Foreign Geopolitical Risk and U.S. Firm Productivity: The Role of Immigrant Labor

Zhongling (Danny) Qin Miao Ben Zhang*

November 17, 2025

Abstract

We demonstrate that foreign geopolitical risk can affect U.S. firm productivity through their immigrant employees. Using confidential U.S. Census employee-employer matched microdata, we measure a firm's labor exposure to foreign geopolitical risk (*FGPR*) based on geopolitical shocks to the origin countries of its immigrant employees. FGPR significantly *boosts* firm labor productivity, profitability, and investment. The effect appears causal, operates on the intensive margin rather than through labor turnover, and is robust among firms without international trade activities. Examining the mechanism at the worker level, we find that immigrants *increase* their working hours when origin-country GPR rises, which positively spills over to their domestic coworkers' labor supply. These effects are consistent with two underlying forces: a reduced option value of return migration and increased remittance motives when origin-country GPR rises. Overall, our study highlights a novel labor channel through which foreign GPR pressures immigrant employees but benefits their employing firms.

Keywords: *Geopolitical Risk, Immigrants, Labor Productivity, Firm Dynamics, Earnings Growth, Time Use, Return Migration, Remittance.*

*Zhongling (Danny) Qin is from Auburn University and can be reached at zzq0018@auburn.edu. Miao Ben Zhang is from the University of Southern California Marshall School of Business and can be reached at miao.zhang@marshall.usc.edu. We thank Tom Chang, Jack He, Matteo Maggiori, Tano Santos, Francesco Trebbi, and Selale Tuzel for helpful discussions. We also thank Dario Caldara and Matteo Iacoviello for sharing data on country-specific geopolitical risk, acts, and threats. Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2838. (CBDRB-FY25-P2838-R12647). This research uses data from the Census Bureau's Longitudinal Employer-Household Dynamics Program, which was partially supported by the following National Science Foundation Grants SES-9978093, SES-0339191 and ITR-0427889; National Institute on Aging Grant AG018854; and grants from the Alfred P. Sloan Foundation. All errors are our own.

Over 19% of workers in the U.S. originate from foreign countries.[1] Geopolitical risk in their home countries, such as wars, military coups, terrorism, and nuclear threats, can potentially affect these workers' work decisions and thus their employing firms in the U.S. Yet, how immigrants react to their origin countries' geopolitical risk (GPR) and to what extent such reactions affect their firms' overall productivity are largely unknown. In this paper, we provide the first evidence on how foreign GPR affects U.S. firm productivity through this "immigrant labor channel."

By merging employees' place of birth in the confidential U.S. Census employee-employer matched data with country-specific geopolitical shocks, we construct a measure of labor exposure to foreign geopolitical risk (FGPR) for U.S. firms over recent decades. We show that FGPR robustly and causally *increases* firms' labor productivity, with a one-standard-deviation increase in FGPR leading to $1,037 in real annual revenues per employee, or $0.7 million in annual revenues for an average firm in our sample, which further transmits to greater profitability and growth. This effect operates through the intensive margin of labor supply rather than labor turnover (e.g., layoffs). Importantly, immigrants work significantly more hours when their origin country's GPR rises, and this effect spills over to their domestic coworkers, which together explains the higher average labor productivity of their employing firms. We further examine the underlying forces for immigrants' responses to origin-country GPR, which point to reduced return migration options and stronger remittance motives.

Our findings enrich the burgeoning literature on how geopolitical risk affects U.S. firms, which mostly focuses on firms' trade exposure to geopolitical risk. Through the trade channel, recent seminal work discovers the substantial negative impact of geopolitical risk on firms through direct supply-chain disruption or uncertainty that halts firm investments (Hassan et al. (2019), Caldara and Iacoviello (2022), and Clayton et al. (2025a)). Our immigrant-labor channel completes this literature by identifying labor as another key channel through which foreign geopolitical risk can affect a firm, beyond intermediary inputs (i.e., imports) and customers (i.e., exports).

Our labor channel differs from the well-documented trade channel in several key respects. First, foreign geopolitical shocks *positively* affect firms with higher immigrant labor exposure, as we demonstrate for firms' labor productivity, profitability, and investment, whereas trade exposure mostly shows *negative* effects. Second, we find that the two channels are largely unrelated, as controlling for one does little to alter the effects of the other. Third, unlike the ubiquitous discussions of trade exposure in corporate disclosures (Hassan et al. (2019)), firms' discussions of the labor exposure are rather "silent." For example, our FGPR measure is uncorrelated with firms' discussions of broad or trade-related political risk during conference

[1] See U.S. Bureau of Labor Statistics news release on May 20, 2025.

calls from Hassan et al. (2019).

A key challenge in studying the labor channel is obtaining high-quality data on firms' exposure to immigrant employees from each foreign country. We overcome this challenge by using the confidential Longitudinal Employer-Household Dynamics (LEHD) microdata from the U.S. Census Bureau, which provides the place of birth for each employee within each firm. Our analysis focuses on firms with at least 100 employees, resulting in nearly all firms having some exposure to immigrant workers, with, on average, 14% of their employees being foreign-born. We then construct geopolitical shocks for each foreign country relative to its past ten years' trailing average (GPR) using the news-based geopolitical risk measure from Caldara and Iacoviello (2022).[2] Finally, a U.S. firm's labor exposure to foreign geopolitical risk ($FGPR$) is an immigrant employment-share weighted average of foreign GPR shocks, following a shift-share design.[3]

Our analysis begins by examining the impact of FGPR on U.S. firms' labor productivity, measured as the ratio of real revenues in 2018 dollars to the number of employees, using the Census revenue-enhanced Longitudinal Business Database (LBD) as outlined in Haltiwanger et al. (2016).[4] This metric allows us to systematically assess the performance of both public and private firms across nearly all industries over an extended period, which would otherwise be challenging. Additionally, we supplement our main analysis with alternative performance measures for public firms based on Compustat data. After merging firms in the LBD and LEHD data using the Census internal crosswalk, our final sample includes about 1 million firm-year observations spanning from 1996 to 2017.

Our main finding is a strong *positive* impact of a firm's labor exposure to foreign geopolitical risk on its labor productivity in the subsequent year. This effect is highly significant even after controlling for a stringent set of factors, including time-varying firm characteristics known to predict labor productivity, such as firm size, age, average worker age, and average worker education (Haltiwanger and Schuh (1996)); firm fixed effects (Syverson (2011)); industry-by-year fixed effects; and a full set of interactions between firms' immigrant labor share and year indicators.[5] Economically, a one-standard-deviation increase in FGPR boosts

[2]In a validation test, we find that our country-level GPR shocks capture the sparse geopolitical disaster events identified in Baker et al. (2024), and are unrelated to natural disaster events.

[3]Since the shares of immigrants from foreign countries do not sum to one, we address the "incomplete share" issue by controlling for interactions between the firm's total share of immigrant employees and year indicators (Borusyak et al. (2022) and Borusyak et al. (2025)).

[4]This measure has been widely adopted by many prior studies (e.g., Haltiwanger et al. (1999), Helpman et al. (2004), Bloom et al. (2012), Haltiwanger et al. (2016), Decker et al. (2020), Wallskog et al. (2024), Haltiwanger et al. (2025), and Larrain et al. (2025)).

[5]Since the shares of immigrants from foreign countries do not sum to one, we address the "incomplete share" issue following the standard approach by controlling for the interactions between the firm's total share of immigrant employees and year indicators (Borusyak et al. (2022) and Borusyak et al. (2025)).

firm labor productivity by $1,037, corresponding to about $0.7 million in higher annual real revenue for an average firm in our sample.

The identification of our main finding relies on the assumption that a firm's labor productivity would not have followed the observed trajectory had the foreign GPR shocks not occurred. We examine this assumption through several tests. First, we do not observe any pre-trend in the effect of FGPR on firm labor productivity. Following the treatment, the effect is highly significant in the ensuing two years. Second, it is unlikely that U.S. firms endogenously adjust their employment composition ahead of foreign GPR shocks in a way that results in the positive relationship between FGPR and future labor productivity. In particular, we find similar results when reconstructing a firm's FGPR based on its immigrant employee share from three years earlier. Third, the foreign GPR shocks, which drive most of the variation in FGPR, appear to be exogenous to U.S. firms—e.g., they significantly capture the rare, unexpected geopolitical disasters in Baker et al. (2024). Fourth, we follow the practical guidance of Borusyak et al. (2025) and comprehensively examine the properties of the shocks and shares. Notably, FGPR reflects dispersed shocks originating from many foreign countries, with these shocks exhibiting low pairwise correlations and no systematic relation to other country-level confounders. These findings significantly mitigate concerns about endogeneity and suggest that FGPR has a causal effect on labor productivity.

Our main finding is also robust to a battery of checks. First, the productivity gain comes from increased revenues rather than reduced employment. In particular, the effect remains when conditioning on firms with zero labor turnover in the treatment year. Second, the effect is driven by positive (rather than negative) shocks that increase the foreign GPR of employees' origin countries. Third, the effect is robust to controlling for foreign GPR's association with U.S. GPR and holds for both geopolitical friends and enemies of the U.S. Fourth, the positive impact on U.S. firms is observed when we use several alternative measures of firm performance, including a measure of labor surplus to firms that excludes wage bills for Census firms, and measures of profitability and investment for publicly traded Compustat firms.

These results complement the well-known effects of geopolitical risk on firms through the trade channel. Specifically, we replicate the effects of the trade channel in our data by showing that (i) import-exporter firms in our sample experience substantially lower average labor productivity when global geopolitical risk rises,[6] and (ii) publicly traded firms with higher overall or trade-related policy risk from Hassan et al. (2019) experience significantly lower labor productivity. Notably, the positive labor channel and the negative trade channel effects do not subsume each other when both are included in the same regression. Moreover,

[6]The effects are very similar when we exclude the U.S. from the global geopolitical risk measure.

the positive effects of FGPR on firm labor productivity remain robust even among firms without any import or export activities.

After establishing our main firm-level findings, we examine the underlying mechanism by inspecting individual immigrant workers' labor supply. Using detailed intraday diary data by individuals from the American Time Use Survey (ATUS), we find that immigrants allocate significantly more time to their main jobs at the cost of leisure when their origin-country GPR is higher. A one-standard-deviation increase in origin-country GPR is associated with 1.2 additional working hours per week by immigrants. This effect is robust after controlling for a full battery of demographic characteristics following Aguiar et al. (2013), driven primarily by increases (but not decreases) in origin-country GPR, and present even when we use the rare unexpected geopolitical disaster events from Baker et al. (2024) instead of our GPR shocks. Consistent with this labor supply response, we observe in the Census LEHD microdata that origin-country GPR also leads to positive future earnings growth in worker-level regressions with individual fixed effects.

Furthermore, there are spillover effects on domestic workers. Using our employee-employer matched LEHD data, we show that when firms' FGPR is higher, both immigrant workers' and their domestic coworkers' earnings growth significantly rise. This finding is consistent with a positive spillover of immigrants' extra labor supply to their domestic coworkers, such as through peer pressure (Mas and Moretti (2009)) or synergy (Jin et al. (2025) and Bernstein et al. (2022)). The effects on domestic coworkers rationalize that, although immigrants are not the majority of U.S. firm employees, foreign GPR can still cause a sizable impact on firms' average labor productivity.

We complete our analysis by exploring why immigrants increase their working hours when origin-country GPR rises. Fully dissecting various mechanisms faces data limitations and is beyond the scope of our study. Instead, we focus on two theoretically grounded forces—return-migration options and remittance motives—unified through a simple extension of the standard labor-supply framework.[7] Using LinkedIn profile data, from which Amanzadeh et al. (2024) highlight that return migration is pervasive, we first show that origin-country GPR substantially reduces return migration. We then estimate the heterogeneous sensitivities of return migration to origin-country GPR across granular demographic groups using machine-learning methods and embed these estimates in the ATUS regressions. Supporting this mechanism, we find that demographic groups exhibiting more negative return migration sensitivity increase their labor supply more when origin-country GPR rises.

[7]Theoretical work on immigrants' return migration options can be found in Dustmann (2003), Borjas and Bratsberg (1996), and Dustmann and Görlach (2016). For remittance motives, see Lucas and Stark (1985) for seminal work on theoretical drivers of immigrants' remittance motives and their work.

For remittance motives, we implement an analogous two-stage approach: we estimate country-level sensitivities of remittance per capita to origin-country GPR using World Bank data, and then interact these sensitivities with immigrants' income in ATUS regressions. We find that immigrants from countries with greater remittance sensitivity increase their working hours more when GPR increases, with the effects being stronger among lower-income individuals. This is consistent with remittance responses binding more tightly for lower-income immigrants, as high-income immigrants may have greater financial slack to remit without immediately increasing their working hours. Collectively, these results indicate that reduced return-migration options and heightened remittance motives both contribute to the observed labor-supply response to foreign geopolitical risk.

Our study contributes to two strands of literature. The first is on the impact of geopolitical risks on firms, which empirically documents substantial effects on firm investment, volatility, and asset prices. Hassan et al. (2019) and Hassan et al. (2024b) construct novel measures of political risk for U.S. firms and worldwide, respectively, based on earnings conference call transcripts and show that such risk substantially reduces firm investment and capital flows. Caldara and Iacoviello (2022) measure firms' mentions of geopolitical risk in conference calls and find similar negative effects on firm growth.[8] Clayton et al. (2025a) and Flynn et al. (2025) examine firms' research and development and show that firms respond to geopolitical pressure by focusing more on innovation. Geopolitical risk also dramatically contributes to stock market risks as shown by recent studies (Boutchkova et al. (2012), Brogaard et al. (2020), Hirshleifer et al. (2023a), Hirshleifer et al. (2023b), Sheng et al. (2025), and Gonçalves et al. (2025)). These studies emphasize the adverse impact of firms' trade exposure to global geopolitical tensions, often through direct supply chain transmission or uncertainty shocks. Our study provides a complementary and novel perspective by demonstrating a channel based on U.S. firms' immigrant labor exposure. Notably, we highlight that geopolitical pressure on immigrant employees ultimately benefits their employing firms.

Second, our study also contributes to the literature on the effect of immigrants on U.S. firms. Bernstein et al. (2022) seminally show that immigrants create large productivity spillovers to their collaborators in the innovation space. Jin et al. (2025) document entrepreneurial synergies to native-immigrant teams. Consistent with their findings, we observe that immigrants' labor supply responses to their origin-country GPR also spill over to their native coworkers. For the effects on long-term outcomes in the U.S., prior studies have focused on *inflows* of immigrants to the U.S., typically caused by conditions in

[8]See also Gulen and Ion (2016) for general economic policy uncertainty effects on corporate investment based on measures from Baker et al. (2016). For measurements of policy uncertainty in other settings, see Baker et al. (2019), Baker et al. (2022), Hassan et al. (2023), and Hassan et al. (2024a), among others. See also Clayton et al. (2023), Clayton et al. (2024), and Clayton et al. (2025b) for recent developments on the importance of geopolitics in economic studies.

their origin countries (e.g., Hunt and Gauthier-Loiselle (2010), Burchardi et al. (2020), and Khanna (2025)). Distinct from these studies, we focus on how *incumbent* immigrant workers in the U.S. respond to the geopolitical risks of their origin countries, which has received little attention.

The rest of this paper is organized as follows: Section 1 describes our data and constructs our firm-level measure of labor exposure to foreign geopolitical risk. Section 2 presents the main finding on firms' labor productivity. Section 3 examines the mechanism based on immigrants' time use and both immigrant and domestic workers' future earnings growth. Section 4 explores the underlying forces driving immigrants' labor supply responses to their origin countries' GPR. Section 5 distinguishes our labor channel from the well-documented trade channel in the literature, and Section 6 concludes.

1. Data and Measures

1.1 Data

Our study uses several datasets from the U.S. Census Bureau and other sources. The core datasets include the confidential Longitudinal Business Database (LBD), which provides firm-level information such as labor productivity; the restricted Longitudinal Employer-Household Dynamics (LEHD) microdata, which includes worker-firm matched data with worker backgrounds that allow us to compute firms' labor exposure to foreign geopolitical risk; and the publicly available American Time Use Survey (ATUS), which records immigrants' time allocation to work, leisure, and other activities, among other datasets.

LBD Data The LBD database covers the universe of non-farm establishments with at least one paid employee. It aggregates establishments under common ownership or control to the firm level, offering annual data on revenues, employment, age, industry, and indicators for import and export activities.[9] Firms' revenue data, available from 1996 to 2018, are derived from business income tax returns and more recently integrated into the LBD following Haltiwanger et al. (2016). We deflate revenues to 2018 U.S. dollars using the GDP Implicit

[9]Firms in the LBD are linked to their establishments through administrative tax records, economic censuses, and the company organization survey. Following the standard approach in the literature (e.g., Haltiwanger et al. (2013)), we define a firm's age as the age of its oldest establishment, based on its first appearance in the LBD database. A firm's main industry code reflects its establishments' primary business activity, constructed from time-consistent NAICS codes as outlined in Fort and Klimek (2018) (see also Chow et al. (2021) for further details). For consistency, we classify firms by their 3-digit NAICS codes, allowing for firms with establishments spanning multiple industries (see Krishnan et al. (2015), Giroud and Mueller (2019), and Dinlersoz et al. (2018)).[10]

Price Deflator. Additionally, the LBD database includes indicators of a firm's engagement in import or export activities, provided by merging LBD data with the Census Bureau's Longitudinal Firm Trade Transactions Database (LFTTD), which tracks the universe of U.S. firms' international trade transactions.

We measure a firm's **labor productivity (LProd)** as its real revenues divided by the total number of employees at the beginning of the year, following a large body of literature (e.g., Haltiwanger et al. (1999), Helpman et al. (2004), Bloom et al. (2012), Haltiwanger et al. (2016), Decker et al. (2020), Wallskog et al. (2024), Haltiwanger et al. (2025), and Larrain et al. (2025)).[11] This measure reflects the standard gross output per worker productivity often used to assess firm productivity at both the micro and macro levels and has been shown to correlate highly with firm total factor productivity.[12]

We note two limitations of this measure. First, it may increase either due to higher worker productivity per hour (the true worker productivity channel) or because workers increase their working hours (the labor supply channel). As discussed in the mechanism section, we consider both channels important for understanding how foreign geopolitical risk affects U.S. *firms' benefits*. In this regard, we also examine alternative measures of firm benefits, such as profitability and growth among publicly traded firms, and find consistent results. Second, this measure relies on gross revenues rather than value-added, which makes it susceptible to the costs of intermediate inputs that can vary substantially across industries. We address this concern in two ways. First, we follow the standard approach of conducting our analyses within industry-years (see Haltiwanger et al. (2016) and Bloom et al. (2012)). Second, we perform robustness checks by reconstructing labor productivity using value-added for publicly traded firms using the Compustat data and find very similar results.

LEHD Data The LEHD program integrates administrative worker records from state unemployment insurance (UI) agencies with existing Census data to produce a matched dataset at the worker-firm-quarter level. The dataset includes workers' place of birth, employer identifier, quarterly earnings, age, education, and other characteristics. Our sample includes LEHD data from 29 states, including population centers such as California and Texas, which together account for roughly 80% of U.S. authorized employment.[13] States start sharing data

[11] Our results are robust when labor productivity is alternatively defined as revenue divided by the average employment at both the beginning and end of the year (see Table IA.3).

[12] Foster et al. (2001) and Foster et al. (2008) report a correlation of about 0.6 between TFP and revenue per worker across firms within industries in the manufacturing sector. In the calibrated model of Decker et al. (2020), the correlation between TFP and revenue labor productivity is 0.90. See Haltiwanger et al. (2016) for further discussion of this measure.

[13] The states that approved our research to use their data from the LEHD database include: Arizona, California, Colorado, Connecticut, Delaware, Indiana, Kansas, Maine, Maryland, Massachusetts, Montana, Nebraska, Nevada, New Jersey, New Mexico, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, South

with the Census LEHD program at different times (see LEHD documentation). We use data from 1995 to 2021, with 1995 being the year when data from most large states, such as Texas, became available in our sample.

We classify employees as **immigrants** if their place of birth is outside the United States, following the standard definition in the literature (e.g., Kerr et al. (2015)). The place of birth variable includes 21 countries with significant immigrant populations in the U.S. and combines other countries into broader regions such as South America, the Middle East, Southeast Asia, etc. For simplicity, we refer to the 33 countries and regions as "countries" throughout our study.[14] We refer to immigrant workers and foreign-born workers interchangeably throughout our study, while noting that all individuals in our LEHD data are authorized immigrant workers eligible to receive UI benefits.

We merge worker-level information from the LEHD database with firm-level data from the LBD.[15] This allows us to calculate each firm's share of immigrant workers from each country and its labor exposure to foreign geopolitical risk, as detailed in Section 1.2. We also compute firm-level worker average age and educational attainment. Additionally, in Section 3, we calculate annual wage growth for both immigrant and domestic workers using this data.

ATUS Data We obtain information on individuals' intraday time-use and characteristics from the American Time Use Survey (ATUS). The ATUS records detailed diaries of participants' time-use on a comprehensive and granular set of activities on the survey date for approximately 26,400 respondents each year starting from 2003.[16] Following Aguiar et al. (2013), we classify the granular activities into five major categories: work time, job search, home production, leisure, and others. Because the ATUS draws its sample from subjects who have completed the Current Population Survey (CPS), we also obtain information on the country of birth, which allows us to identify whether the subject is an immigrant, and various other characteristics of the surveyed individuals from the CPS.

Geopolitical Risk Data We obtain country-specific geopolitical risk (GPR) data from Caldara and Iacoviello (2022) and Caldara et al. (2024), who provide newspaper-based measures of GPR for 44 advanced and emerging countries for each month from January 1985 to

Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, Washington, Wisconsin, and Wyoming.

[14] A full list of countries and regions can be found in the LEHD codebook.

[15] Firms in the LEHD dataset are identified by State Employer Identification Numbers (SEIN), and we use an internal Census crosswalk to match these to firm identifiers (FIRMID) in the LBD.

[16] Only one individual per household is sampled. Respondents in the sample, via a telephone survey, complete a detailed time diary of their previous day. The BLS staff then aggregates the survey responses into time-use categories. See a more detailed description of the data from Aguiar et al. (2013).

June 2023.[17] Caldara and Iacoviello (2022) define geopolitical risk as *the threat, realization, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political actors that affect the peaceful course of international relations.* They construct the "recent version" of the country-specific GPR measures by counting the share of articles in ten major Western newspapers from primarily the U.S., but also the United Kingdom and Canada, that mention both GPR-related keywords – such as those related to wars, terrorism, military buildups, and nuclear threats – and the name of the country or its main city (see Caldara and Iacoviello (2022) for more details). These country-specific GPR measures reflect how mainstream media perceive and portray geopolitical risks associated with each respective country for people living in the Western world.

Other Data We also collect individuals' LinkedIn profile information from Revelio Labs to measure immigrants' return migration activities following Amanzadeh et al. (2024) and country-level remittance amount and total number of immigrants from the World Bank Group's World Development Indicators database. We use the Compustat database to obtain financial and accounting information for our analyses on publicly traded firms. We discuss these datasets in subsequent sections when describing the corresponding tests.

1.2 Measuring Firms' Labor Exposure to Foreign Geopolitical Risk

To measure a U.S. firm's labor exposure to foreign geopolitical risk, we start by standardizing the country-month-level geopolitical risk (GPR) measure within each country. Caldara and Iacoviello (2022) demonstrate that the within-country standardized GPR measure strongly predicts tail risk in the country, i.e., the occurrence of economic disasters (Nakamura et al. (2013)).[18] To avoid look-ahead bias, we standardize each country's GPR for each month by comparing it with its 120-month trailing history. Specifically, we pool the GPR of country c in month m with the country's past 120 months of observations, $GPR_{c,m-1}$, ..., $GPR_{c,m-120}$, and compute the mean ($\mu_{c,m}$) and standard deviation ($\sigma_{c,m}$) of the 121 observations. Then, we compute the standardized GPR of country c in month m as $(GPR_{c,m} - \mu_{c,m})/\sigma_{c,m}$.[19] Intuitively, this standardized measure reflects how unusually prominent the country's GPR is discussed in the Western media in a given month relative to its past history. The end result is a panel of standardized GPR representing the GPR shocks for 44 countries, including the U.S., for each month starting in January 1995.

[17] We obtain the data at https://www.matteoiacoviello.com/gpr_country.htm [accessed in July 2023].

[18] This ex post prediction is consistent with novel findings by Hirshleifer et al. (2025) and Hirshleifer et al. (2023b) that war discourse in the media captures investors' perception of rare disaster risk in asset pricing.

[19] This standardization procedure is commonly used for the analyses of news tests in the literature, see, e.g., Hanley and Hoberg (2019), Bybee et al. (2024), and Chen et al. (2024).

To validate that our standardized GPR measure captures "unexpected" geopolitical shocks in a foreign country, we examine the association between our measure and unexpected shocks to geopolitical disasters and natural disasters from Baker et al. (2024). Baker et al. (2024) identify a sparse set of disaster events that are unexpected by the media and count the number of such events in a country within a quarter.[20] Table IA.1 shows that our standardized GPR significantly correlates with these sparse exogenous geopolitical events, such as terrorist attacks, political coups, revolutions, and war, in foreign countries at both quarterly and yearly levels. As a placebo test, we observe that the standardized GPR is not associated with the occurrences of unexpected natural disasters in a foreign country. These results bolster our confidence that standardizing the GPR measure helps to capture exogenous geopolitical shocks in a foreign country.

After validating our country-level GPR shock measure, we construct each U.S. firm's "labor exposure to foreign geopolitical risk" in a shift-share style. First, we average the monthly standardized GPR within each year, which yields our country-year-level GPR shock measure ($GPR_{c,t}$). Next, from the LEHD data described in Section 1.1, we obtain each firm's share of foreign-born employees from each foreign country based on their place of birth ($Share_{f,c,t-1}$). Finally, we match the country-year-level GPR shocks with the place of birth in the LEHD data, which includes both countries and broader regions. We match individual countries to the LEHD data whenever possible and assign the remaining GPR countries to the corresponding regions in the LEHD data.[21] This procedure leads to yearly GPR shocks for the U.S. and 22 foreign countries or regions, which we call countries in the rest of this article for simplicity.

For firm f in year t, we construct its **labor exposure to foreign geopolitical risk (FGPR)** as:

$$FGPR_{f,t} = \sum_{c \in \text{non-U.S.}} Share_{f,c,t-1} \times GPR_{c,t}, \tag{1}$$

[20] Baker et al. (2024) obtain terrorist attacks and political shocks, including successful assassination attempts, coups, revolutions, and wars, for fifty-nine countries from the Center for Systemic Peace database. The authors then select exogenous shocks using a novel methodology based on whether media mentions jump in the 15 days following the event, relative to the 15 days before the event. They construct exogenous shocks to natural disasters by applying the same procedure for natural disaster events obtained from the Center for Research on the Epidemiology of Disasters database. We obtain media-weighted intensity measures of the exogenous natural disaster events and geopolitical disaster events (including terrorist attacks, political coups, and revolutions) for each country-quarter from Nicholas Bloom's website.

[21] This process matches the 44 GPR countries to 23 out of the 33 LEHD places of birth, which covers approximately 80% of workers observed in the LBD data. In our main analysis, we exclude immigrant workers from the unmatched countries before we compute firm-level measures. Nevertheless, our main results remain robust when we keep unmatched immigrants and bundle them with domestic workers when computing firm-level measures (see Table IA.3).

where $Share_{f,c,t-1}$ is the firm's proportion of immigrant workers from country c out of its total number of employees at the beginning of year t.

1.3 Summary Statistics

Our final firm-year-level LBD-LEHD sample includes U.S. firms with non-missing labor productivity in the next year and non-missing FGPR in the current year. In addition, to ensure that firms have enough immigrant labor exposure to foreign GPR, we require firms to have 100 or more employees from the LBD database. These sample filters result in about 1,039,000 firm-year observations from 1996 to 2017.[22] We winsorize all unbounded continuous variables at the 1% and 99% per year to mitigate the impact of outliers.

Panel A of Table 1 reports summary statistics for firms in our final sample. Our sample firms have about 636 employees on average and generate $164 million in revenue per year with large dispersion. Nearly all firms have some foreign-born workers, on average, despite only about 14.1% of firms' employees being foreign-born.[23] There is substantial variation in firms' FGPR in the cross-section and over time: a variance decomposition exercise shows that year fixed effects explain 28% of FGPR's variation, and firm fixed effects explain 20%. Combining firm fixed effects with industry-year fixed effects explains 46% of FGPR's variation in the sample, indicating substantial time-series variation related to firm-specific immigrant employment-weighted GPR shocks. On average, firms' labor productivity is $247,600 per employee in 2018 U.S. dollars. Finally, approximately 40% of firms in the sample engage in importing or exporting activities.

2. Impact of FGPR on Firm Labor Productivity

This section presents our main findings of a robust causal effect showing that labor exposure to foreign geopolitical risk (FGPR) increases U.S. firms' labor productivity.

[22] 1996 is the first year the FGPR measure, which uses the previous year's LEHD information, is available, and 2017 is the last year when the labor productivity measure, which uses next year's LBD revenues, is available.

[23] This firm-level average is closely comparable to the 13.6% nationally representative immigrant share among the U.S. population that we estimate from the publicly available American Community Survey.

2.1 Empirical Design

The variation in our firm-level FGPR measure constructed in equation (1) resembles that of a shift-share (or Bartik (1991)) instrument. The time-series variation of FGPR derives largely from the heterogeneous arrival of foreign countries' GPR shocks. The cross-sectional variation stems from differences in firms' immigrant employment structure at the beginning of year t. This variation arises from two sources: the differential concentration of the firm's immigrant employees versus domestic employees and the composition of immigrant employees from high-GPR shock countries. Differences in immigrant employment shares are not the primary source of variation: in untabulated tests, the firm's beginning-of-year immigrant employment share, $FLabor_{f,t-1} = \sum_{c \in \text{non-U.S.}} Share_{f,c,t-1}$, explains little variation in FGPR in a bivariate regression. Moreover, we follow the prescriptions of Borusyak et al. (2025) and include controls for $FLabor_{f,t-1}$ interacted with year dummies to account for the impact of incomplete shares in our measurement.[24]

Equipped with this measure, we examine how firms' FGPR affects their future labor productivity using the following regression specification:

$$LProd_{f,t+1} = \beta \cdot FGPR_{f,t} + \sum_{\tau=1996}^{2017} \theta_\tau \cdot [FLabor_{f,t-1} \times \mathbb{1}(t = \tau)] + X_{f,t} + \phi_f + \mu_{i,t} + \epsilon_{f,t+1}, \tag{2}$$

where $LProd_{f,t+1}$ is the firm's labor productivity next year; $FGPR_{f,t}$ is the firm's labor exposure to foreign geopolitical risk defined in equation (1); $FLabor_{f,t-1}$ is the firm's beginning-of-year immigrant employment share; $X_{f,t}$ is a set of time-varying firm characteristics, including firm employment size in logarithm, firm age in logarithm, average worker age, and average worker education as the percentage of workers with college degrees or above (Haltiwanger et al. (1999)); ϕ_f is the firm fixed effects; and $\mu_{i,t}$ is the industry-year fixed effects to ensure the comparison of labor productivity is within industry (Haltiwanger et al. (2016)), where industry is classified at the 3-digit NAICS level. We cluster standard errors at the firm level.

2.2 Main Findings

Table 2 reports our main results. Column (1) shows that firms' labor exposure to foreign GPR shocks significantly boosts labor productivity within an industry-year and without any firm controls. A one-standard-deviation increase in FGPR increases average annual labor

[24] The discussion by Borusyak et al. (2025) recommends controlling for the sum of shares over renormalizing the incomplete shares to add up to one. See also the discussions by Autor et al. (2013) and Borusyak et al. (2022).

productivity by \$7,112 per worker, or 3% relative to the sample mean. Column (2) shows that our finding remains highly robust after controlling for firm fixed effects. This is an important result, as persistent differences between firms play a significant role in driving firm productivity in the cross-section (Syverson (2011)), which can substantially alter the explanatory power and direction of well-known determinants of firm productivity in the cross-section (Dhawan (2001)). Column (3) further controls for time-varying firm characteristics, including firm size and firm age, on top of firm fixed effects.[25] Column (4) controls for firms' average worker characteristics, including workers' age and education, that have also been shown to affect firm labor productivity (Haltiwanger et al. (1999)). Column (5) includes all controls. Across all specifications, we observe that FGPR statistically significantly boosts firm labor productivity at the 1% level.

The economic magnitude is attenuated after we control for firm fixed effects. Using our most stringent estimate in Column (5), a one-standard-deviation increase in FGPR increases average annual labor productivity by \$1,037 per worker, corresponding to an increase of \$0.66 million in revenues for a firm with the average employment size.[26]

These main findings are highly robust in the data. First, our findings are driven by *increases* in foreign geopolitical tension. In Table IA.2, we decompose FGPR into the firm's labor exposure to *positive* standardized foreign GPR shocks and *negative* ones, respectively, in equation (1).[27] We observe that the effects are predominantly driven by firms' labor productivity rising when their immigrant labor's origin countries experience increased geopolitical tensions. This finding suggests that we can interpret our results through the lens of firm responses to the arrival of geopolitical events discussed in the literature (e.g., Baker et al. (2024)).

Second, our findings are robust to controlling for the effects of U.S. GPR on firms with varying immigrant compositions. We note that our specification in equation (2) already controls for the interactions between firms' FLabor and year dummies that account for the heterogeneous effects of domestic GPR shocks, such as the 9/11 attack in 2001, on U.S. firms with varying shares of immigrant workers. It may still be possible that U.S. GPR

[25] We caution against a direct comparison of the coefficients on firm size and age in this table with the effects documented in prior literature (e.g., Foster et al. (2001), Haltiwanger et al. (1999), Haltiwanger et al. (2016)), which focuses on explaining firm productivity in the cross-section and does not control for firm fixed effects. For instance, Dhawan (2001) highlights that the association between firm size and firm productivity can switch signs from positive to negative once firm fixed effects are controlled for, consistent with that found in Krishnan et al. (2015), which controls for both firm and year fixed effects.

[26] A one-standard-deviation shock to FGPR (12.11 from Table 1) increases average annual labor productivity by \$1,037 $= (12.11 \times 0.0856 \times 1,000)$ per worker. For a firm with an average size (635.5 employees from Table 1), this magnitude corresponds to \$0.66 $= \$1,037 \times 635.5/1,000,000$ million in additional revenues.

[27] That is, we replace the country-year $GPR_{c,t}$ with $\max(GPR_{c,t}, 0)$ when constructing the positive FGPR and $\min(GPR_{c,t}, 0)$ when constructing the negative FGPR in equation (1).

has heterogeneous associations with GPR across different foreign countries and thus affects U.S. firms through the composition of their immigrant labor beyond the total foreign-born share. We mitigate this concern by constructing an alternative FGPR based on foreign countries' GPR that are each orthogonalized to U.S. GPR via a country-specific time-series regression.[28] Table IA.3 again shows that this alternative FGPR significantly boosts U.S. firms' labor productivity.

Third, our findings are also not driven by U.S. firms' engagement in international trade, as Table 3 shows our main findings remain among firms without any import or export activities. Specifically, we run our baseline specification in equation (2) while further controlling for the interaction between FGPR and firms' time-varying trade status indicators (importer, exporter, or import-exporter). The coefficient on the standalone FGPR term indicates that FGPR consistently and strongly boosts firm labor productivity among firms that do not engage in international trade. The interaction term between FGPR and the trade indicators is negative but not statistically significant.

Fourth, our findings are robust to additional alternative ways of constructing our key measures as reported in Table IA.3, such as reconstructing a firm's labor productivity using the average of the firm's employment at the beginning and end of the year as the denominator (instead of using the beginning-of-year employment), reconstructing a firm's FGPR using geopolitical acts or geopolitical threats to measure a foreign country's GPR, and alternatively measuring a firm's labor productivity using value-added instead of revenue based on Compustat data for publicly traded firms.

2.3 Identification Checks

Our identification relies on the assumption that a firm's labor productivity would not have followed the documented trajectory had the shocks to its labor-exposed foreign countries' geopolitical risk not occurred. Below, we examine this identifying assumption through several tests.

Parallel pre-trends Figure 1 plots the empirical impulse responses of firms' labor productivity to the FGPR using local projection. In particular, we examine the regression

[28] Specifically, in each month t, we regress a country c's raw GPR measure from Caldara and Iacoviello (2022) on the U.S. GPR measure over the past 120 months (including the current month) to obtain the constant ($\alpha_{c,t}$) and loading of the country's GPR on U.S. GPR ($\beta_{c,t}$). Then, we compute the orthogonalized GPR for country c in month t as the raw GPR subtracted by $\alpha_{c,t}$ and $\beta_{c,t}$ times the U.S. GPR in month t. We then use this orthogonalized GPR instead of raw GPR for the country to compute the alternative FGPR measure for firms following the procedure described in Section 1.2.

specification in equation (2) but replace the dependent variable with firms' labor productivity from year $t-2$ to $t+3$, one at a time. From the figure, we do not observe a significant effect of FGPR on firm labor productivity during the pre-period in $t-2$ and $t-1$, suggesting that firms with high and low FGPR are unlikely to be on different trajectories prior to the foreign GPR shocks. In contrast, firm labor productivity becomes boosted by FGPR from t, and this effect is substantially elevated during $t+1$ and $t+2$ and diminishes at $t+3$.

Properties of foreign GPR shocks and firm exposures Our firm-level FGPR is an employment-weighted average of foreign countries' GPR shocks, as defined in a shift-share style in equation (1). Borusyak et al. (2022) emphasize that the causal effect of a shift-share measure is achieved if the underlying shocks are "*as-good-as-randomly assigned, mutually uncorrelated, large in number, and sufficiently dispersed in terms of their average exposure.*"

We examine how the country-level GPR shocks in our study meet this identifying assumption following the suggested tests by Borusyak et al. (2022). We summarize our findings below and relegate more details to the Internet Appendix IA.1. First, while foreign country GPR shocks do not arrive randomly, we have shown in Section 1.1 that our GPR shock measure can capture the sparse geopolitical disaster events across foreign countries and years, carefully identified by Baker et al. (2024). In Tables IA.4 and IA.5, we follow Borusyak et al. (2022) and further show that our GPR shocks are unrelated to the confounding factors of U.S. immigrant workers born in that country. Second, foreign countries' GPR shocks also exhibit very low correlations, suggesting that they are mutually uncorrelated with each other. Third, foreign countries' average exposures in our firm-year sample, $s_{c,t} = avg(Share_{f,c,t-1})$, also exhibit a low Herfindahl–Hirschman index (HHI) across country and year, suggesting that the effect of FGPR derives from dispersed shocks from a broad set of foreign countries.

Firms' anticipatory decisions It is unlikely that U.S. firms can endogenously dictate foreign countries' GPR shocks to systematically generate our main finding on firm labor productivity. One remaining concern could be that U.S. firms' choice of immigrant workers at $t-1$, which determines their FGPR at t, may be endogenously affected by their anticipation of foreign GPR shocks at t and their expectation of future labor productivity at $t+1$, raising reverse-causality concerns about our main finding. The data suggest that this concern is unlikely to drive our results, as firms' composition of immigrant workers is rather sticky. In Table IA.3, we construct an alternative FGPR measure by lagging firms' immigrant labor exposure to each foreign country further to $t-3$, instead of $t-1$ as in the baseline measure, while keeping the country-level GPR shocks at t. By further lagging the firms' labor exposures, this alternative FGPR measure is less subject to the concern of firms' endogenous

labor choice in anticipation of far-future labor productivity and foreign GPR shocks. While further lagging the exposures tends to introduce measurement errors in the alternative FGPR measure, this measure still positively predicts firm labor productivity at $t+1$.

2.4 Extensive vs. Intensive Margins

Given that labor productivity is a ratio between firms' revenues and lagged employment, our main findings can be open to two distinct interpretations. First, FGPR boosts existing workers' productivity in exposed firms, i.e., through impacting the intensive margin. Second, FGPR causes exposed firms to reduce employment, which can artificially boost the labor productivity measure if revenues adjust slowly, i.e., through impacting the extensive margin. Below, we conduct tests on these two interpretations, which strongly support the intensive-margin interpretation.

2.4.1 Revenue or employment?

Table 4 shows the effect of FGPR on firms' revenues at $t+1$ (the numerator) and employment at t (the denominator) separately, using the specification in equation (2). Column (1) shows that FGPR substantially increases firms' revenues; in contrast, Column (3) shows that FGPR does not affect firms' employment. This is consistent with the intensive-margin interpretation that FGPR boosts workers' productivity but is not consistent with the extensive-margin inference, which predicts that FGPR reduces firm employment. Reinforcing this inference, Columns (2) and (4) show similar findings when inspecting changes in revenue and changes in employment, instead of levels.

2.4.2 Interacting with labor turnover

An advantage of our employee-employer matched LEHD data is that we can measure a firm's labor turnover, which is a prerequisite for the extensive-margin interpretation. We construct a measure of firms' labor turnover as the sum of the number of new hires and the number of separations in the firm divided by the firm's beginning-of-year total employment.[29]

In Column (5) of Table 4, we expand our main specification on labor productivity in equation (2) by including the interaction between firms' FGPR and labor turnover. As a

[29]The results are very similar if we construct the turnover measure using the average of firms' employment at the beginning and end of the year as the denominator. We caveat that our labor turnover measure derives from the LEHD data, which does not necessarily capture all the business establishments of a firm in the LBD data (see discussions on mapping the LEHD firms with the LBD firms in Section 1).

result, the coefficient of the standalone FGPR bears a conditional interpretation, reflecting FGPR's impact on firms without labor turnover within the treatment year. Again, we observe that FGPR strongly boosts firm labor productivity even in the absence of labor turnover. This finding goes against the extensive-margin interpretation and reinforces the intensive-margin interpretation.

2.5 Do U.S. Firms Benefit from FGPR?

Our analyses so far demonstrate that foreign geopolitical risk can positively affect U.S. firms' labor productivity through their immigrant labor exposure. Below, we further examine whether this labor productivity effect translates to actual benefits to U.S. firms in terms of profitability and growth.

Our first test focuses on the firms in the Census LBD sample and asks whether FGPR benefits U.S. firms after accounting for labor expenses. To do so, we measure a firm's **surplus per worker** as its revenues minus total labor pay from the LBD and normalized by its employment at the beginning of the period. We then examine the response of a firm's surplus per worker next year to FGPR using the same specification as equation (2). Column (1) of Table 5 shows that a firm's labor exposure to foreign geopolitical risk significantly boosts its surplus per worker. This finding suggests that the increased firm labor productivity in response to FGPR is not fully appropriated by employees, leaving some benefits for the firms.

Our second test complements the LBD firm-level results by using the LBD-Compustat-merged sample, where we can directly measure a publicly traded firm's profitability and capital investment. We measure a firm's profitability as gross profits normalized by total assets at the beginning of the year, following the standard accounting approach (Novy-Marx (2013)). We measure a firm's investment as capital expenditures divided by total physical assets at the beginning of the year. Column (2) of Table 5 shows that FGPR similarly boosts a firm's profitability, and Column (3) shows that firms also invest more in capital in response to FGPR. Taken together, these results suggest that U.S. firms actually benefit from their labor exposure to foreign geopolitical risk. This positive effect indicates that our labor-based channel is novel and distinct from those studied in the literature, which overwhelmingly documents the negative impact of geopolitical risk on exposed firms.

In summary, our analyses in this section demonstrate a robust causal effect showing that foreign geopolitical risk can positively affect U.S. firms' labor productivity through firms' immigrant labor exposure. In the next section, we examine the mechanism by focusing on immigrants' work responses to their origin countries' geopolitical risk.

3. Mechanism: Evidence from Worker Level

Our firm-level evidence highlights that when a firm's immigrant workers' origin countries experience increased geopolitical risk, the firm's output per employee rises. This effect appears causal and is not driven by firms' international-trade exposure or their labor turnover. Do immigrant workers produce more output when their origin countries' GPR is higher? How do their domestic coworkers respond to FGPR? In this section, we examine the responses of individual workers to shed light on the underlying mechanism.

3.1 Evidence from Immigrant Labor Supply

The increase in firms' labor productivity can be driven by increased labor supply or increased worker productivity per hour. We examine how origin-country GPR affects immigrants' supply of working hours using the ATUS data. Examining the impact on worker productivity per hour is challenging due to data limitations. We instead indirectly infer the worker productivity channel through several pieces of individual-level results.

3.1.1 Evidence from Immigrants' Time Use

To the best of our knowledge, the impact of origin-country GPR on a U.S. immigrant's work activity is not well-understood in the literature. We provide the first evidence by examining how immigrants' intraday time spent on work and non-work activities is affected by their origin country's GPR shocks using the American Time Use Survey (ATUS) data.

The ATUS data provides each surveyed individual's intraday time spent on many detailed activities. Following Aguiar et al. (2013), we group the activities into five broader categories, including work, job search, home production, leisure, and other activities. We map individuals' place of birth to the country-year-level geopolitical shocks constructed based on Caldara and Iacoviello (2022) (see Section 1), resulting in a set of immigrants originating from 42 foreign countries.[30] Finally, we require individual immigrants to be between 25 and 65 years old, where 25 corresponds to roughly the average age when an immigrant arrives in the U.S.[31] Our final sample comprises 15,768 immigrants' time use from 2003 to 2019, where the time-use measures are expressed in hours per week (Jiang et al. (2025)) and winsorized

[30]The country-level GPR data from Caldara and Iacoviello (2022) covers the U.S. and 43 foreign countries. We do not observe individuals born in Tunisia in the ATUS data.

[31]E.g., the 2000 U.S. Census reports that the average age of immigrants upon arrival in the U.S. is 25, which has increased a bit in recent years as reflected in the American Community Survey (ACS) data.

at the 1% and 99% thresholds each year to mitigate survey reporting errors. We use the survey-provided weights for individuals to ensure national representativeness of all statistics.

Panel C of Table 1 reports that immigrants in our sample spend, on average, 31.6 hours working in a week, which includes working on their main job, time spent on activities related to their main jobs such as commuting or work meals, and other income-generating activities. In comparison, they spend 104.4 hours per week on leisure on average, which includes sleeping, eating and personal care, socializing, watching TV, and other leisure activities.

We examine how immigrant j's time use on activity k, $T(k)_{j,c,t}$, responds to her origin country's GPR shock by estimating the following regression:

$$T(k)_{j,c,t} = \beta \cdot GPR_{c,t} + X_{j,c,t} + \nu_c + \mu_t + \epsilon_{j,c,t}, \tag{3}$$

where $GPR_{c,t}$ is the standardized GPR constructed in Section 1.2 representing the country's GPR shock relative to its prior ten years' benchmark, $X_{j,t}$ includes a battery of individual demographic indicators for age groups, education groups, race, gender, marital status, and parental status following Aguiar et al. (2013), and ν_c and μ_t are country and year fixed effects, respectively. We weight each observation by the survey-provided weights and cluster standard errors by country.

Table 6 reports the coefficient β for each time use category. We observe that immigrants allocate significantly more time to work and reduce the time spent on leisure when their origin country's GPR is higher. A one-standard-deviation increase in origin-country GPR relative to the country's past ten-year GPR results in immigrants spending 1.6 hours per week more on work, at the expense of reduced leisure by 1.2 hours per week.

In addition, zooming in on work activities, we observe that the positive effects on work time stem entirely from immigrants spending more time on their "main jobs." In fact, the effect of origin country GPR is negative on immigrants' other work-related activities, such as commuting to work, work meals, or other income-generating activities outside the main job. These results suggest that the effect is unlikely to be due to immigrants prolonging peripheral work hours but is consistent with them focusing more and exerting greater effort during their core hours in their main jobs. In comparison, the effect on reduced leisure time is observed across all sub-categories, including sleeping, eating and personal care, watching TV, socializing, and others, with the effect on socializing being statistically significant. Taken together, these results suggest that when origin countries' GPR rises, immigrants allocate more time and likely more efforts to working on their main jobs at the expense of their leisure time, providing a greater labor supply.

The finding is robust to additional checks as reported in Table IA.7. First, similar to

our firm-level findings, the responses are mostly concentrated on the *increases* in origin countries' GPR, as shown in Columns (2) and (3). Second, our results are robust when we further remove the association between a foreign country's GPR and the U.S. GPR by adopting an orthogonalized foreign-country GPR measure, as shown in Column (4).[32]

The effects are also likely to reflect their *responses* to their origin countries' GPR. First, Figure 2 plots the empirical impulse response of time-use on main jobs in each year from $t-2$ to $t+3$ based on local projection. We observe no pre-trend but strong positive responses at t and $t+1$. This pattern is consistent with the impulse responses of firms' labor productivity in Section 2.2, which are most pronounced at $t+1$ and $t+2$, as it may take up to one period for labor input to be reflected in the output.

Second, we opt for an alternative measure of unexpected geopolitical disaster events in foreign countries from Baker et al. (2024). Baker et al. (2024) identify geopolitical and natural disaster events that are truly unexpected by the public media. Different from our country-level GPR shocks, geopolitical disaster events identified by Baker et al. (2024) are limited to terrorist attacks, political coups, and revolutions, e.g., without covering wars, and they are sparse, with only 3% of immigrants in our ATUS sample having non-zero events at their origin country throughout the year. Nonetheless, Column (5) of Table IA.7 shows similar results that immigrants spend more hours working on their main jobs when their origin countries experience greater geopolitical disaster events.[33] In a placebo test, we do not find similar results when we replace the geopolitical disaster events with natural disaster events, as shown in Column (6).

We note that this effect is not obviously expected a priori. In particular, one could expect the opposite effect, as the mental stress imposed by geopolitical tensions in their origin countries may increase immigrants' disutility of working and reduce their equilibrium labor supply.[34] In Section 4, we conduct additional analyses to further shed light on the positive response of immigrants' labor supply to their origin countries' GPR.

One limitation is that the ATUS data is cross-sectional, which prevents us from examining the time-use responses within a person. As a result, we cannot fully rule out the selection issue of immigrants participating in the survey. Nonetheless, we believe our tests controlling for country, time, a battery of demographic fixed effects, and weighting observations based on the survey weights likely mitigate this concern. Another limitation is that the ATUS data

[32] Section 2.2 details the orthogonalization procedure.

[33] Data of country-quarter geopolitical events are downloaded from Nicholas Bloom's website at https://nbloom.people.stanford.edu/research. We thank the authors for making their data publicly available. From the data, we construct each year's media-weighted number of geopolitical events.

[34] Immigrants may also spend more time following the news about the tensions in their origin countries and engaging in social and political mobilizations in the U.S.

does not provide information on employers. Hence, we cannot directly link these findings to the firm-level results. To overcome this limitation, in the next subsection, we examine the subsequent earnings growth of individual immigrants in our sample firms based on LEHD employee-employer-matched panel data.

3.1.2 Evidence from Immigrants' Earnings

Given that immigrants spend more time on their main jobs in response to their origin countries' GPR, we conjecture that their earnings grow more accordingly.

We measure immigrant workers' year-to-year growth in total annual earnings from their main jobs using the LEHD individual-level panel data constructed in Section 1.1 (Guvenen et al. (2021)).[35] This massive panel dataset also allows us to control for additional fixed effects and firm characteristics. Specifically, we estimate the following individual-level regression:

$$EarningGrowth_{j,c,f,t+1} = \beta \cdot GPR_{c,t} + X_{j,t+1} + X_{f,t+1} + \nu_j + \phi_f + \mu_{i,t} + \epsilon_{j,c,f,t+1}, \qquad (4)$$

where the worker fixed effects ν_j control for time-invariant worker characteristics, which subsume the workers' education, race, and gender in the data, $X_{j,t+1}$ controls for time-varying worker characteristics including age, the firm fixed effects ϕ_f control for time-invariant firm characteristics, $X_{f,t+1}$ controls for firms' time-varying characteristics as in Section 2.2, and industry-year fixed effects $\mu_{i,t}$ control for time trends for each industry. Standard errors are double-clustered by country and year.

Our sample includes about 71 million observations of immigrant workers employed in firms in our final sample from 1996 to 2017, aged between 25 and 65, with available earnings growth in the next year.[36] Panel B of Table 1 shows that the average earnings growth is about 3% per year.

Columns (1) to (3) in Table 7 show a significant positive effect of origin-country GPR on immigrants' earnings growth next year, with and without including firm controls. A one-

[35] Guvenen et al. (2021) highlight that workers' earning growth is highly non-normal, exhibiting state-dependent skewness and kurtosis. In our measurement, we aggregate immigrants' earnings across quarters to form their annual earnings. The annual growth rate is the immigrant's annual earnings next year divided by the annual earnings this year minus 1. According to the BLS, who collects the underlying Unemployment Insurance-based records, LEHD wages include "*...all compensation received by an employee, including salaries, hourly pay, piecework pay, bonuses, commissions, vacation and sick leave pay, severance pay, the cash value of meals and lodging, and tips and other gratuities.*" See, https://www.bls.gov/wrp/technical-notes.htm. Following standard Census procedures (see the documentation at https://lehd.ces.census.gov/doc), we assign a main job to each worker-quarter when constructing wages and wage growth. We treat the firm at the beginning of the year as the individual's employer.

[36] Following the literature (Lopresti and Mumford (2016)), we also exclude observations with earnings growth exceeding 1000% to rule out outliers.

standard-deviation increase in origin-country GPR relative to its prior ten years' benchmark corresponds to a 0.43% increase in immigrants' earnings growth. To further connect immigrants' labor supply with their current firms' changes in labor productivity, we present results on "job stayers" who remain in the same firm from t to $t+1$. In Columns (4) to (6), we again observe that the stayer immigrants' experience similarly increased growth in earnings when their origin countries' GPR rises.

Taken together, these results show cohesive evidence that immigrants provide greater labor supply when their origin countries' GPR is higher, contributing to the greater output-per-worker of their employed firms. Two questions remain: First, why do immigrants provide a greater labor supply when their origin countries' GPR is higher? Second, a firm's average output-per-employee derives from both its immigrant workers and domestic workers. How does domestic workers' labor supply respond to FGPR? Answering this question is more involved, which we leave for the next section. Below, we provide evidence on the second question.

3.2 Response of Domestic Workers to Firm FGPR

We examine domestic workers' labor supply through their total earnings growth.[37] To do so, we construct a sample of about 484.4 million worker-year observations of domestic and immigrant workers employed in firms in our final sample from 1996 to 2017 from the LEHD data using the same filters as in Section 3.1.2 above. Using this sample, we test domestic and immigrant workers' labor supply in response to their firms' FGPR through the following specification:

$$\begin{aligned} EarningGrowth_{j,f,t+1} =& \beta \cdot FGPR_{f,t} + \gamma \cdot FGPR_{f,t} \times Immigrant_j \\ &+ \sum_{\tau=1996}^{2017} \theta_\tau \cdot [FLabor_{f,t-1} \times \mathbb{1}(t=\tau)] \\ &+ \sum_{\tau=1996}^{2017} \zeta_\tau \cdot [FLabor_{f,t-1} \times \mathbb{1}(t=\tau) \times Immigrant_j] \\ &+ X_{j,t+1} + X_{f,t+1} + \nu_j + \phi_f + \mu_{i,t} + \epsilon_{j,f,t+1}, \end{aligned} \tag{5}$$

where descriptions of each variable can be found in equations (2) and (4). We focus on the coefficient β, which represents the response of domestic workers' earnings growth to their firms' FGPR, and γ, which represents the differential responses between immigrant and domestic workers to their firms' FGPR.

[37] Note that the ATUS data does not include individuals' employer information.

Table 8 reports the results. Column (1) shows a significantly positive estimate of β, suggesting that domestic workers' annual earnings grow by roughly $0.42\% = (12.11 \times 0.03431)$ in response to a one-standard-deviation increase in their firms' FGPR. This finding is consistent with Mas and Moretti (2009) and suggests that the productivity of a domestic worker can potentially depend on that of their immigrant co-workers. The estimate of γ suggests that the increase in labor supply is greater for immigrants than domestic workers, resulting in about 0.55% in response to a one-standard-deviation increase in their firms' FGPR. This discrepancy remains robust and shows an even greater coefficient if we further compare immigrant and domestic workers *within-firm-year*, as shown in Column (2). Finally, Columns (3) and (4) show that the results are similar if we focus on job stayers.

In summary, our results in this section suggest that immigrant workers provide substantially greater labor supply when their origin countries' GPR is higher. Domestic workers also appear to increase their labor supply in firms with higher FGPR, which can facilitate FGPR's substantial impact on firms' average output per employee, despite our sample firms on average having 14.12% of labor that is foreign-born.

4. Immigrant Labor Supply and Origin-Country GPR

A large body of literature suggests several important theoretical mechanisms that connect immigrants with their origin country. However, granular data that allows for systematically testing these mechanisms remains scarce. In this section, we explore the potential mechanisms that could contribute to our findings by combining several new data sets.

A rise in origin-country geopolitical tensions can influence existing immigrants' labor supply through at least two potential mechanisms. First, geopolitical tensions in origin countries may reduce the value of return migration, leading immigrants to exert more effort to ensure job security in the U.S. Second, geopolitical tensions can worsen economic and humanitarian conditions in the origin country, raising immigrants' remittance motives to financially support their family members and communities back home.

4.1 A Simple Framework for the Mechanisms

We consider a simple theoretical framework to motivate how origin-country GPR can affect immigrant labor supply via the three mechanisms. We note that our goal is not to tie each channel to deep parameters but rather to convey the plausibility of the mechanism. Our framework integrates job losses into a standard labor supply model (Shimer (2005) and

Topel and Ward (1984)): An immigrant worker in the U.S. who, at the beginning of each period, chooses working hours $h \geq 0$. The worker is paid a wage rate of w per hour, which brings utility from income uwh, where $u > 0$ represents a simple linear mapping from income to utility with $u = 1$ representing the standard model, and incurs a strictly increasing convex disutility of effort $v(h)$ (Borjas (2016) and Cahuc et al. (2014)). Her discount rate is β.

Following Shapiro and Stiglitz (1984), we model an immigrant's probability of retaining her U.S. job next period as strictly increasing in working hours, $0 < p(h) < 1$.[38] If the immigrant loses her job, she receives a permanent outside-option utility value V_U, representing her expected life quality of staying unemployed in the U.S. or returning to her origin country. Let V_E denote the value function associated with being employed in the U.S. The Bellman equation is thus:

$$V_E = \max_{h \geq 0} \{uwh - v(h) + \beta [p(h)V_E + (1 - p(h))V_U]\}. \tag{6}$$

Let h^* be the optimal choice of hours. The first-order condition (FOC) for h^* satisfies:

$$\frac{\partial V_E}{\partial h} = \frac{\partial}{\partial h} \left(\frac{uwh^* - v(h^*) + \beta(1 - p(h^*))V_U}{1 - \beta p(h^*)} \right) = 0. \tag{7}$$

We discuss how the three potential mechanisms discussed above can facilitate origin-country GPR to increase h^* in this setup and empirically examine each of them.

4.2 Return Migration

The return migration mechanism can be motivated through the immigrant's outside option value V_U in our framework. A strong theoretical grounding in the migration literature argues that return migration is a highly viable option when immigrants lose jobs in the hosting countries (see Dustmann (2003), Borjas and Bratsberg (1996), and Dustmann and Görlach (2016)), suggesting that the prospect of return migration is an important contributor to V_U for immigrants. In our framework, a decline in outside option value V_U strictly incentivizes the immigrant to provide greater working hours h^* for job retention, i.e., $\frac{\partial h^*}{\partial V_U} < 0$ (see proof in the Internet Appendix IA.2.1). Hence, a rise in the immigrant's origin country's GPR can potentially reduce her V_U through a declined return migration prospect and increase the immigrant's labor supply. The more sensitive an immigrant's return migration is to her origin

[38] We use hours worked as a proxy for worker effort, recognizing that individual workers' effort is typically unobserved in the data. This modeling choice is consistent with a large body of literature highlighting that observed hours and unobserved effort co-move in response to incentives: when the cost of job loss rises or monitoring tightens, workers increase attendance, overtime, and on-the-job intensity (Shapiro and Stiglitz (1984), Engellandt and Riphahn (2005), and Mas and Moretti (2009)).

country's GPR, the greater GPR can incentivize her labor supply. Below, we empirically examine this mechanism by exploring the heterogeneity in the sensitivity of return migration to origin country GPR across demographic groups.

Return migration is a highly relevant consideration for immigrants in practice. Amanzadeh et al. (2024) document that approximately 38% of immigrants worldwide return to their origin countries within ten years of initial migration. We likewise measure return migration events using LinkedIn individual profile data provided by Revelio Labs. Following Amanzadeh et al. (2024), we identify a person's country of origin by the location of her first school or first job. A return migration event is defined as an immigrant who has stayed for at least 3 years in the U.S. (to minimize the influence of seasonal migrants) and returns to her origin country to stay there for at least 1 year. Like before, we focus on U.S. immigrants aged 25 to 65, which results in about 7.73 million immigrant-year observations from 1997 to 2023.[39] To improve the national representativeness of our LinkedIn sample, we construct a weight for each individual by benchmarking her demographics to the immigrant distribution by country of origin, age, gender, and income in each year using survey weights from the Census ACS data.[40]

Table IA.10 provides a first-pass validation test that origin-country GPR indeed dampens return migration for an average immigrant living in the U.S. Columns (1)-(4) show that this effect is robust under both conditional logistic regressions and linear panel regressions, and after controlling for country fixed effects, year fixed effects, and a rich set of worker demographics, including age, gender, and income. Column (5) further shows that this effect remains even after controlling for individual fixed effects. This finding is consistent with Amanzadeh et al. (2024), who show that industry growth in workers' origin countries affects return migration.

We then examine the return migration mechanism for the labor supply effects in two steps. The **first step** estimates the heterogeneous sensitivities of return migration to origin country GPR across demographic groups. Specifically, we construct a set of 688 demographic bins $F_{c,age,gender,income}$ based on the full interaction of indicator variables for the 43 foreign countries with the GPR measure, four age brackets ($[25, 35]$, $(35, 45]$, $(45, 55]$, or $(55, 65]$), gender (male or female), and two income brackets (above or below the median salary cutoff

[39] To maintain the same underlying sample as our subsequent analysis, we also restrict this sample to so that there are least 10 observations within the 688 demographic bins $F_{c,age,gender,income}$ that individuals belong to, as described in equation (8)

[40] Specifically, we construct the survey weights using the "person weight" (ACS mnemonic: PERWT) variable in the ACS. In each year of an ACS wave, we sum up PERWT by country of origin (ACS mnemonic: BPLD), age (ACS mnemonic: AGE), gender (ACS mnemonic: SEX), and above or below median by year income (ACS mnemonic: INCWAG). Median income breakpoints are computed using LinkedIn earnings within our sample. We then merge these bin-level weights to the worker in the LinkedIn data assigned to the same demographic bins as used in Eq. (8).

each year).[41] We then estimate the sensitivity of return migration to origin country GPR for each demographic group using the following logistic regression[42] model,

$$RetMigrat_{j,k,t+1} = \sum_{k \in F(c,age,gender,income)} \mathbb{1}_{j,k} \times (\alpha_k + \beta_k \cdot GPR_{c,t}), \tag{8}$$

where each immigrant j in the Revelio Labs sample belongs to a group k of the 688 demographic bins and is weighted for national representativeness using ACS survey weights. β_k estimates the return migration to origin country GPR shock sensitivity for immigrant bin k.

To overcome the high dimensionality of this model and to avoid spurious overfitting, we adopt the elastic net machine learning technique (Tibshirani (1996) and Zou and Hastie (2005)), which compromises between LASSO (L^1-norm) and ridge (L^2-norm) regression. The former helps to select variables, while the latter shrinks coefficients towards each other. This combination in the elastic net helps to account for the potentially complicated correlations among the 688 demographic groups.[43] These procedures optimally select the LASSO model without shrinkage, and produce 411 non-zero estimates of β_k, 275 estimates optimally set to zero due to the LASSO penalty, and 2 missing estimates due to a lack of sufficient data (we require at least 10 observations per bin).

Figures 3 report heatmaps summarizing the resulting sensitivity estimates for the demographics bins across country, age, and income, averaging male between female. We observe that the vast majority of the groups have negative β_k, highlighting that the negative impact of origin-country GPR on return migration is a pervasive phenomenon across the demographic backgrounds of immigrants in the U.S. There is also rich heterogeneity across demographic groups uncaptured by linear comparisons via a single demographic variable. For ease of interpretation, we define the sensitivity of group k's return migration sensitivity to GPR as $\epsilon_k^{RetMigrat} = -\beta_k$, so that a higher value of sensitivity represents a more negative impact of origin-country GPR on return migration.

Our **second step** embeds these heterogeneous sensitivities in the following regression to examine how demographic groups with highly negative return migration-GPR sensitivity

[41] We select these immigrant characteristics because they are common to our LinkedIn, ATUS, and Census LEHD samples, which facilitates studying the role of these sensitivities across different settings.

[42] Note, our logistic regression model with fixed effect bins does not incur the incidental parameters problem because the number of bins is fixed as the sample size asymptotically increases.

[43] Specifically, in the first stage, we tune the L^1-norm and L^2-norm hyperparameters with 10-fold cross-validation under the area-under-the-curve (AUC) loss criterion, which is well-specified for the binary return migration response variable that we are modeling (Bradley, 1997). In a second stage, since the LASSO penalty introduces bias into the estimated coefficients, we take the selected variables under the tuned first-stage hyperparameters and re-estimate the model under a relaxed fit that de-biases the elasticities (Hastie et al., 2017). In particular, we use the "glmnet" package in R to estimate both the first and second stages. In the second-stage de-biasing, there is an additional 10-fold cross-validation under the AUC criteria to optimally weight between the first-stage coefficients and an unpenalized fit of the selected variables.

differ from other groups in their labor supply responses to their origin-country GPR:

$$\begin{aligned} T(MainJob)_{j,c,t} =& \gamma_1 \cdot GPR_{c,t} \times \epsilon_k^{RetMigrat} + \gamma_2 \cdot GPR_{c,t} \\ &+ \gamma_3 \cdot \epsilon_k^{RetMigrat} + X_{j,c,t} + \nu_c + \mu_t + \epsilon_{j,c,t}, \end{aligned} \tag{9}$$

where the dependent variable is weekly main job working hours for immigrant j, and the control variables follow our previous specification in equation (3). The return migration mechanism predicts that $\gamma_1 > 0$, i.e., immigrants whose return migration is more susceptible to the negative impact from origin-country GPR tend to increase their working hours more when their origin-country GPR rises.

Column (1) of Table 9 shows supporting results. We observe that while GPR significantly incentivizes greater immigrant labor supply when the return migration sensitivity is zero per the γ_2 estimate, this effect is substantially stronger among demographic groups with return migration more susceptible to origin-country GPR, as demonstrated by the highly significant interaction term γ_1. This finding is consistent with the return migration mechanism that immigrants respond with increased labor supply in response to origin country GPR shocks.

4.3 Remittance Motives

The literature suggests that the remittance motive is an important driver of immigration (see reviews from Rapoport and Docquier (2006) and Yang (2011)). Remittance has been growing substantially since the 1990s (Yang (2011)), reaching 3% of GDP on average among 60 major countries in 2023 (see World Bank).

One way to motivate the remittance motive mechanism in our framework is through the immigrant's utility for income u. The seminal work by Lucas and Stark (1985) suggests that the remittance motive can be micro-founded through altruistic utility and risk-sharing with family members in the origin country. This mechanism thus predicts that a rise in the origin country's GPR can increase immigrants' immediate need for income to send to their family and community back home. As a rise in marginal utility for income strictly increases with the optimal working hours h^*, i.e., $\frac{\partial h^*}{\partial u} > 0$ (see proof in the Internet Appendix IA.2.2), an increase in GPR can thus increase the immigrant's labor supply in equilibrium.

The remittance motives are known to vary substantially across origin countries (Bollard et al. (2011)), reflecting deeper socioeconomic differences. Relevant to the remittance motive mechanism for our study, we further hypothesize that the remittance motives may be more sensitive to labor supply among low-income immigrants, as high-income immigrants are likely to possess financial slack to timely support their family members in the origin country under

high geopolitical risk. Our test for this mechanism thus explores the labor supply effect across immigrants' income interacted with their origin countries' remittance-GPR sensitivity.

We obtain the total U.S. dollar remittance and number of immigrants for each origin country from 2003 to 2019 via the World Bank Group's World Development Indicators database. Of note, this data provides the total dollar remittance sent back by *all immigrants* originating from each country.[44] Thus, one limitation is that this data provides the remittance intensity for all immigrants originating from that country, rather than immigrants living in the U.S.[45] Using this data, we compute the remittance per immigrant for each country in each year.

To estimate the sensitivity of remittance to GPR, $\epsilon_{c,t}^{Remittance}$, we adopt a similar elastic-net procedure as that applied to our return migration measurement. Specifically, we estimate the following country-level linear regression model for remittance per immigrant,

$$Remittance_{c,t+1} = \sum_{c \in F(country)} \mathbb{1}_{j,c} \times (\alpha_c + \epsilon_c \cdot GPR_{c,t}). \tag{10}$$

The estimation is weighted for U.S. population representativeness using ACS survey weights at the country level. We observe that, via cross-validation, the two-stage elastic net under a mean-squared error loss criterion optimally imposes a combination of LASSO and shrinkage penalties. We estimate the model over a 10-year window starting from 1990 to 1999 to produce a coefficient for 1999, and then iteratively expand the window one year at a time to 2019. We require at least 10 years of data per country for the estimation. This produces time-varying estimates of $\epsilon_{c,t}^{Remittance}$, which measure remittance to origin country GPR shock sensitivity.

We examine the remittance motive mechanism for explaining labor supply based on the

[44]This data is compiled based on the International Monetary Fund's Balance of Payments Manual. Specifically, we select "international migrant stock, total" and "personal remittances, received (current US$)" from https://databank.worldbank.org/source/world-development-indicators/preview/on. Personal remittances comprise "personal transfers," including all current transfers in cash or in kind received from households originating from the focal country, and "compensation of employees," including income sent by employers in the hosting country to border, seasonal, and other short-term workers originating from the focal country. Migration stocks are available every five years for each country. We linearly interpolate the values in between.

[45]An alternative dataset is the World Bank's Bilateral Remittance Matrix, which provides the estimated remittance of immigrants living in the U.S. However, remittance values in this dataset are model-generated and cover only 2010 to 2018 (Kim et al. (2024)).

following regression specification:

$$\begin{aligned} T(MainJob)_{j,c,t} =& \gamma_1 \cdot GPR_{c,t} \times \epsilon_{c,t}^{Remittance} \times Income_{j,t} + \gamma_2 \cdot GPR_{c,t} \times \epsilon_{c,t}^{Remittance} \\ &+ \gamma_3 \cdot GPR_{c,t} \times Income_{j,t} + \gamma_4 \cdot \epsilon_{c,t}^{Remittance} \times Income_{j,t} + \\ &+ \gamma_5 \cdot GPR_{c,t} + \gamma_6 \cdot \epsilon_{c,t}^{Remittance} + \gamma_7 \cdot Income_{j,t} \\ &+ X_{j,c,t} + \nu_c + \mu_t + \epsilon_{j,c,t}. \end{aligned} \tag{11}$$

The key variables of interest are γ_1 and γ_2. Our hypothesis derived from the remittance motive mechanism predicts $\gamma_2 > 0$, i.e., among low-income immigrants, origin country GPR incentivizes immigrant labor supply more if their country has higher remittance intensity. More importantly, it also predicts $\gamma_1 < 0$, i.e., the heterogeneous effects based on origin countries' remittance intensity are weaker if the immigrants earn higher income.

Columns (2) and (3) of Table 9 report the results. In Column (2), we report the result for a specification interacting origin country GPR with only the country-level remittance sensitivity. Consistent with the remittance motive explanation, we observe that immigrants from countries with higher remittance sensitivity to geopolitical risk increase their labor supply more when their origin-country GPR rises. In Column (3), we report the result for the full specification in equation (11), where we observe that γ_2 is positive and significant, and γ_1 for the triple interaction term is negative and significant. This finding lends further support for the remittance motive mechanism.

In Columns (4) and (5), we include variables corresponding to both mechanisms in a single regression. We observe a consistent pattern that the mechanisms remain highly salient in explaining immigrants' positive responses to their origin-country GPR. Notably, the coefficients for each mechanism are significant and similar to those when tested in separation as in Columns (1)-(3), suggesting that the estimated effects are largely orthogonal to each other in the data.[46]

5. Distinguishing Labor and Trade Exposures

An increasing body of literature empirically measures firms' exposure to geopolitical or political risk (Caldara and Iacoviello (2022), Hassan et al. (2019), and Clayton et al. (2025a)). These studies bring to light many novel insights regarding firms' concerns about geopolit-

[46]Nonetheless, we note that this can be due to the particular measures chosen to capture the distinct aspect of each mechanism. In theory, however, these mechanisms can overlap to some degree. For instance, the remittance motive can be more salient if the immigrant has a greater intent to return migrate (Lucas and Stark (1985)). Future research that structurally separates these mechanisms by linking them to deep parameters remains fruitful.

ical risk and the impact of such risk on firms. An important insight is that geopolitical tensions can hinder U.S. firms' import and export activities with their international suppliers and customers and thus negatively affect firm productivity and growth.[47] Our study focuses on a complementary yet distinct channel through firms' existing immigrant labor exposure to foreign geopolitical risk. Hence, a rather stark distinction is that FGPR affects firms indirectly through their foreign-born employees, while existing measures tend to capture geopolitical risk's direct impact on firm production. Consistent with this conceptual distinction, we present three results contrasting the positive effect of FGPR with the negative effects associated with existing geopolitical risk measures.

First, Table 10 shows that controlling for the same firms' trade exposure barely affects the positive effect of FGPR on firm labor productivity. In Panel A, we construct a proxy for LBD firms' trade exposure to geopolitical risk by interacting an indicator of whether the firm is either an importer or an exporter in the year from the LBD data with the global GPR measure from Caldara and Iacoviello (2022).[48] Column (1) shows that when global GPR is higher, firms engaging in international trade experience a significant decline in labor productivity next year compared to their industry peers in the same year, after controlling for firm characteristics and firm fixed effects. This confirms the findings from prior studies that geopolitical risk, through the trade channel, negatively affects firms. Column (2) includes both the trade exposure and FGPR and shows that controlling for one another does not affect each exposure's impact on firm labor productivity, suggesting that the effects of the two exposures are rather orthogonal.

In Panel B, we examine extensively-adopted measures of firms' overall and trade-related political risk (PRisk) from Hassan et al. (2019), which is extracted from publicly traded firms' earnings conference calls. We aggregate labor productivity, FGPR, and immigrant labor share measures from LBD firms to the Compustat firms using a link table between LBD and Compustat, internally provided by the Census. In Columns (1)–(3), we again observe the positive effects of FGPR and the negative effects of PRisk on firms' labor productivity next year. Controlling for one another does not affect each measure's impact on firm labor productivity. Columns (4) and (5) show that the results are robust if we further use the trade component of the PRisk measure from Hassan et al. (2019).

Second, we directly examine the relation between FGPR and PRisk. Table IA.9 shows that both PRisk and the trade component of PRisk are uncorrelated with FGPR. This finding suggests that the immigrant labor exposure in our study is largely orthogonal to corporate

[47] A recent exception is Flynn et al. (2025), who show that firms increase domestic innovation to counter the disruption to the supply of foreign inputs due to foreign political risk.

[48] Table IA.8 shows that the results are very similar if we use the U.S. GPR or the average of foreign countries' GPR.

executives' concerns about geopolitical risk.

Taken together, these results suggest that our labor exposure to foreign geopolitical risk is distinct from existing measures of firms' geopolitical risk proposed by the literature, which typically focus on the trade channel. This also reconciles our finding of a positive effect of FGPR on firm labor productivity with the literature, which typically shows a negative effect of geopolitical risk on firms.

6. Conclusion

This paper establishes a new and previously overlooked channel through which foreign geopolitical tensions influence the U.S. economy: the labor-supply responses of immigrant workers. Combining the confidential Census employee-employer matched microdata with country-level geopolitical risk shocks in a shift-share design, we show that U.S. firms with greater immigrant labor exposure to foreign geopolitical risk experience sizable increases in labor productivity, profitability, and investment. These gains are driven not by reductions in employment or labor turnover, but by immigrants' increased labor input on the intensive margin—working more hours and producing more—when geopolitical risks rise in their origin countries. The effect on firms is reinforced by spillovers to domestic coworkers, ultimately enhancing firm-level output per worker.

Our evidence highlights that immigrants' labor supply responses are systematic and economically meaningful. Using individual time use data, we show that origin-country geopolitical shocks prompt immigrants to reallocate time away from leisure toward their main jobs. Using LEHD worker-level panel data, we further document higher subsequent earnings growth for both immigrant and domestic workers in high-FGPR firms. We then trace these responses to two primary mechanisms: diminished return-migration prospects and heightened remittance motives under origin country geopolitical risk.

Overall, our findings add a new dimension to the literature on geopolitical risk, which has focused predominantly on trade disruptions, supply-chain fragility, and investment slowdowns. In contrast to the largely negative trade-exposure effects documented in prior work, we show that foreign geopolitical risk can benefit U.S. firms through the immigrant labor channel. This "silent channel"—unreflected in corporate disclosures or political-risk discussions—reveals an important economic linkage between geopolitical events abroad and firm performance at home. More broadly, our study underscores the critical role of immigrants in the U.S. economy and calls for future research to examine how global political dynamics shape domestic labor markets, firm outcomes, and broader macroeconomic resilience.

References

Aguiar, Mark, Erik Hurst, and Loukas Karabarbounis, 2013, Time Use during the Great Recession, *American Economic Review* 103, 1664–1696.

Amanzadeh, Naser, Amir Kermani, and Timothy McQuade, 2024, Return Migration and Human Capital Flows, Technical report, National Bureau of Economic Research.

Autor, David H., David Dorn, and Gordon H. Hanson, 2013, China Syndrome: Local Labor Market Effects of Import Competition in the United States, *American Economic Review* 103, 2121–68.

Baker, Scott R, Nicholas Bloom, and Steven J Davis, 2016, Measuring economic policy uncertainty, *Quarterly Journal of Economics* 131, 1593–1636.

Baker, Scott R, Nicholas Bloom, Steven J Davis, and Kyle J Kost, 2019, Policy news and stock market volatility, *NBER Working Paper* .

Baker, Scott R., Nicholas Bloom, and Stephen J. Terry, 2024, Using disasters to estimate the impact of uncertainty, *Review of Economic Studies* 91, 720–747.

Baker, Scott R, Steven J Davis, and Jeffrey A Levy, 2022, State-level economic policy uncertainty, *Journal of Monetary Economics* 132, 81–99.

Bartik, Timothy J, 1991, Who benefits from state and local economic development policies?, *(WE Upjohn Institute for Employment Research Kalamazoo, MI)* .

Bernstein, Shai, Rebecca Diamond, Abhisit Jiranaphawiboon, Timothy McQuade, and Beatriz Pousada, 2022, Contribution of High-Skilled Immigrants to Innovation in the United States.

Bloom, Nicholas, Raffaella Sadun, and John Van Reenen, 2012, Americans do IT better: US multinationals and the productivity miracle, *American Economic Review* 102, 167–201.

Bollard, Albert, David McKenzie, Melanie Morten, and Hillel Rapoport, 2011, Remittances and the Brain Drain Revisited: Microdata Show That More Educated Migrants Remit More, *World Bank Economic Review* 25, 132–156.

Borjas, George J., 2016, *Labor Economics*, 7th edition (McGraw-Hill, New York).

Borjas, George J., and Bernt Bratsberg, 1996, Who Leaves? Outmigration of the Foreign-Born, *Review of Economics and Statistics* 78, 165–176.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, 2022, Quasi-Experimental Shift-Share Research Designs, *Review of Economic Studies* 89, 181–213.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, 2025, A Practical Guide to Shift-Share Instruments, *Journal of Economic Perspectives* 39, 181–204.

Boutchkova, Maria, Hitesh Doshi, Art Durnev, and Alexander Molchanov, 2012, Precarious politics and return volatility, *Review of Financial Studies* 25, 1111–1154.

Bradley, Andrew P, 1997, use of the area under the roc curve in the evaluation of machine learning algorithms, *Pattern Recognition* 30, 1145–1159.

Brogaard, Jonathan, Lili Dai, Phong TH Ngo, and Bohui Zhang, 2020, Global political uncertainty and asset prices, *Review of Financial Studies* 33, 1737–1780.

Burchardi, Konrad B., Thomas Chaney, Tarek Alexander Hassan, Lisa Tarquinio, and Stephen J. Terry, 2020, Immigration, Innovation, and Growth.

Bybee, Leland, Bryan Kelly, Asaf Manela, and Dacheng Xiu, 2024, Business news and business cycles, *Journal of Finance* 79, 3105–3147.

Cahuc, Pierre, Stéphane Carcillo, and André Zylberberg, 2014, *Labor Economics*, second edition (MIT Press, Cambridge, MA).

Caldara, Dario, Sarah Conlisk, Matteo Iacoviello, and Maddie Penn, 2024, Do geopolitical risks raise or lower inflation?, *Federal Reserve Board of Governors* 1–34.

Caldara, Dario, and Matteo Iacoviello, 2022, Measuring Geopolitical Risk, *American Economic Review* 112, 1194–1225.

Chen, A. J., Gerard Hoberg, and Miao Ben Zhang, 2024, Institutional Participation in Information Production and Anomaly Returns, *USC Marshall School of Business Research Paper Sponsored by iORB* .

Chow, Melissa C., Teresa C. Fort, Christopher Goetz, Nathan Goldschlag, James Lawrence, Elisabeth Ruth Perlman, Martha Stinson, and T. Kirk White, 2021, Redesigning the longitudinal business database, Technical report, National Bureau of Economic Research.

Clayton, Christopher, Antonio Coppola, Matteo Maggiori, and Jesse Schreger, 2025a, Geoeconomic Pressure.

Clayton, Christopher, Matteo Maggiori, and Jesse Schreger, 2023, A framework for geoeconomics, *NBER Working Paper* .

Clayton, Christopher, Matteo Maggiori, and Jesse Schreger, 2024, A theory of economic coercion and fragmentation, *NBER Working Paper* .

Clayton, Christopher, Matteo Maggiori, and Jesse Schreger, 2025b, Putting economics back into geoeconomics, *NBER Working Paper* .

Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda, 2020, Changing business dynamism and productivity: Shocks versus responsiveness, *American Economic Review* 110, 3952–3990.

Dhawan, Rajeev, 2001, Firm size and productivity differential: Theory and evidence from a panel of US firms, *Journal of Economic Behavior & Organization* 44, 269–293.

Dinlersoz, Emin, Sebnem Kalemli-Ozcan, Henry Hyatt, and Veronika Penciakova, 2018, *Leverage over the Life Cycle and Implications for Firm Growth and Shock Responsiveness* (National Bureau of Economic Research Cambridge, MA).

Donangelo, Andres, François Gourio, Matthias Kehrig, and Miguel Palacios, 2019, Cross-section of labor leverage and equity returns, *Journal of Financial Economics* 132, 497–518.

Dustmann, Christian, 2003, Return migration, wage differentials, and the optimal migration duration, *European Economic Review* 47, 353–369.

Dustmann, Christian, and Joseph-Simon Görlach, 2016, Economics of Temporary Migrations, *Journal of Economic Literature* 54, 98–136.

Engellandt, Axel, and Regina T. Riphahn, 2005, Temporary contracts and employee effort, *Labour Economics* 12, 281–299.

Flynn, Joel P., Antoine B. Levy, Jacob Moscona, and Mai Wo, 2025, Foreign political risk and technological change, Technical report, National Bureau of Economic Research.

Fort, Teresa C, and Shawn D Klimek, 2018, effects of industry classification changes on us employment composition, *Working Paper* .

Foster, Lucia, John Haltiwanger, and Chad Syverson, 2008, Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?, *American Economic Review* 98, 394–425.

Foster, Lucia, John C. Haltiwanger, and Cornell John Krizan, 2001, Aggregate productivity growth: Lessons from microeconomic evidence, in *New Developments in Productivity Analysis*, 303–372 (University of Chicago Press).

Giroud, Xavier, and Holger M. Mueller, 2019, Firms' internal networks and local economic shocks, *American Economic Review* 109, 3617–3649.

Gonçalves, Andrei, Alessandro Melone, and Andrea Ricciardi, 2025, Pricing of Geopolitical Tensions over a Century, *Fisher College of Business Working Paper* 010.

Gulen, Huseyin, and Mihai Ion, 2016, Policy uncertainty and corporate investment, *Review of Financial Studies* 29, 523–564.

Guvenen, Fatih, Fatih Karahan, Serdar Ozkan, and Jae Song, 2021, What Do Data on Millions of U.S. Workers Reveal About Lifecycle Earnings Dynamics?, *Econometrica* 89, 2303–2339.

Haltiwanger, J. C., and S. Schuh, 1996, *Job Creation and Destruction* (MIT Press).

Haltiwanger, John, Henry Hyatt, Erika McEntarfer, and Matthew Staiger, 2025, Cyclical worker flows: Cleansing vs. sullying, *Review of Economic Dynamics* 55, 101252.

Haltiwanger, John, Ron S. Jarmin, Robert Kulick, and Javier Miranda, 2016, High growth young firms: Contribution to job, output, and productivity growth, in *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges*, 11–62 (University of Chicago Press).

Haltiwanger, John, Ron S Jarmin, and Javier Miranda, 2013, Who creates jobs? small versus large versus young, *Review of Economics and Statistics* 95, 347–361.

Haltiwanger, John C., Julia I. Lane, and James R. Spletzer, 1999, Productivity Differences across Employers: Roles of Employer Size, Age, and Human Capital, *American Economic Review* 89, 94–98.

Hanley, Kathleen Weiss, and Gerard Hoberg, 2019, Dynamic interpretation of emerging risks in the financial sector, *Review of Financial Studies* 32, 4543–4603.

Hassan, Tarek A, Stephan Hollander, Laurence Van Lent, and Ahmed Tahoun, 2024a, The global impact of brexit uncertainty, *The Journal of Finance* 79, 413–458.

Hassan, Tarek A, Stephan Hollander, Laurence Van Lent, Markus Schwedeler, and Ahmed Tahoun, 2023, Firm-level exposure to epidemic diseases: Covid-19, sars, and h1n1, *The Review of Financial Studies* 36, 4919–4964.

Hassan, Tarek A., Stephan Hollander, Laurence van Lent, and Ahmed Tahoun, 2019, Firm-Level Political Risk: Measurement and Effects, *Quarterly Journal of Economics* 134, 2135–2202.

Hassan, Tarek A, Jesse Schreger, Markus Schwedeler, and Ahmed Tahoun, 2024b, Sources and transmission of country risk, *Review of Economic Studies* 91, 2307–2346.

Hastie, Trevor, Robert Tibshirani, and Ryan J Tibshirani, 2017, Extended comparisons of best subset selection, forward stepwise selection, and the lasso, *arXiv preprint arXiv:1707.08692* .

Helpman, Elhanan, Marc J Melitz, and Stephen R Yeaple, 2004, Export Versus FDI with Heterogeneous Firms, *American Economic Review* 94, 300–316.

Hirshleifer, David, Dat Mai, and Kuntara Pukthuanthong, 2023a, War Discourse and Disaster Premia: 160 Years of Evidence from Stock and Bond Markets.

Hirshleifer, David, Dat Mai, and Kuntara Pukthuanthong, 2023b, War discourse and the cross section of expected stock Returns, Technical report, National Bureau of Economic Research.

Hirshleifer, David, Dat Mai, and Kuntara Pukthuanthong, 2025, War Discourse and Disaster Premium: 160 Years of Evidence from the Stock Market, *Review of Financial Studies* 38, 457–506.

Hunt, Jennifer, and Marjolaine Gauthier-Loiselle, 2010, How Much Does Immigration Boost Innovation?, *American Economic Journal: Macroeconomics* 2, 31–56.

Jiang, Wei, Junyoung Park, Rachel Jiqiu Xiao, and Shen Zhang, 2025, AI and the Extended Workday: Productivity, Contracting Efficiency, and Distribution of Rents, Technical report, National Bureau of Economic Research.

Jin, Zhao, Amir Kermani, and Timothy McQuade, 2025, Native-immigrant entrepreneurial synergies, *NBER Working Paper* .

Kerr, Sari Pekkala, William R. Kerr, and William F. Lincoln, 2015, Skilled Immigration and the Employment Structures of US Firms, *Journal of Labor Economics* 33, S147–S186.

Khanna, Gaurav, 2025, From Asia, With Skills.

Kim, Kijin, Zemma Ardaniel, Aiko Kikkawa, and Benjamin Endriga, 2024, Bilateral Remittance Inflows to Asia and the Pacific: Countercyclicality and Motivations to Remit, *Asian Development Review* 41, 257–300.

Krishnan, Karthik, Debarshi K. Nandy, and Manju Puri, 2015, Does financing spur small business productivity? Evidence from a natural experiment, *Review of Financial Studies* 28, 1768–1809.

Larrain, Borja, Gordon M Phillips, Giorgo Sertsios, and Francisco Urzúa I, 2025, Effects of Going Public on Firm Profitability and Strategy, *Review of Financial Studies* 38, 2467–2514.

Lopresti, John W, and Kevin J Mumford, 2016, Who benefits from a minimum wage increase?, *ILR Review* 69, 1171–1190.

Lucas, Robert E. B., and Oded Stark, 1985, Motivations to Remit: Evidence from Botswana, *Journal of Political Economy* 93, 901–918.

Mas, Alexandre, and Enrico Moretti, 2009, Peers at Work, *American Economic Review* 99, 112–145.

Nakamura, Emi, Jón Steinsson, Robert Barro, and José Ursúa, 2013, Crises and Recoveries in an Empirical Model of Consumption Disasters, *American Economic Journal: Macroeconomics* 5, 35–74.

Novy-Marx, Robert, 2013, Other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.

Rapoport, Hillel, and Frédéric Docquier, 2006, Economics of migrants' remittances, *Handbook of the Economics of Giving, Altruism and Reciprocity* 2, 1135–1198.

Shapiro, Carl, and Joseph E. Stiglitz, 1984, Equilibrium Unemployment as a Worker Discipline Device, *American Economic Review* 74, 433–444.

Sheng, Jinfei, Zheng Sun, and Qiguang Wang, 2025, Geopolitical Risk and Stock Returns.

Shimer, Robert, 2005, Cyclical behavior of equilibrium unemployment and vacancies, *American Economic Review* 95, 25–49.

Syverson, Chad, 2011, What Determines Productivity?, *Journal of Economic Literature* 49, 326–365.

Tibshirani, Robert, 1996, Regression shrinkage and selection via the lasso, *Journal of the Royal Statistical Society Series B: Statistical Methodology* 58, 267–288.

Topel, Robert H., and Michael P. Ward, 1984, Equilibrium earnings, turnover, and unemployment: New evidence, *Journal of Labor Economics* 2, 500–522.

Wallskog, Melanie, Nicholas Bloom, Scott W. Ohlmacher, and Cristina Tello-Trillo, 2024, Within-firm pay inequality and productivity, Technical report, National Bureau of Economic Research.

Yang, Dean, 2011, Migrant remittances, *Journal of Economic Perspectives* 25, 129–152.

Zou, Hui, and Trevor Hastie, 2005, Regularization and variable selection via the elastic net, *Journal of the Royal Statistical Society Series B: Statistical Methodology* 67, 301–320.

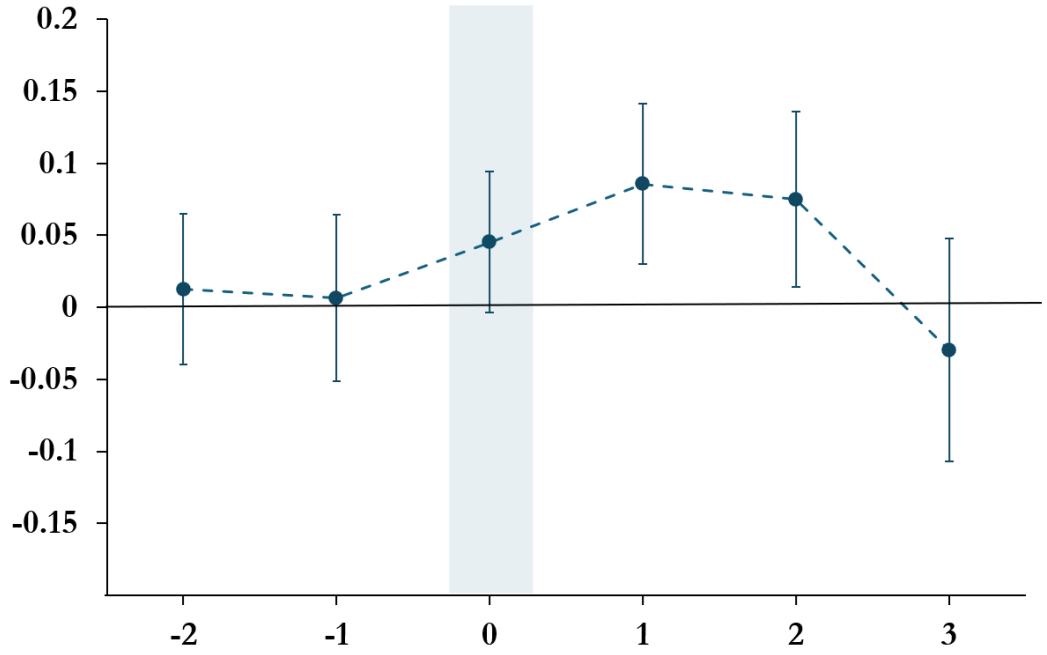


Figure 1: Response of Firm Labor Productivity to FGPR

This figure plots the impulse response to a firm-level foreign geopolitical risk ($FGPR$) shock in the current year ($t = 0$) on firms' labor productivity from years $t - 2$ to $t + 3$. The data is based on Census LBD-LEHD samples of firms with greater than 100 employees from 1996 to 2017. Each solid dot is the coefficient from regressing labor productivity on their labor exposure to foreign geopolitical risk ($FGPR$) as in equation (2). The error bars represent 95% confidence intervals based on standard errors clustered by firm.

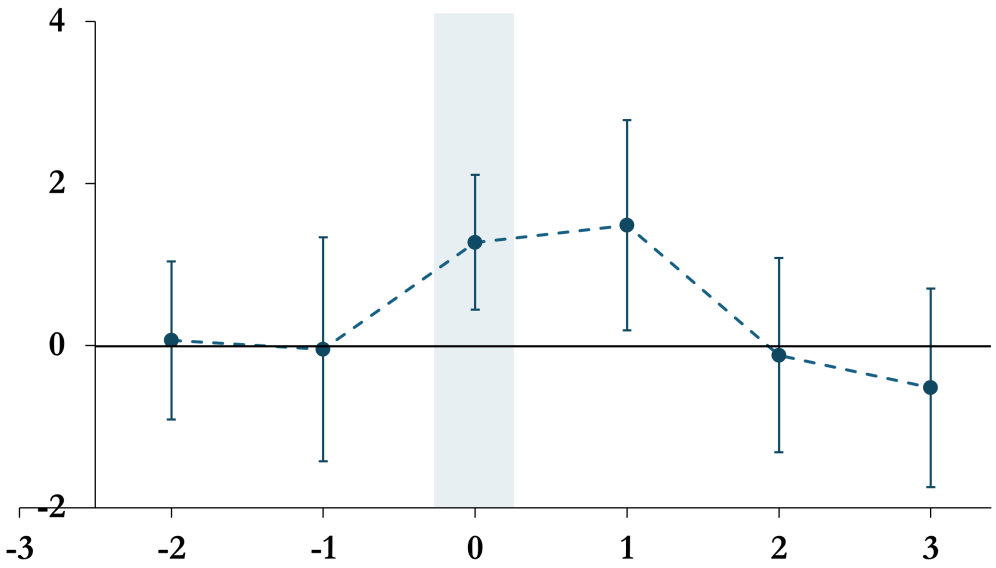


Figure 2: Response of Immigrant Time Spent on Main Job to Origin Country GPR

This figure plots the impulse response to a origin country geopolitical risk (GPR) shock in the current year ($t = 0$) on individuals' time spent on main job from years $t-2$ to $t+3$. The data is based on the individual-level American Time Use Survey (ATUS) from 2003 to 2019. Each solid dot is the coefficient from regressing work (top) or main job (bottom) time-use on GPR, the geopolitical risk shock to an individual's country of origin as in equation (3). Time-use, measured in hours per week, are categorized following Aguiar et al. (2013). The error bars represent 95% confidence intervals based on standard errors clustered by country.

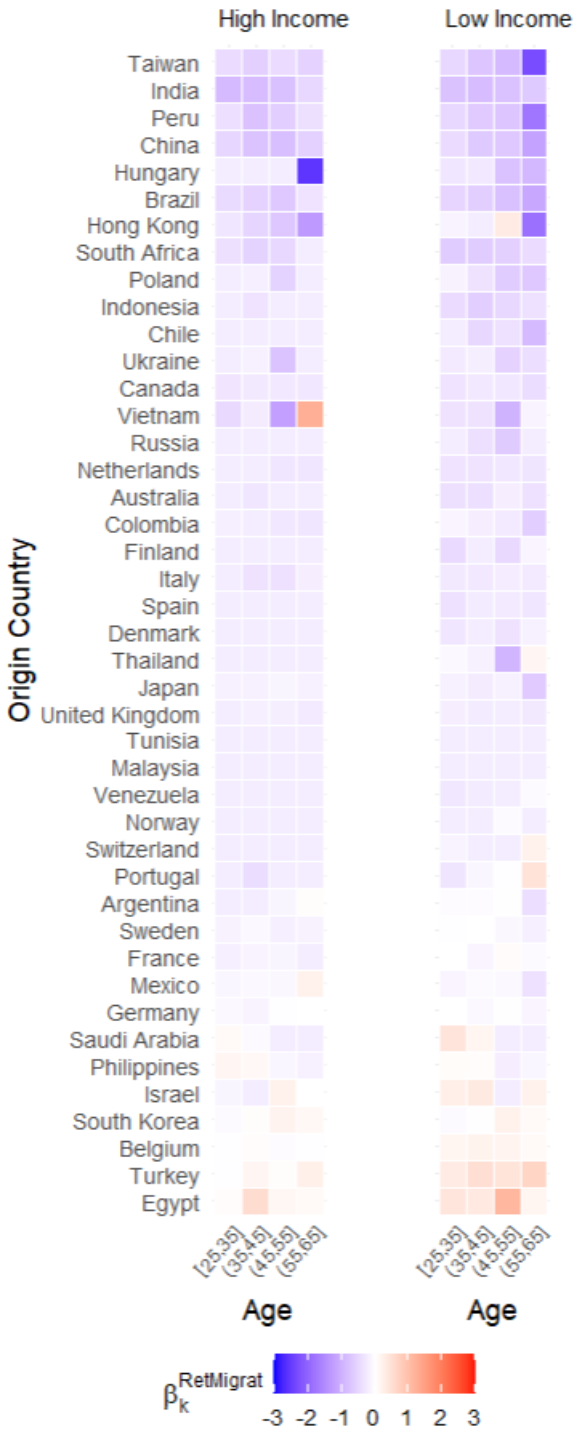


Figure 3: Heterogeneous Sensitivities of Return Migration to Origin Country GPR

This figure plots a heatmap of the sensitivity (β_k^{RetMig}) of individual return migration to origin country geopolitical risk estimated from LinkedIn profile data as in equation (8). Individuals are assigned into 688 bins based on 43 country of origin $\times$ 4 age brackets $\times$ gender (male vs. female) $\times$ income (above or below median by year) population groups. We then report the average within country of origin $\times$ age bracket $\times$ income. The dependent variable is whether an individual return migrates to his or her country of origin in year $t+1$ for an origin country GPR shock in year t. The coefficients are estimated via cross-validated elastic net logistic regressions under an Area Under the Curve (AUC) loss criteria. The regression observations are weighted within each bin to be nationally representative of the same demographic bins observed in the American Community Survey (ACS).

Table 1
Summary Statistics

This table reports on summary statistics, in Panel A, at the firm-year level for our LBD-LEHD merged sample from 1996 to 2017, in Panel B, at the individual-level for a sample of LEHD workers aged 25 to 65 from 1996 to 2017, and in Panel C, at the individual-level for a sample of individuals aged 25 to 65 in the American Time-Use Survey (ATUS) from 2003 to 2019. *Labor Productivity* is the ratio of firm-level real revenue in year $t+1$ to employment in t in 2018 dollars. *Labor Exposure to Foreign Geopolitical Risk (FGPR)* is the firm-level labor exposure to origin country geopolitical risk (GPR) shocks constructed in equation (1). *Import-Exporter* is an indicator for when the firm is either an importer or an exporter based on the universe of individual trade transactions by U.S. firms. *Firm Age* is the logarithm of the firm's age in the LBD database. *Firm Average Worker Age* is the average age of workers employed by the firm in the year. *Firm Average Worker Education* is the percentage of workers with a college degree or higher employed by the firm in the year. In Panel B, *Worker Real Earnings Growth* is the year-to-year percentage change in individual earnings in 2018 dollars. *Worker Age* is the individual worker's age. In Panel C, time use by immigrants on each of the categories defined following Aguiar et al. (2013) is measured in hours per week.

Variable	Mean	SD	Observations
Panel A: Firm-Level (LBD-LEHD)			
Labor Productivity ($ thousands per worker)	247.6	319.7	1,039,000
Revenue ($ million)	164.1	524.1	1,039,000
Employment	635.5	1656	1,039,000
Labor Exposure to Foreign Geopolitical Risk (*FGPR*)	-0.06394	12.11	1,039,000
Share of Foreign-born Labor (*FLabor*, %)	14.12	17.25	1,039,000
Importer or Exporter (indicator)	0.4067	0.4912	1,039,000
Firm Age (log of years)	3.016	0.6259	1,039,000
Firm Average Worker Age (years)	40.58	5.96	1,039,000
Firm Average Worker Education (%)	26.42	17.86	1,039,000
Panel B: Individual-Level (LEHD)			
Foreign-born Worker Real Earnings Growth (%)	3.021	55.28	71,030,000
Foreign-born Worker Age (years)	42.31	10.24	71,030,000
Domestic Worker Real Earnings Growth (%)	0.1729	56.19	413,300,000
Domestic Worker Age (years)	42.44	10.81	413,300,000
Panel C: Time Use by Immigrants (ATUS)			
Work (Hours per Week)	31.63	33.23	15,768
Work - Main Job (Hours per Week)	28.12	29.94	15,768
Job Search (Hours per Week)	0.05	0.41	15,768
Home Production (Hours per Week)	24.81	23.16	15,768
Leisure (Hours per Week)	104.39	26.21	15,768
Other (Hours per Week)	6.65	12.40	15,768

Table 2
Effect of FGPR on Firm Labor Productivity

This table reports on the results of regressing firms' labor productivity at year $t+1$ on their labor exposure to foreign geopolitical risk shocks (*FGPR*) at t. Columns (1)–(5) report on the results across progressively more stringent specifications. Together with firm fixed effects and industry-year fixed effects, controls as of the current year include the the log of firm employment (*Firm Size*), the log of firm age in years measured relative to the oldest firm establishment (*Firm Age*), the firm average worker age (*Firm Avg Worker Age*), and the firm average percentage of workers with a 4-year college degree or higher (*Firm Avg Worker Edu*). *FLabor-Year* represents an interaction of the year fixed effect with the firm's share of foreign-born workers. Industry is classified at the NAICS 3-digit level. Standard errors, reported in parentheses, are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dep. Variable:	Labor Productivity$_{t+1}$				
	(1)	(2)	(3)	(4)	(5)
FGPR	0.5871***	0.1086***	0.0904***	0.1012***	0.0856***
	(0.0506)	(0.0286)	(0.0283)	(0.0287)	(0.0284)
Firm Size			-64.26***		-63.21***
			(1.3)		(1.302)
Firm Age			-5.361***		-5.593***
			(1.746)		(1.745)
Firm Avg Worker Age				0.6091***	0.4166***
				(0.0415)	(0.0395)
Firm Avg Worker Edu				1.428***	0.3917***
				(0.1259)	(0.1242)
FLabor-Year Ctrls	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,039,000	1,039,000	1,039,000	1,039,000	1,039,000
R^2	0.3554	0.8630	0.8659	0.8632	0.8659

Table 3
Effects Conditional on Firm Trade Exposure

This table reports on the results of regressing firms' year $t+1$ labor productivity on their labor exposure to foreign geopolitical risk ($FGPR$), while controlling for an interaction with firms' importer and/or exporter status. Column (1) interacts FGPR with whether the firm is an $Importer$, Column (2) with whether the firm is an $Exporter$, and Column (3) with whether the firm is an importer or exporter ($Import\text{-}Exporter$). Together with firm fixed effects and industry-year fixed effects, controls as of the current year include the the log of firm employment ($Firm\ Size$), the log of firm age in years measured relative to the oldest firm establishment ($Firm\ Age$), the firm average worker age ($Firm\ Avg\ Worker\ Age$), and the firm average percentage of workers with a 4-year college degree or higher ($FirmAvgWorkerEdu$). The $FLabor\text{-}Year$ control is an interaction of the year fixed effect with the firm's share of foreign-born workers. Industry is classified at the NAICS 3-digit level. Standard errors, reported in parentheses, are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dep. Variable:	Labor Productivity$_{t+1}$		
	(1)	(2)	(3)
FGPR	0.1046***	0.1056***	0.1065***
	(0.0324)	(0.0302)	(0.0335)
Importer	1.527		
	(0.9946)		
FGPR × Importer	-0.0612		
	(0.0604)		
Exporter		0.8471	
		(0.9594)	
FGPR × Exporter		-0.0579	
		(0.0607)	
Import-Exporter			0.5161
			(0.8282)
FGPR × Import-Exporter			-0.0541
			(0.0568)
FLabor-Year Ctrls	Yes	Yes	Yes
Firm Ctrls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	1,039,000	1,039,000	1,039,000
R^2	0.8660	0.8660	0.8660

Table 4
Effect on Firm Labor Productivity: Revenue or Employment

This table reports on the results of regressing firms' year $t+1$ revenue (Rev), year t employment (Emp), or year $t+1$ labor productivity ($LProd$) on their labor exposure to foreign geopolitical risk ($FGPR$). Columns (1) and (2) focus on the log and change in log firm revenues, respectively. Columns (3) and (4) focus on the log and change in log firm employment, respectively. Column (5) examines an interaction with firm worker turnover in year t, the sum of hiring and separations relative to employment ($Turnover$). Together with firm fixed effects and industry-year fixed effects, controls as of the current year include the the log of firm employment ($Firm\,Size$), the log of firm age in years measured relative to the oldest firm establishment ($Firm\,Age$), the firm average worker age ($FirmAvgWorkerAge$), and the firm average percentage of workers with a 4-year college degree or higher ($Firm\,Avg\,Worker\,Edu$). The $FLabor\text{-}Year$ control is an interaction of the year fixed effect with the firm's share of foreign-born workers. Industry is classified at the NAICS 3-digit level. Standard errors, reported in parentheses, are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dep. Variable:	$\log(\text{Rev}_{t+1})$	$\Delta\log(\text{Rev}_{t+1})$	$\log(\text{Emp}_t)$	$\Delta\log(\text{Emp}_t)$	LProd_{t+1}
	(1)	(2)	(3)	(4)	(5)
FGPR	0.0372***	0.0138**	-0.0035	-0.0038	0.0817***
	(0.0097)	(0.0067)	(0.0054)	(0.0049)	(0.0291)
Turnover					-0.0026
					(0.0101)
FGPR × Turnover					0.0035
					(0.0049)
FLabor-Year Ctrls	Yes	Yes	Yes	Yes	Yes
Firm Ctrls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,039,000	1,039,000	1,039,000	1,039,000	1,039,000
R^2	0.9238	0.2157	0.9488	0.3024	0.8659

Table 5
U.S. Firm Performance and FGPR

This table reports on the results of regressing firms' surplus per worker, gross profitability, and capital investment at $t+1$ on firms' labor exposure to foreign geopolitical risk (FGPR) at t. *Surplus per worker* is Census LBD firms' revenues minus total labor pay and then scaled by beginning-of-period employment (see Section 2.5). *Profitability* is Compustat firms' gross profitability, defined as gross profits divided by total assets at the beginning of the year following Novy-Marx (2013). *Investment* is Compustat firms' capital expenditure divided by total physical assets (PPEGT) at the beginning of the year. Together with firm fixed effects and industry-year fixed effects, controls as of the current year include the the log of firm employment ($Firm\ Size$), the log of firm age in years measured relative to the oldest firm establishment ($Firm\ Age$), the firm average worker age ($Firm\ Avg\ Worker\ Age$), and the firm average percentage of workers with a 4-year college degree or higher ($Firm\ Avg\ Worker\ Edu$). The $FLabor\text{-}Year$ control is an interaction of the year fixed effect with the firm's share of foreign-born workers. Industry is classified at the NAICS 3-digit level. Standard errors, reported in parentheses, are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Data Source:	Census LBD	Compustat	
Dep. Variable:	Surplus Per Worker$_{t+1}$	Profitability$_{t+1}$	Investment$_{t+1}$
	(1)	(2)	(3)
FGPR	0.0801***	0.0526**	0.0417**
	(0.0259)	(0.0265)	(0.0203)
FLabor-Year Ctrls	Yes	Yes	Yes
Firm Ctrls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	No	No
Observations	1,039,000	47,500	47,500
R^2	0.8671	0.7789	0.4809

Table 6
Origin Country Geopolitical Risk and Immigrant Time-Use

This table reports results of regressing foreign-born individuals' time-use in year t on their origin countries' geopolitical risk shocks (*Ori-Country GPR*) at t as described in Section 1.1. Time-use in hours per week from the American Time-Use Survey (ATUS) is categorized following Aguiar et al. (2013). Each coefficient is obtained from a separate regression, which controls for an array of immigrant demographic characteristics including individual age (via five-year age dummies), education attainment (via four education dummies), race, marital status, gender, and a dummy variable indicating whether or not the individual has a child (Aguiar et al. (2013)), along with origin country fixed effects and year fixed effects. Standard errors are clustered by country. The sample includes 15,762 individual-year observations from 2003 to 2019. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Time Use Category	Coeff.	S.E.
Work	1.368***	(0.479)
Main job	1.275***	(0.424)
Other work-related	0.052	(0.097)
Job Search	−0.015	(0.015)
Home Production	−0.565	(0.387)
Leisure	−0.940*	(0.545)
Socializing	−0.310*	(0.164)
Sleeping	−0.263	(0.240)
Eat & personal care	−0.080	(0.197)
TV watching	−0.081	(0.385)
Other leisure	−0.255	(0.311)
Other	0.232	(0.337)

Table 7
Origin Country Geopolitical Risk and Immigrant Earnings Growth

This table reports on the results of regressing foreign-born workers' real wage growth at year $t+1$ on their origin-country *GPR* at t, the geopolitical risk shocks to the country of their place of birth. The sample includes all foreign-born workers aged 25 to 65 in the LEHD Database from 1996 to 2017. Columns (1)–(3) examine the relation within the sample of foreign-born workers, while Columns (4)–(6) focus on the foreign-born who stayed at their firms from year t to $t+1$. All regressions control for worker fixed effects, worker age, firm fixed effects, industry-year fixed effects, the firm average worker age ($Firm\ Avg\ Worker\ Age$), the firm average percentage of workers with a 4-year college degree or higher ($Firm\ Avg\ Worker\ Edu$), and the firm's share of foreign-born workers ($FLabor\text{-}Year$). Industry is classified at the NAICS 3-digit level. Standard errors, reported in parentheses, are double-clustered by country and year. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dep. Variable:	Foreign-born Worker Real Earnings Growth$_{t+1}$					
Sample:	All			Job Stayers		
	(1)	(2)	(3)	(4)	(5)	(6)
GPR	0.4903***	0.4505***	0.4325***	0.4304***	0.4242***	0.4036***
	(0.02627)	(0.01906)	(0.1054)	(0.001529)	(0.02951)	(0.09026)
Worker FE	Yes	Yes	Yes	Yes	Yes	Yes
Worker Age Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Firm Ctrls	No	No	Yes	No	No	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	71,030,000	71,030,000	71,030,000	58,650,000	58,650,000	58,650,000
R^2	0.09179	0.1027	0.1033	0.1281	0.136	0.137

Table 8
Domestic vs. Immigrant Workers and Firm FGPR

This table reports on the results of regressing workers' year $t+1$ real earnings growth on their labor exposure to foreign geopolitical risk ($FGPR$), in a combined sample of foreign-born and non-foreign-born workers. The sample includes all workers aged 25 to 65 in the LEHD database from 1996 to 2017. *Immigrant* is an indicator for if a worker was born outside the U.S. All regressions control for worker fixed effects and age. Additional controls include firm-year fixed effects or the set of firm fixed effects, industry-year fixed effects, the firm average worker age ($Firm\,Avg\,Worker\,Age$), the firm average percentage of workers with a 4-year college degree or higher ($Firm\,Avg\,Worker\,Edu$), and the firm's share of foreign-born workers ($FLabor\text{-}Year$). Industry is classified at the NAICS 3-digit level. Standard errors, reported in parentheses, are double-clustered by country and year. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dep. Variable:	Worker Real Earnings Growth$_{t+1}$			
Sample:	All		Job Stayers	
	(1)	(2)	(3)	(4)
FGPR × Immigrant	0.01189***	0.01317***	0.009084***	0.01217***
	(0.002989)	(0.001982)	(0.003224)	(0.001999)
FGPR	0.03431***		0.03488***	
	(0.01025)		(0.01159)	
Worker FE	Yes	Yes	Yes	Yes
Worker Age Ctrl	Yes	Yes	Yes	Yes
FLabor-Year Ctrls	Yes	No	Yes	No
Firm Ctrls	Yes	No	Yes	No
Firm FE	Yes	No	Yes	No
Industry-Year FE	Yes	No	Yes	No
Firm-Year FE	No	Yes	No	Yes
Observations	484,400,000	484,400,000	396,900,000	396,900,000
R^2	0.0944	0.1265	0.1306	0.1817

Table 9
Mechanism Tests for Immigrant Labor Supply Effects

This table reports the results of regressing foreign-born individuals' main job working hours in year t on their origin countries' geopolitical risk shocks (GPR) at t interacted with various measures. Main job time spent in hours per week by immigrants is from the American Time-Use Survey (ATUS) from 2003 to 2019. $\epsilon^{RetMigrat}$ is the sensitivity of immigrants' return migration to origin country GPR estimated across 688 demographic bins from a panel of 7 million immigrant-year observations constructed from LinkedIn profile data (see Section 4.2): A higher value means the return migration of immigrants in the group is more *negatively* impacted by their origin country GPR. $\epsilon^{Remittance}$ is the sensitivity of remittance per immigrant to origin-country GPR, estimated using country-year level data from the World Bank database (see Section 4.3). *Income* is the natural logarithm of the individual's income in the ATUS database. All regressions control for immigrants' demographic characteristics following Aguiar et al. (2013) that include age (via five-year age dummies), education attainment (via four education dummies), race, marital status, gender, and a dummy variable indicating whether or not the individual has a child, along with origin country fixed effects and year fixed effects. Columns in even numbers further control for country by year fixed effects. Standard errors are clustered by country. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dep. Variable:	Working Hours on Main Job				
Tested mechanism:	Return Migration	Remittance Motive		All Together	
	(1)	(2)	(3)	(4)	(5)
GPR × $\epsilon^{RetMigrat}$	0.850***			0.919***	0.897***
	(0.253)			(0.262)	(0.216)
GPR × $\epsilon^{Remittance}$		0.650***	0.683***	0.740***	0.773***
		(0.186)	(0.187)	(0.163)	(0.170)
GPR × $\epsilon^{Remittance}$ × Income			-0.263**		-0.263*
			(0.128)		(0.135)
GPR	1.097**	1.118*	0.986*	1.074*	0.988*
	(0.477)	(0.613)	(0.581)	(0.581)	(0.568)
$\epsilon^{RetMigrat}$	0.778*			0.631	0.643
	(0.408)			(0.458)	(0.444)
$\epsilon^{Remittance}$		-0.883*	-0.978**	-0.824*	-0.921**
		(0.475)	(0.462)	(0.451)	(0.433)
Income			2.537***		2.558***
			(0.328)		(0.326)
GPR × Income			0.274		0.060
			(0.540)		(0.529)
$\epsilon^{Remittance}$ × Income			0.391***		0.407***
			(0.118)		(0.115)
Demographic Ctrls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	10,230	9,873	9,873	9,873	9,873
R-squared	0.034	0.035	0.04	0.036	0.041

Table 10
U.S. Firms' Labor vs. Trade Exposures to GPR

This table reports on the results of regressing firms' labor productivity at $t+1$ on firms' labor exposure to foreign geopolitical risk (FGPR) at t while controlling for firms' trade exposure to geopolitical risk at t. In Panel A, within our LBD-LEHD sample, the proxy for firms' trade exposure is an interaction of Global GPR with whether a firm is an importer or exporter (*Import-Exporter*). See the regression specifications in Table 2. In Panel B, within our Compustat sample, the proxy for firms' trade exposure is the firm-level overall (*PRisk*) or trade-related (*PRisk_Trade*) political risk extracted from earnings conference calls by Hassan et al. (2019). Importantly, labor productivity for Compustat firms is computed as firms' next year's real value-added (rather than gross revenues) divided by this year's total employment. Industry is classified at the NAICS 3-digit level. Standard errors, reported in parentheses, are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Controlling for Trade Exposure to Geopolitical Risk (LBD Firms)

Dep. Variable:	Labor Productivity$_{t+1}$	
	(1)	(2)
Global GPR × Import-Exporter	-3.825***	-3.749***
	(0.6746)	(0.6734)
Import-Exporter	1.152*	1.078*
	(0.6375)	(0.6367)
FGPR		0.0860***
		(0.0284)
FLabor-Year Ctrls	No	Yes
Firm Ctrls	Yes	Yes
Firm FE	Yes	Yes
Industry-Year FE	Yes	Yes
Observations	1,039,000	1,039,000
R^2	0.8659	0.8659

Panel B: Controlling for PRisk (Compustat Firms)

Dep. Variable:	Labor Productivity$_{t+1}$				
	(1)	(2)	(3)	(4)	(5)
FGPR	1.667***		1.664***		1.663***
	(0.6405)		(0.6403)		(0.6403)
PRisk		-3.149**	-3.069**		
		(1.299)	(1.297)		
PRisk_Trade				-0.0688**	-0.0696**
				(0.0343)	(0.0340)
FLabor-Year Ctrls	Yes	No	Yes	No	Yes
Firm Ctrls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	28,000	28,000	28,000	28,000	28,000
R^2	0.8447	0.8444	0.8447	0.8443	0.8447

Internet Appendix for

"Foreign Geopolitical Risk and U.S. Firm Productivity: The Role of Immigrant Labor"

Zhongling (Danny) Qin Miao Ben Zhang

IA.1. Shift-share Properties of the FGPR Measure

Our firm-level FGPR is an immigrant employment-weighted average of foreign country GPR shocks as defined in a shift-share style in equation (1). Borusyak et al. (2022) emphasize that the causal effect of a shift-share measure is achieved if the underlying shocks, i.e., the country-level GPR shocks in our case, are "*as-good-as-randomly assigned, mutually uncorrelated, large in number, and sufficiently dispersed in terms of their average exposure*." Below, we examine these identifying assumptions following the suggested tests in Borusyak et al. (2022).

First, while a foreign country's GPR shocks do not arrive randomly, we have shown in Section 1.1 that our GPR shock measure captures the sparse and unexpected geopolitical disasters across foreign countries and years carefully identified by Baker et al. (2024). Below, we follow Borusyak et al. (2022) and further show that our GPR shocks are unlikely to reflect confounding factors among U.S. immigrant workers born in that country. We choose three factors that are known to be associated with firm labor productivity (Haltiwanger et al. (2016)) that we can also measure from our individual-level LEHD data: the yearly average age, percentage with college or above educational attainment, and average real earnings of immigrant workers born in a given country. Panel A of Table IA.5 reports the results of our balance tests at the country-level, which show that foreign countries' GPR shocks are not significantly associated with immigrant worker confounding characteristics in the cross-section. Panel B of Table IA.5 reports the results of our balance tests at the firm-level, where we examine the association between firms' FGPR with the four time-varying firm-level controls in Table 2 and firm labor productivity during the pre-period from $t-2$ to t. We again find no statistically significant relationships between FGPR and most of these variables, except for firm size.

Second, foreign countries' GPR shocks appear to be cross-sectionally mutually uncorrelated. The average of the cross-section correlations among the 43 foreign country GPR shocks from 1996 to 2017 is -0.021.

Third, in our sample, foreign countries' average immigrant labor exposure in firms also appears to be highly dispersed. Specifically, we follow Borusyak et al. (2022) and construct the average employment share across firms for each foreign country and year, $s_{c,t} = avg(Share_{f,c,t})$. Table IA.4 reports a large value of the inverse Herfindahl–Hirschman index (HHI) of $s_{c,t}$, suggesting that the average exposures are not concentrated in a few countries.

IA.2. Proofs

IA.2.1 Proving $\frac{\partial h^*}{\partial V_U} < 0$

From the Bellman equation (6) in Section 4.1, we have

$$V_E = \max_{h \geq 0} \left\{ \frac{uwh - v(h) + \beta(1 - p(h))V_U}{1 - \beta p(h)} \right\}.$$

The first-order condition (FOC) is:

$$F(h, V_U) = [uw - v'(h) - \beta p'(h)V_U][1 - \beta p(h)] + \beta p'(h)[uwh - v(h) + \beta(1 - p(h))V_U] = 0.$$

By the implicit function theorem:

$$\frac{\partial h^*}{\partial V_U} = -\frac{F_V}{F_h},$$

where $F_V = \frac{\partial F}{\partial V_U}$, $F_h = \frac{\partial F}{\partial h}$. Compute F_V:

$$\begin{aligned} F_V &= \frac{\partial}{\partial V_U} \left([uw - v'(h) - \beta p'(h)V_U][1 - \beta p(h)] + \beta p'(h)[uwh - v(h) + \beta(1 - p(h))V_U] \right) \\ &= -\beta p'(h)[1 - \beta p(h)] + \beta^2 p'(h)(1 - p(h)) \\ &= -\beta p'(h) \left(1 - \beta p(h) - \beta(1 - p(h))\right) \\ &= -\beta(1 - \beta)p'(h). \end{aligned}$$

Since $p'(h) > 0$, $F_V < 0$. The second-order condition (SOC) for a maximum requires $F_h < 0$ at h^*. Therefore,

$$\frac{\partial h^*}{\partial V_U} = -\frac{F_V}{F_h} < 0.$$

IA.2.2 Proving $\frac{\partial h^*}{\partial u} > 0$

Applying implicit function theorem to the FOC above, we have

$$\frac{\partial h^*}{\partial u} = -\frac{F_u}{F_h},$$

where $F_u = \frac{\partial F}{\partial u}$, $F_h = \frac{\partial F}{\partial h}$. Compute F_u:

$$\begin{aligned} F_u &= \frac{\partial}{\partial u} \left([uw - v'(h) - \beta p'(h)V_U][1 - \beta p(h)] + \beta p'(h)[uwh - v(h) + \beta(1 - p(h))V_U] \right) \\ &= w[1 - \beta p(h)] + \beta p'(h)wh. \end{aligned}$$

Hence, $F_u > 0$. The second-order condition (SOC) for a maximum requires $F_h < 0$ at h^*. Therefore,

$$\frac{\partial h^*}{\partial u} = -\frac{F_u}{F_h} > 0.$$

Table IA.1
Validation: GPR Measure and Geopolitical Disaster Shocks

This table reports on the results of regressing country-level geopolitical and natural disaster events from Baker et al. (2024) on their contemporaneous standardized geopolitical risk (GPR). The dependent variable is the media-weighted geopolitical or natural disaster shock in a foreign country at the quarter or yearly frequency from Baker et al. (2024) and multiplied by 100. The independent variable is the standardized GPR constructed in Section 1.2 and aggregated to country-quarter or country-year level. Standard errors, reported in parentheses, are clustered by country. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Geopolitical Disaster Shocks		Natural Disaster Shocks	
Data Frequency	Quarterly	Yearly	Quarterly	Yearly
	(1)	(2)	(3)	(4)
GPR	0.292**	0.865**	0.061	0.249
	(0.132)	(0.402)	(0.073)	(0.610)
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	4,352	1,088	4,344	1,086
R^2	0.045	0.081	0.066	0.164

Table IA.2
Robustness: Main Results Using Positive vs. Negative FGPR Shocks

This table reports a robustness check of the results of Table 2, by showing the results of regressing firms' year $t+1$ labor productivity on their labor exposures to the positive and negative components of foreign geopolitical risk ($FGPR$). See the regression specification and control variables in Table 2. Following equation (1), we define

$$FGPR(Positive)_{f,t} = \sum_{c \in \text{non-U.S.}} Share_{f,c,t-1} \times \max(GPR_{c,t}, 0)$$
$$FGPR(Negative)_{f,t} = \sum_{c \in \text{non-U.S.}} Share_{f,c,t-1} \times \min(GPR_{c,t}, 0).$$

Standard errors, reported in parentheses, are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dep. Variable:	Labor Productivity$_{t+1}$		
	(1)	(2)	(3)
FGPR (Positive)	0.1583***		0.1739***
	(0.0406)		(0.0426)
FGPR (Negative)		0.0079	-0.0724
		(0.0521)	(0.0546)
FLabor-Year Ctrls	Yes	Yes	Yes
Firm Ctrls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	1,039,000	1,039,000	1,039,000
R^2	0.8659	0.8659	0.8659

Table IA.3
Robustness: Main Results Using Alternative Models

This table reports on a variety of robustness check results of Table 2, by showing the results of alternative models of regressing firms' year $t+1$ labor productivity on their labor exposure to foreign geopolitical risk ($FGPR$). Models 1–7 are estimated in the baseline LBD-LEHD sample described in Section 1.3. All models control for the interactions of $FLabor$ and year dummies, firm characteristics, firm fixed effects, and industry-year fixed effects as described in Table 2 unless otherwise stated. Industry is classified at the NAICS 3-digit level unless otherwise stated. Standard errors, reported in parentheses, are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dep. Variable: Labor Productivity$_{t+1}$	
Alternative Model	FGPR Coef.
Model 1: Alternative FGPR (Acts) use country-specific GPR Acts obtained from Matteo Iacoviello to measure FGPR	0.2272*** (0.0655)
Model 2: Alternative FGPR (Threats) use country-specific GPR Threats obtained from Matteo Iacoviello to measure FGPR	0.1157** (0.0457)
Model 3: Alternative FGPR (U.S. Orthogonalized) use the residual of regressing a foreign country's GPR on the U.S. GPR over the past 120 months to measure FGPR	0.0871*** (0.0264)
Model 4: Alternative FGPR (Redefined Shares) in equation (1), use $Share_{f,c,t-1}$ that bundle immigrants from countries without the Caldara and Iacoviello (2022) GPR index with U.S. domestic workers in the denominator	0.0924*** (0.0312)
Model 5: Alternative FGPR (Using Lagged Shares) in equation (1), lag the firm's foreign employment share by three years, i.e., $Share_{f,c,t-3}$	0.0709** (0.0282)
Model 6: Alternative Labor Productivity (Alternative Employment Measure) redefine a firm's labor productivity as revenues divided by the average of employment in years $t-1$ and t	0.0648*** (0.0231)
Model 7: Alternative Industry FE use industry-year where industry is categorized at the 4-digit NAICS level	0.0761*** (0.0288)
Model 8: Alternative Sample (Using Compustat Firms) aggregate all variables from LBD firms to Compustat firms with available observations	1.416*** (0.5129)
Model 9: Alternative Labor Productivity (Using Value-Added, Compustat) define labor productivity as value-added (value of production minus cost of intermediary goods) following Donangelo et al. (2019) using the Compustat sample with 47,500 obsevations and no industry fixed effects	0.5320*** (0.1859)

Table IA.4
Identification Check: Shock Summary Statistics

This table reports an identification check of the properties of our shift-share FGPR measure following the guidance of Borusyak et al. (2025) by summarizing the distribution of geopolitical risk shocks $GPR_{c,t}$ across foreign countries c and years t. Shocks are measured as the geopolitical risk from Caldara and Iacoviello (2022) standardized relative to its past 10 years as described in Section 1.2. All statistics are weighted by the average firm exposure shares $s_{c,t} = Avg(Share_{f,c,t-1})$, where $Share_{f,c,t-1}$ is measured from firms' lagged foreign-born employment, as described in Section 1.2. Column (2) residualizes GPR shocks on period indicators. We report the effective sample size (the inverse Herfindahl–Hirschman index of the $s_{c,t}$ weights, where $s_{c,t}$ is renormalized to sum up to 1 in each year).

Variables	(1)	(2)
Mean	-0.0114	0
Standard deviation	0.644	0.4607
Specification: Residualizing on year FE		✓
Effective sample size (1/HHI of $s_{c,t}$ weights)	160.7	160.7
Observation counts		
No. of country-year shocks	462	462
No. countries	22	22

Table IA.5
Identification Check: Shock Balance Tests

This table reports an identification check of the properties of our shift-share FGPR measure by conducting balance tests at the underlying country level in Panel A and firm level in Panel B. Panel A reports coefficients from regressions of country-level covariates on geopolitical risk (GPR) shocks, controlling for year fixed effects and weighting by average firm exposure shares. Standard errors, reported in parentheses, are clustered by country. Panel B reports coefficients from regressions of firm-level covariates and pre-trends of firms' labor productivity on the shift-share FGPR measure, controlling for $FLabor_{f,t-1}$ interacted with year indicators, industry-year fixed effects, and firm fixed effects. Standard errors, reported in parentheses, are obtained from equivalent country-level regressions using the Stata package *ssaggregate* developed by Borusyak et al. (2022). Independent variables in both panels are normalized to have a variance of one in the sample.

Balance variable	Coef.	SE
Panel A: Country-level balance		
Share of college attainment among immigrants from the country	1.890	(2.413)
Age of immigrants from the country	0.456	(0.275)
Real earnings of immigrants from the country	850.7	(3016.)
No. of country-years	462	
Panel B: Firm-level balance		
Firm employment size in log, $t-1$	-0.00334	(0.001428)
Firm age in log, $t-1$	-0.001209	(0.001185)
Firm average worker age, $t-1$	0.000233	(0.01305)
Firm average worker college attainment, $t-1$	0.1472	(0.09464)
Firm labor productivity, t	0.01432	(0.04525)
Firm labor productivity, $t-1$	0.03556	(0.1031)
Firm labor productivity, $t-2$	0.08809	(0.1356)
No. of firm-years	1,039,000	

Table IA.6
Robustness: Interaction with Alternative Turnover Measures

This table reports robustness checks of the results of Column (5) of Table 4, by showing the results of regressing firms' year $t+1$ labor productivity on their labor exposure to foreign geopolitical risk ($FGPR$), while controlling for an interaction with worker job turnover in year t. Column (1) interacts $FGPR$ with the firm's overall worker turnover defined as the sum of the absolute values of hiring and separation normalized by the firm's beginning of year employment, while Column (2) does so with the firm's foreign-born worker turnover defined as sum of the absolute values of hiring and separation of foreign-born workers normalized by the firm's beginning of year employment. See the regression specification and control variables in Table 2. Standard errors, reported in parentheses, are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dep. Variable:	Labor Productivity$_{t+1}$	
	(1)	(2)
FGPR	0.0817***	0.0833***
	(0.0291)	(0.0291)
Turnover	-0.0026	
	(0.0101)	
FGPR × *Turnover*	0.0035	
	(0.0049)	
Foreign-born Turnover		0.0540
		(0.0556)
FGPR × *Foreign-born Turnover*		0.0045
		(0.0095)
FLabor-Year Ctrls	Yes	Yes
Firm Ctrls	Yes	Yes
Firm FE	Yes	Yes
Industry-Year FE	Yes	Yes
Observations	1,039,000	1,039,000
R2	0.8659	0.8659

Table IA.7
Robustness: Immigrant Labor Supply and Origin-Country GPR

This table reports robustness checks of the results of Table 6, by showing the results of regressing immigrant individuals' hours per week spent on main job work in year t on various measures of their origin countries' geopolitical risk shocks at t. Time-use is from the American Time-Use Survey (ATUS) from 2003 to 2019 and categorized following Aguiar et al. (2013). The baseline *GPR* is the standardized geopolitical risk shocks of the origin country constructed in Section 1.1. The *GPR (Positive)* is the maximum of the *GPR* shocks and zero. *GPR (negative)* is the minimum of the *GPR* shocks and zero. *GPR (U.S. Orthogonalized)* is the standardized GPR shocks of the origin country based on the country's GPR that is orthogonalized with the U.S. GPR during the past 120 months. *Geopolitical (Natural) Disaster* are the media-weighted geopolitical (or natural) disaster events occurring in an origin country constructed by Baker et al. (2024), where the natural disaster measure acts as a placebo test. The regression specification controls for the immigrant demographic characteristics, including age (via five-year age dummies), education attainment (via four education dummies), race, marital status, gender, and a dummy variable indicating whether or not the individual has a child, along with origin country fixed effects and year fixed effects. Standard errors are clustered by country. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dep. Variable:	Hours per Week spent on Work (Main Job)					
	(1)	(2)	(3)	(4)	(5)	(6)
GPR (Baseline)	1.275***					
	(0.424)					
GPR (Positive)		1.864***	1.883***			
		(0.616)	(0.692)			
GPR (Negative)			-0.117			
			(1.095)			
GPR (U.S. Orthogonalized)				0.928**		
				(0.374)		
Geopolitical Disaster (Baker et al. (2024))					3.586***	
					(0.920)	
Natural Disaster (Baker et al. (2024))						-3.674
						(2.413)
Demographic Ctrls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,762	15,762	15,762	15,762	15,530	15,530
R^2	0.103	0.103	0.103	0.103	0.102	0.102

Table IA.8
Robustness: U.S. Firms' Labor vs. Trade Exposures to GPR

This table reports robustness checks of the results of Panel A in Table 10, by showing the results of regressing firms' year $t+1$ labor productivity on their labor exposure to foreign geopolitical risk ($FGPR$) while controlling for proxies for import and export confounding effects. Importer or exporter status ($Import\text{-}Exporter$) is an indicator for if a firm is linked to the universe of individual trade transactions to U.S. firms. Column (1)–(2) examine an interaction of $Import\text{-}Exporter$ with $Global\ GPR$, Column (3)–(4) with the average across all non-US origin countries ($Avg\ Non\text{-}US\ GPR$), and Column (5)–(6) with $U.S.\ GPR$. Together with firm fixed effects and industry-year fixed effects, controls as of the current year include the the log of firm employment ($FirmSize$), the log of firm age in years measured relative to the oldest firm establishment ($Firm\,Age$), the firm average worker age ($Firm\,Avg\,Worker\,Age$), and the firm average percentage of workers with a 4-year college degree or higher ($Firm\,Avg\,Worker\,Edu$). The $FLabor\text{-}Year$ control is an interaction of the year fixed effect with the firm's share of foreign-born workers. Industry is classified at the NAICS 3-digit level. Standard errors, reported in parentheses, are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dep. Variable:	Labor Productivity$_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
FGPR		0.0860***		0.0868***		0.0858***
		(0.0284)		(0.0284)		(0.0284)
Global GPR × Import-Exporter	-3.825***	-3.749***				
	(0.6746)	(0.6734)				
Avg Non-US GPR × Import-Exporter			-3.363***	-3.31***		
			(0.6147)	(0.6136)		
US GPR × Import-Exporter					-3.433***	-3.36***
					(0.6120)	(0.6110)
Import-Exporter	1.152*	1.078*	1.591**	1.511**	1.2*	1.125*
	(0.6375)	(0.6367)	(0.6474)	(0.6465)	(0.6380)	(0.6372)
FLabor-Year Ctrls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Ctrls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,039,000	1,039,000	1,039,000	1,039,000	1,039,000	1,039,000
R^2	0.8659	0.8659	0.8659	0.8659	0.8659	0.8659

Table IA.9
FGPR and Firm-level Political Risk

This table reports on the Compustat sample results from contemporaneously regressing firm-level political risk ($PRisk$) extracted from earnings conference calls by Hassan et al. (2019) on their labor exposure to foreign geopolitical risk ($FGPR$), and proxies of $FGPR$-related trade exposure. In Panel A, Column (1) relates $PRisk$ to $FGPR$. Columns (2)–(3) relates $PRisk$ to interactions of importer or exporter status ($Import\text{-}Exporter$) with $Global\,GPR$, Columns (4)–(5) with the average $Non\text{-}U.S.\,GPR$, and Columns (6)–(7) with $U.S.\,GPR$. In Panel B, $PRisk$ is replaced with the firm-level political risk related to trade topics ($PRisk_Trade$). Together with firm fixed effects and industry-year fixed effects, controls as of the current year include the the log of firm employment ($Firm\,Size$), the log of firm age in years measured relative to the oldest firm establishment ($Firm\,Age$), the firm average worker age ($Firm\,Avg\,Worker\,Age$), and the firm average percentage of workers with a 4-year college degree or higher ($Firm\,Avg\,Worker\,Edu$). The $FLabor\text{-}Year$ control is an interaction of the year fixed effect with the firm's share of foreign-born workers. Industry is classified at the NAICS 3-digit level. Standard errors, reported in parentheses, are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Relation with Overall Firm-level Political Risk

	PRisk_t						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FGPR	-0.0010		-0.0011		-0.0010		-0.0011
	(0.0026)		(0.0026)		(0.0026)		(0.0026)
Global GPR × Import-Exporter		0.1590*	0.1596*				
		(0.0842)	(0.0845)				
Avg Non-US GPR × Import-Exporter				0.1143	0.1144		
				(0.0767)	(0.0770)		
US GPR × Import-Exporter						0.1409**	0.1423**
						(0.0703)	(0.0705)
Import-Exporter		-0.0933	-0.0945	-0.1019	-0.1030	-0.0930	-0.0943
		(0.0623)	(0.0623)	(0.0656)	(0.0657)	(0.0619)	(0.0619)
FLabor-Year Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	
Firm Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,000	28,000	28,000	28,000	28,000	28,000	28,000
R^2	0.4527	0.4526	0.4530	0.4525	0.4529	0.4526	0.4530

Panel B: Relation with Trade-related Firm-level Political Risk

	PRisk_Trade$_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FGPR	-0.0520		-0.0519		-0.0510		-0.0518
	(0.0596)		(0.0597)		(0.0599)		(0.0598)
Global GPR × Import-Exporter		4.45**	4.409**				
		(1.928)	(1.934)				
Avg Non-US GPR × Import-Exporter				3.775**	3.742**		
				(1.617)	(1.623)		
US GPR × Import-Exporter						4.631**	4.635**
						(1.8)	(1.806)
Import-Exporter		-0.6747	-0.6708	-1.051	-1.044	-0.7555	-0.7571
		(1.371)	(1.371)	(1.43)	(1.431)	(1.367)	(1.366)
FLabor-Year Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	
Firm Ctrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,000	28,000	28,000	28,000	28,000	28,000	28,000
R^2	0.3426	0.3422	0.3427	0.3422	0.3427	0.3423	0.3428

Table IA.10
Origin Country Geopolitical Risk and Immigrant Return Migration

This table reports on individual-level regressions of a return migration dummy on geopolitical risk shocks in their origin country (GPR) using LinkedIn profile data from Revelio Labs. Columns (1)–(2) estimate conditional logit regressions, while Columns (3)–(5) estimate linear OLS regressions. All estimates are weighted to be nationally representative of the demographic distribution observed in the American Community Survey (ACS) in terms of Country-Age-Gender-Income bins. The Country-Age-Gender-Income FE is a fixed effect defined by workers being assigned into 688 cells based on 43 country of origin × 4 age brackets × gender (male vs. female) × income (above or below median by year) population groups. Standard errors, reported in parentheses, are clustered by country. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dep. Variable:	Return Migration				
	Logit		OLS		
	(1)	(2)	(3)	(4)	(5)
GPR	-0.247***	-0.237***	-0.367***	-0.356***	-0.102***
	(0.00407)	(0.00406)	(0.0960)	(0.0879)	(0.0282)
Country FE	Yes	No	Yes	No	No
Country-Age-Gender-Income FE	No	Yes	No	Yes	Yes
Individual FE	No	No	No	No	Yes
Observations	7,730,009	7,730,009	7,730,009	7,730,009	7,730,009