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Global Value Chains in a World of Uncertainty and Automation

Abstract

The world economy has become more and more globalized as firms have organized production along global value chains. But more recently, globalization has stalled. This paper shows that higher uncertainty, in combination with better automation technologies, has likely contributed to that trend reversal. We show that plausibly exogenous exposure to uncertainty in developing countries leads to reshoring to high-income countries, but only if industrial robots have made this economically feasible. In contrast, we find no strong evidence of nearshoring or diversification. We address concerns about reverse causality by showing that results hold when using two alternative identification strategies. In a narrative approach, we use only locally generated spikes in uncertainty, for which the narrative around the events suggest that they are plausibly exogenous. In a small open economy approach, we restrict the sample to small developed countries that are unlikely to cause uncertainty in the developing world. Moreover, we show that results are robust to the main threats to identification related to shift-share instruments.

JEL-Codes: F140, F150, F160, J230.

Keywords: global value chains, uncertainty, automation, reshoring, shift-share design.

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1 Introduction

After a long period of strong growth, globalization has come to a halt since the Global Financial Crisis (GFC), largely owing to a slowdown in trade between developed and developing countries. While trade as a share of GDP had risen by more than one percentage point per year between 1990 and 2008, it has since entered a period of decline (Figure 1).[1] This slowdown can, in large part, be attributed to a halt in the growth of intermediate goods trade with the developing world. Between 2000 and 2007, the share of total inputs sourced from developing countries had almost tripled, corresponding to an average annual growth rate of about 15 percent. But with the GFC, this rapid expansion ended abruptly, being followed by a period of decline since 2011.

While many factors may be at play, two major developments have likely contributed to the declining globalization since the GFC: First, economic uncertainty shocks have become larger and more frequent, partly owing to international trade linkages. Examples are the European debt crisis from 2011 to 2014, Brexit in 2016, the US-China trade war since 2018, and the Covid-19 crisis starting in 2020 (Figure 1). After experiencing the risks associated with high exposure to trade, firms have likely started to reconsider their relationships.[2] Second, automation technologies have made substantial advances, now having the ability to perform a range of tasks that had previously been offshored. In an effort to fight low inflation, central banks have ensured extraordinarily favorable financing conditions after the GFC, effectively lowering the cost of capital relative to labor. This made it especially attractive for firms to invest in ever-more-capable, domestically installed automation technologies rather than to employ foreign labor as a means of production.[3] Higher uncertainty may have thus dampened globalization, especially in highly automated industries.

While it seems plausible to assume that uncertainty and automation reduce globalization, their impacts are, in fact, theoretically ambiguous. Regarding uncertainty, the direction of the effect depends partly on whether firms view the domestic or the foreign economy as more prone to shocks (Grossman et al., 2023). For example, if all countries are perceived to be equally likely to experience a supply-disrupting shock, then firms may find it optimal to diversify supply relationships across as many countries as possible, leading to less domestically sourced supplies and more offshoring. Conversely, if firms view their home country as less prone to such shocks, it may instead be optimal to reshore. Re-

[1] As pointed out in Baldwin et al. (2024), this trend break is due to goods trade, whereas services trade as a share of GDP had continued to rise.

[2] Barrot and Sauvagnat (2016) and Carvalho et al. (2021) show that firms whose suppliers were hit hard by a natural disaster suffered substantial sale losses. Relatedly, at the height of the Covid-19 pandemic, 93% of supply chain leaders planned to increase their supply chain resilience, about half of which explicitly mentioned relocation of production (Alicke et al., 2021).

[3] For example, Artuc et al. (2019) and Faber (2020) find evidence of reshoring from Mexico due to US robotization.

garding automation, the direction of the effect depends largely on the relative strength of the (negative) displacement and the (positive) productivity effect (Artuc et al., 2020). For example, productivity effects from using robots may be so large that the expanded demand for foreign inputs requiring mainly non-automated tasks outweights the reduced demand for those requiring mainly automated tasks.

Because of this theoretical ambiguity, in this paper, we empirically estimate the effect of uncertainty on reshoring – and the role played by automation in facilitating it.[4] In our empirical strategy, we exploit the fact that country-industry pairs were differentially exposed to uncertainty shocks in the developing world between 2000 and 2014 because of their pre-existing trade relationships in 2000. We argue that our (shift-share) measure of exposure to developing countries' uncertainty induces plausibly exogenous variation in uncertainty, as *i)* uncertainty shocks in developing countries are unlikely to be *caused by* reshoring decisions in the developed world and *ii)* it is based on pre-determined country-industry-level trade patterns, alleviating concerns related to simultaneity. In addition to these more conceptual arguments, we implement several recommended econometric tests to alleviate the most prominent concerns about identification and inference using shift-share instruments.[5] Finally, we control for a large battery of potential third factors that may be related to both uncertainty shocks and reshoring decisions. Armed with this measure, we then compare how the domestic-to-developing countries' input mixes have developed between country-industry pairs with a high exposure and those with a low exposure to uncertainty in developing countries. To explore the role played by automation, we ask whether this relationship differs by the degree to which tasks in each industry are replaceable by industrial robots.

Results show that higher uncertainty in developing countries significantly increases the relative use of domestic inputs, but only in highly robotized industries. This suggests that firms do use reshoring (the reverse of offshoring) as a coping mechanism to deal with adverse shocks to global value chains, if automation has made this economically feasible. Regarding the different margins of adjustment, we find that this effect stems from a reduction in inputs from developing countries, and not from an increase in domestic inputs.[6] Our estimates imply that a one standard deviation increase in exposure to uncertainty in developing countries reduces demand for inputs from the developing world by about 10% in robotized industries. This effect is even stronger for inputs from Eastern Europe, Latin America and China, and it increases substantially after the GFC.[7] We cannot, however,

[4] Throughout the paper, we refer to reshoring as the increased use of domestic relative to foreign inputs, following Krenz et al. (2021).

[5] As pointed out in Adao et al., 2019, Borusyak and Hull, 2023, de Chaisemartin and Lei, 2022 and Goldsmith-Pinkham et al., 2020, among others.

[6] This suggests that reshoring happens rather via the reintroduction of parts of the value chain to within the same firm rather than more sourcing from domestic input suppliers.

[7] We presume that these heterogeneities can be accounted for by *i)* differing comparative advantages

find clear evidence of nearshoring (reshoring from faraway to closeby developing countries) or diversification across developing countries as coping mechanisms.

We also find spillover effects on the use of inputs from other developed countries. In particular, an uncertainty shock in the developing world increases the reliance on inputs from other developed countries in non-robotized industries, but reduces it in robotized industries. This suggests that firms use inputs from other developed countries as a substitute if automation possibilities are limited; but if robots allow them to reshore, they may, in the process, also demand less such inputs from the developed world.

Results are robust to several threats to identification, including the most important ones arising from the use of shift-share instruments. First, we show that results are unlikely to be driven by reverse causality, by implementing two alternative approaches to identification – a "narrative approach" in which we focus only on uncertainty shocks where the source of the shock is plausibly exogenous, and a "small open economy approach" where we restrict the sample to small developed economies which are unlikely to meaningfully affect uncertainty in developing countries. Second, we show that exposure to developing countries' uncertainty is not associated with pre-existing reshoring trends. Third, following Borusyak and Hull (2023), we show that the realized uncertainty shocks are as good as randomly assigned. Fourth, building on the previous point and using a "modified" shift-share instrument following de Chaisemartin and Lei (2022), we show that our results are robust to heterogeneous treatment effects. Fifth, we rule out that any single developing country plays an outsized role in our results, alleviating concerns identified in Goldsmith-Pinkham et al. (2020). Sixth, we show that our results are not driven by noise and are robust to a variety of alternative ways to calculate standard errors, including the ones recommended in Adao et al. (2019). Seventh, we rule out that our results are driven by any single developed country or industry, differential trends by country, industry, period, or even country-industry pair, and a battery of third factors. Finally, we show that our results remain unchanged when using an alternative measure of uncertainty, based on 10-year bond spreads relative to the US.

Our paper is most closely related to two separate strands of the literature: on the one hand, a literature examining the impact of uncertainty on trade and, on the other, one studying the impact of automation on trade. To the best of our knowledge, our paper is the first to document the complementarity of uncertainty and automation for reshoring, and to quantify the role of these factors for the slowdown in globalization.

Several papers explore the effect of uncertainty on international trade, though none of them documents the complementarity between uncertainty and automation in reshoring

(and their overlap with robots' capabilities) across regions and *ii)* more favorable financing conditions or higher risk aversion following the traumatic GFC experience.

decisions. Novy and Taylor (2020) argue that firms faced with higher uncertainty disproportionately cut orders of foreign inputs because of higher fixed costs. They are able to explain the trade collapse of 2008/2009 with US data. Martin et al. (2023) show with French firm-level export data that uncertainty inhibits the creation of new firm-to-firm relationships in longer lasting trade relationships and reduces the separation of these trade relationships. Handley and Limão (2015, 2017), Graziano et al. (2021) and Pierce and Schott (2016) study the impact of uncertainty-affecting events such as Portugal's accession to the European Community, the US granting Permanent Normal Trade Relations to China and Brexit on international trade. Grossman et al. (2023) analyse theoretically optimal policy in response to the risk of supply chain disruptions, showing that a subsidy for diversification and (under some conditions) reshoring may increase welfare.

Another set of papers explore the effect of robots on offshoring, albeit without considering the role of uncertainty. The relationship between robots and offshoring is in principle ambiguous, and the scarce available evidence reflects this ambiguity. On the one hand, robots may substitute for foreign workers and thus reduce inputs sourced from these countries (displacement effect). On the other, robots reduce costs and increase productivity, which may cause firms to expand and import more inputs from foreign countries in non-automated tasks (productivity effect). Artuc et al. (2020) present evidence suggesting that automation and robots in industrial countries have boosted imports from developing countries. Stapleton and Webb (2020) also find a positive effect of robots on imports from developing countries for Spanish firms. In contrast, Faber (2020) finds that increased robot penetration in the US reduced imports from Mexico. Krenz et al. (2021) and Bonfiglioli et al. (2022) also find evidence for robot-induced reshoring. Our paper contributes to this literature by showing that independent from a potential direct effect on reshoring, robots affect reshoring by mediating the effect of uncertainty.

The paper is organized as follows. Section 2 presents the empirical strategy. Section 3 introduces our data. Section 4 presents our main empirical results and various robustness checks. Section 5 concludes. The appendix presents additional tables.

2 Empirical strategy

In this section, we first describe our estimating equation and then discuss the identifying assumption behind this estimation strategy as well as threats to identification and how we address them.

Estimating equation. We consider 18 developed countries, 17 developing countries and 19 industries, and stack the data into five two-year periods, 2000-2, 2002-4, 2004-6, 2010-12 and 2012-14.[8] To identify the effect of connected developing countries' uncertainty on

[8] See Table A1 for summary statistics on our main variables and Table A2 for a full list of countries incl. their shares of imported inputs from developing countries. We omit the periods 2006-8 and 2008-10 to

reshoring, and the role played by robotization as a mediator, we estimate a regression of the form:

$$\text{reshoring}_{ij,t} = \beta\, \Delta \begin{array}{c}\text{exposure to}\\ \text{developing}\\ \text{countries'}\\ \text{uncertainty}_{ij,t}\end{array} + \gamma \begin{array}{c}\text{robot}\\ \text{replaceability}_j\end{array} + \delta\, \Delta \begin{array}{c}\text{exposure to}\\ \text{developing}\\ \text{countries'}\\ \text{uncertainty}_{ij,t}\end{array} \times \begin{array}{c}\text{robot}\\ \text{replaceability}_j\end{array}$$
$$+ \eta_i + \theta_t + \kappa\, \boldsymbol{X}_{ij,t} + \epsilon_{ij,t} \quad (1)$$

where $\text{reshoring}_{ij,t} = \Delta \log(\text{domestic inputs}_{ij,t}/\text{inputs from developing countries}_{ij,t})$ measures the (log) change in the reliance on domestic inputs relative to inputs from the developing world in country i in industry j in period t.[9] In our analysis, we also estimate versions of this equation in which we change the dependent variable (e.g., we fix the numerator and the denominator at their initial levels to understand the main channel behind changes in this reshoring variable, or we look at related measures of nearshoring or diversification).

We measure a country-industry pair's exposure to uncertainty in connected developing countries in each period using a shift-share approach. We define:

$$\Delta \begin{array}{c}\text{exposure to}\\ \text{developing}\\ \text{countries'}\\ \text{uncertainty}_{ij,t}\end{array} = \sum_{k \in K} \alpha_{ijk} \Delta \text{uncertainty}_{k,t} \quad (2)$$

where $\text{uncertainty}_{k,t}$ is developing country k's level of uncertainty in the World Uncertainty Index (Ahir et al., 2022), and $\alpha_{ijk} = \text{inputs}_{ijk,2000}/\text{inputs}_{ij,2000}$ is the share of developing country k's inputs of all inputs of (developed) country i in industry j in 2000.[10] Thus each country-industry pair is exposed to a unique combination of uncertainty shocks in the developing world, depending on its initial dependence on the various countries. Moreover, by dividing by total inputs, a country-industry pair with low (high) reliance on inputs from the developing world more generally features, on average, a low (high) exposure to uncertainty shocks there.

The variable robot replaceability_j is a dummy variable taking the value 1 if the industry features above median replaceability in the correspondent measure developed by Graetz and

avoid contamination and measurement error from the tumultuous global financial crisis and the resulting recession. Table A3 shows that the main results do not hinge on that choice.

[9] We follow the recommendation of Krenz et al. (2021) and use the ratio of domestic to foreign inputs as opposed to just changes in either of the two. This is useful to avoid unintentionally capturing changes in total production. In principle, one may also use the linear ratio (not logs). Table A4 shows that results remain qualitatively unchanged when doing so.

[10] Dividing by total inputs ensures that, by construction, country-industry pairs with a high/low reliance on inputs from developing countries have a high/low exposure. However, one may argue that dividing by inputs from developing countries instead provides a closer connection to our definition of reshoring. Reassuringly, results in Table A5 show that this choice makes no difference for our results.

Michaels (2018), and 0 otherwise.[11] The underlying measure is based on each industry's share of occupations in the US in 1980 that required skills which are nowadays among the key capabilities of industrial robots. The goal of this variable is to capture whether or not an industry has had a relatively cheap technological alternative to domestic labor when deciding whether or not to reshore production.

In our main specification, we include country and period dummies to account for differential trends across countries and time periods.[12] Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry pair level.

Identification. The coefficients of interest, β, γ and δ are thus identified from comparing how the input mixes have developed between different country-industry pairs, taking into account that some countries and periods feature generally more reshoring or larger rises in uncertainty than others. The identifying assumption behind this strategy is that country-industry pairs with high and low exposures to developing countries' uncertainty would have adjusted their domestic-to-developing-country input mix similarly without uncertainty shocks in developing countries. Moreover, regarding the heterogeneity with respect to robot replaceability, the identifying assumption is that manufacturing industries with above and below median shares of occupations with robot-replaceable tasks in the US in 1980 would have adjusted their domestic-to-developing-country input mix similarly in the absence of industrial robots.

The main threats to identification in our setting are related to reverse causality, simultaneity and third factors being correlated with both reshoring and uncertainty changes in developing countries.[13] First, there may be reverse causality and/or simultaneity. It is possible that reshoring causes changes in uncertainty in developing countries, not just the other way around. While there is some evidence that tight economic relationships can lower the risk of conflict between regions and thus uncertainty, this potential channel is presumably, if anything, quantitatively small compared to the large movements in uncertainty triggered by adverse domestic politics-, climate- or health-related events that drive the variation in our data.[14]

[11] We prefer the dummy variable as our main specification for ease of interpretation. However, in Table 9, we replicate our main results with the original continuous measure and show that they remain qualitatively unchanged.

[12] In robustness checks, we also include country-period, industry, and country-industry fixed effects to account for differential trends along these dimensions, as well as a battery of controls, $\boldsymbol{X}_{ij,t}$, to capture factors that are not well captured by these sets of fixed effects mentioned above, and may potentially be correlated to our dependent or explanatory variables. See Section 4.2 for details.

[13] Apart from the more conceptual identification issues discussed here, a recent literature highlights a range of more technical identification issues with shift-share instruments. We discuss and address those in detail in Section 4.2.

[14] Martin et al. (2008), in fact, show that the relationship between trade and peace is ambiguous.

Nevertheless, to bolster our confidence that our estimates do not suffer from reverse causality, we implement two alternative approaches to identification, which we refer to as the "narrative approach" (similar in spirit to the narrative approach used in the macroeconomics literature to identify the effects of monetary and fiscal policy; e.g., Romer and Romer, 1989) and the "small open economy approach," respectively. In the first, we use only uncertainty spikes in developing countries where the narrative for why the spike happened (e.g., from the respective country reports by the Economist Intelligence Unit) suggests that the event was plausibly exogenous to reshoring decisions in developed countries.[15] In the second, we estimate the effects only from a set of "small" developed countries (from the perspective of developing countries). Reshoring by these countries is less likely to affect uncertainty in the developing world, given that they represent only a small share of the total demand for inputs from developing countries.

Another potential threat is simultaneity. For example, firms may anticipate an uncertainty shock in a developing country (perhaps due to scheduled upcoming elections) and decide to move back production already beforehand. We tackle this concern in two ways: First, we use import shares from 2000 as opposed to contemporaneous ones when calculating α_{ijk} in Equation (2).[16] This rules out that the exposure to uncertainty shocks in developing countries captures variation induced by changes in import shares, which may be affected by either anticipated or previously realized uncertainty shocks within our sample period. Second, we inspect the uncertainty shocks in developing countries more closely to understand whether these could have been anticipated. Figure 2 provides background information for uncertainty shocks in the developing countries we consider. The majority of these shocks seem quite difficult to anticipate by firms in the developed world.[17] Moreover, any anticipation would, if anything, cause our estimates to be biased to the downside in absolute terms, as any adjustments happening after the shock happened would seem smaller than they actually were.

Finally, there may be third factors that are correlated with both reshoring and uncertainty changes in developing countries. While this always remains a possibility, we rule out the arguably most important ones by including various combinations of fixed effects (to account for unobservable differential trends at the industry, country-industry, and country-period level) and controlling for various other contemporaneous developments.[18]

[15] See Figure 2 for a chart with annotations for all uncertainty spikes used in that test.

[16] 2000 is the earliest year for which data on inputs by source country is available.

[17] One may be worried that part of the uncertainty induced by scheduled elections/political handovers (as in Mexico or China) could have been anticipated by firms. Reassuringly, in the robustness checks, we show that our estimates remain virtually unchanged when excluding any single country from the set of developing countries. This suggests that even if some political events may have been anticipated, these do not meaningfully change our estimates.

[18] Precisely, we control for relative wages between countries, tariff changes, the rise of China as a major exporter, domestic uncertainty shocks, exposures to changes in climate, mental health and political change in developing countries, relationship stickiness, supplier concentration, labor market institutions, routine

Regarding the heterogeneity with respect to robot replaceability, it is important to note that the measure we use (developed in Graetz and Michaels, 2018) does not reflect the actual robot adoption of country-industry pairs, which is likely to be endogenously determined by labor market conditions prevailing at the time. Instead, the measure captures the extent to which industries have historically relied on tasks that have in recent decades become technologically feasible to automate.

3 Data

In this section, we describe the data sources we use to construct our main variables.

3.1 Reshoring

We rely on the World Input-Output Database (WIOD) 2016 Release to measure reshoring (Timmer et al., 2015).[19] It contains information on intermediate input flows from producing to consuming industries between the set of 28 EU and 15 other major countries at the ISIC Rev. 4 industry classification level. We apply a crosswalk to harmonize industry classifications across the different datasets we use.

3.2 Uncertainty

We use the World Uncertainty Index (WUI) developed by Ahir et al. (2022) to measure uncertainty changes at the country level. The WUI is computed by counting the share of the word "uncertain" (or its variants) in the Economist Intelligence Unit country reports.[20] Note that while the WUI is available only at the country level, our variable of changes in developing countries' uncertainty varies at the country-industry level, as we interact country-level uncertainty changes with each country-industry pair's own relative reliance on inputs from various developing countries.

3.3 Robot replaceability

We rely on the robot replaceability measure developed by Graetz and Michaels (2018) to define whether an industry can be classified as requiring tasks that may be performed by robots. This measure is based on the task requirements of occupations in the United States in 1980. First, occupations are classified as "replaceable" if, by 2012, their work could have been replaced, fully or in part, by industrial robots. Then, the fraction of each industry's hours worked in 1980 that have in subsequent years become prone to replacement by robots is computed, resulting in a measure of robot replaceability that varies by industry. For our heterogeneity analysis, we define industries with above median scores as "replaceable" and those below as "non-replaceable."[21]

task intensity, and offshorability.

[19] We use the same data to construct measures of nearshoring and diversification, as described in the results section.

[20] See Figure 2 for the development of the WUI for the developing countries in our sample.

[21] See Table A6 for details.

3.4 Controls

Relative wages. We compute each country-industry pair's wage level relative to the weighted average wage of its input suppliers in the developing world in 2000. Data on wages by country-industry pair is taken from the socio-economic accounts of the WIOT. Data on each country-industry pair's input reliance on the individual developing countries included in our sample (to compute the weights) is taken from the WIOT.

Import tariffs. We compute the average tariff changes faced by each country-industry pair from the UN Comtrade database, which reports tariffs at the HS2 product level. To aggregate these to the industry level, we compute a weighted average of product-level tariff changes, using each product's share of total imported inputs in the industry as weights.

China shock. We use data from the WIOT to measure the rise of China as an export nation. In particular, we compute, for each industry, China's share of world exports of intermediate inputs, using China's exported inputs to all countries except the own country.[22]

Stickiness. We include an industry-level measure of relationship-specificity developed by Nunn (2007) to account for the fact that some industries may have stickier supplier relationships than others.[23]

Climate, political situation and mental health in developing countries. To account for changes in climate, the political situation and mental health in developing countries, we use data on average temperatures from the World Bank (2024), the Economic Left-Right Index from Lindberg et al., 2022), and the suicide rate from the World Health Organization (2024).

Routine task intensity. To account for computerization, we use an industry's routine task intensity, following Autor et al. (2015), based on the distribution of occupations across industries in the United States in 1990.

Offshorability. To account for the importance of offshoring, we include each country-industry pair's 2000 share of developing country inputs of total non-energy inputs, following Feenstra and Hanson (1999).

Labor market institutions. To account for the changing role of unions in each developed country over time, we use the "union coordination index" from OECD and AIAS (2021), which measures the predominant level at which wage bargaining takes place (fol-

[22] We use Chinese exports of intermediates to all countries *other than the own country* to avoid mechanical correlation with the outcome variable. However, results remain robust to controlling for an alternative measure that does not correct for own-country imports from China.

[23] This measure is calculated as the fraction of input values not traded on an exchange in total value of all inputs used. The larger this fraction, the more relationship-specific the industry is assumed to be.

lowing Bhuller et al., 2022).

4 Effect of uncertainty and robots on reshoring

In this section, we present our main results on the effect of uncertainty and robots on reshoring and show that they are robust to a set of alternative explanations. Next, we identify the channels driving the documented reshoring response and discuss the magnitude of the effect. Finally, we explore heterogeneity across regions and time periods as well as alternative margins of adjustment, such as nearshoring or diversification.

4.1 Main results

We examine the effect of uncertainty on reshoring by estimating Equation (1), using only the change in developing countries' uncertainty as well as country and period fixed effects as explanatory variables.[24] We report results in column (1) of Table 1. The point estimate suggests a small positive, but insignificant, effect of connected developing countries' uncertainty on reshoring.

In columns (2) to (4), we then turn to the role of robots as a potential mediator. We start by adding only a dummy variable that indicates whether an industry features above-median robot replaceability, following Graetz and Michaels (2018). The point estimate suggests that industries with a high share of tasks than nowadays can be automated feature slightly less reshoring. However, the effect is significant only at the 10 percent level.

In column (3), we then interact the robot replaceability dummy with exposure to developing countries' uncertainty to examine whether robots play a role in facilitating reshoring in response to an uncertainty shock. Results show that, while uncertainty shocks do not trigger a significant reshoring response in non-robotized industries, they do so in robotized industries (as evident in the non-significant estimates in the first row and the positive, significant estimate in the third row). Thus, reshoring in response to uncertainty in developing countries seems to become (economically) feasible if tasks can be performed (at relatively low cost) by a domestically installed robot. Our point estimate implies that a one standard deviation higher uncertainty shock in connected developing countries increases the relative use of domestic inputs (i.e., reshoring) by about 7 percent ($\delta + \beta = 7.5 - 0.5 = 7$). This estimate is significant at all conventional levels.[25]

In column (4), we repeat the same regression as in column (3), but restrict the sample to the

[24] If not mentioned otherwise, exposure to uncertainty in developing countries is normalized, such that point estimates should be interpreted as the effect of a one standard deviation change in this variable.

[25] Balli and Sørensen (2013) highlight that linear regression models with interaction terms in panel data may pick up spurious correlations, for example because effects vary across countries. To be sure that our estimates do not suffer from such bias, we follow their recommendation in Table A7 and orthogonalize the exposure to developing countries' uncertainty in the interaction term. The coefficient on the interaction term becomes somewhat smaller, but reassuringly remains significant at the 1% level and is not statistically significantly different from our main results in Table 1.

set of manufacturing industries.[26] This is useful for two reasons. First, it allows us to rule out that results are confounded by unobservable differences between manufacturing and non-manufacturing, as industrial robots are almost entirely concentrated within manufacturing. It is thus useful to test whether results remain the same when exploiting variation across industries only within manufacturing. Second, the specification serves as a baseline for a set of robustness checks we perform in the next subsection, most of which involve variables that are only available for manufacturing industries. Results show that dropping non-manufacturing industries leaves the main results from column (3) qualitatively and quantitatively almost unchanged.

4.2 Robustness

There are several potential alternative explanations for our results, some related to reverse causality, others related to issues with identification and inference when using so-called Bartik or shift-share instruments, and others related to third factors that may be correlated with both offshoring and uncertainty. In this subsection, we show that our main results are robust to the most important alternative explanations.

Reverse causality. It is conceivable that reshoring (or reduced offshoring) by developed countries from developing countries causes uncertainty shocks in the developing world. In that case, our estimates would not (only) capture the effects of uncertainty on reshoring, but (also) those of reshoring on uncertainty.

We tackle this concern with two approaches. First, we follow what we refer to as the "narrative approach". The idea is that for many of the uncertainty spikes in developing countries, there is a narrative (e.g., taken from the underlying country reports by the Economist Intelligence Unit) about what caused them. We isolate only those for which we believe it is due to causes that are plausibly exogenous to offshoring/reshoring decisions in developed countries. In Figure 2, we provide an annotated chart that describes each of those narratives. For example, we classify the 2013 uncertainty spike caused by the Petrobras corruption scandal in Brazil as plausibly exogenous. However, we classify the 2014 high in India as possibly endogeneous, as it was due to Prime Minister Modi's rise to power, which may have been in part connected to the economic growth slowdown (and reduced offshoring/reshoring by developed countries) in the years leading up to the election.

In Table 2, we then rerun our main specification, but now use only uncertainty changes in the time periods and developing countries for which we have identified a plausibly exogenous spike in uncertainty (i.e., we set all other changes in uncertainty to zero) when constructing the exposure to uncertainty in developing countries variable. Therefore, in this exercise, we identify the effect of uncertainty in developing countries on reshoring only

[26] More precisely, we drop the agriculture, mining, utilities, construction as well as education and R&D industries.

from movements in the uncertainty index where we are confident that they are due to plausibly exogenous events. We view this as a demanding specification, considering that we isolate only a few events and thus drop a large part of the variation included in our main exposure variable. Nevertheless, estimates remain virtually unchanged, bolstering our confidence that our results are not biased by reverse causality.

Second, we follow what we refer to as the "small open economy approach." The idea is that small developed countries have a lower potential to cause uncertainty in developing countries than large ones (similar in spirit to the idea that small open economies are price takers on global markets). To identify small and large developed countries in our sample, we focus on whether they are small or large from the perspective of developing countries (i.e., whether a developed country is an important destination country for developing countries' inputs), as this should matter more for reverse causality in our setting than the total size of the economy (e.g., in terms of GDP, labor force, etc.).

In Table 3, we rerun our main specifications, only now excluding the five largest importers of developing countries' inputs among the set of developed countries (USA, Germany, South Korea, France, Italy). Together, these five countries represent almost 70% of all imported inputs from the developing to the developed world in our sample. Given this high share, we are quite confident that reshoring by the remaining developed countries has a much smaller potential to drive uncertainty in developing countries. It is reassuring that the coefficient on the interaction term remains positive and significant at the 5% level, even if it becomes somewhat smaller in absolute terms compared to our main results in Table 1.[27]

Pre-trends. Our estimates would likely be biased if uncertainty shocks in one period were correlated with changes in the input mixes in the period before. This would suggest that country-industry pairs with high exposure to developing countries' uncertainty would have been on differential trends relative to those with low exposures before the shocks happened. In Table 4, we show that this is not the case, i.e., that changes in input mixes are uncorrelated with uncertainty shocks in the next period. None of the estimated coefficients of interest is statistically significantly different from zero.

Non-random shock exposure. A central concern with shift-share instruments, where the shocks, or "shifts" (in our case, uncertainty changes in a number of developing countries), are assumed to be exogenous, is that exposure to these shocks may not be random (Borusyak and Hull, 2023). For example, in our setting, highly tradeable industries in

[27] One may argue that some small developed economies may still be large from the perspective of some particular developing countries. Therefore, we implement a more refined variant of the small open economy exercise in Table A8. In that exercise, we sequentially exclude the top-3 developing countries for which a developed country is (among) the most important input export destinations. For example, if Germany is the largest buyer of inputs from Poland, we disregard uncertainty changes in Poland when constructing the exposure to uncertainty in developing countries for German industries. Reassuringly, results remain similar to those in Tables 1 and 3.

small open economies may be systematically more exposed to shocks, due to their location in the global production network. It is possible that this characteristic is correlated with contemporaneous changes other than uncertainty shocks. If so, our results would partly reflect such differences as opposed to the effects of random uncertainty shocks. In Table 5, we thus follow the recommendations of Borusyak and Hull (2023) and recenter the exposure to developing countries' uncertainty by subtracting the "expected" exposures, which we get from simulating 1,000 counterfactual sets of uncertainty shocks and averaging out the resulting counterfactual shocks. Reassuringly, results remain almost identical, suggesting that the realized shocks are as-good-as-randomly assigned.

Heterogeneous treatment effects. With heterogeneous treatment effects (across units or periods), estimates from shift-share designs may be biased, because regressions may identify non-convex combinations of unit-and-period-specific treatment effects (de Chaisemartin and Lei, 2022). As our shocks appear to be as-good-as-randomly assigned (see paragraph above), we follow the recommendation of de Chaisemartin and Lei (2022), and calculate a "modified" shift-share estimator, where shocks are standardized by their period-specific standard deviation, which is fully robust to heterogeneous effects, both over time and across units. Table 6 shows that our results remain unchanged if we use this modified shift-share estimator instead of our original one. The coefficient remains positive, significant at the 1% level, and similar in size.

Impact of single shifts. Another concern is that with a finite number of "shifts," it is possible that single shifts play an outsized role for the estimated coefficients (Goldsmith-Pinkham et al., 2020). If so, the results may reflect, in truth, not the impact of uncertainty, but rather some other contemporaneous shock to that developing country. To rule out this possibility, in Figure 3, we present the estimated coefficients on the interaction term in column (4) of Table 1, but now excluding each developing country in our sample, one at a time. The fact that results remain almost identical, no matter which developing country we drop, reassures us that no single "shift" drives our estimates.

Noise. Shift-share designs may lead to too narrow confidence intervals because residuals may be correlated across units with similar shares (Adao et al., 2019). If so, even hypothetical shifts that represent noise may yield significant results more often than should statistically be expected. Consequently, standard errors associated with realized shocks may be too small. In Figure 4, we show 1,000 point estimates and confidence intervals of the interaction term of column (4) of Table 1, where each time the realized shift-share instrument is replaced by one that uses hypothetical shocks drawn from a normal distribution. Results show that there is some overrejection, however, it is substantially smaller than in any of the applications shown in Adao et al. (2019).

Nevertheless, to alleviate this concern, we calculate standard errors in several alternative ways in Figure 5, including the ones proposed in Adao et al. (2019). Results show that the interaction term in column (4) of Table 1 remains significant at the 5% level, irrespective of the way we calculate standard errors. Overall, our baseline approach of clustering standard errors by country-industry pair produces relatively conservative (i.e., wide) confidence intervals. Confidence intervals calculated using the approach suggested in Adao et al. (2019) are much smaller.[28]

Differential trends and third factors. Apart from the more technical econometric issues with shift-share instruments addressed above, we next rule out alternative explanations that the period and country fixed effects in our preferred specification in column (4) of Table 1 may not be able to fully capture. To this end, we show that our main results remain unchanged after the inclusion of alternative sets of fixed effects in Table 7 and a battery of control variables accounting for other contemporaneous developments in Table 8.

In Table 7, we show that results are not driven by differential trends across industries, country-industry pairs or country-period pairs.[29] In columns (1) and (2), we include industry fixed effects in addition to the country and period fixed effects of our baseline specification. This exercise confirms our main results, showing that the effect of uncertainty in the set of low-robot-replaceability industries remains insignificant (coefficient on main effect) and the one in the set of high-robot-replaceability industries remains positive and significant at the 1% level.

In columns (3)-(6), we next include country-period fixed effects instead of separate country and period fixed effects, once to the specification without and once to that with industry fixed effects. Results remain again broadly unchanged, even if somewhat less significant (at the 5% level), suggesting that differential trends at the country-period level do not drive our results.

Finally, in columns (7) and (8), we show that even when we add country-industry fixed effects, results remain again unchanged. This is in our view a remarkable result, given that this is a very challenging specification exploiting an entirely different variation. While in our main results in Table 1, the estimation exploits variation across ($18 \times 19 = 342$)

[28] It should be noted, however, that the number of clusters is relatively small in many of the alternative approaches, since there are 18 developed countries, 19 industries, and 17 developing countries in our dataset. As pointed out in Cameron and Miller (2015), a small number of clusters can overstate estimator precision.

[29] These exercises also alleviate various concerns about third factors that vary at the industry, country-industry or country-period level, including an industry's routine task intensity or relationship stickiness (to account for heterogeneous elasticities being correlated with robot replaceability), the importance of offshoring in the different country-industry pairs, a country's wages relative to those in developing countries in a given period, or the changing role of labor unions in each country over time. Nevertheless, we explore the role of these characteristics for our results explicitly in a separate exercise in Table A9.

country-industry pairs, in these two columns, estimates are based on variation within country-industry pairs over (five) time periods. The fact that results remain broadly unchanged in these last two columns suggests that even when comparing the reshoring response to uncertainty shocks within country-industry pairs across different time periods, we see a similarly stronger response in industries with a high robot replaceability than in those with a low robot replaceability as when comparing the response across country-industry pairs.

Next, in Table 8, we turn to various third factors that might alternatively explain our results, which cannot be captured well by the inclusion of additional fixed effects. In column (1), we test whether contemporaneous tariff changes may explain our results. To do so, we include a weighted average of import tariff changes faced by each country-industry pair in period t. Weights reflect each country-industry pair's reliance on the respective developing country. The estimates show that an increase in import tariffs is associated with slightly more reshoring, although the estimate is not significant at any conventional level. More importantly, including tariff changes does not alter the main results.

In column (2), we show that the rise of China as a leading exporter does not confound our results. Chinese exports skyrocketed since the early 1990s, with their share of world exports growing from 2 percent to more than 12 percent between 1990 and 2015. The opening of China to the world economy may have acted as a drag on reshoring, as it created vast offshoring opportunities in industries in which China had a comparative advantage. We thus control for the share of Chinese exports in world exports at the beginning of each period, as a proxy for China's comparative advantage and thus the downward pressure its opening to world trade has put on reshoring in each industry. Results show that the higher China's comparative advantage in an industry, the lower the extent of reshoring (or, the stronger the offshoring) was, in line with intuition. Crucially, however, China's specialization seems sufficiently distinct from that of robots, such that it does not alter the size or significance of the main results.

In column (3), we show that our estimates do not capture the effect a country's own uncertainty shocks on reshoring. Uncertainty shocks may be correlated across countries, such that the previous results may be confounded by the effects of uncertainty shocks happening directly to each developed country we examine. To account for this possibility, we include each developed country's own uncertainty shock as a control. Results show that higher uncertainty in the home country is associated with more reshoring. We conjecture that this may be because of a lower willingness to take risks and invest into long-distance trade relationships during turbulent times. Similarly to the previous exercises, the main results remain unchanged.

Next, in columns (4)-(6), we show that results are not driven by changes in the climate, political landscape or mental health situation in developing countries. In particular, we create Bartik measures identical to our exposure to uncertainty in developing countries variable, but using each developing countries' 2-year changes in *i)* the "Left-Right Index" of the governing party (from the V-Dem project), *ii)* average temperatures, and *iii)* the suicide rate, instead of uncertainty scores as shifters. Results show that except for the exposure to mental health in developing countries (which is associated with more reshoring), none of the controls appears to have a direct effect on reshoring. More importantly, however, neither of these controls meaningfully changes our main results.

In column (7), we show that results do not reflect differences in the concentration of input suppliers across country-industry pairs. It is possible that some country-industry pairs may prefer reshoring over diversification to other developing countries, because the concentration of suppliers is relatively high (or, in other words, there are only few potential alternative suppliers). To test for this possibility, we include a Hirsch-Herfindahl-inspired index of concentration of input suppliers at the beginning of the period, based on each developing country's share of inputs sourced from the developing world, as a control variable (see Section 4.6 for details). Results show that a country-industry pair's initial concentration seems to have no effect on subsequent reshoring and, crucially, also does not confound our main results.

In column (8), we include all additional control variables from columns (1) to (7) at the same time. Results still remain unchanged.

Finally, in Table 9, we show that results remain qualitatively unchanged if we use the continuous robot replaceability measure instead of the above/below median dummy variable. While we think the dummy variable is the more natural approach to studying heterogeneity and easier to interpret, we see two main advantages to using the continuous variable instead. First, it runs a lower risk of accidentally picking up broader trends in larger clusters of industries and second, it uses all the information available (i.e., also variation across industries within the sets of above/below median replaceability). For both of these reasons, we find it reassuring that our main coefficient of interest (i.e., on the interaction term) remains positive and significant at the 1% level.

Exclusion of single countries or industries. In another set of robustness checks, we show that the results do not hinge on the inclusion of any single industry or country in our sample. This is reassuring, since otherwise, results may merely reflect the effect of idiosyncratic shocks to a certain industry or country, rather than that of uncertainty shocks abroad. We test for this by excluding every industry and country from our sample one at a time in Figure 6. Results show that the point estimates of the interaction term do not meaningfully change after the exclusion of any industry or country; all estimates remain significant at the 10 percent level.[30]

Alternative measure of uncertainty. To bolster confidence that our results are not driven by some peculiar features of the Ahir et al. (2022) uncertainty index, we next replicate our main analysis with a different measure of uncertainty in developing countries. In particular, we use 10-year bond spreads of developing countries relative to the US instead of the Ahir et al. (2022) uncertainty index. The idea behind this measure is that an uncertainty shock should increase the risk premium included in a country's bond price, increasing its yield relative to the US benchmark. One advantage of this measure relative to the many alternative ones is that it has a comparatively good data coverage, even if it is not as complete as the uncertainty index we use in our main results.[31] A disadvantage is that while being correlated with uncertainty shocks, bond price changes can reflect also other developments such as inflation developments and debt sustainability. For these reasons, we view this as a quite challenging robustness check.

It is reassuring that, despite the lower data coverage and also other forces partly driving bond prices, our main results still hold when we replicate our analysis with the exposure to uncertainty in developing countries variable based on 10-year bond spreads relative to the US in Table 10. The point estimates on the interaction in columns (3) and (4) are also positive and significant at the 5% level.

4.3 Channels

Next, we explore the margins of adjustment through which higher uncertainty in developing countries leads to more reshoring in robotized industries. In our measure, reshoring may rise either because of a fall in the use of inputs from developing countries, a rise in the use of domestic inputs from other industries, or both.

In Table 11, we explore each of these channels. In column (1), we report again results from column (4) of Table 1 for comparison. In column (2), we estimate the same specification, but fix the value of inputs from developing countries at their level at the beginning of each period. The estimated effects in this specification thus reflect only adjustments in the use of domestic inputs. In column (3), we do the reverse, namely hold the value of domestic inputs constant, such that estimated effects reflect only adjustments in the use of inputs from developing countries. Results show that the reshoring response documented before stems entirely from fewer inputs from developing countries (as evident in the results in column (3) remaining almost identical to those in column (1)), and not from more domestic

[30] The exclusion of the petroleum industry plays the largest role for the precision of our estimate. We suspect that this is because the petroleum industry represents a large share of imports, and, at the same time, features a very low robot replaceability. Together, this makes it an important data point as a comparison to highly robotized industries (in other words, it represents an industry that is exposed to uncertainty shocks but has no economically feasible way of reshoring production).

[31] More precisely, in order to have a full panel, we need to drop only two time periods (2000-2, 2002-4) and five developing countries (Bulgaria, Croatia, Romania, Slovenia, Turkey) from the sample.

inputs. As our regressions are estimated in first differences, this may represent either more firms deciding to reshore or less firms deciding to offshore in the face of uncertainty abroad.

This result suggests that reshoring implies a reconfiguration of firms' production strategy. Production is no longer at arm's length but rather moves in-house.[32] In particular, there are two steps involved in firms' reshoring decisions. First, firms move away from foreign suppliers. Second, firms move towards in-house production rather than relying on domestic suppliers. This suggests that it is, on average, more costly for firms to find new suppliers than to produce the input in-house.[33]

4.4 Magnitude

In this subsection, we briefly explain why our estimates imply quite sizeable effects of higher uncertainty on demand for inputs from developing countries.

Our preferred estimate of column (4) in Table 1 implies that a one standard deviation increase in exposure to uncertainty in developing countries increases the ratio of domestic to developing countries' inputs by about 7.2% ($\delta + \beta = 7.79 - 0.59 = 7.2$) in robotized industries. In the previous section, we showed that this increase stems entirely from a reduction in inputs from developing countries. On average, the ratio of domestic to developing countries' inputs in our sample is 14.7, corresponding to roughly 69% of all inputs being domestic ones, and 5% of all inputs being from developing countries. A reduction in this ratio by 7.2% corresponds to a rise from 14.7 to 15.8. This is consistent with a drop in the share of developing countries' inputs from 5% to 4.5%, or by 10%. Given that exports in robotized industries (automotive, metal products, plastics, textiles and apparel, electronics) make up a large share of some developing countries' exports (and thus GDP), a 10% drop is economically significant.

4.5 Heterogeneity across regions and time periods

In this subsection, we disaggregate the effect of uncertainty on reshoring in robotized industries across regions and time periods.

Regions. To disaggregate our main result across different regions, we rerun our preferred specification in column (4) of Table 1, but now replace total inputs from developing countries in the denominator of our dependent variable with those from different broad regions. Results are visualized in Figure 7 and show that our main effect reflects primarily reshoring from Eastern Europe, Latin America and China. Instead, reshoring from Asia (other than China) seems not to play a significant role. We suspect that the reason for this is the

[32] A survey among German firms by the ifo institute finds that reshoring in-house is particularly prevalent among small and medium-sized firms (Baur et al., 2021).

[33] This result is consistent with our findings from Panel A of Table 12, where we find no impact of uncertainty in developing countries on diversification. For the modeling of domestic and foreign outsourcing margins, see Antràs and Helpman (2008).

better overlap between task specializations of some Eastern European countries, Mexico and China, and the tasks that industrial robots are able to perform.

Time periods. To explore whether our main results hide strong differences in the effect size over different time periods, we rerun our preferred specification, but split the sample into two subperiods, the pre-GFC and the post-GFC period. Results are presented at the right end of Figure 7 and show that the point estimate becomes substantially higher after the GFC. Even though the two effects are not statistically significantly different from one another (likely due to the strongly reduced sample size), it appears that the effect has meaningfully increased after the GFC. Potential reasons for this may be higher risk aversion following the traumatic experience of the GFC, advances in automation making robots more efficient over time, a low-interest-rate environment making investments in robots more attractive relative to hiring workers, or higher uncertainty levels (pointing at non-linear effects).

In addition to showing that effect sizes become larger in the post-GFC period, Figure 7 assuages a possible endogeneity concern related to the baseline (2000) shares used in our shift-share measure of exposure to uncertainty in developing countries. In particular, it would be ideal to use lagged instead of baseline shares, as is often done in the literature. But this is not possible in our main sample because of data availability. The fact that the effect remains in the regressions using only the post-GFC sample, where we effectively use lagged shares, should alleviate such endogeneity concerns.

4.6 Other margins of adjustment

In this subsection, we show that, apart from reshoring, the main other margin of adjustment used to deal with uncertainty shocks in developing countries was increased offshoring to other developed countries in non-robotized industries (i.e., where reshoring was not economically feasible). In contrast, we find no strong evidence for either diversification across developing countries or nearshoring.

Diversification across developing countries. In theory, it may be optimal for firms to respond to higher uncertainty also by diversification, i.e., to import inputs from a larger set of locations, to make sure supplies are still available even if one location is shocked. To test for this potential margin of adjustment, we construct a measure of diversification that is similar in spirit to a Hirsch-Herfindahl-Index (HHI). In our setting, a country-industry pair's supplier concentration is measured as $HHI_{ij,t} = \frac{1}{G}\sum_{\in G}\sum_{\in K} s^2_{ijkg,t}$, where $s_{ijkg,t}$ is developing country k's share of country-industry pair ij's inputs of good g from the developing world.

In Panel A of Table 12, we rerun our main regressions, only now using the change in the HHI as the dependent variable. Results show no significant impact of developing countries' uncertainty on diversification.[34]

Nearshoring. Another coping mechanism that is often cited is so-called nearshoring, i.e., reshoring to nearby developing countries. To test for this, we construct a measure of nearshoring based on the change in the ratio of inputs sourced from nearby to faraway developing countries, analogous to our reshoring variable. For this, we assign to each developed country in our sample distinct sets of developing countries that are classified as nearby and one classified as faraway. For example, for Germany, all Eastern European developing countries are considered nearby, while all others are considered faraway.

In Panel B of Table 12, we rerun our main regressions, only now using nearshoring as the dependent variable. None of the point estimates is statistically significantly different from zero, suggesting that uncertainty shocks in developing countries have no effect on nearshoring, neither overall, nor in robotized or non-robotized industries.[35]

Offshoring to other developed countries. In Panel C of Table 12, we finally explore whether uncertainty shocks in developing countries also affect reshoring from or offshoring to other *developed* countries. Results suggest that an uncertainty shock in connected developing countries *increases* a country's reliance on inputs from other developed countries in non-robotized industries (the estimated coefficient on uncertainty in developing countries is positive and significant at the 10% level), but *reduces* it in robotized ones (the estimated coefficient on the interaction term is negative and significant at the 5% level). This suggests that firms diversify to developed countries when domestic production with robots is not an option, but that when it is, they simultaneously reduce their inputs from developed countries.[36]

5 Conclusion

Trade openness has been declining since the GFC, after having previously risen strongly and steadily for almost two decades. Our paper unveils possible drivers of this reversal of globalization. We examine whether the rise in uncertainty in source countries in combination with more powerful automation technologies can help explain this trend reversal.

[34] The absence of a diversification response (in line with firm-level evidence in Balboni et al., 2024) may be surprising to some, given the many references to it as an optimal coping mechanism in the media and academic literature. Results in Table 12 suggest that while this argument is attractive, in practice it may not hold. Reasons for this could be that it may be quite difficult to find alternative, high-quality suppliers elsewhere in a highly specialized global economy (Aiyar et al., 2023), or that other developing countries are perceived to be more prone to shocks than, for example, the home country.

[35] Similarly to the muted diversification response, this may signal the difficulty to find or build up the necessary capabilities in a nearby location in a global economy that has become highly specialized.

[36] For example, robots may not make reshoring of natural gas any easier, such that a country like Germany, when faced with an uncertainty shock in Russia, moves to other developed countries (e.g., the United States) for liquefied natural gas. Conversely, if the China-Taiwan conflict lead German companies to assemble cars using robots in Germany instead of Chinese labor, they may also close down factories in Spain as part of the reorganization.

Our paper shows that the retreat from globalization is intensified by uncertainty shocks on the one hand and the option to automate production on the other. Cost savings from offshoring to low-wage countries have become smaller as various uncertainty shocks increased the risk of default of input delivery. Sectors able to substitute the tasks of developing countries by domestic robots reshore production to their home countries. Sectors not able to automate these tasks diversify their supply chains to the less risky, nearby developed countries. Reshoring in-house rather than to domestic input suppliers in other industries appears to dominate among the different reshoring strategies. As it seems, having control becomes more valuable when firms realize that the world has become an ever riskier place.

6 Tables and figures

Table 1: The impact of uncertainty on reshoring

	dep. variable: $\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$			
	(1)	(2)	(3)	(4)$^{\pm}$
Δ exposure to uncertainty in developing countries	0.423	0.403	-0.547	-0.594
	(0.658)	(0.663)	(0.633)	(0.671)
1{robot replaceability}		-3.373*	-2.859	-3.457
		(1.810)	(1.761)	(2.654)
Δ exposure to uncertainty in developing countries $\times$ 1{robot replaceability}			7.527***	7.790***
			(2.162)	(2.366)
Period FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Observations	1710	1710	1710	1260
R^2	0.204	0.209	0.224	0.219
Joint hypothesis test $\left[H_0 : \beta + \delta = 0\right]$ p-value:	—	—	0.001	0.002

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
$^{\pm}$ manufacturing only
Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries variable is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. All specifications include time period and country dummies.

Table 2: The impact of uncertainty on reshoring (narrative approach)

	dep. variable: $\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$			
	(1)	(2)	(3)	$(4)^{\pm}$
Δ exposure to uncertainty in developing countries	0.452	0.456	-0.330	-0.378
	(1.123)	(1.127)	(1.030)	(1.073)
1{robot replaceability}		-3.388*	-3.615**	-4.267
		(1.806)	(1.837)	(2.744)
Δ exposure to uncertainty in developing countries			7.693***	8.170***
× 1{robot replaceability}			(1.797)	(2.045)
Period FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Observations	1710	1710	1710	1260
R^2	0.204	0.209	0.224	0.219
Joint hypothesis test $\left[H_0 : \beta + \delta = 0\right]$ p-value:	—	—	0.001	0.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$^{\pm}$ manufacturing only

Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries variable is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. All specifications include time period and country dummies. The Δ exposure to uncertainty in developing countries variable is constructed similarly to the one in Table 1, but is based upon an adjusted World Uncertainty Index (Ahir et al., 2022), which assigns a value of zero to all uncertainty changes in developing country-period pairs, for which no plausibly exogenous uncertainty event has been identified (see Figure 2 for details).

Table 3: Impact of uncertainty on reshoring (small open economy approach)

	dep. variable: $\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$			
	(1)	(2)	(3)	(4)$^{\pm}$
Δ exposure to uncertainty in developing countries	-0.684	-0.691	-1.010*	-0.921*
	(0.541)	(0.543)	(0.517)	(0.547)
1{robot replaceability}		-1.868	-1.634	-2.456
		(1.888)	(1.869)	(2.496)
Δ exposure to uncertainty in developing countries $\times$ 1{robot replaceability}			4.217**	4.785**
			(1.827)	(2.300)
Period FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Observations	1235	1235	1235	910
R^2	0.156	0.157	0.161	0.161
Joint hypothesis test $\left[H_0 : \beta + \delta = 0\right]$ p-value:	—	—	0.075	0.095

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$^{\pm}$ manufacturing only

Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries variable is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. All specifications include time period and country dummies. The five largest importers from developing countries (USA, Germany, South Korea, France, and Italy) are excluded from the sample.

Table 4: The impact of uncertainty on reshoring (placebo test)

	dep. variable: $L\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$			
	(1)	(2)	(3)	$(4)^{\pm}$
Δ exposure to uncertainty in developing countries	0.241	0.255	0.390	0.296
	(1.419)	(1.427)	(1.596)	(1.681)
1{robot replaceability}		1.475	1.367	2.289
		(1.852)	(1.806)	(2.649)
Δ exposure to uncertainty in developing countries			-1.166	-1.261
$\times$ 1{robot replaceability}			(1.694)	(1.782)
Period FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Observations	1368	1368	1368	1008
R^2	0.186	0.188	0.188	0.201
Joint hypothesis test $\left[H_0 : \beta + \delta = 0\right]$ p-value:	—	—	0.457	0.362

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
$^{\pm}$ manufacturing only
Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries in the period before. The Δ exposure to uncertainty in developing countries variable is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. All specifications include time period and country dummies.

Table 5: The impact of uncertainty on reshoring (testing for non-random shock exposure)

	dep. variable: $\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$			
	(1)	(2)	(3)	(4)$^{\pm}$
Δ exposure to uncertainty in developing countries (adj.)	0.410	0.386	-0.584	-0.630
	(0.661)	(0.667)	(0.636)	(0.676)
1{robot replaceability}		-3.372*	-2.871	-3.473
		(1.811)	(1.765)	(2.662)
Δ exposure to uncertainty in developing countries (adj.) $\times$ 1{robot replaceability}			7.542***	7.821***
			(2.147)	(2.357)
Period FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Observations	1710	1710	1710	1260
R^2	0.204	0.209	0.224	0.219
Joint hypothesis test $[H_0 : \beta + \delta = 0]$ p-value:	—	—	0.001	0.002

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$^{\pm}$ manufacturing only

Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries variable is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. Δ *exposure to uncertainty in developing countries (adj.)* is constructed by simulating 1,000 hypothetical "shifts" along with the resulting shocks, and then subtracting the averaged hypothetical "shifts" from the original Δ *exposure to uncertainty in developing countries* variable, following Borusyak and Hull (2023). All specifications include time period and country dummies.

Table 6: Impact of uncertainty on reshoring (testing for heterogeneous treatment effects)

	dep. variable: $\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$			
	(1)	(2)	(3)	$(4)^{\pm}$
Δ exposure to uncertainty in developing countries$^{\kappa}$	0.444	0.411	-0.719	-0.831
	(0.592)	(0.599)	(0.610)	(0.642)
1{robot replaceability}		-3.358*	-2.834	-3.443
		(1.818)	(1.765)	(2.672)
Δ exposure to uncertainty in developing countries$^{\kappa}$ × 1{robot replaceability}			5.795***	6.113***
			(1.788)	(1.952)
Period FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Observations	1710	1710	1710	1260
R^2	0.204	0.209	0.224	0.219

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$^{\pm}$ manufacturing only

Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries variable is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. Δ exposure to uncertainty in developing countries$^{\kappa}$ is based on shocks standardized by their period-specific standard deviation, following de Chaisemartin and Lei (2022). All specifications include time period and country dummies.

Table 7: Impact of uncertainty on reshoring (alternative sets of fixed effects)

	dep. variable: $\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$							
	(1)	(2)$^{\pm}$	(3)	(4)$^{\pm}$	(5)	(6)$^{\pm}$	(7)	(8)$^{\pm}$
Δ exposure to uncertainty in developing countries	-0.599	-0.641	-0.390	-0.141	-0.488	-0.228	-0.799	-0.850
	(0.671)	(0.700)	(0.689)	(0.834)	(0.742)	(0.875)	(0.666)	(0.699)
1{robot replaceability}			-3.470**	-4.236				
			(1.752)	(2.580)				
Δ exposure to uncertainty in developing countries × 1{robot replaceability}	7.577***	7.875***	6.369**	7.355**	6.341**	7.345**	8.293***	8.584***
	(2.211)	(2.420)	(2.731)	(3.326)	(2.756)	(3.359)	(2.321)	(2.535)
period FE	✓	✓					✓	✓
country FE	✓	✓						
period-country FE			✓	✓	✓	✓		
industry FE	✓	✓			✓	✓		
industry-country FE							✓	✓
Observations	1710	1260	1710	1260	1710	1260	1710	1260
R^2	0.246	0.244	0.346	0.346	0.372	0.374	0.338	0.331

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$^{\pm}$ manufacturing only

Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries variable is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level.

Table 8: The impact of uncertainty on reshoring (controlling for third factors)$^{\pm}$

	dep. variable: $\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ exposure to uncertainty in developing countries	-0.592	-0.510	-0.813	-0.571	-0.592	-1.677***	-0.592	-2.249***
	(0.672)	(0.668)	(0.638)	(0.645)	(0.709)	(0.513)	(0.689)	(0.581)
1{robot replaceability}	-3.473	0.489	-3.554	-3.421	-3.461	-5.224**	-3.494	0.437
	(2.653)	(2.441)	(2.617)	(2.577)	(2.607)	(2.662)	(2.558)	(2.041)
Δ exposure to uncertainty in developing countries $\times$ 1{robot replaceability}	7.812***	7.489***	7.065***	8.091***	7.801***	7.633***	7.794***	6.306***
	(2.362)	(2.332)	(2.386)	(2.534)	(2.348)	(2.200)	(2.374)	(1.983)
Δ import tariffs	0.618							0.691
	(0.448)							(0.436)
China exports		-4.044***						-4.578***
		(1.548)						(1.567)
Δ uncertainty			4.691***					5.400***
			(1.796)					(1.698)
Δ exposure to political change in developing countries				-1.698				-1.673
				(1.375)				(1.481)
Δ exposure to climate change in developing countries					0.044			-1.020
					(1.626)			(1.652)
Δ exposure to mental health in developing countries						3.516***		4.647***
						(1.362)		(1.493)
HHI_{-2}							-0.159	7.569**
							(4.676)	(3.683)
period FE	✓	✓	✓	✓	✓	✓	✓	✓
country FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1260	1259	1260	1260	1260	1260	1260	1259
R^2	0.219	0.235	0.228	0.223	0.219	0.237	0.219	0.278

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$^{\pm}$ manufacturing only

Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries variable, along with the other variables besides the 1{robot replaceability} dummy variable, is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. All specifications include time period and country dummies. Δ import tariffs denote the normalized two-year change in the weighted average of import tariffs faced by the country-industry pair, where weights are each country-industry pair's reliance on the respecting developing country. Chinese exports corresponds to China's share of world exports of intermediate inputs in each industry at the beginning of each period. Δ uncertainty refers to the normalized two-year changes in the log developed country uncertainty based on Ahir et al. (2022). The three control variables–Δ exposure to political change in developing countries, Δ exposure to climate change in developing countries, and Δ exposure to mental health in developing countries–are constructed similarly to the Δ exposure to uncertainty in developing countries variable, but with different shifts replacing the World Uncertainty Index (Ahir et al., 2022). The Δ exposure to political change variable is based on the Economic Left-Right scale, as outlined in Lindberg et al. (2022). The Δ exposure to climate change variable relies on average temperature data (World Bank, 2024), while the Δ exposure to mental health variable is derived from suicide rate data (World Health Organization, 2024). HHI_{-2} is the normalized lagged value of the Hirsch-Herfindahl-inspired index of supplier concentration.

Table 9: Impact of uncertainty on reshoring (continuous robot replaceability)

	dep. variable: $\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$			
	(1)	(2)	(3)	$(4)^{\pm}$
Δ exposure to uncertainty in developing countries	0.423	0.413	1.899**	2.050**
	(0.658)	(0.660)	(0.837)	(1.010)
robot replaceability		-1.164*	-0.935	-1.977
		(0.670)	(0.646)	(2.189)
Δ exposure to uncertainty in developing countries			3.599***	4.305***
$\times$ robot replaceability			(1.059)	(1.406)
Period FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Observations	1710	1710	1710	1260
R^2	0.204	0.206	0.218	0.214
Joint hypothesis test $\left[H_0 : \beta + \delta = 0\right]$ p-value:	—	—	0.001	0.005

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$^{\pm}$ manufacturing only

Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries variable, as well as the robot replaceability variable, is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. All specifications include time period and country dummies.

Table 10: Impact of uncertainty on reshoring (using exposure based on developing-country-to-US bond spreads instead of the uncertainty index from Ahir et al., 2022)

	dep. variable: $\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$			
	(1)	(2)	(3)	(4)$^{\pm}$
Δ exposure to uncertainty in developing countries	-0.593	-0.696	-1.335	-1.355
	(1.763)	(1.746)	(1.729)	(1.815)
1{robot replaceability}		-5.239**	-5.046**	-6.058*
		(2.379)	(2.417)	(3.526)
Δ exposure to uncertainty in developing countries × 1{robot replaceability}			4.589**	5.082**
			(2.014)	(2.218)
Period FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Observations	1026	1026	1026	756
R^2	0.192	0.203	0.212	0.208

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
$^{\pm}$ manufacturing only

Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries variable is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. Δ exposure to uncertainty in developing countries is constructed identically to the one used in the main analysis, except that it uses 10-year bond spreads between the selected developing country and the US instead of the WUI from Ahir et al. (2022). The periods included in the analysis are 2004–6, 2010–12, and 2012–14. The developing countries include Brazil, China, Czechia, Hungary, India, Indonesia, Latvia, Lithuania, Mexico, Poland, Russia, and Slovakia.

Table 11: Channels of reshoring$^{\pm}$

	$\Delta\log\frac{\text{domestic}}{\text{developing}}$	$\Delta\log\frac{\text{domestic}}{\text{developing}_{fix}}$	$\Delta\log\frac{\text{domestic}_{fix}}{\text{developing}}$
	(1)	(2)	(3)
Δ exposure to uncertainty in developing countries	-0.594	2.292*	-1.472
	(0.671)	(1.267)	(0.904)
1{robot replaceability}	-3.457	-3.289*	1.466
	(2.654)	(1.699)	(1.610)
Δ exposure to uncertainty in developing countries $\times$ 1{robot replaceability}	7.790***	-0.085	7.116***
	(2.366)	(1.695)	(2.590)
Period FE	✓	✓	✓
Country FE	✓	✓	✓
Observations	1260	1260	1260
R^2	0.219	0.280	0.396
Joint hypothesis test $\left[H_0 : \beta + \delta = 0\right]$ p-value:	0.002	0.074	0.018

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$^{\pm}$ manufacturing only

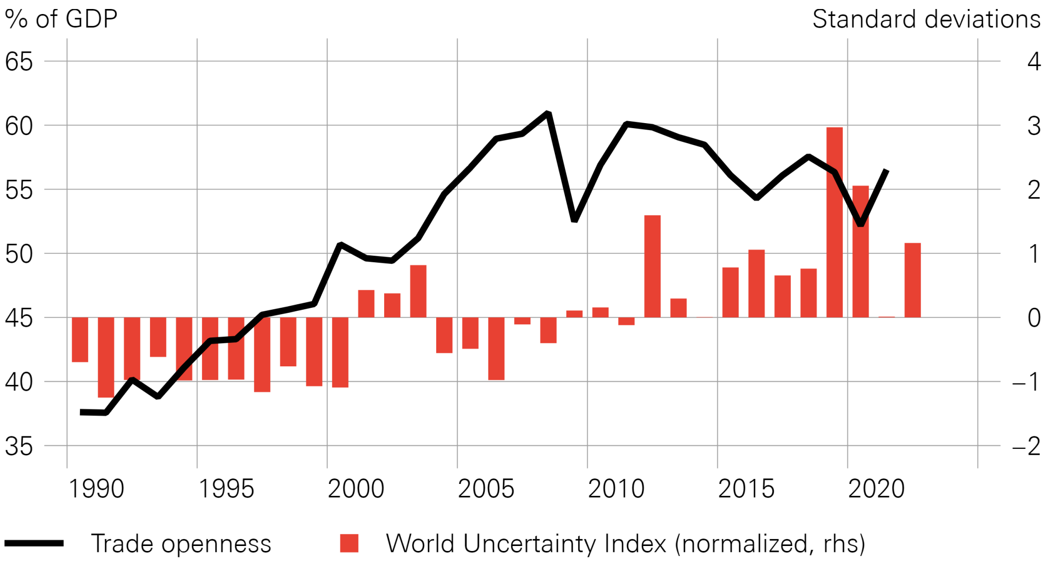
Notes. The dependent variables in columns (1), (2), and (3) are the changes in the log of the ratio of domestic inputs and inputs from developing countries, where in columns (2) and (3) the denominator and the numerator are fixed at their beginning-of-period levels, respectively. The Δ exposure to uncertainty in developing countries variable is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. All specifications include time period and country dummies.

Table 12: Other margins of adjustment

	(1)	(2)	(3)	(4)$^{\pm}$
Panel A. Diversification across developing countries	dep. variable: Δ HHI			
Δ exposure to uncertainty in developing countries	0.022	0.024	0.032	0.037
	(0.041)	(0.040)	(0.041)	(0.044)
1{robot replaceability}		0.218**	0.214*	0.322**
		(0.107)	(0.110)	(0.141)
Δ exposure to uncertainty in developing countries			-0.069	-0.084
$\times$ 1{robot replaceability}			(0.138)	(0.129)
Panel B. Nearshoring	dep. variable: $\Delta \log \frac{\text{nearby developing}}{\text{faraway developing}}$			
Δ exposure to uncertainty in developing countries	0.958	0.948	0.820	0.810
	(0.873)	(0.871)	(0.946)	(0.983)
1{robot replaceability}		-1.656	-1.586	-1.632
		(1.776)	(1.790)	(2.526)
Δ exposure to uncertainty in developing countries			1.016	0.772
$\times$ 1{robot replaceability}			(2.147)	(2.334)
Panel C. Offshoring to other developed countries	dep. variable: $\Delta \log \frac{\text{developed}}{\text{developing}}$			
Δ exposure to uncertainty in developing countries	0.705	0.713	1.085*	1.137*
	(0.564)	(0.563)	(0.620)	(0.639)
1{robot replaceability}		1.508	1.307	0.939
		(1.089)	(1.055)	(1.439)
Δ exposure to uncertainty in developing countries			-2.942**	-3.301**
$\times$ 1{robot replaceability}			(1.329)	(1.519)
Period FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
$^{\pm}$ manufacturing only
Notes. The dependent variables in Panels A, B and C are the change in the HHI (see main text for details), the change of the log of the ratio of inputs from nearby developing countries and faraway developing countries, and the change of the log of the ratio of inputs from developed and developing countries, respectively. The Δ exposure to uncertainty in developing countries variable is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. All specifications include time period and country dummies.

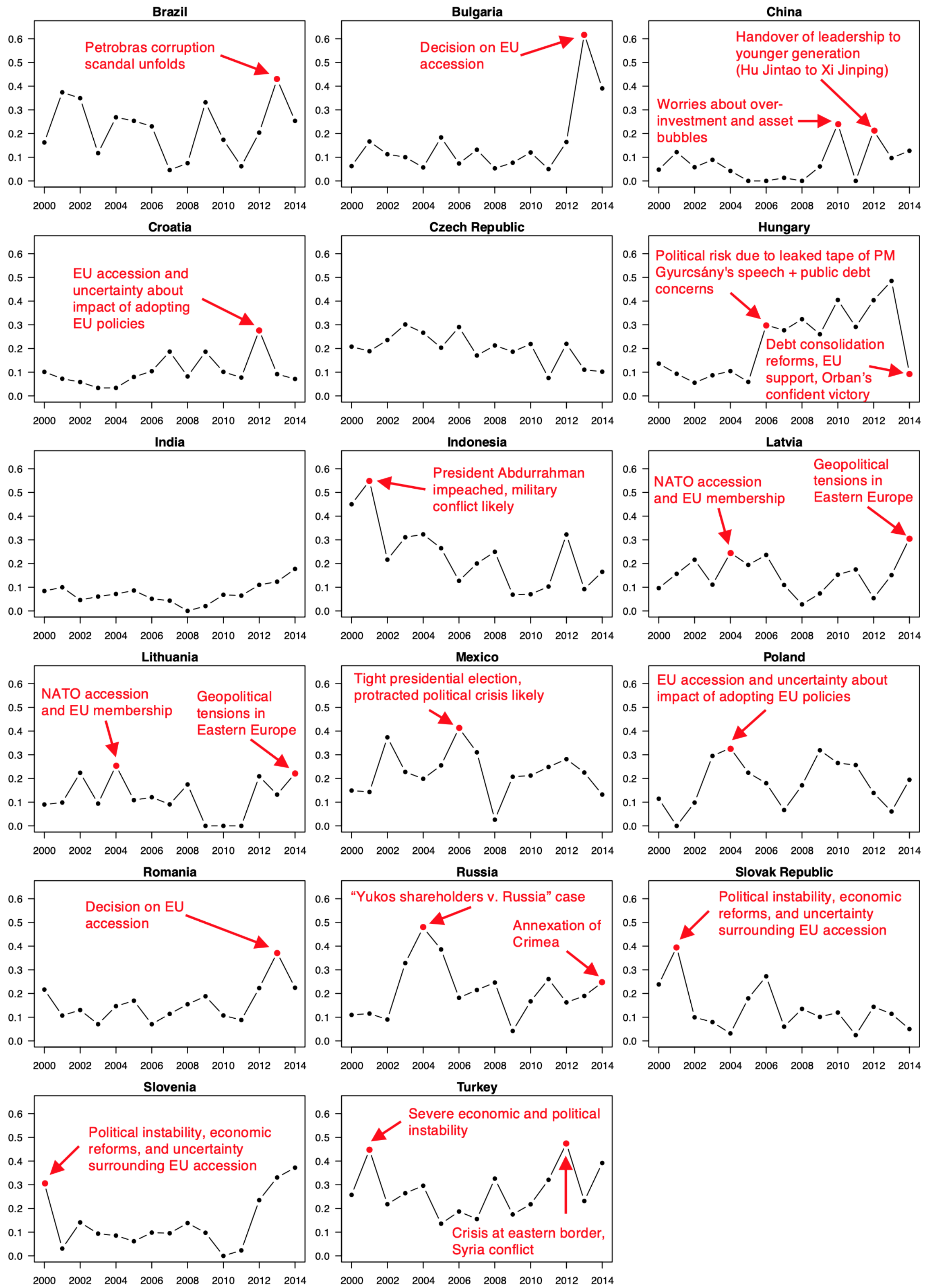
Figure 1: Trade openness and World Uncertainty Index (WUI) since 1990



Sources: World Bank, Ahir et al. (2022)

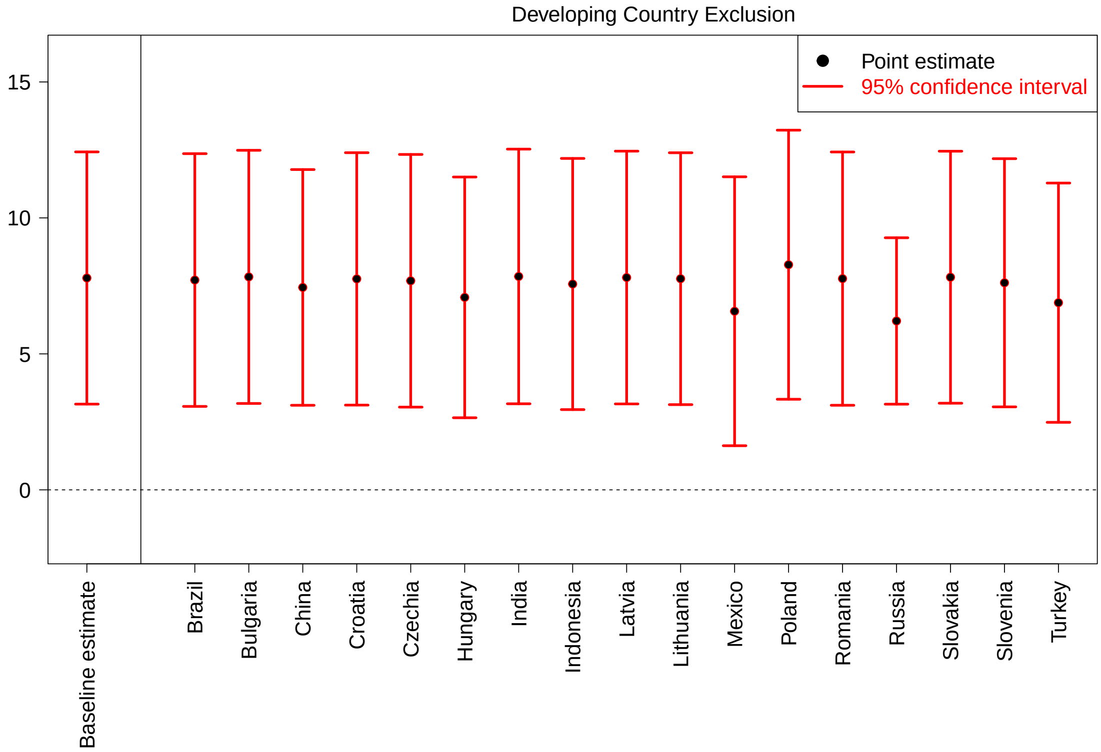
Notes. Trade openness is measured as the sum of exports and imports as a share of GDP. The World Uncertainty Index (WUI) is computed by counting the share of words that are either "uncertain" or a variant of it in the Economist Intelligence Unit country reports.

Figure 2: WUI in developing countries, 2000–2014 (annotated)



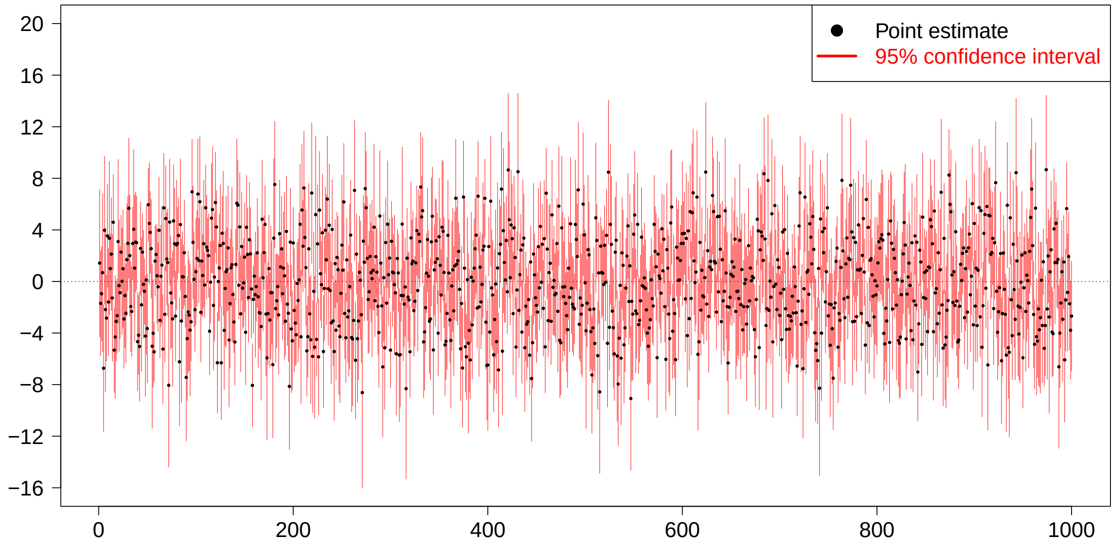
Notes. This figure presents yearly averages of the WUI (Ahir et al., 2022) for the set of developing countries in the sample. Annotations to individual data points added by authors.

Figure 3: Sensitivity of main results to dropping single developing countries



Notes. This figure presents the point estimates and 95% confidence intervals of the coefficient on the interaction term when estimating specification (4) of Table 1, leaving out one country at a time from the set of developing countries used in the construction of the exposure to uncertainty in developing countries variable.

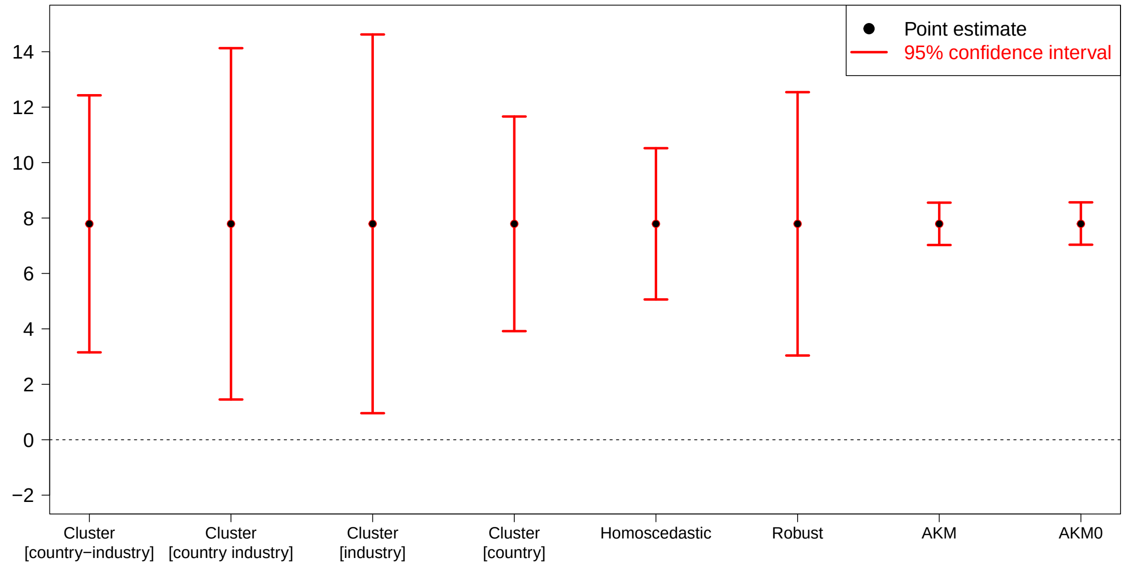
Figure 4: Adao et al. (2019) placebo test



% significant positive at 1% level = 5.9; % significant negative at 1% level = 5.6;
% significant positive at 5% level = 13.1; % significant negative at 5% level = 13.8.

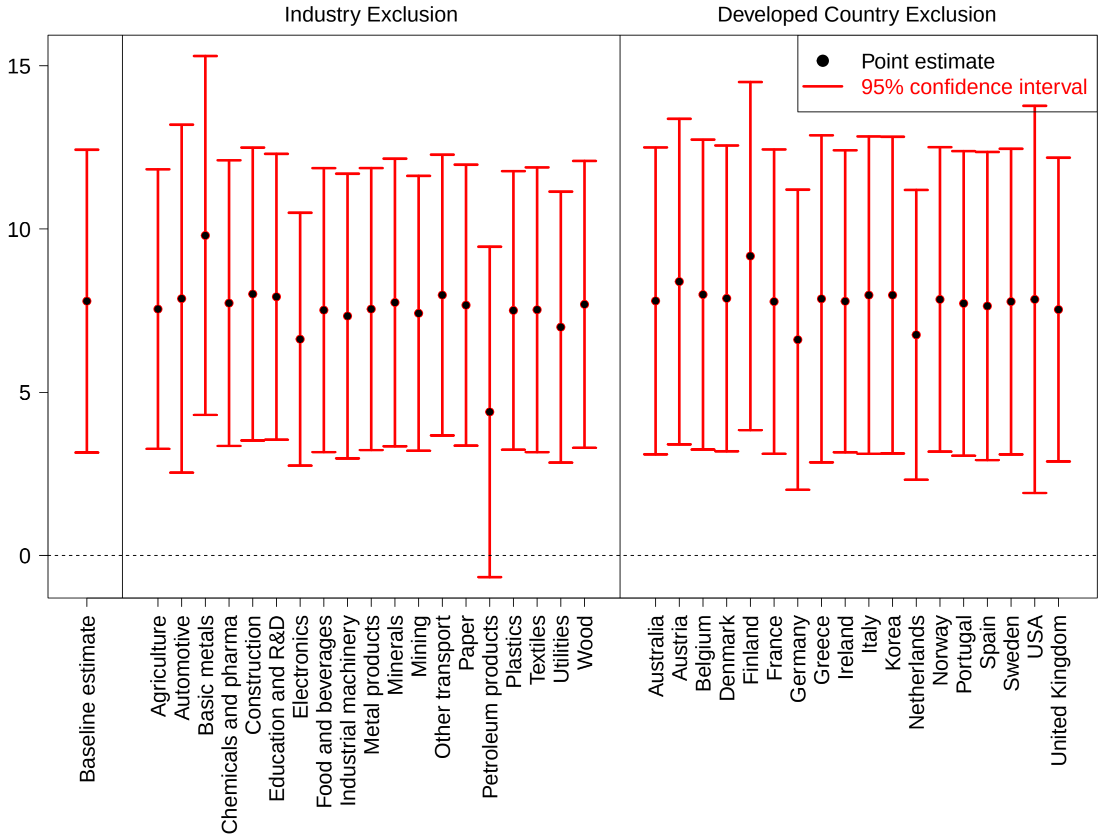
Notes. This figure shows the point estimates and 95% confidence intervals on the interaction term in specification (4) of Table 1 from 1,000 placebo tests, following Adao et al. (2019). The share of point estimates significantly different from zero at the 1% and 5% level are reported below the figure.

Figure 5: Different ways of clustering standard errors



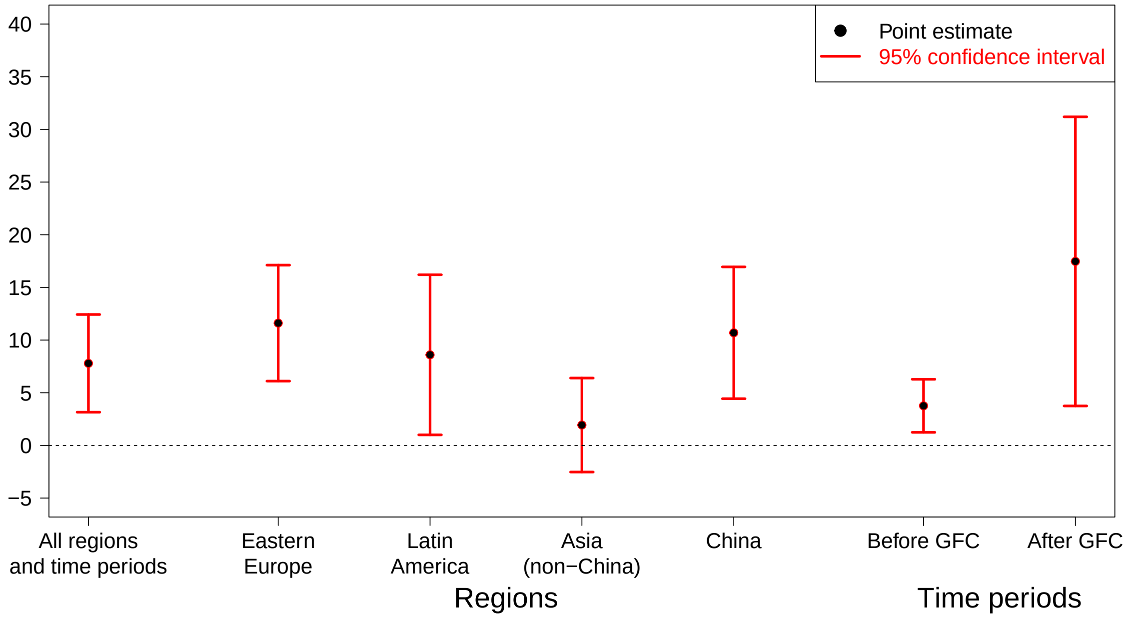
Notes. This figure presents point estimates and 95% confidence intervals from estimating specification (4) in Table 1 with different ways of clustering standard errors. "Cluster [country-industry]" refers to standard errors clustered at the country-industry level. "Cluster [country industry]" refers to standard errors two-way clustered at the country and industry level. "Cluster [industry]" refers to standard errors clustered at the industry level. "Cluster [country]" refers to standard errors clustered at the country level. "Homoscedastic" refers to conventional standard errors. "Robust" refers to Eicker-Huber-White standard errors. "AKM" and "AKM0" refer to the two ways of calculating standard errors proposed in Adao et al. (2019).

Figure 6: Sensitivity of main results to dropping single countries or industries



Notes. This figure presents point estimates and 95% confidence intervals of the coefficient on the interaction term. The baseline estimate, along with all estimates for the developing country exclusion, is based on the estimation of specification (4) in Table 1. In contrast, the estimates for the industry exclusion are derived from the estimation of specification (3) in Table 1.

Figure 7: Heterogeneity across regions and time periods



Notes. This figure presents point estimates and 95% confidence intervals of the coefficient on the interaction term when estimating specification (4) of Table 1, focusing either on imported inputs from a subset of developing countries (regions) or specific time periods.

References

Adao, Rodrigo, Michal Kolesár, and Eduardo Morales, "Shift-share designs: Theory and inference," *The Quarterly Journal of Economics*, 2019, *134* (4), 1949–2010.

Ahir, Hites, Nicholas Bloom, and Davide Furceri, "The world uncertainty index," *NBER Working Paper 29763*, 2022.

Aiyar, Mr Shekhar, Mr Jiaqian Chen, Mr Christian H Ebeke, Mr Roberto Garcia-Saltos, Tryggvi Gudmundsson, Ms Anna Ilyina, Mr Alvar Kangur, Tansaya Kunaratskul, Mr Sergio L Rodriguez, Michele Ruta et al., *Geo-economic fragmentation and the future of multilateralism*, International Monetary Fund, 2023.

Alicke, Knut, ED Barriball, and Vera Trautwein, "How COVID-19 is reshaping supply chains," *McKinsey and Co.*, 2021, *23.*

Antràs, Pol and Elhanan Helpman, "Contractual Frictions and Global Sourcing," in "The Organization of Firms in a Global Economy (Elhanan Helpman, Dalia Marin and Thierry Verdier, Editors)," Cambridge, MA and London, England: Harvard University Press, 2008, pp. 9–54.

Artuc, Erhan, Luc Christiaensen, and Hernan Winkler, "Does automation in rich countries hurt developing ones?: Evidence from the US and Mexico," *World Bank Policy Research Working Paper*, 2019, (8741).

_ , Paulo Bastos, and Bob Rijkers, "Robots, tasks, and trade," *CEPR Discussion Paper No. DP14487*, 2020.

Autor, David H, David Dorn, and Gordon H Hanson, "Untangling trade and technology: Evidence from local labour markets," *The Economic Journal*, 2015, *125* (584), 621–646.

Balboni, Clare, Johannes Boehm, and Mazhar Waseem, "Firm Adaptation in Production Networks: Evidence from Extreme Weather Events in Pakistan," *Working Paper*, 2024.

Baldwin, Richard, Rebecca Freeman, and Angelos Theodorakopoulos, "Deconstructing Deglobalization: The Future of Trade is in Intermediate Services," *Asian Economic Policy Review*, 2024, *19* (1), 18–37.

Balli, Hatice Ozer and Bent E Sørensen, "Interaction effects in econometrics," *Empirical Economics*, 2013, *45*, 583–603.

Barrot, Jean-Noël and Julien Sauvagnat, "Input specificity and the propagation of idiosyncratic shocks in production networks," *The Quarterly Journal of Economics*, 2016, *131* (3), 1543–1592.

Baur, Andreas, Lisandra Flach, Jasmin Gröschl, Marina Steininger, and Feodora Teti, "Internationale Wertschöpfungsketten – Reformbedarf und Möglichkeiten," *Studie im Auftrag der Konrad-Adenauer-Stiftung e.V. (in German)*, 2021.

Bhuller, Manudeep, Karl Ove Moene, Magne Mogstad, and Ola L Vestad, "Facts and fantasies about wage setting and collective bargaining," *Journal of Economic Perspectives*, 2022, *36* (4), 29–52.

Bonfiglioli, Alessandra, Rosario Crinò, Gino Gancia, and Ioannis Papadakis, "Robots, offshoring and welfare," in L.Y. Ing and G.M. Grossman, eds., *Robots and AI: a New Economic Era*, Routledge, 2022, pp. 40–81.

Borusyak, Kirill and Peter Hull, "Nonrandom exposure to exogenous shocks," *Econometrica*, 2023, *91* (6), 2155–2185.

Cameron, A Colin and Douglas L Miller, "A practitioner's guide to cluster-robust inference," *Journal of Human Resources*, 2015, *50* (2), 317–372.

Carvalho, Vasco M, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi, "Supply chain disruptions: Evidence from the Great East Japan Earthquake," *The Quarterly Journal of Economics*, 2021, *136* (2), 1255–1321.

de Chaisemartin, Clément and Ziteng Lei, "Are Bartik Regressions Always Robust to Heterogeneous Treatment Effects?," Technical Report 2022.

Faber, Marius, "Robots and reshoring: Evidence from Mexican labor markets," *Journal of International Economics*, 2020, *127*, 103384.

Feenstra, Robert C. and Gordon H. Hanson, "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates For the United States, 1979–1990," *The Quarterly Journal of Economics*, 08 1999, *114* (3), 907–940.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik instruments: What, when, why, and how," *American Economic Review*, 2020, *110* (8), 2586–2624.

Graetz, Georg and Guy Michaels, "Robots at work," *Review of Economics and Statistics*, 2018, *100* (5), 753–768.

Graziano, Alejandro G, Kyle Handley, and Nuno Limão, "Brexit uncertainty and trade disintegration," *The Economic Journal*, 2021, *131* (635), 1150–1185.

Grossman, Gene M, Elhanan Helpman, and Hugo Lhuillier, "Supply chain resilience: Should policy promote international diversification or reshoring?," *Journal of Political Economy*, 2023, *131* (12), 3462–3496.

Handley, Kyle and Nuno Limão, "Trade and investment under policy uncertainty: theory and firm evidence," *American Economic Journal: Economic Policy*, 2015, *7* (4), 189–222.

_ **and** _ , "Policy uncertainty, trade, and welfare: Theory and evidence for China and the United States," *American Economic Review*, 2017, *107* (9), 2731–83.

Krenz, Astrid, Klaus Prettner, and Holger Strulik, "Robots, reshoring, and the lot of low-skilled workers," *European Economic Review*, 2021, *136*, 103744.

Lindberg, Staffan I, Nils Düpont, Masaaki Higashijima, Yaman Berker Kavasoglu, Kyle L Marquardt, Michael Bernhard, Holger Döring, Allen Hicken, Melis Laebens, Juraj Medzihorsky et al., "Codebook varieties of party identity and organization (V–party) v2," *Varieties of Democracy (V–Dem) Project. doi.org/10.23696/vpartydsv2*, 2022.

Martin, Julien, Isabelle Mejean, and Mathieu Parenti, "Relationship stickiness, international trade, and economic uncertainty," *Review of Economics and Statistics*, 2023, pp. 1–45.

Martin, Philippe, Thierry Mayer, and Mathias Thoenig, "Make trade not war?," *The Review of Economic Studies*, 2008, *75* (3), 865–900.

Novy, Dennis and Alan M Taylor, "Trade and uncertainty," *Review of Economics and Statistics*, 2020, *102* (4), 749–765.

Nunn, Nathan, "Relationship-specificity, incomplete contracts, and the pattern of trade," *The Quarterly Journal of Economics*, 2007, *122* (2), 569–600.

OECD and AIAS, "OECD/AIAS ICTWSS Database: Note on Definitions, Measurement and Sources," 2021. Paris: OECD. www.oecd.org/employment/ictwss-database.htm. Accessed: 2024-08-15.

Pierce, Justin R and Peter K Schott, "The surprisingly swift decline of US manufacturing employment," *American Economic Review*, 2016, *106* (7), 1632–62.

Romer, Christina D and David H Romer, "Does monetary policy matter? A new test in the spirit of Friedman and Schwartz," *NBER macroeconomics annual*, 1989, *4*, 121–170.

Stapleton, Katherine and Michael Webb, "Automation, trade and multinational activity: Micro evidence from Spain," *Available at SSRN 3681143*, 2020.

Timmer, Marcel P, Erik Dietzenbacher, Bart Los, Robert Stehrer, and Gaaitzen J De Vries, "An illustrated user guide to the world input–output database: the case of global automotive production," *Review of International Economics*, 2015, *23* (3), 575–605.

World Bank, "Climate Change Knowledge Portal," 2024. Accessed: 2024-08-19.

World Health Organization, "Crude suicide rates (per 100 000 population)," 2024. Accessed: 2024-08-19.

Appendix

Table A1: Summary statistics

	Mean	Median	S.D.	Min	Max	N
$\Delta \log \frac{\text{domestic}}{\text{developing}}$	-15.33	-15.67	28.31	-259.78	313.59	1710
$\Delta \log \frac{\text{domestic}}{\text{foreign}}$	-0.03	-0.03	0.12	-1.09	0.76	1710
$\Delta \log \frac{\text{domestic}}{\text{developed}}$	-0.01	-0.01	0.15	-1.10	0.93	1710
$\Delta \log \frac{\text{domestic}}{\text{EastEU}}$	-0.16	-0.17	0.36	-3.10	3.27	1710
$\Delta \log \frac{\text{domestic}}{\text{Latin America}}$	-0.04	-0.05	0.46	-2.57	2.65	1710
$\Delta \log \frac{\text{domestic}}{\text{Asia (non-China)}}$	-0.10	-0.08	0.34	-2.00	2.02	1710
$\Delta \log \frac{\text{domestic}}{\text{China}}$	-0.25	-0.22	0.31	-2.01	2.47	1710
ΔHHI	-0.14	-0.11	2.00	-18.81	11.81	1710
$\Delta \log \frac{\text{nearby developing}}{\text{faraway developing}}$	-0.79	0.31	22.48	-120.19	109.35	1710
$\Delta \log \frac{\text{developed}}{\text{developing}}$	2.99	2.46	12.30	-260.30	97.92	1710
Δ exposure to uncertainty in developing countries	0.00	-0.04	1.00	-12.05	15.55	1710
robot replaceability dummy	0.47	0.00	0.50	0.00	1.00	1710
Δ import tariffs	-0.00	0.06	1.00	-13.59	15.65	1260
China exports	0.00	-0.36	1.00	-1.02	4.51	1259
Δ uncertainty	0.00	-0.11	1.00	-2.80	2.74	1710
Δ exposure to political change in developing countries	0.00	0.03	1.00	-6.50	7.22	1710
Δ exposure to climate change in developing countries	0.00	-0.04	1.00	-6.09	6.80	1710
Δ exposure to mental health in developing countries	-0.00	0.26	1.00	-15.93	0.99	1710
HHI_{-2}	-0.00	-0.25	1.00	-1.50	3.94	1710
stickiness	-0.00	0.53	1.00	-2.06	0.85	1260
relative hourly wages	0.00	-0.12	1.00	-1.91	3.50	1710
routine share	-0.00	0.26	1.00	-2.41	1.26	1710
offshorability	0.00	-0.29	1.00	-1.07	7.29	1710
union coordination index	0.00	0.13	1.00	-1.65	1.91	1710

Notes. $\Delta \log \frac{\text{domestic}}{\text{developing}}$ is the two-year change in the log of domestic inputs relative to imported inputs from developing countries multiplied by 100. $\Delta \log \frac{\text{domestic}}{\text{foreign}}$, $\frac{\text{domestic}}{\text{developed}}$, $\Delta \log \frac{\text{domestic}}{\text{EastEU}}$, $\Delta \log \frac{\text{domestic}}{\text{Latin America}}$, $\Delta \log \frac{\text{domestic}}{\text{Asia (non-China)}}$, $\Delta \log \frac{\text{domestic}}{\text{China}}$ are the two-year changes in the log of domestic inputs relative to imported inputs from foreign countries, developed countries, Eastern European countries, Latin American countries, Asian countries (excl. China), and China, respectively, multiplied by 100. $\Delta \log \frac{\text{nearby developing}}{\text{faraway developing}}$ is the two-year changes in the log of inputs from developing countries nearby a developed country relative to inputs from developing countries faraway from a developed country, multiplied by 100. $\Delta \log \frac{\text{developed}}{\text{developing}}$ is the two-year change in the log inputs from developed countries relative to inputs from developing countries, multiplied by 100. ΔHHI is the two-year change in the Hirsch-Herfindahl-inspired index of supplier concentration (see main text for more details), multiplied by 100. Δ exposure to uncertainty in developing countries refers to the normalized two-year change in the weighted average of developing country uncertainty based on Ahir et al. (2022), where the country-industry-level weights are the share of imported inputs from the developing country i in the total input consumption of the developed country j. 1{robot replaceability} is a dummy variable with value 1 if the industry-level robots replaceability measure by Graetz and Michaels (2018) is above the median, and 0 otherwise.

Table A2: Shares of inputs sourced domestically, from other developed countries, and from other developing countries (2000–2014)

	Inputs from...		
Country	...the own country	...developed countries	...developing countries
Australia	82.0	5.4	3.2
Austria	58.8	27.3	8.1
Belgium	51.6	35.2	5.5
Denmark	59.6	31.0	5.1
Finland	68.1	19.9	8.4
France	70.2	20.3	3.2
Germany	71.1	17.9	6.3
Great Britain	72.8	17.7	3.4
Greece	76.7	10.9	5.4
Ireland	46.8	41.4	2.8
Italy	79.2	10.7	3.8
Netherlands	53.9	27.9	8.2
Norway	74.2	17.9	2.9
Portugal	65.1	24.0	3.3
South Korea	77.2	5.0	4.7
Spain	76.5	14.2	3.0
Sweden	65.6	26.0	4.8
USA	85.0	3.3	3.2
Overall	68.6	19.8	4.7

Notes. Summary statistics are based on the sample of industry-level domestic inputs, and imported inputs from developed and developing countries in % of total inputs in the period 2000–2014. Developing countries are Brazil, Bulgaria, China, Croatia, Czechia, Hungary, India, Indonesia, Latvia, Lithuania, Mexico, Poland, Romania, Russia, Slovakia, Slovenia, and Turkey.

Table A3: Impact of uncertainty on reshoring (GFC period included)

	dep. variable: $\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$			
	(1)	(2)	(3)	(4)$^{\pm}$
Δ exposure to uncertainty in developing countries	-1.288*	-1.293*	-2.059**	-2.059**
	(0.767)	(0.769)	(0.929)	(0.929)
1{robot replaceability}		-4.758**	-4.534**	-4.534**
		(2.082)	(2.043)	(2.043)
Δ exposure to uncertainty in developing countries $\times$ 1{robot replaceability}			4.204**	4.204**
			(1.805)	(1.805)
Period FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Observations	1764	1764	1764	1764
R^2	0.141	0.149	0.157	0.157
Joint hypothesis test $\left[H_0 : \beta + \delta = 0\right]$ p-value:	—	—	0.144	0.144

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
$^{\pm}$ manufacturing only

Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries variable is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. All specifications include time period and country dummies.

Table A4: Impact of uncertainty on reshoring (linear dependent variable)

	dep. variable: $\Delta \frac{\text{domestic inputs}}{\text{developing country inputs}}$			
	(1)	(2)	(3)	$(4)^{\pm}$
Δ exposure to uncertainty in developing countries	21.126***	21.793***	6.846	3.114
	(7.793)	(8.055)	(5.878)	(5.494)
1{robot replaceability}		116.115*	124.202**	-11.370
		(62.438)	(61.768)	(59.904)
Δ exposure to uncertainty in developing countries × 1{robot replaceability}			118.363***	91.972***
			(35.414)	(30.507)
Period FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Observations	1710	1710	1710	1260
R^2	0.249	0.258	0.265	0.337
Joint hypothesis test $\left[H_0 : \beta + \delta = 0\right]$ p-value:	—	—	0.001	0.002

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
$^{\pm}$ manufacturing only
Notes. The dependent variable is the change of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries variable is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. All specifications include time period and country dummies.

Table A5: Impact of uncertainty on reshoring (alternative denominator of α_{ijk})

	dep. variable: $\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$			
	(1)	(2)	(3)	(4)$^{\pm}$
Δ exposure to uncertainty in developing countries$^{\gamma}$	1.884**	1.862**	0.114	-0.705
	(0.806)	(0.816)	(0.973)	(1.330)
1{robot replaceability}		-3.336*	-3.127*	-3.768
		(1.789)	(1.771)	(2.717)
Δ exposure to uncertainty in developing countries$^{\gamma}$ × 1{robot replaceability}			6.154***	7.129***
			(1.816)	(2.145)
Period FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Observations	1710	1710	1710	1260
R^2	0.210	0.214	0.232	0.229

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$^{\pm}$ manufacturing only

Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries variable is standardized to have a mean of zero and a standard deviation of one. The variable Δ exposure to uncertainty in developing countries$^{\gamma}$ is calculated using α_{ijk} weights that are adjusted compared to equation (2), namely using the share of developing country k's inputs of all inputs of (developed) country i *sourced from developing countries* in industry j in 2000. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. All specifications include time period and country dummies.

Table A6: Robot Replaceability

Industry	Graetz and Michaels (2018)	Replaceability dummy
Education, research and development	.01	0
Agriculture, hunting, and forestry; Fishing	.01	0
Electricity, gas, and water supply	.04	0
Construction	.08	0
Mining and quarrying	.14	0
Unspecified chemical, petroleum products	.17	0
Paper and paper products, publishing & printing	.18	0
Other transport equipment	.24	0
Chemical products and pharmaceuticals, cosmetics	.25	0
Food products and beverages; Tobacco products	.30	0
Electrical/electronics	.32	1
Glass, ceramics, stone, mineral products	.34	1
Textiles, leather, wearing apparel	.35	1
Industrial machinery	.36	1
Wood and wood products	.36	1
Basic metals	.39	1
Metal products	.42	1
Rubber and plastics products	.42	1
Automotive	.45	1

Notes. Graetz and Michaels (2018) measure of replaceability is the fraction of each industry's hours worked in occupations classified to become prone to replacement by robots. *Replaceability dummy* is a dummy variable with value 1 if the industry-level robots replaceability measure by Graetz and Michaels (2018) is above the median, and 0 otherwise.

Table A7: Impact of uncertainty on reshoring (orthogonalizing interaction term)

	dep. variable: $\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$			
	(1)	(2)	(3)	$(4)^{\pm}$
Δ exposure to uncertainty in developing countries	0.423	0.403	-0.247	-0.339
	(0.658)	(0.663)	(0.649)	(0.687)
1{robot replaceability}		-3.373*	-3.404*	-3.965
		(1.810)	(1.817)	(2.680)
Δ exposure to uncertainty in developing countries$^{\psi}$			4.399***	4.543***
$\times$ 1{robot replaceability}			(1.566)	(1.619)
Period FE	✓	✓	✓	✓
Country FE	✓	✓	✓	✓
Observations	1710	1710	1710	1260
R^2	0.204	0.209	0.213	0.205

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$^{\pm}$ manufacturing only

Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries$^{\psi}$ variable is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. Δ exposure to uncertainty in developing countries$^{\psi}$ is the Δ exposure to uncertainty in developing countries variable net of its projection on 1{robot replaceability}, country fixed effects, and period fixed effects, as recommended in Balli and Sørensen (2013).

Table A8: Impact of uncertainty on reshoring (more refined small open economy approach)

	dep. variable: $\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$							
	Baseline estimates		Top-1 excluded		Top-2 excluded		Top-3 excluded	
	(1)	(2)$^{\pm}$	(3)	(4)$^{\pm}$	(5)	(6)$^{\pm}$	(7)	(8)$^{\pm}$
Δ exposure to uncertainty in developing countries	-0.547	-0.594	-0.853*	-0.751	-1.142**	-1.086*	-1.008*	-0.975
	(0.633)	(0.671)	(0.450)	(0.477)	(0.551)	(0.575)	(0.573)	(0.593)
1{robot replaceability}	-2.859	-3.457	-3.715**	-4.878**	-2.551*	-3.345	-3.289**	-3.468
	(1.761)	(2.654)	(1.608)	(2.126)	(1.445)	(2.065)	(1.517)	(2.143)
Δ exposure to uncertainty in developing countries × 1{robot replaceability}	7.527***	7.790***	5.209***	5.779***	6.263***	6.996***	4.582**	4.968**
	(2.162)	(2.366)	(1.883)	(2.173)	(2.219)	(2.656)	(1.787)	(2.015)
period FE	✓	✓	✓	✓	✓	✓	✓	✓
country FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1710	1260	1710	1260	1710	1260	1710	1260
R^2	0.224	0.219	0.192	0.192	0.186	0.188	0.206	0.207

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
$^{\pm}$ manufacturing only
Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries variable is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. All specifications include time period and country dummies. The first two columns show the baseline estimates mimicking specifications (3) and (4) of Table 1. Columns (3) and (4) present results from the same specifications, only now excluding - for each developed country - the uncertainty changes in developing countries for which it is the most important export destination from the Δ exposure to uncertainty in developing countries variable. Columns (5) and (6), and (7) and (8) do the same, only now excluding uncertainty changes from developing countries, for which the developed country is among the top-2 and top-3 export destinations.

Table A9: The impact of uncertainty on reshoring (controlling for additional third factors)$^{\pm}$

	dep. variable: $\Delta \log \frac{\text{domestic inputs}}{\text{developing country inputs}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ exposure to uncertainty in developing countries	-0.607	-0.637	-0.600	-0.610	-0.622	-0.689
	(0.672)	(0.675)	(0.677)	(0.689)	(0.682)	(0.700)
1{robot replaceability}	-1.715	-1.924	-2.637	-3.034	-3.490	-0.002
	(2.393)	(1.933)	(2.129)	(2.532)	(2.657)	(1.680)
Δ exposure to uncertainty in developing countries $\times$ 1{robot replaceability}	7.765***	7.729***	7.815***	7.858***	7.827***	7.783***
	(2.340)	(2.373)	(2.381)	(2.383)	(2.364)	(2.361)
stickiness	-2.286***					-2.348***
	(0.669)					(0.824)
relative hourly wages		-4.919***				-4.840***
		(1.750)				(1.689)
routine share			-3.901			0.426
			(3.019)			(2.780)
offshorability				1.518		1.005
				(1.137)		(1.027)
union coordination index					4.666	4.671
					(5.233)	(5.245)
Period FE	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Observations	1260	1260	1260	1260	1260	1260
R^2	0.226	0.233	0.220	0.222	0.221	0.244

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
$^{\pm}$ manufacturing only
Notes. The dependent variable is the change of the log of the ratio of domestic inputs and inputs from developing countries. The Δ exposure to uncertainty in developing countries variable, along with the other control variables except 1{robot replaceability} dummy variable, is standardized to have a mean of zero and a standard deviation of one. Regressions are weighted by each country-industry pair's inputs from the developing world. Standard errors allow for arbitrary clustering at the country-industry level. All specifications include time period and country dummies. Stickiness refers to the normalized industry-level stickiness calculated as the fraction of inputs not traded on an exchange, the larger the fraction the more relationship-specific the industry based on Nunn (2007). Relative hourly wages denote the normalized level of hourly wages relative to the weighted average of hourly wages in developing countries in 2000, where weights are the share of inputs sourced from each developing country. The routine share measure is constructed using the distribution of occupations across industries in the US in 1990, which is based on "routine task intensity score" (following Autor et al., 2015). Offshorability is each country-industry pair's 2000 share of developing inputs of total non-energy inputs (following Feenstra and Hanson, 1999). The union coordination index measures the predominant level at which wage bargaining takes place (OECD and AIAS, 2021) for each developed country (following Bhuller et al., 2022).