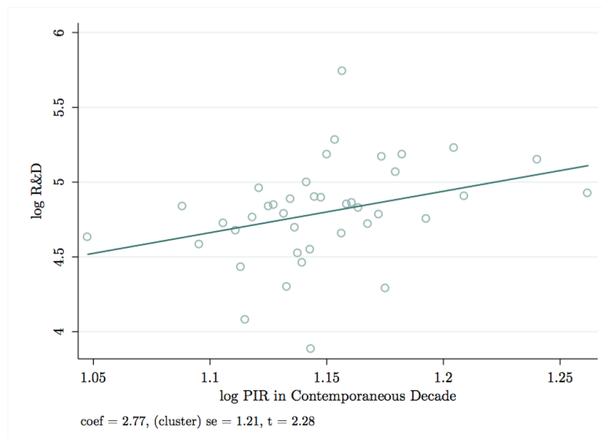
Notes: This figure shows the effect of political import risk in the contemporaneous decade on total forward citations within 5 years in the US, applying different specifications. Panel (a) uses the political import risk measure which is weighted by pre-period import shares. Panel (b) uses the political import risk measure which is weighted by pre-period import shares without squaring. Panel (c) uses the political import risk measure which is weighted by contemporaneous import shares, and controls for the sum of squared import shares (HHI). Panel (d) uses the political import risk measure which is weighted by contemporaneous import shares without squaring. Panel (e) uses the political import risk measure which is weighted by contemporaneous imports, and controls for the sum of squared imports. Panel (f) uses the political import risk measure which is weighted by contemporaneous imports without squaring, and controls for the sum of imports. In all six 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.

Figure A.7: Foreign Political Risk and US R&D

(a) Correlation b/w Patenting and R&D



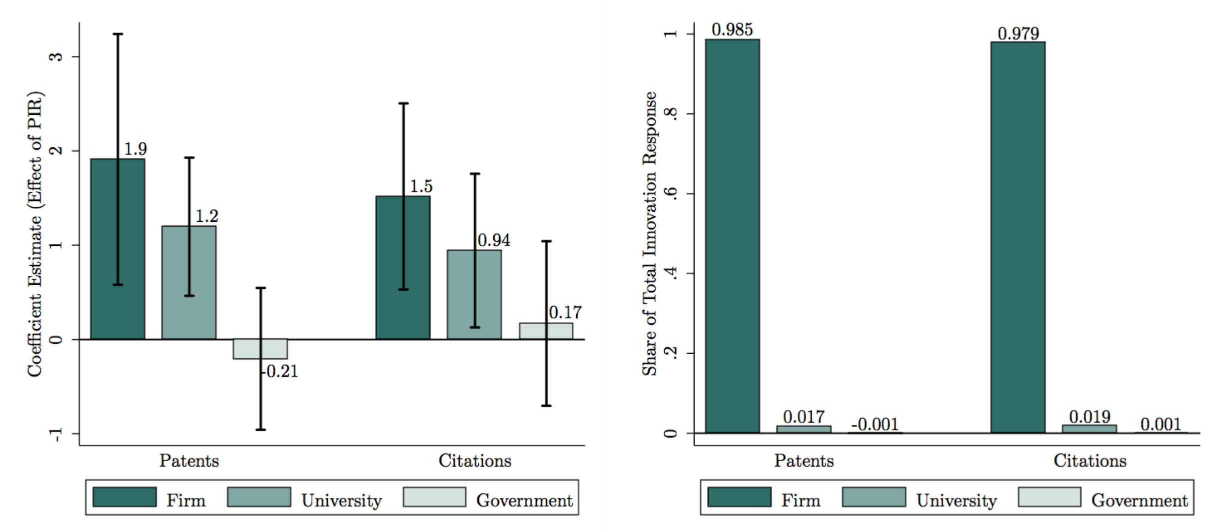
(b) PIR and R&D



Notes: Panel (a) shows the correlation between R&D expenditure and patent applications. Panel (b) shows the effect of imported political risk in the contemporaneous decade on R&D expenditure among publicly listed firms in Compustat. 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. In panel (b), we use the imported 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.

Figure A.8: Foreign Political Risk and US Innovation, by Inventor Type

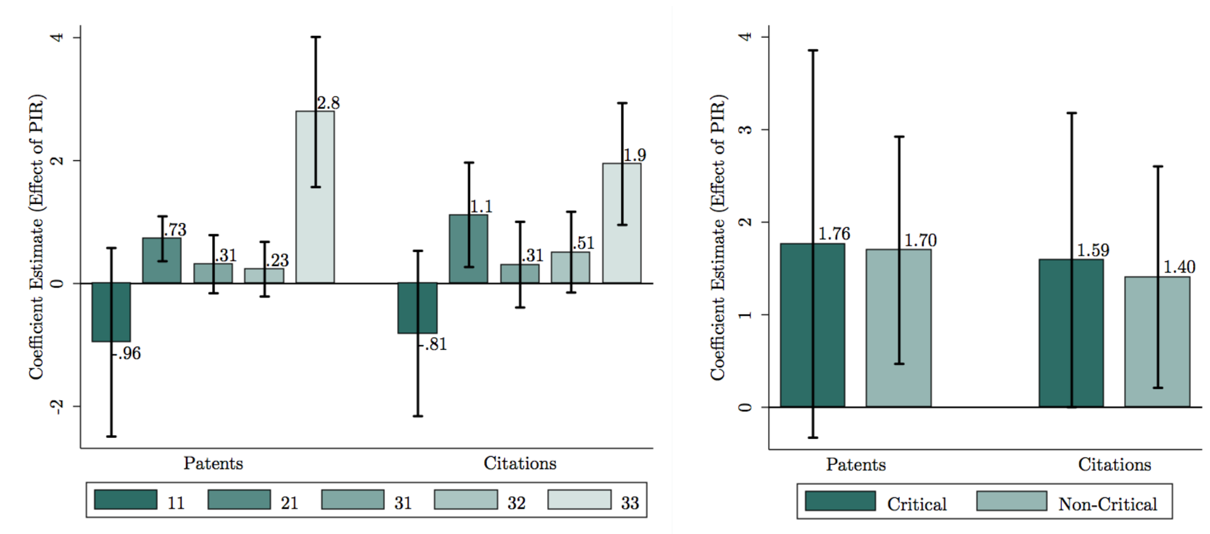
(a) Marginal Effects **(b)** Share of Innovation Response



Notes: Panel (a) shows effects of political import risk on patent applications from firms, universities, and governments, respectively. We regress log patent applications from each type of inventor on the political import risk measure which is weighted by pre-period import shares. 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 depicted in the chart. In panel (b), we calculate the share of innovation response from firms, universities, and governments, considering that innovation sizes of these three inventor types are different.

Figure A.9: Foreign Political Risk and US Innovation, Sector Heterogeneity

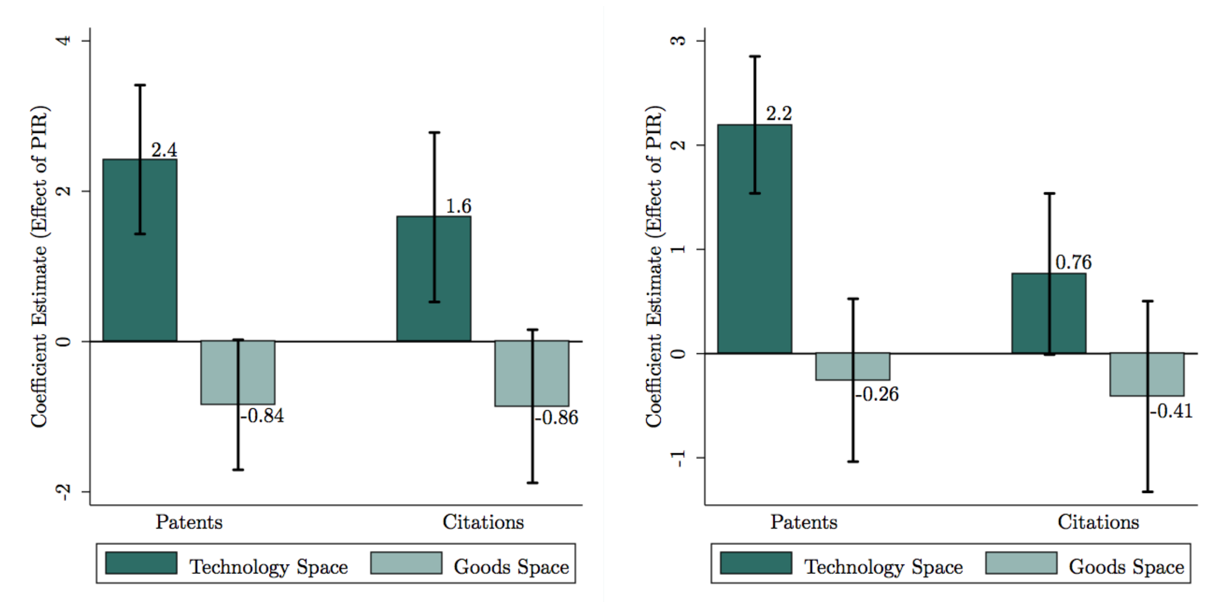
(a) 2-digit NAICS Sector **(b)** Critical vs Non-Critical Sector



Notes: Panel (a) shows the effect of political import risk in the contemporaneous decade on total patent applications and forward citations within 5 years in US, across five 2-digit NAICS sectors. Specifically, we run the following regression: log innovation$_{it}$ $= \sum_{k=1}^{5} \beta_k \log \text{PIR}_{it} \times 1[i \in k] + \delta_i + \delta_{kt} + \epsilon_{it}$, where k stands for 2-digit NAICS sector and t stands for decade. The standard errors are clustered at 6-digit NAICS level. Then we draw point estimates and 95% CIs of β_k. Panel (b) shows the effect of political import risk 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 ITA (international trade administration). Specifically, we run the following regression: log innovation$_{it}$ $=$ $\beta_C$log import risk$_{it}$ $\times 1[i \in C] + \beta_{NC}$log imported risk$_{it}$ $\times 1[i \in NC] + \delta_i + \delta_{Ct} + \epsilon_{it}$, where C stands for critical sector and NC stands for non-critical sector, and t stands for decade. The standard errors are clustered at 6-digit NAICS level. Then we draw point estimates and 95% CIs of β_C and β_{NC}. In both panels, we use the political import risk measure which is weighted by pre-period import shares. In both panels, we weight observations by 6-digit NAICS level patent applications during 1990-1999.

Figure A.10: Foreign Political Risk and US Innovation, Technology vs Goods Space

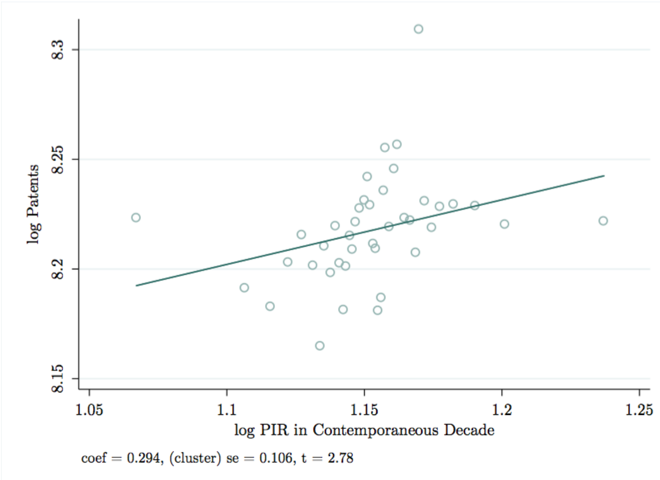
(a) Pooled Regression　　　　**(b)** Separate Regression



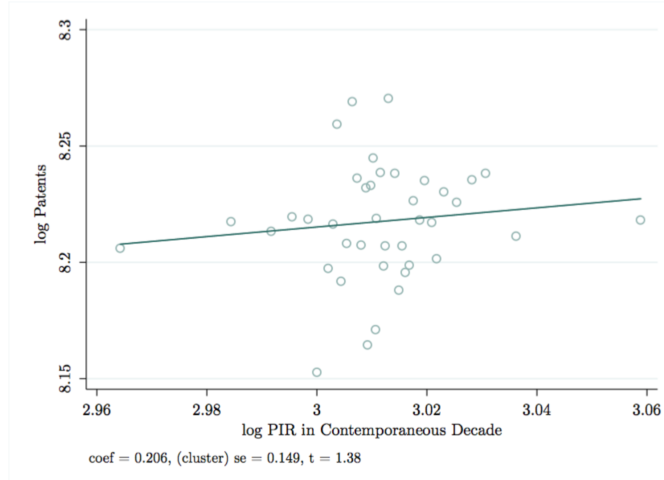
Notes: Panel (a) shows the effect of political import risk in the contemporaneous decade on total patent applications or forward citations within 5 years in US, from either technology space or goods space. Specifically, we run the following regression: $y_{ijt} = \gamma \log \text{PIR}_{jit}^{\text{TECH}} + \phi \log \text{PIR}_{jit}^{\text{GOODS}} + \alpha_i + \delta_t + \epsilon_{jit}$, where j stands for firm, i stands for sector, and t stands for decade. We cluster the standard errors at firm level. Then we draw point estimates and 95% CIs of γ and ϕ. Panel (b) shows the effect of political import risk from either technology space or goods space, in separate regressions. Specifically, we run the following regressions: $y_{ijt} = \gamma \log \text{PIR}_{jit}^{\text{TECH}} + \alpha_i + \delta_t + \epsilon_{jit}$, $y_{ijt} = \phi \log \text{PIR}_{jit}^{\text{GOODS}} + \alpha_i + \delta_t + \epsilon_{jit}$, where j stands for firm, i stands for sector, and t stands for decade. We cluster the standard errors at firm level. Then we draw point estimates and 95% CIs of γ and ϕ. In both panels, we use the political import risk measure which is weighted by pre-period import shares.

Figure A.11: Foreign Political Risk and Global Innovation (Patents), Alternative Specifications

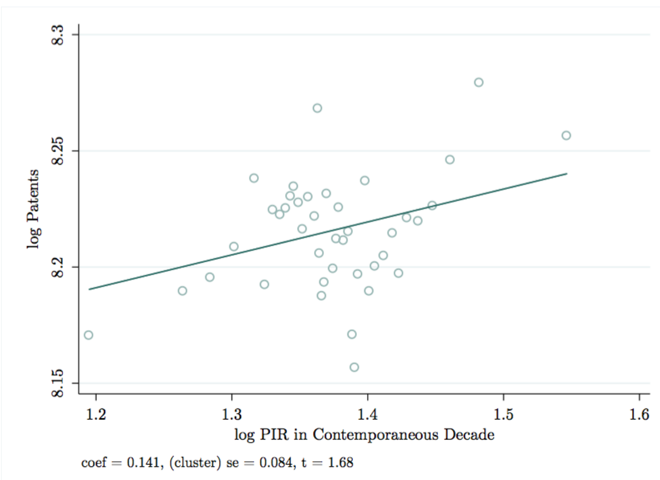
(a) Pre-period Import Shares



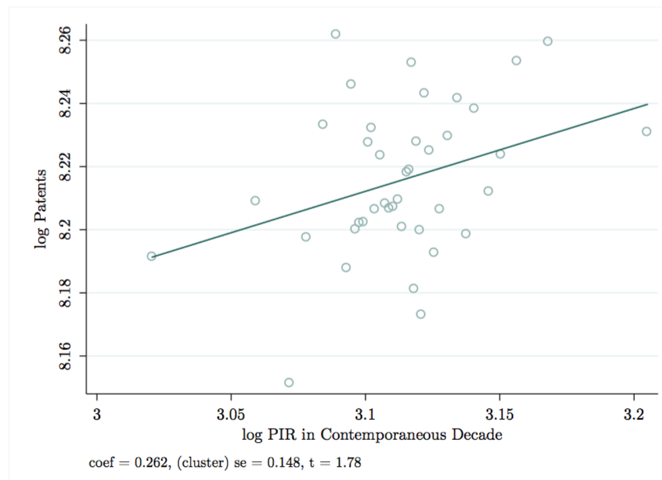
(b) Pre-period Import Shares, no Square



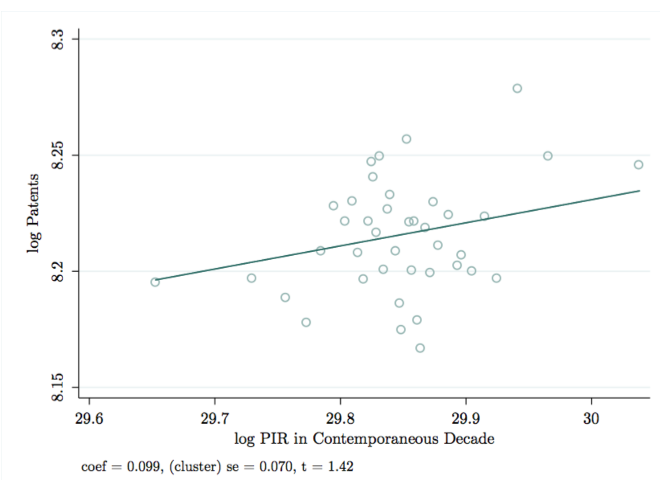
(c) Contemporaneous Import Shares



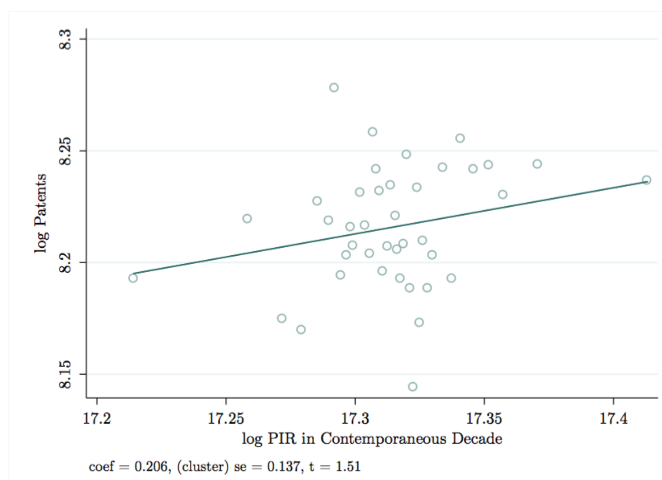
(d) Contemporaneous Import Shares, no Square



(e) Contemporaneous Import Levels



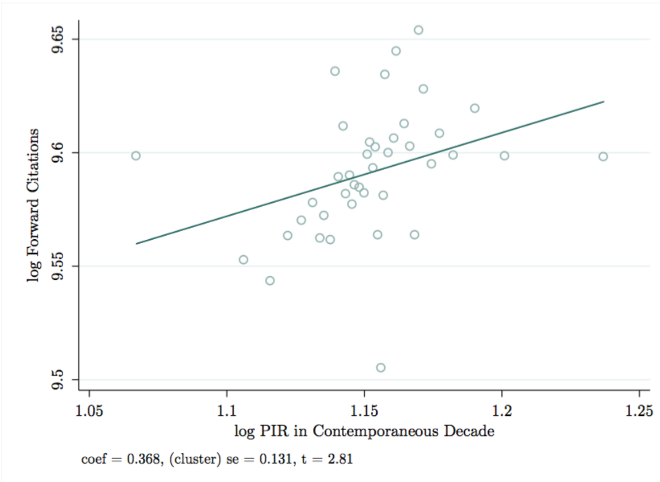
(f) Contemporaneous Import Levels, no Square



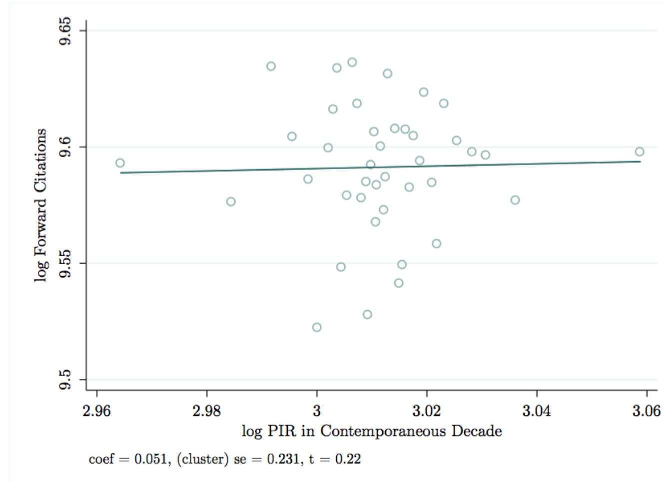
Notes: This figure shows the effect of political import risk in the contemporaneous decade on total patent forward citations within 5 years, applying different specifications. Panel (a) replicates Figure 5a, using the political import risk measure which is weighted by pre-period import shares. Panel (b) uses the political import risk measure which is weighted by pre-period import shares without squaring. Panel (c) uses the political import risk measure which is weighted by contemporaneous import shares, and controls for the sum of squared import shares (HHI). Panel (d) uses the political import risk measure which is weighted by contemporaneous import shares without squaring. Panel (e) uses the political import risk measure which is weighted by contemporaneous imports, and controls for the sum of squared imports. Panel (f) uses the political import risk measure which is weighted by contemporaneous imports without squaring, and controls for the sum of imports. 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 for the fitted line are displayed below each sub-figure.

Figure A.12: Foreign Political Risk and Global Innovation (Forward Citations), Alternative Specifications

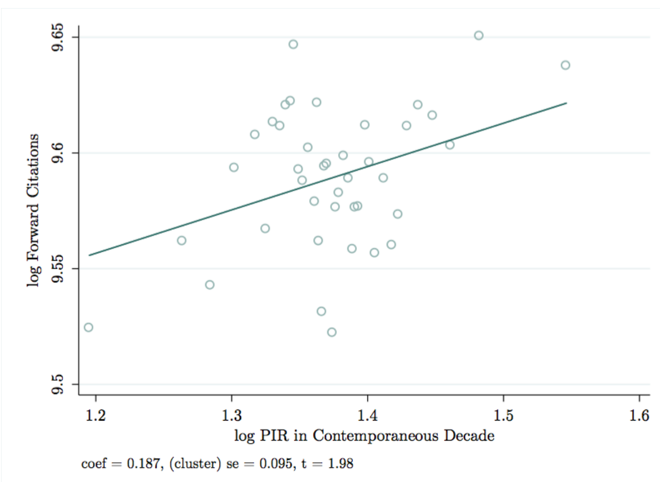
(a) Pre-period Import Shares



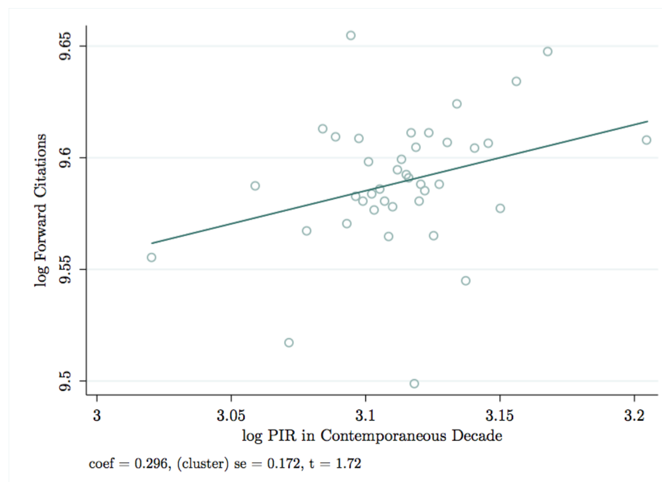
(b) Pre-period Import Shares, no Square



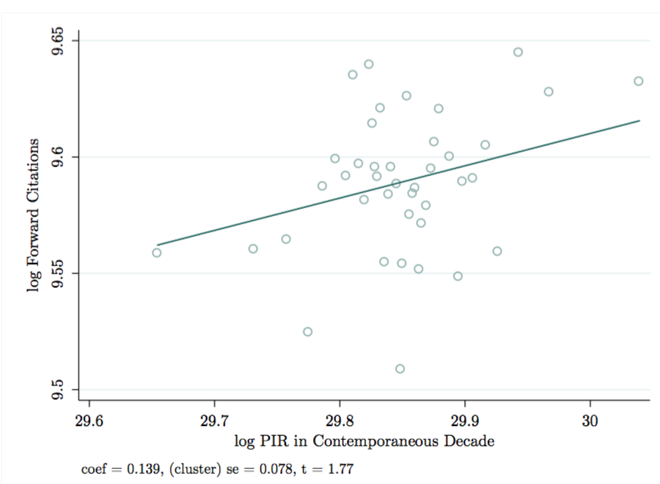
(c) Contemporaneous Import Shares



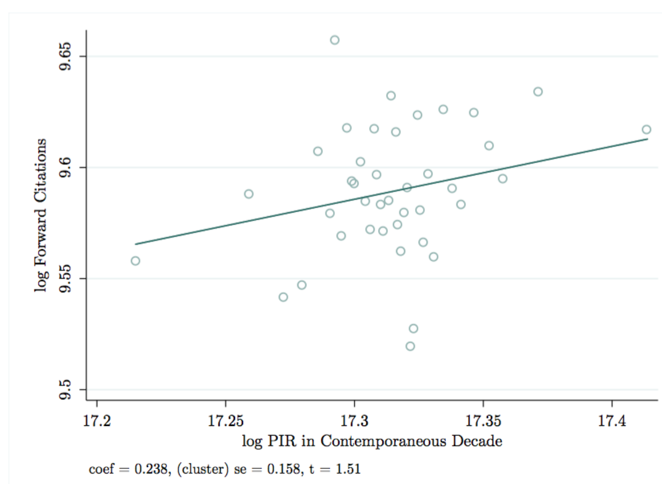
(d) Contemporaneous Import Shares, no Square



(e) Contemporaneous Imports



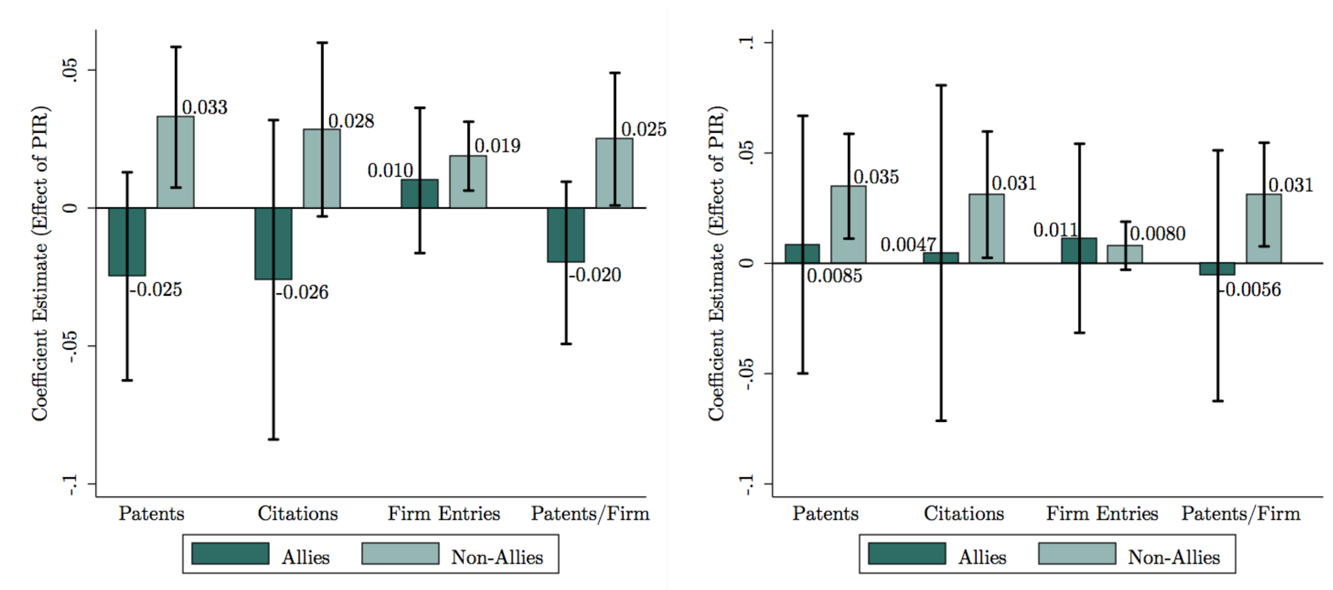
(f) Contemporaneous Imports, no Square



Notes: This figure shows the effect of political import risk in the contemporaneous decade on total forward citations within 5 years, applying different specifications. Panel (a) uses the political import risk measure which is weighted by pre-period import shares. Panel (b) uses the political import risk measure which is weighted by pre-period import shares without squaring. Panel (c) uses the political import risk measure which is weighted by contemporaneous import shares, and controls for the sum of squared import shares (HHI). Panel (d) uses the political import risk measure which is weighted by contemporaneous import shares without squaring. Panel (e) uses the political import risk measure which is weighted by contemporaneous imports, and controls for the sum of squared imports. Panel (f) uses the political import risk measure which is weighted by contemporaneous imports without squaring, and controls for the sum of imports. 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 for the fitted line are displayed below each sub-figure.

Figure A.13: Foreign Political Risk from Allies vs Non-Allies and Global Innovation

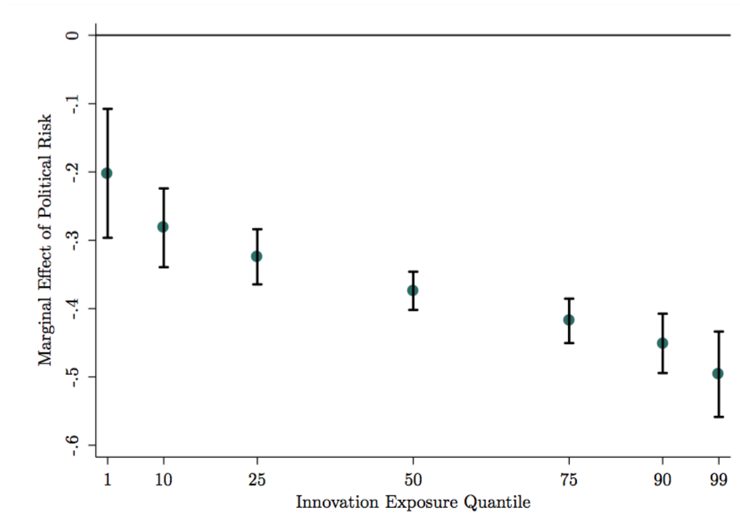
(a) Annual **(b)** Decennial



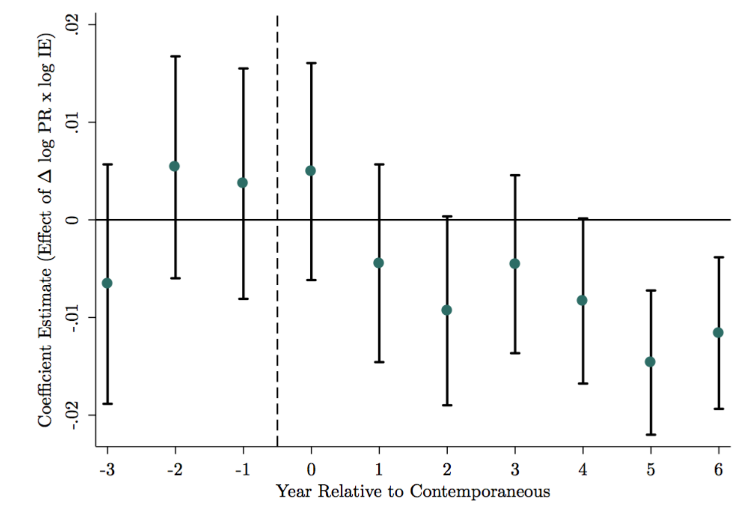
Notes: This figure shows the effect of political import risk form allies and non-allies on global innovation, at both annual and decennial frequencies. For the annual frequency, we run the following regression: $y_{cit} = \beta^A \log\,\text{PIR}^{\text{ALLY}}_{cit-1} + \beta^E \log\,\text{PIR}^{\text{NON-ALLY}}_{cit-1} + \alpha_{ci} + \delta_{ct} + \eta_{it} + X'\Gamma + \epsilon_{cit}$, and standard errors are clustered at 6-digit NAICS $\times$ country level. Then we draw point estimates and 95% CIs of β^A and β^E. For the decennial frequency, we run the following regression: $y_{cit} = \beta^A \log\,\text{PIR}^{\text{ALLY}}_{cit} + \beta^E \log\,\text{PIR}^{\text{NON-ALLY}}_{cit} + \alpha_{ci} + \delta_{ct} + \eta_{it} + X'\Gamma + \epsilon_{cit}$, and standard errors are clustered at 6-digit NAICS $\times$ country level. Then we draw point estimates and 95% CIs of β^A and β^E. In all specifications, we use the political import risk measure which is weighted by pre-period import shares. In all specifications, we weight observations by 6-digit NAICS $\times$ country level patent applications during 1990-1999.

Figure A.14: Political Risk and Exports: Effect of Innovation Exposure (Export Share Weighted)

(a) Effect of PR by Exposure Quantile



(b) Effect of $\Delta\text{PR} \cdot \text{IE}$, Leads and Lags



Notes: Panel (a) shows the marginal effect of political risk on exports, evaluating at different quantiles of innovation exposure. Specifically, we run the following regression: $\log \text{Exports}_{cit} = \gamma \log \text{PR}_{ct} + \beta \log \text{PR}_{ct} \cdot \log \text{IE}_{ci} + \alpha_{ic} + \eta_{it} + X'\Gamma + \epsilon_{cit}$. Standard error is clustered at 6-digit NAICS $\times$ country level. Then we calculate the marginal effect of political risk at different quantiles of innovation exposure. Coefficients and 95% confidence intervals are drawn in the chart. 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 draw point estimates and 95% CIs of 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.

Table A.1: Foreign Political Risk and US Innovation: Controlling for Lagged Imports

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	log Patents	Patents	log Fwd Citations	log Patent Value	log New Firms	log Patents per Firm
	Panel A: Risk Measure Using Contemporaneous Imports					
log PIR, First Lag	0.299	0.275	0.207	0.310	0.044	0.231
	(0.147)	(0.126)	(0.083)	(0.147)	(0.125)	(0.092)
log HHI, First Lag	-0.034	-0.030	-0.076	0.023	0.037	-0.060
	(0.165)	(0.140)	(0.103)	(0.183)	(0.141)	(0.098)
log Imports, First Lag	0.130	0.135	0.111	0.112	0.016	0.129
	(0.062)	(0.044)	(0.037)	(0.072)	(0.042)	(0.068)
Mean Dep. Var.	2.31	173	3.74	4.02	4.19	-2.89
Observations	13926	15432	12092	12788	13822	13916
	Panel B: Risk Measure Using Pre-Period Imports					
log PIR, First Lag	0.390	0.462	0.312	0.301	0.306	0.082
	(0.154)	(0.152)	(0.141)	(0.150)	(0.122)	(0.156)
log Imports, First Lag	0.136	0.156	0.121	0.122	0.016	0.134
	(0.094)	(0.073)	(0.044)	(0.111)	(0.044)	(0.087)
Mean Dep. Var.	2.31	174	3.75	4.02	4.19	-2.89
Observations	13571	14942	11902	12518	13471	13561
NAICS 6-digit FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	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 import risk 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 import risk measure which is weighted by pre-period import shares, and control for log imports. The dezpendent 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, log number of new patenting firms in column 5, and log patents per firm in column 6. 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 are clustered at the 6-digit NAICS level.

Table A.2: Foreign Political Risk and US Innovation: Cross Sector Spillovers

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:			log Patent		
log PIR^{UP}, First Lag	0.792		0.377		0.199
	(0.339)		(0.326)		(0.272)
log PIR^{DOWN}, First Lag		0.931	0.811		0.517
		(0.246)	(0.259)		(0.332)
log PIR^{SUB}, First Lag				1.845	1.270
				(0.757)	(0.892)
Mean Dep. Var.	2.26	2.24	2.24	2.25	2.24
Observations	15071	14708	14708	14972	14708
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. We use the imported political risk measure which is weighted by pre-period import shares. The dependent variable is log patent applications. We weight observations by 6-digit NAICS level patent applications during 1990-1999. Standard errors are clustered at the 6-digit NAICS level.

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

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	log Patents	Patents	log Fwd Citations	log New Firms	log Patents per Firm
log PIR, First Lag	0.081	0.071	0.134	0.033	0.066
	(0.033)	(0.039)	(0.049)	(0.019)	(0.028)
log Imports, First Lag	0.068	0.044	0.076	0.041	0.039
	(0.020)	(0.017)	(0.030)	(0.013)	(0.013)
Mean Dep. Var.	-0.92	1.99	-0.034	1.73	-3.15
Observations	242247	2359652	184974	206293	239667
NAICS 6-digit × Country FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
NAICS 6-digit × Year FE	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 imported political risk 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 number of new patenting firms in column 4, and log patents per firm in column 5. 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.4: 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.5: 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.