From Sanctions to Tariffs: How U.S. Economic Measures Shape Artificial Intelligence Diffusion through Industrial robots?

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Abstract

This paper investigates how U.S. economic measures, specifically sanctions and tariffs, shape the global diffusion of artificial intelligence (AI), proxied by the deployment of industrial robots. Using a panel of 49 countries from 2002 to 2019, we employ the Entropy Balancing method to address endogeneity and selection bias. Our findings reveal that both sanctions and tariffs significantly reduce the diffusion of AI, with the effect of tariffs being more pronounced. Sanctions hinder AI adoption mainly through restrictions on finance, trade, and technology transfer, while tariffs operate by raising input costs and disrupting global supply chains. The results further show strong cross-country heterogeneity: low-income and trade-dependent economies are more adversely affected, whereas resource-rich and industrialized countries exhibit greater resilience. Mechanism analyses highlight three key transmission channels, macroeconomic recession, uncertainty, and technological constraints through which economic measures suppress automation. These results suggest that U.S. economic statecraft, while serving geopolitical objectives, may slow global technological progress and widen existing innovation divides. The paper concludes with policy recommendations emphasizing the need for international coordination, technological resilience, and balanced governance of AI diffusion amid rising geopolitical tensions.

Keywords: US Economic Sanctions • Artificial Intelligence • Entropy Balancing • US Tariffs

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"'This barrage of legal, commercial, financial, and technological restrictions has drastically impeded . . . access to the world economy." — Nicholas Mulder, "The Sanctions Weapon" — IMF Finance & Development

1 Introduction

In recent years, the global economy has witnessed a growing reliance on economic instruments as tools of geopolitical influence. States increasingly deploy sanctions, export controls, and tariffs not merely as responses to specific political crises, but as components of broader strategies to secure technological dominance and reshape global value chains. The United States, in particular, has resorted to a wide spectrum of economic measures to constrain rivals' access to critical technologies, reflecting what scholars describe as the rise of geoeconomic statecraft (Blackwill and Harris, 2016; Farrell and Newman, 2019). This trend marks a departure from the liberal era of economic globalization characterized by openness and interdependence, toward a system where economic integration is selectively curtailed in pursuit of strategic advantage. The scope and intensity of these measures have expanded substantially over the past decade. As of 2023, more than 30 countries were subject to U.S. sanctions, covering roughly 29% of global GDP when including secondary effects on trade partners.[1] Similarly, the volume of trade affected by U.S. tariffs reached unprecedented levels during and after the U.S.–China trade confrontation: average tariff rates on Chinese goods increased from 3.1% in 2017 to nearly 20% in 2020, with sustained levels above 18% through 2023 (Pierson et al., 2023). In May 2025, the US administration unveiled 30 per cent tariffs on Chinese goods. It even threatened in october to impose additional tariffs of 100 per cent on China. These measures have not only disrupted traditional supply chains but also spurred the geographic reorganization of production, with multinational firms relocating operations to Southeast Asia, Mexico, or Eastern Europe to circumvent tariff and sanction risks. Beyond immediate trade effects, such economic instruments are increasingly designed to influence the diffusion of strategic technologies. The United States' Export Control Reform Act (2018) and subsequent regulations under the CHIPS and Science Act (2022) explicitly target advanced semiconductors, quantum computing, and artificial intelligence capabilities, especially those linked to China and Russia. The October 2022 and October 2023 export control packages imposed by the U.S. Department of Commerce restrict the sale of high-end chips and manufacturing equipment to Chinese firms such as Huawei, SMIC, and others involved in AI development. These measures directly affect global technological diffusion: according to the Semiconductor Industry Association, the restrictions could reduce China's access to high-performance chips by over 40% in volume relative to 2021 levels.[2] This intensification of economic statecraft represents a structural transformation in the global political economy. Economic measures are no longer isolated punitive actions but components of systemic competition over technology, data, and innovation capacity. The emerging framework of weaponized interdependence highlights how states leverage control over critical nodes in global networks, financial systems, data infrastructures, and technological supply chains to influence other economies (Farrell and Newman, 2019). The resulting fragmentation of the global

[1] See discussion on American Sanctions Programs.
[2] See report of Semiconductor Industry Association.

economy has profound implications for technological progress and diffusion. By restricting cross-border investment, knowledge transfer, and access to high-tech input, such measures risk creating a technological bifurcation: a dual global system divided between Western-led and China-centered innovation ecosystems. This process of technological bifurcation, characterized by the emergence of parallel innovation ecosystems, one centered around the United States and its allies, the other increasingly dominated by China and its partners, raises profound questions about the future of global technological diffusion. Within this new landscape, AI occupies a pivotal position. As a general-purpose technology, AI has the potential to transform virtually all sectors of economic activity, from manufacturing and logistics to finance, health, and education. The global race for AI dominance has thus become both an economic and a geopolitical contest, shaping industrial policies, trade strategies, and international alliances.

AI diffusion has accelerated rapidly over the past decade. The number of AI-related patents filed worldwide exceeded US$190 billion in 2023, almost quadrupling compared to 2018.[3] The number of AI-related patents filed worldwide has increased by more than 150% since 2015, with East Asia (particularly China, Japan and South Korea) now accounting for more than 60% of global filings.[4] In the industrial sector, the tangible manifestation of AI is often observed through the deployment of industrial robots, machines capable of executing complex automated tasks that integrate perception and reasoning. The International Federation of Robotics (2024) reports that more than 3.9 million industrial robots were operational worldwide by the end of 2023, with installations growing at an average annual rate of 12% over the past decade. East Asia remains the epicenter of this transformation: China alone accounted for over 52% of all new robot installations in 2023, followed by Japan (10%), the United States (8%), and Germany (6%).[5]

However, the diffusion of artificial intelligence and automation technologies is not taking place in a vacuum; it is deeply conditioned by international economic and political constraints. A growing body of literature demonstrates that economic sanctions and trade barriers can have substantial and persistent adverse effects on technological development and diffusion. By restricting access to international markets, exporting technology, capital, and knowledge flows, sanctions tend to isolate targeted economies and hinder their capacity to adopt and integrate frontier technologies. As Mirkina (2018) and Nguyen and Ahmed (2023) show, sanctions significantly reduce foreign direct investment, an essential channel for technology transfer and innovation diffusion. Similarly, Neuenkirch and Neumeier (2015) and Escribà-Folch and Wright (2010) find that sanctions induce economic recessions and weaken industrial output, thereby lowering firms' capacity to finance automation or digital transformation projects. In parallel, tariffs and protectionist measures can also distort technology adoption by raising input costs and generating uncertainty within global value chains. Evenett (2002) and Handley et al. (2025) argue that increased trade barriers reduce export competitiveness and investment incentives, leading firms to postpone long-term innovation projects. The escalation of U.S.–China trade tensions since 2018 provides an illustrative example: higher tariffs on machinery, electronics, and intermediate components disrupted global production networks and constrained access to essential inputs for automation equipment and

[3] See OECD report.
[4] See discussion on WIPO website.
[5] See 2024 Executive Summary of IFR.

semiconductor-based technologies. These disruptions amplify production costs and uncertainty, especially in manufacturing sectors characterized by tight margins and high capital intensity. Moreover, sanctions and tariffs can exacerbate macroeconomic instability, which in turn discourages firms from investing in technologies with long payback periods, such as industrial robots or AI-driven systems. Hatipoglu and Peksen (2018) and Gavkalova et al. (2022) emphasize that restrictions on financial flows and trade often trigger currency depreciation, inflationary pressures, and fiscal tightening, all of which undermine firms' investment capacity. In sanctioned or trade-constrained economies, the combination of shrinking fiscal space, limited access to foreign technology, and elevated uncertainty creates a hostile environment for technological diffusion. As a result, the global adoption of artificial intelligence and industrial automation exhibits pronounced geographic asymmetries, reflecting not only differences in domestic capabilities but also the geopolitical configuration of access to technologies, markets, and capital.

Contribution. While the economic and political effects of sanctions and tariffs have been widely examined in the literature, their implications for technological diffusion, particularly in the field of artificial intelligence and automation remain relatively underexplored. A vast body of research has documented the macroeconomic consequences of sanctions, including their effects on trade (Neuenkirch and Neumeier, 2015), foreign direct investment (Mirkina, 2018), and financial stability (Hatipoglu and Peksen, 2018). Similarly, numerous studies have analyzed the impact of tariffs on global value chains, productivity, and firm-level innovation (Handley et al., 2025). However, much less attention has been devoted to understanding how such measures influence the diffusion of general-purpose technologies, that is, innovations whose benefits depend on international spillovers, technological complementarities, and access to global markets. Recent work has begun to explore related questions. For example, (Andreoni et al., 2023) show that geopolitical tensions can redirect innovation efforts toward self-sufficiency rather than efficiency. Studies by (Chen et al., 2024) and (Prasad Agrawal, 2024) highlight that AI diffusion depends heavily on access to advanced hardware, international data flows, and cross-border partnerships, all of which can be disrupted by geopolitical frictions. Furthermore, (Kim and Cho, 2024) provide evidence that U.S. export controls on semiconductors have constrained technological upgrading and exports in Korea, particularly in industries relying on automation and robotics. These findings suggest that economic statecraft may generate significant technological externalities beyond its intended political objectives. Most existing studies either focus on the direct trade and investment effects of sanctions or analyze AI diffusion in isolation from international political economy dynamics. This research gap is particularly salient given the strategic importance of AI and robotics for productivity growth and global competitiveness (Agrawal et al., 2019; Acemoglu and Restrepo, 2020; Brynjolfsson et al., 2021; Lu and Zhou, 2021). This article aims to bridge this gap by providing the first cross-country empirical investigation of how U.S. economic measures, specifically sanctions and tariffs, shape the global diffusion of AI through industrial automation. By linking comprehensive data on industrial robot deployment from the International Federation of Robotics (IFR) with datasets on U.S. economic sanctions and tariff exposure, this study identifies the causal channels through which economic statecraft influences technological diffusion. In particular, the paper highlights three main mechanisms: (1) economic recession effects, whereby sanctions and tariffs depress aggregate demand and investment; (2) macroe-

conomic uncertainty, which increases risk premia and delays adoption decisions; and (3) technological transfer constraints, which limit access to frontier knowledge, hardware, and international partnerships. In doing so, the article contributes to three strands of literature: (i) the political economy of sanctions and tariffs (Hufbauer et al., 1990); (ii) the economics of technological diffusion and automation (Comin and Mestieri, 2014; Graetz and Michaels, 2018); and (iii) the emerging field of AI political economy (Prasad Agrawal, 2024; Chen et al., 2024). It thus provides novel empirical evidence on how geopolitical measures influence global technological transformation, offering new insights into the intersection between international economics, industrial policy, and innovation dynamics. This article finally contributes to the literature by showing that the negative effect of sanctions on the diffusion of artificial intelligence can extend up to 8 years after the imposition of economic sanctions.

To estimate the causal impact of U.S. economic measures on the global diffusion of artificial intelligence, we focus primarily on economic sanctions while also considering tariffs as complementary instruments of economic statecraft. To mitigate endogeneity concerns, we rely on the Entropy Balancing method, introduced by Hainmueller (2012). A key threat to identification in our setting is that the imposition of economic sanctions is not random: countries that become sanctioned often differ systematically from non-sanctioned ones in ways that are also correlated with the adoption and diffusion of AI technologies, for example, in terms of political stability, institutional quality, technological readiness, or macroeconomic performance. Such pre-existing differences create a classic selection-bias problem, whereby the observed gap in AI deployment may reflect underlying structural characteristics rather than the causal impact of sanctions themselves. Following recent applications in the sanctions literature (Apeti and Edoh, 2024; Nandnaba, 2025), entropy balancing reweights the control group so that it matches the treated countries on all relevant pre-treatment covariates. This ensures that both groups are comparable prior to sanction episodes, thereby improving causal inference and isolating the effect of sanctions on AI deployment. This technique reweights the control group to match the treated group across observed covariates, ensuring covariate balance and allowing for consistent estimation of causal effects. Using a panel of 49 countries covering the period 2002–2019, we combine data on industrial robot deployment from the International Federation of Robotics with detailed information on U.S. Economic sanctions and US. tariff exposure. Our baseline results show that economic sanctions reduce AI diffusion by approximately 5.9 robots per 10,000 manufacturing workers, equivalent to a decline of about 17% relative to the mean. In addition, U.S. tariffs exert a stronger negative effect on AI diffusion than economic sanctions. These different effects are statistically and economically significant and remain robust across alternative model specifications, estimation techniques, and sample definitions. The analysis reveals that the adverse effects of U.S. economic sanctions on AI diffusion are structurally heterogeneous across countries. The negative impact of these measures is stronger in economies with lower GDP levels and higher trade openness, indicating that smaller and more globally integrated countries are particularly vulnerable to external restrictions. By contrast, the effect is weaker in resource-rich economies that can use natural rents to cushion external shocks, and in countries with a strong manufacturing base, which are better able to maintain automation through domestic production capacities and technological substitution. Three mechanisms explain these outcomes: (i) economic recession, (ii) increased macroeconomic and geopolitical uncertainty, and (iii) constraints on technology transfer. Together, these findings highlight

how U.S. economic measures intended to achieve geopolitical objectives can slow global technological diffusion and automation.

Our article is organized as follows. Section 2 discusses the theoretical framework and outlines the main transmission channels through which U.S. economic sanctions may affect AI diffusion. Section 3 describes the data sources and empirical methodology. Section 4 presents key stylized facts on the evolution of industrial robot deployment and exposure to U.S. sanctions and tariffs. The main empirical results are reported in Section 5, followed by robustness and sensitivity analyses in Sections 6 and 7, which also examine heterogeneity across countries. Sections 8 and 9 extend the analysis by exploring the specific effects of tariffs and empirically testing the proposed transmission mechanisms. Finally, Section 10 concludes with a summary of findings and policy implications.

2 Theoretical Channels

This section presents the transmission channels through which economic sanctions can impact the spread of artificial intelligence.

Economic recession

One of the primary mechanisms through which economic sanctions exert their negative effects on the adoption and diffusion of advanced technologies, including artificial intelligence in industrial robotics, is the economic recession they induce in targeted economies. As a coercive policy tool, sanctions often generate substantial macroeconomic costs by reducing overall economic output, destabilizing exchange rates, fueling inflationary pressures, and disrupting key economic activities such as trade, investment, and human capital accumulation (Hufbauer et al., 1990; Peksen and Son, 2015; Wang et al., 2019; Afesorgbor, 2019; Gutmann et al., 2021). Empirical studies confirm the magnitude of these effects. For instance, Neuenkirch and Neumeier (2015), analyzing data from 67 sanctioned countries, found that sanctions led to a persistent fall in output per capita of approximately 25.5% over a ten-year horizon following their imposition. Similarly, Splinter and Klomp (2022) demonstrated that sanction episodes significantly increase the likelihood of growth deceleration during the first three years of enforcement, while Gutmann et al. (2021) showed that sanctions undermine human capital accumulation, thereby slowing long-term growth prospects. These economic disruptions often weaken fiscal stability, raising the risk of sovereign debt default. Esteves et al. (2021), for example, highlight how recessions reduce governments' capacity to mobilize sufficient resources for debt repayment, thereby exacerbating default risks. The recessionary effects of sanctions are not limited to macroeconomic aggregates but also extend to sectoral investment priorities. Evidence suggests that during downturns induced by sanctions, governments are compelled to reallocate scarce resources away from long-term, capital-intensive projects, such as investments in renewable energy and advanced technologies toward immediate social priorities like healthcare and education (Cylus et al., 2012; Chen et al., 2019; Vural, 2021; Apeti and Edoh, 2024). As sanctions make economies poorer, countries experience mounting constraints in pursuing innovation. Neuenkirch and Neumeier (2016) documents how sanctions increased poverty between 1982 and 2011, while Splinter

and Klomp (2022) corroborates the growth-depressing effects of sanctions. Choi and Luo (2013) even links sanctions-driven poverty to rising terrorism in 152 countries, demonstrating the far-reaching consequences of economic distress. More recently, while Moteng et al. (2023) provides evidence that sanctions exacerbate energy poverty through both poverty and recession channels, (Nandnaba, 2025) shows that economic sanctions reduce renewable energy production by increasing economic recession in sanctioned countries. This body of evidence illustrates how sanctions-induced recessions erode the economic and fiscal capacity of sanctioned states, forcing them to delay or abandon investments in transformative technologies. In the context of industrial robotics, such downturns reduce firms' willingness and ability to commit to costly AI-driven automation projects, while governments scale back support for industrial modernization in favor of short-term social stabilization.

Technology Transfer

A further and indirect mechanism through which economic sanctions undermine the diffusion of advanced technologies, including artificial intelligence in industrial robotics, is by disrupting international technology transfer. Broadly defined, technology transfer encompasses both trade in high-tech equipment and materials, as well as foreign direct investment (FDI), each of which is essential for building technological capacity and scaling up industrial modernization (Wilkins, 2010; Vural, 2021; Doytch and Narayan, 2016; Zhang et al., 2021). Trade-based transfers, such as imports of precision sensors, advanced semiconductors, and robotic components, directly introduce state-of-the-art hardware into local industries. Meanwhile, FDI does not only provide capital, but also brings managerial expertise, engineering know-how, and organizational capabilities that accelerate the adoption of new technologies. Domestic firms benefit through learning-by-doing, observing best practices, and building absorptive capacity, which together foster technological upgrading. Sanctions, however, impose significant barriers to these flows. On the trade side, financial restrictions, especially those targeting banking systems and cross-border payment mechanisms, severely curtail imports and exports of high-tech goods (Afesorgbor, 2019; Dai et al., 2021; Nguyen and Ahmed, 2023). For example, Besedeš et al. (2024), show that targeted financial sanctions against Germany significantly reduced importation of high-tech products. Likewise, Jena et al. (2024), using a structural gravity model covering 1990–2019, finds that sanctions depressed bilateral trade volumes by up to 20–30% across affected sectors, with advanced equipment among the most heavily impacted. Case studies reinforce these results. Mancini et al. (2024) documents that sanctions following Russia's 2022 invasion of Ukraine led to a 50% collapse in Russia's high-tech imports within a year, while Simola and Röyskö (2023) highlights a sharp contraction in technology flows from East Asia to Russia over the same period. On the FDI front, the evidence is equally compelling. Mirkina (2018), analyzing data from 184 countries over 1970–2010, shows that the imposition of sanctions was associated with a substantial and persistent decline in foreign investment inflows, a result corroborated by Nguyen and Ahmed (2023) using a panel of 172 countries between 2003 and 2019. The withdrawal of foreign investors does not only reduce capital inflows but also deprives local firms of access to critical managerial practices and tacit knowledge, thereby slowing down innovation spillovers. For example, in the case of Iran, sanctions have been found to reduce FDI inflows by more than 60% during peak sanction episodes, severely constraining the country's access to advanced manufacturing technologies

(Haidar, 2017). By constraining trade in high-tech components and deterring foreign investors, sanctions limit access to cutting-edge innovations and knowledge flows. In the specific context of industrial robotics, this manifests in reduced availability of advanced chips, machine vision systems, and software frameworks essential for integrating artificial intelligence. Firms are forced to rely on outdated or domestically produced substitutes, which are often less efficient and more costly, thereby delaying or even preventing the large-scale diffusion of AI-enabled robotics. Ultimately, the erosion of technology transfer channels entrenches a technological gap between sanctioned economies and the global frontier, further marginalizing their capacity for industrial modernization.

Macroeconomic and geopolitical uncertainty

Beyond the channels of economic recession and technology transfer, a third and equally important mechanism through which sanctions hinder the diffusion of artificial intelligence in industrial robotics is the macroeconomic and geopolitical uncertainty they generate. Sanctions typically disrupt trade flows, financial transactions, and diplomatic relations, thereby creating a climate of instability in which economic agents face difficulties forecasting future returns and policy outcomes. This climate of uncertainty, as highlighted by Liu et al. (2024b), tends to increase economic policy uncertainty indices in sanctioned countries, reflecting instability in fiscal, monetary, and exchange-rate expectations. Similarly, Biglaiser and Lektzian (2020) show that sanctions heighten financial volatility in target states, as measured by stock market fluctuations, while Spaniel and Smith (2015) argues that sanctions exacerbate political uncertainty by undermining leadership stability and policy continuity. The consequences of this uncertainty for technology adoption are substantial. A growing body of research emphasizes that firms tend to delay or scale down investments in capital-intensive and long-horizon projects under conditions of heightened risk. Qin and Zhang (2024), studying Chinese manufacturing firms between 2009 and 2019, demonstrates that increases in economic policy uncertainty (EPU) significantly reduce the adoption of industrial robots, as companies prefer to "wait and see" rather than commit to irreversible expenditures. Faber et al. (2025) reach similar conclusions in their analysis of global value chains, showing that heightened uncertainty slows the pace of robot integration in production networks.[6] The mechanism operates through several channels. First, uncertainty raises the risk premium and thus increases financing costs, reducing the net present value of automation projects. Second, it increases the value of waiting, encouraging firms to delay investment until conditions stabilize. Third, it amplifies volatility in input prices, complicating budget planning and reducing confidence in investment returns. Finally, it heightens regulatory and policy risk, as governments under sanctions may be forced to adjust subsidies, tariffs, or industrial policies abruptly. As mentioned above, in sanctioned economies, these effects are magnified. Governments prioritize short-term stabilization over long-term modernization, while firms face tighter credit conditions, costlier imports, and greater uncertainty about future market access. As a result, the macroeconomic uncertainty channel represents a powerful brake on the diffusion of AI-enabled industrial robotics, complementing the recession and technology transfer channels and reinforcing the technological lag of sanctioned states.

[6]Other reports highlight that uncertainty-driven cost volatility in robotic components (such as semiconductors and sensors) compelled firms to postpone automation plans. See discussion on current trends in robotics.

3 Methodology and Data

In this section, we present the methodology we will use to analyze the impact of economic sanctions, as well as the data we use.

3.1 Methodology

This paper aims to analyze the effects of economic sanctions on AI diffusion. In the literature on the effects of sanctions, several methodological approaches have been adopted. For example, Neuenkirch and Neumeier (2015) analyze the effect of sanctions on economic growth using the Ordinary Least Squares (OLS) method. This same methodology is applied by several other authors, including Afesorgbor and Mahadevan (2016); Hatipoglu and Peksen (2018); Gutmann et al. (2023, 2024). Gharehgozli (2017) and Farzanegan (2022) use the synthetic control method to analyze the impact of economic sanctions. However Synthetic control is poorly suited to our context for several reasons. First, it is designed to construct a counterfactual for a single treated unit, whereas our study involves 12 countries entering sanctions at different times (Arkhangelsky et al., 2021). Applying synthetic control separately to each country would be cumbersome and sacrifice statistical power. Second, synthetic control requires a long pre-treatment period to fit a reliable donor-pool combination; many of our treated countries have relatively short sanction histories, making valid synthetic matches difficult. Finally, it discards much of the sample by focusing only on a small set of control units for each case, reducing efficiency and generalizability. To address these different issues and the endogeneity problem of economic sanctions, a number of papers in the literature turned to impact analysis methods. For example, Neuenkirch and Neumeier (2016) assess the effect of economic sanctions on poverty using the impact analysis method Entropy Balancing. Similarly, Afesorgbor (2019) and Gutmann et al. (2023) complete their respective analysis of the effect of sanctions on trade and economic growth using this method. Gutmann et al. (2021) use this method to analyze the effect of sanctions on life expectancy and mortality. Alternative methods such as the GMM system method have been applied to contain the endogeneity of sanctions (Afesorgbor and Mahadevan, 2016; Lv and Xu, 2017; Sun et al., 2021; Moteng et al., 2023). In this study, we follow the recent literature of Neuenkirch and Neumeier (2016), Gutmann et al. (2021), Apeti and Edoh (2024) and Nandnaba (2025) using entropy balancing.[7] This choice is justified by the fact that country sanctions are not a random phenomenon, but can depend on several factors, such as the country's economic growth, institutional governance, the fragility of countries characterized for example by coups d'état, and the country's economic situation. Among other things, these factors can also prevent a country's deploying many industrial robots and thus penalizing the deployment of artificial intelligence, leading to the effect of sanctions being endogenous due to selection bias. Thus, the use of entropy balancing allows us to correct this bias. In addition to the problem of selection bias, there may be imbalance in the data, characterized by a difference between observations subject to sanction and those not subject to sanction (Apeti and Edoh, 2024; Nandnaba, 2025). As a result, the problem of identification may arise if

[7] Compared to Propensity Score Matching, which may suffer from residual imbalance and sample loss, Entropy Balancing directly optimizes covariate weights to achieve balance, improving estimation precision. It is also more suitable than the Synthetic Control Method, which is typically designed for single-country case studies (Gharehgozli, 2017). Nevertheless, we use these other methods in section 10 to verify the robustness of our results.

observed differences are also correlated with differences in AI deployment (Allcott, 2015; Baccini et al., 2019; Apeti and N'doua, 2023), or if they reflect unobserved differences that could be at the origin of the correlation between sanctions and AI deployment. Using entropy balancing helps to correct this bias too.[8] Entropy balancing helps to select matches for the units exposed to treatment and to estimate the ATT (Average Treatment Effect on the Treated).

We now define the average treatment effect on treatment using the following specification :

$$ATT=E[\ Y_{(1)}|\ T=1] - E[\ Y_{(0)}|T=1\ ]$$

Y(.) represents AI deployment characterized by the number of Industrial Robots. T is our variable of interest and is a dummy which takes the value 1 if a country was subject to economic sanctions (financial or commercial) in a given year t and 0 otherwise. However, there may be a problem in our control group. Indeed, it cannot be excluded that the number of Industrial robots in the control group decreases as in the treated group, mainly due to the various factors we mentioned above. This could therefore bias our results, as the allocation of sanction treatment is no longer random. To this end, the matching procedure will reproduce a situation where our observation units are randomly affected by the treatment (economic sanctions). These units will then be matched with those who were not exposed to the treatment, taking into account their characteristics and similarities. We can therefore rewrite the following new specification:

$$ATT=E[\ Y_{(1)}|\ T=1,\ X=x] - E[\ Y_{(0)}|T=0, X=x\ ] \quad (1)$$

$X=x$ represents a vector of variables that can affect both the treatment(sanctions) and AI deployement. Entropy balancing requires two steps. First, we compute weights that are assigned to units not exposed to treatment. These weights are chosen to satisfy pre-specified equilibrium constraints involving sample moments of the pre-treatment characteristics while, at the same time, remaining as close as possible to uniform base weights. In our analysis, the equilibrium constraints require equal covariates means between the treatment and control groups, which ensures that the control group contains non-treatment units that are, on average, as similar as possible to the units that received treatment(Neuenkirch and Neumeier, 2016; Gutmann et al., 2021; Apeti and Edoh, 2024; Nandnaba, 2025). In the second step, these

[8]This method is widely used in the economic literature including, Gutmann et al. (2023) to analyze the effect of sanctions on growth and its components, Wen et al. (2024) to assess the impact of sanctions on innovation, Huang and Yeh (2014) and Ogrokhina and Rodriguez (2019) to assess, respectively, the effect of inflation targeting on unemployment and debt composition, Neuenkirch and Neumeier (2016) to assess the impact of US sanctions on poverty, Balima (2020) to assess the effect of Coups d'Etat on the cost of debt, Gutmann et al. (2021), Apeti and Edoh (2024) to study the effect of economic sanctions on debt default and recently and Combes et al. (2025) to analyze the effect of economic sanctions on Global Value Chains.

weights obtained in the first step are used in a weighted regression analysis that includes the treatment indicator as an explanatory variable. We thus have the following equation:

$$Y_{it} = \beta_i + \rho T_{it} + \alpha X_{it} + \mu_t + \varepsilon_{it} \tag{2}$$

In this equation "i" and "t" represent countries and years respectively, while ρ represents the ATT as defined above. Since there is no universally accepted measure of AI deployment covering the whole economy and available over a sufficiently long period for a large number of countries, AI deployment is proxied here by the stock of industrial robots per 10,000 manufacturing workers, denoted as "Y" following Acemoglu and Restrepo (2020); Dong et al. (2024). The country and year fixed effects are represented respectively by β_i and μ_t.[9] We also include a vector of control variables (X_{it}), thus representing the determinants of AI deployment to strengthen our model. The control variables include the corruption control index as a proxy for institutional quality; the number of patents as a proxy for research and development, capturing the level of innovation; the country's economic size measured by GDP; CO2 emissions[10].

3.2 Data

Our dependent variable is industrial robots and is drawn from the International Federation of Robotics, which provides the most authoritative and widely cited statistics on global robot adoption in manufacturing and related industries. The IFR defines an industrial robot as an "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes," consistent with the standard ISO 8373 definition. The dataset offers comprehensive annual information on robot stocks and new installations across countries. The coverage spans several decades, enabling cross-country comparisons of the diffusion of robotics technologies. Specifically, the IFR provides annual data on new robot installations and the operational stock of robots at the country level. These measures allow us to capture the overall diffusion of industrial robots over time and across countries, offering a reliable indicator of technological adoption in automation. For our study, we use country-level data on industrial robot installations and stocks represented by the stock of industrial robots per 10,000 manufacturing workers. Following the literature (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Dong et al., 2024; Zhang et al., 2025), we rely on these measures as proxies for the diffusion of Artificial Intelligence.This choice is motivated by the fact that modern industrial robots increasingly embed artificial intelligence technologies, including machine learning, computer vision, and advanced control algorithms, which enable real-time adaptation, predictive maintenance, and autonomous decision-making in production processes. Unlike earlier generations of purely mechanical automation, contemporary industrial robots are tightly integrated with AI-driven software and data-processing capabilities, making their diffusion a

[9]Country and year fixed effects are powerful tools to control for unobserved heterogeneity in panel data and obtain more reliable estimates of causal relationships. They provide a better understanding of the factors that influence the variables of interest, taking into account the specificities of each country and temporal variations.

[10](Zhong et al., 2024; Luo and Wang, 2025) suggest that AI can reduce CO2 emissions, so countries with high emissions may be encouraged to increase the spread of AI; and the level of human capital. The selection of these variables is directly grounded in the existing literature on AI deployment(Radhakrishnan and Chattopadhyay, 2020; Amankwah-Amoah and Lu, 2024)

concrete and observable manifestation of applied artificial intelligence in the manufacturing sector.[11]

Our analysis relies on data from the Global Sanction Database (Syropoulos et al., 2024), which represents the most widely used source in empirical research on international sanctions (Wang et al., 2019; Morgan et al., 2023; Apeti and Edoh, 2024; Nandnaba, 2025). The database records sanction cases on an annual basis, covering measures imposed by individual states, groups of states, or international organizations such as the European Union (EU) and the United Nations (UN) against targeted countries in response to violations of international norms. These cases are defined with the purpose of capturing coercive actions intended to pressure target states into altering their behavior. The dataset includes approximately 1,325 sanction episodes (bilateral, multilateral, and plurilateral) spanning the years 1950 to 2022. For the purposes of this study, however, we restrict our time frame to 2002-2019 due to data availability on industrial robots. The database provides detailed information on sanction characteristics, including the type of measure, the sender, and the intended objectives. Sanctions are categorized into trade, financial, travel restrictions, arms embargoes, military assistance, and other forms. Based on these classifications, we construct our primary treatment variable: U.S. economic sanctions, defined as trade and financial sanctions.[12] Following Apeti and Edoh (2024); Nandnaba (2025), this variable equals 1 if country i is subject to U.S. economic sanctions in year t, and 0 otherwise. Within this framework, our study investigates how U.S. economic sanctions influence the adoption and deployment of artificial intelligence (AI) technologies in targeted countries. Focusing on U.S. sanctions is justified for several reasons. First, the United States has historically been the most active user of sanctions, accounting for roughly one-third of all cases worldwide (Felbermayr et al., 2022; Morgan et al., 2023). Second, as the predominant global power since the end of the Cold War, the United States has been central in shaping the international sanctions regime (Adam and Tsarsitalidou, 2019). Moreover, the U.S. not only frequently imposes sanctions unilaterally but also plays a leading role in driving sanctions adopted by multilateral institutions such as the UN and coalitions of states (Morgan et al., 2023). Its leadership has been especially evident in recent sanctions directed at Russia, where U.S. initiatives have set the tone for allied responses. At the same time, focusing solely on U.S. sanctions risks underestimating the broader spectrum of restrictive measures implemented by other states and international organizations. To account for this, we conduct robustness checks by incorporating sanctions imposed by the EU and UN, as well as a more comprehensive measure capturing global sanctions. Within our sample of 49 countries, 12 have been subject to U.S. sanctions (see Appendix Table 4 for the complete list).

Our selection of covariates builds on the existing literature that applies Entropy Balancing to study the effects of U.S. sanctions on various outcomes (Neuenkirch and Neumeier, 2016; Gutmann et al., 2021; Apeti and Edoh, 2024; Nandnaba, 2025). To ensure comparability between treated and untreated units, we construct a control group that is statistically similar to the treatment group with respect to relevant pre-treatment characteristics. The covariates are organized into two main categories. The first captures the broader economic environment and includes measures of economic growth, inflation, and

[11] The IFR dataset is regarded as the benchmark source in empirical research on robotics because it is compiled directly from national robot associations and major manufacturers worldwide, ensuring reliability and comparability across countries.

[12] This measure therefore does not take personal sanctions into account following Gutmann et al. (2023); Apeti and Edoh (2024).

trade openness. The second accounts for political conditions, such as the degree of democracy and the number of coups d'état. Descriptive statistics for these variables are reported in Table A3, while Table 5 provides a complete description along with their sources. In addition, to strengthen the analysis, we incorporate control variables that reflect the determinants of artificial intelligence adoption in the second stage of entropy balancing, following Radhakrishnan and Chattopadhyay (2020); Amankwah-Amoah and Lu (2024). These include indicators of innovation capacity, GDP, CO2 emissions, and human capital. Their descriptive statistics are also presented in Table A3, with further details and sources documented in Table 5.

4 Stylized facts

This section presents a set of stylized facts that illustrate key empirical patterns relevant to the relationship between Economic sanctions and AI deployment through Industrial Robots.

Figure 1 complements this observation by tracing the dynamic evolution of industrial robot use among countries that have experienced sanctions. The solid green line reflects the actual trajectory of robot adoption, while the dashed black line represents a counterfactual scenario in which sanctions had not occurred. The divergence between the two curves becomes more pronounced over time, suggesting a cumulative and persistent negative effect of sanctions on technological advancement. While the affected countries continue to increase their use of robots, the rate of growth is markedly slower than the simulated path, pointing to a widening technological gap. This pattern is consistent with the idea that sanctions not only impose immediate economic costs but also constrain a country's long-run capacity for innovation and industrial modernization.

Figure 2 provides descriptive evidence of a substantial disparity in industrial robot adoption between sanctioned and non-sanctioned year-countries. On average, non-sanctioned countries host approximately 37 industrial robots per 10,000 manufacturing workers, compared to only 14 in sanctioned counterparts. This nearly threefold difference suggests that sanctions may act as a structural barrier to technological upgrading, particularly in automation. Sanctions often limit access to capital goods, foreign direct investment, and international technology transfers, which are critical for industrial robot deployment. For instance, during the 2010s, Iran faced significant challenges in acquiring advanced manufacturing equipment due to trade restrictions, which stifled productivity growth in key sectors like automotive and petrochemicals.

Taken together, these patterns indicate that sanctions may significantly hamper automation processes in targeted economies. Beyond short-term trade disruptions, the evidence points to a longer-term developmental consequence: constrained access to frontier technologies. In this context, sanctions function not only as a geopolitical tool but also as a technological bottleneck, with potentially far-reaching implications for productivity, employment structures, and global value chain integration.

Figure 1: Evolution of Industrial Robots



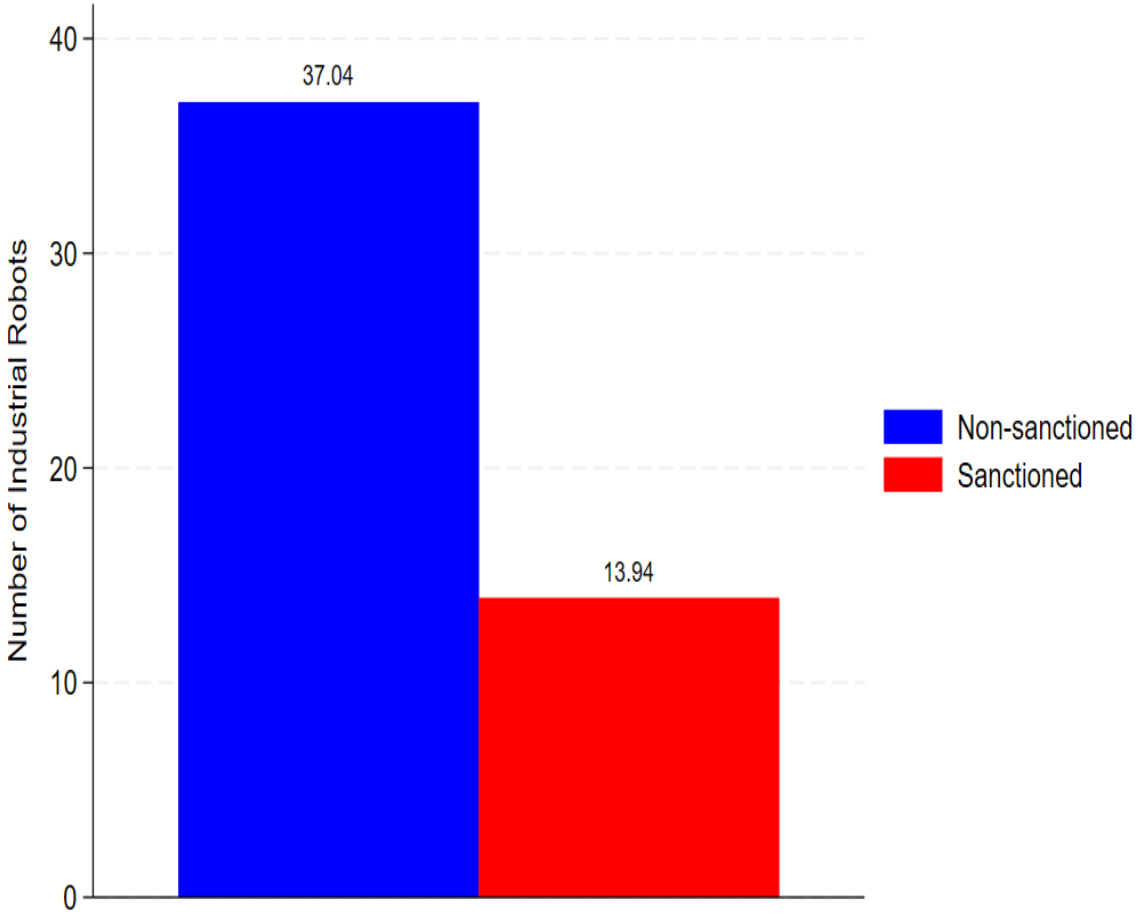
Notes: The Figure plots the evolution of Industrial Robots over time.

5 Main Findings

5.1 Balancing treated and control groups

Panel A of Table 1 reports the pre-weighting comparison of sample means for the matching covariates between sanctioned units (Column [1]) and their control counterparts or the synthetic group (Column [2]). The results indicate notable imbalances, as most of the p-values in Column [4] fall below the conventional 10% level. For example, average inflation rates and public debt levels differ significantly between sanctioned and non-sanctioned countries. Other covariates, such as trade openness and democracy scores, show smaller economic gaps, yet their differences remain statistically significant at conventional levels. These patterns suggest the presence of selection bias between sanctioned and control groups, thereby motivating the use of a suitable matching technique to address endogeneity concerns. Panel B applies Entropy Balancing to re-weight the control units so that their pre-treatment covariates more closely resemble those of sanctioned units. As displayed in Column [4] of Panel B, this procedure eliminates statistically significant pre-treatment differences across all variables. Consequently, the re-weighted synthetic group can be regarded as a highly credible counterfactual for the sanctioned units,

Figure 2: Average of Industrial Robots by Countries statuts



Notes: This graph shows the Average of Industrial Robots per 10,000 manufacturing workers.

which strengthens the identification strategy in assessing the causal effects of sanctions on AI diffusion.

Table 1: Covariates Balancing

Panel A: Before Weighting	[1] With Sanctions	[2] Without Sanctions	[3] = [2] - [1] Difference	[4] p-Value
Inflation	4.215	3.096	-1.119	0.02
GDP. Growth	2.716	2.965	0.249	0.53
Democracy Index	4.905	5.162	0.257	0.08
Coups d'Etat	0.023	0.001	-0.022	0.00
Trade Openness	78.2	94.23	16.03	0.02
Public Debt	68.25	57.03	-11.22	0.012
Observations	***84***	***798***		
Panel B: After Weighting	**[1] With Sanctions**	**[2] Without Sanctions**	**[3] = [2] - [1] Difference**	**[4] p-Value**
Inflation	4.215	4.211	13.72	0.993
GDP. Growth	2.716	2.721	-0.16	0.982
Democracy Index	4.905	4.905	-0.52	0.997
Coups d'Etat	0.023	0.023	0.451	0.990
Trade Openness	78.2	78.44	0.001	0.938
Public Debt	68.25	68.19	0.001	0.984
Observations	***84***	***798***		
Total of Weights	***84***	***84***		

Notes: We lag all covariates by one year to reduce endogeneity due to simultaneity bias with Sanctions.

5.2 Treatment effects

This section presents the results of the impact of Economic sanctions on AI diffusion through Industrial robots. We estimate the following econometric model based on equation 3:

$$Y_{i,t} = \alpha + \beta_1 EconomicSanctions_{i,t} + \beta_2 X_{i,t} + \mu_i + \phi_t + \varepsilon_{i,t} \tag{3}$$

$Y_{i,t}$ denotes the number of industrial robots per 10,000 industrial workers in country i at period t. $EconomicSanctions_{i,t}$ is a dummy variable capturing our treatment variable of economic sanctions. It takes the value of one when a country i has been sanctioned at period t, and zero otherwise. $X_{i,t}$ is a set of control variables used in the second step of entropy to strengthen the model; μ_i captures country-specific effects; ϕ_t captures time-fixed effects. Finally, $\varepsilon_{i,t}$ represents the idiosyncratic error term.

Entropy balancing estimates. Using the weights computed in Table 1, we estimate Eq.3 using Weighted Least Squares (WLS) in which the dependent variable is the number of industrial robots, and EconomicSanctions is the treatment. Column [2] of Table 2 presents our baseline results. We include country and year-fixed effects to control for unobserved heterogeneity in panel data and obtain more reliable estimates of causal relationships. They provide a better understanding of the factors that influence the variables of interest, considering each country's specificities and temporal variations. The estimated effect of Economic sanctions on Industrial Robots deployment is negative and statistically significant. With a coefficient of 5.87, sanctions reduce approximately 5 industrial robots per 10,000 industrial workers compared to non-sanctioned countries. This result is economically sizeable as it accounts for around 16.85% of the mean of Industrial Robots. Therefore, our results support the idea that sanctions reduce AI diffusion in sanctioned countries and the economic losses resulting from economic sanctions have a significant economic impact.

Table 2: Economic sanctions and AI Deployment

	(1) AI	(2) AI	(3) AI	(4) AI
Economic Sanctions	-4.650***	-5.875***	-4.969***	-7.271***
	(1.462)	(1.589)	(1.449)	(1.381)
Observation	882	811	766	583
R-squared	0.900	0.908	0.919	0.962
Controls	NO	YES	YES	YES
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes : This table reports estimates of the impact of Economic sanctions on industrial robots deployment. Our main result is given in column [2]. Columns [3]-[4] present results using alternative samples. Column [3] displays results excluding 2008-2009 years and Column [4] show results excluding 2015-2019. The control variables included in the second step are Patents, Control of corruption, GDP, CO2 emissions and Human capital. All regressions include the constant, not reported in the table. Robust standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6 Sensitivity

Our main findings showed that sanctions penalize the deployment of artificial intelligence by reducing the number of industrial robots in sanctioned countries. In this section, we provide evidence of the robustness of these various findings.

6.1 Alternative specifications

First, regarding the treatment variable, we begin with a placebo sanction variable. This falsification test is designed to assess whether the estimated effects are truly attributable to sanctions rather than spurious correlations or unobserved shocks. If the placebo yields insignificant effects, it strengthens the claim that the baseline results capture a genuine sanction effect (Nandnaba, 2025). We then differentiate between U.S. sanctions (used in the baseline model) and European Union sanctions. This is important because the scope, enforcement, and economic reach of these sanctions differ. U.S. sanctions tend to have extraterritorial reach due to the dominance of the dollar in global finance, whereas EU sanctions may rely more on trade restrictions within European markets. By comparing the two, we can assess whether the effects on industrial robot adoption are consistent across sanctioning authorities or whether they depend on the geopolitical source of the sanction (Apeti and Edoh, 2024). Finally, we construct an "all sanctions" variable, which takes the value one if a country is sanctioned by either the U.S. or the EU. This broader treatment definition captures the possibility of overlapping or coordinated sanctions regimes, thereby testing whether the results are robust to considering sanctions as a global phenomenon rather than tied to a single sender country. The results of these initial tests are presented in columns [1]-[3] of Table 3.

Second, on the side of the independent variable, we replace the operational stock of industrial robots used in the baseline model with the annual installation density of robots, measured as the number of newly installed robots per 10,000 manufacturing workers following (Graetz and Michaels, 2018; Dong et al., 2024). This alternative indicator captures the flow of new automation investments rather than the accumulated stock, allowing us to assess whether our findings are sensitive to short-run dynamics in AI

adoption. By relying on installation density, we also account for cross-country differences in industrial structure and employment size, ensuring that the estimated effects are not mechanically driven by the scale of national manufacturing sectors. If the adverse impact of sanctions remains significant under this alternative specification, it suggests that our main results do not merely reflect long-term technological endowments, but are robust to measuring AI diffusion through recent investment intensity. The results are presented in column [4] of Table 3 and confirm that sanctions reduce the spread of artificial intelligence.

Together, these robustness checks serve two purposes. On the one hand, the placebo and alternative sanction definitions provide confidence that the treatment effect is not an artifact of how sanctions are coded. On the other hand, the use of robot density addresses concerns that the main results are driven by large economies with more robots in absolute terms. Overall, the consistency of results across these alternative specifications presented in Table 3 reinforces the credibility of the baseline finding: sanctions significantly hinder the diffusion of industrial robots.

6.2 Alternative subsamples and additional controls

In this section we use alternative samples and add additional control variables and covariates to verify the robustness of our results.

6.2.1 Alternative subsamples

In a second set of robustness checks, we restrict the sample by excluding periods characterized by major global shocks that could potentially confound the estimated effects of sanctions on industrial robot adoption. These exercises serve to demonstrate that the results are not driven by extraordinary events unrelated to sanctions but rather reflect systematic patterns. First, we exclude the years 2008–2009, which correspond to the global financial crisis. This crisis was marked by severe contractions in investment and international trade, as well as significant volatility in industrial production. Since such dynamics could independently affect firms' automation decisions, removing these years ensures that the observed effects are not simply capturing the consequences of the financial crisis (Combes et al., 2025). Second, we exclude the period 2015–2019, often associated with the rapid expansion of cryptocurrencies and digital assets. While cryptocurrencies are not directly linked to industrial robot adoption, their rise coincided with increased attention to alternative forms of technological investment and financial innovation. Moreover, some sanctioned countries, such as Iran, Venezuela, and Russia experimented with cryptocurrencies as a tool to circumvent restrictions. Excluding this period helps ensure that the baseline results are not influenced by these alternative technological responses to sanctions (Nandnaba, 2025).

The persistence of the results across these restricted subsamples, presented in three last columns of Table 2 strengthens the argument that the estimated sanction effects are not artifacts of global crises or exceptional periods. Instead, they reflect a more structural relationship between sanctions and the diffusion of industrial robots, independent of external macroeconomic shocks.

6.2.2 Additional controls and covariates

To reinforce the credibility of the counterfactual, we expand the set of covariates used in the entropy balancing procedure. Entropy balancing reweights the control group (non-sanctioned countries) such that it matches the treatment group (sanctioned countries) on a rich set of observable characteristics. This ensures that subsequent comparisons are not driven by systematic differences in pre-treatment characteristics but instead reflect the sanction treatment itself. In addition to the baseline covariates, inflation, GDP growth, democracy, coups d'état, debt, and trade openness, we include further institutional indicators: freedom status, rule of law, and property rights. These variables capture structural and institutional dimensions along which sanctioned and non-sanctioned countries might otherwise differ systematically. For instance, sanctioned countries may tend to have weaker institutions or lower scores on property rights, which could bias the comparison if not accounted for. By explicitly balancing on these dimensions, the methodology ensures that institutional differences are not confounded with sanction effects. Incorporating these additional covariates strengthens the balancing exercise by addressing both macroeconomic and institutional sources of imbalance. As a result, the reweighted control group more closely mirrors the treated group across observable characteristics, improving the validity of the estimated sanction effects.

With the previous augmented covariates, we augment the baseline specification(Second stage of our empirical Method) by including a richer set of control variables that account for potential confounders and thereby mitigate concerns of omitted variable bias. The inclusion of these control variables aims to isolate the effect of sanctions from other economic, institutional, and structural determinants of automation. Specifically, we control for macroeconomic conditions such as inflation and the unemployment rate, both of which shape firms' investment decisions and labor market dynamics. Elevated inflation can erode purchasing power and investment capacity, while high unemployment may reduce incentives for automation by lowering the relative cost of labor. In addition, public investment is included to capture the role of government spending in supporting infrastructure and technological adoption. We also account for institutional quality, proxied by indicators such as rule of law and property rights. Stronger institutions provide more secure environments for investment, protect intellectual property, and foster business confidence, all of which are critical for adopting capital-intensive technologies such as industrial robots. On the structural side, we include controls for industrial composition, measured by the value added in the manufacturing sector. Since automation is particularly relevant for manufacturing-intensive economies, differences in industrial structure could confound the relationship between sanctions and robot adoption. Similarly, population size is added to capture the scale of the economy and potential labor supply dynamics. Finally, we incorporate measures of political stability and trade openness, both of which may influence access to technology and foreign capital. Political instability may deter long-term investments in automation, while openness to trade facilitates technology diffusion and integration into global value chains. The persistence of the sanction effect after controlling for this comprehensive set of covariates and control variables provides strong evidence in Table A1, that the results are not merely driven by selection bias or omitted macroeconomic factors. Instead, they underscore a robust and independent relationship between sanctions and the diffusion of industrial robots.

7 Heterogeneity

7.1 Type of sanctions

While the core analysis in this study focuses on economic sanctions, particularly trade and financial restrictions, it is important to recognize that sanctions are not a homogeneous policy instrument. Different types of sanctions may operate through distinct transmission channels, generate heterogeneous economic impacts, and produce varying consequences for technological diffusion, including the adoption of AI-enabled industrial robotics. A growing body of literature stresses the value of sanction disaggregation in empirical research. First, sanctions differ in their scope and intensity of economic disruption. Trade sanctions, by restricting imports and exports, directly affect supply chains, access to critical components, and international technology flows. Financial sanctions, in contrast, primarily constrain access to capital, international credit markets, and payment systems, which may disproportionately affect investment and innovation financing. Trade sanctions may create more immediate bottlenecks in production networks by limiting access to imported technologies and equipment (Afesorgbor, 2019).

Second, disaggregating sanctions allows us to better capture heterogeneity in uncertainty and risk transmission. Financial sanctions, by targeting banks and international payment systems, directly raise uncertainty in financial markets, often increasing volatility in exchange rates and stock markets (Liu et al., 2024b; Biglaiser and Lektzian, 2020). Trade sanctions, by contrast, heighten uncertainty primarily through supply chain disruptions, tariff escalations, and unpredictable shifts in import–export regulations. These distinct pathways suggest that lumping all sanctions into a single category may obscure the nuanced ways in which uncertainty shapes countries' decisions about automation and technology adoption.

Third, the literature also shows that the political signalling effect of sanctions may differ across types. Comprehensive trade embargoes are often seen as blunt instruments, producing wide-ranging economic costs but also creating incentives for domestic substitution. Financial sanctions, particularly those targeting elite networks, may send stronger political signals while at the same time creating systemic uncertainty in investment environments (Peksen and Son, 2015). This divergence in political economy effects further supports the case for disaggregation.

Finally, from a methodological perspective, analyzing heterogeneity by sanction type enables a more precise understanding of the mechanisms at work. If trade sanctions show larger effects, this would point instead to the centrality of global value chains and technology transfer in sustaining robotics diffusion. Such insights are crucial not only for academic understanding but also for policy debates on the design and expected consequences of sanctions. Results are presented in the last two columns of Table 3. The stronger impact of trade sanctions compared to non-significant impact of financial sanctions can be explained by their direct disruption of supply chains and technology transfers, which immediately constrain production and innovation in sectors such as robotics (Afesorgbor, 2019; Jena et al., 2024). By restricting imports and exports, trade sanctions reduce access to critical inputs and markets, thereby lowering firms' incentives to invest in automation. Financial sanctions, by contrast, operate through more indirect channels, mainly access to credit and international payment systems, which are often mitigated

Table 3: Alternative specifications and Type of sanctions

	(1) AI	(2) AI	(3) AI	(4) AI Install	AI	AI
Placebo Sanctions	-0.943					
	(0.822)					
EU Sanctions		-2.601**				
		(1.227)				
All sanctions			-5.766***			
			(1.647)			
Economic sanctions				-0.994***		
				(0.297)		
Trade sanctions					-8.07***	
					(1.820)	
Financial sanctions						-0.063
						(1.1693)
Observation	811	767	767	811	811	811
R-squared	0.966	0.911	0.918	0.839	0.911	0.936

Notes : This table reports estimates of the impact of economic sanctions on Industrial robots using alternative specifications and type of sanctions. Column [1] considers results using Placebo sanctions instead of real sanctions imposition date. Columns [2] considers results using Eu sanctions instead of US sanctions. Columns [3] shows results of the impact of all sanctions on Industrial robots. All regressions include the constant, not reported in the table. Robust standard errors are shown in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

by substitution toward domestic banks, non-Western partners, or informal networks (Mirkina, 2018). Moreover, trade sanctions are generally broader in scope and easier to enforce, while financial sanctions tend to be narrower and more symbolic (Biersteker et al., 2016). These differences explain why trade sanctions generate significant negative effects in the data, whereas financial sanctions appear statistically insignificant.

7.2 Structural factors

In this section, we look at the macroeconomic effects that may condition the effect of economic sanctions on AI diffusion. To do so, we always start with our main model and then interact these different variables with our variable of interest capturing economic sanctions. We then plot these different results on Graph 3 for a better reading of the results. In this study, we consider the initial level of four macroeconomic variables: (i) GDP, (ii) Trade Openness, (iii) Natural resources rents and (iv) Manufacturing Value added.

The marginal effect of U.S. sanctions on AI diffusion becomes less negative as GDP increases. For countries with lower levels of GDP, sanctions significantly reduce AI adoption through robotics. However, as GDP rises, this negative effect weakens and eventually disappears. This suggests that larger economies are better able to cushion the disruptive effects of sanctions, possibly due to stronger domestic innovation systems, larger internal markets, or greater bargaining power in accessing technology (Apeti and Edoh, 2024).

Here, sanctions have increasingly negative effects as trade openness rises. For countries that are highly integrated into global trade, the adverse impact of sanctions on AI diffusion is particularly severe. This indicates that reliance on international markets makes economies more vulnerable to sanctions, since restrictions on trade and cross-border technology flows directly constrain access to industrial robotics and AI-related inputs. By contrast, more closed economies appear less affected.

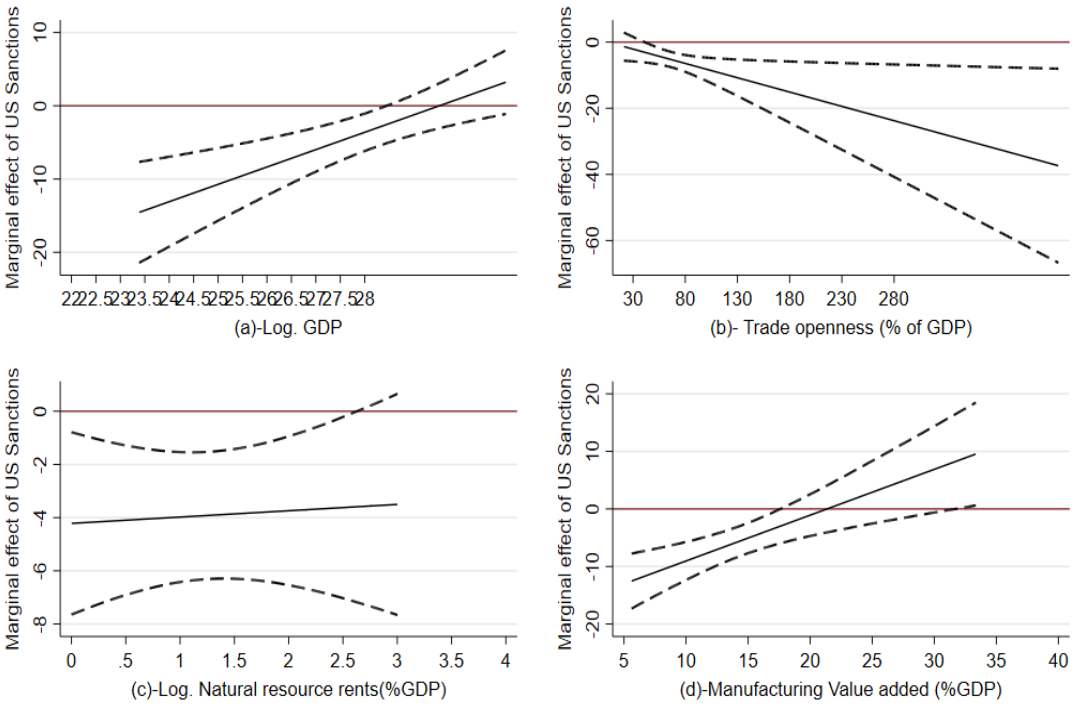
The negative impact of sanctions on AI diffusion weakens as natural resource rents increase. In resource-dependent countries, the ability to generate rents from oil, gas, or minerals seems to provide a buffer, enabling governments and firms to finance alternative technology channels or engage in sanction circumvention strategies (e.g., resource-backed trade or partnerships with non-sanctioning states). Thus, natural wealth appears to mitigate the constraining effects of sanctions on AI adoption.

The marginal effect of sanctions becomes less negative, as the share of manufacturing value added rises. This suggests that economies with a strong manufacturing base are better able to absorb the shock of sanctions and maintain or even accelerate AI adoption in robotics. Manufacturing-intensive countries may rely more on domestic production capabilities, local supply chains, and innovation ecosystems, allowing them to substitute away from restricted foreign technologies.

7.3 Effects of Sanctions over time

In this section, we examine whether the effect of economic sanctions on the diffusion of artificial intelligence is temporary or persistent over time. Analyzing the dynamic effects is crucial for understanding whether sanctions merely slow AI adoption in the short term or whether they impose lasting constraints on technological diffusion. Indeed, sanctions may initially generate significant disruptions, such as restricted access to advanced robotics, supply chain bottlenecks, or reduced investment incentives, but these effects may weaken or even disappear as firms and governments adapt by developing alternative suppliers, fostering domestic innovation, or seeking external partnerships. By examining year-to-year variations in these effects, it is possible to determine whether sanctions create only transitory barriers or whether they result in long-term structural obstacles to AI diffusion. This distinction is essential for

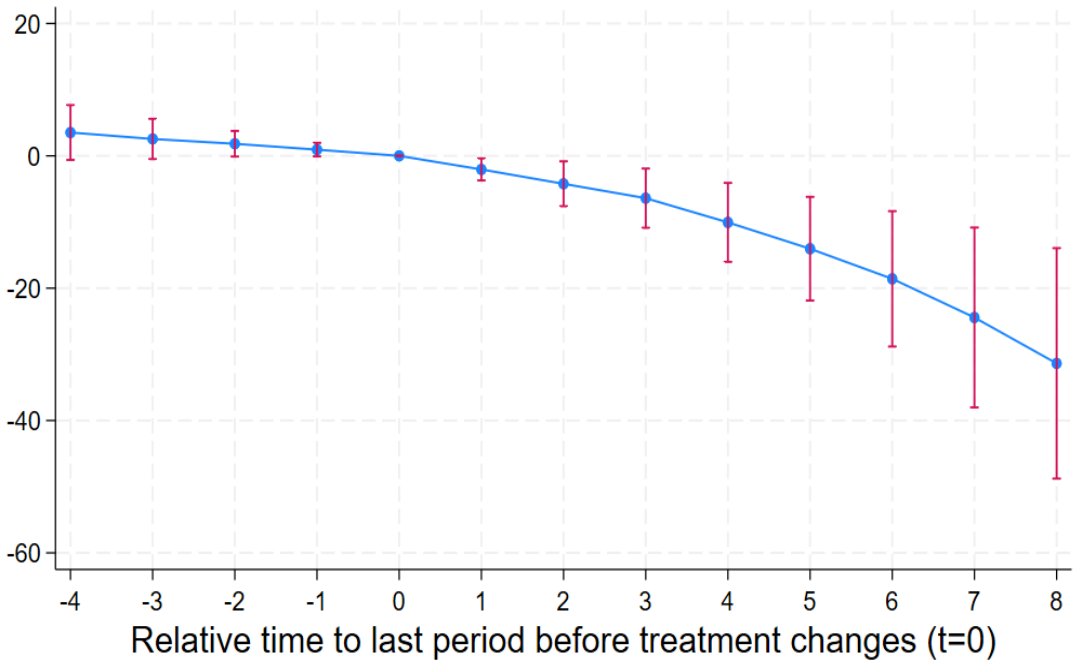
Figure 3: Structural factors



interpreting the results, particularly when the evidence suggests that the negative impact fades after a certain period of time. Some authors have also sought to quantify sanction effects over time (Mirkina, 2018; Apeti and Edoh, 2024). Mirkina (2018) shows that the effects of sanctions can be confined to the short term, depending on their costs, the type of primary sanction imposed, and the historical period. Similarly, Apeti and Edoh (2024); Nandnaba (2025) find that sanction effects are often limited in duration (up to a maximum of seven or eight years). While this method offers several advantages, as outlined in Section 3, it also has limitations (see, e.g., De Chaisemartin and d'Haultfoeuille (2020); Callaway and Sant'Anna (2021); Liu et al. (2024a); Apeti et al. (2025)). First, entropy balancing does not account for the staggered timing of sanction adoption, i.e., the fact that countries face sanctions at different moments. Second, it assumes that the treatment effect is constant over time, which may not hold in our setting. In particular, the diffusion of AI through robotics may evolve as countries adjust by reallocating resources, encouraging domestic innovation, or integrating into alternative trade networks. Moreover, recent literature has shown that using untreated observations from already treated units as part of the comparison group can generate negative weights, potentially biasing the estimated treatment effects.[13]To address these concerns and strengthen the robustness of our findings, we re-estimate our main model using the Two-way fixed effects estimators with heterogeneous treatment effects proposed by De Chaisemartin and d'Haultfoeuille (2020). The dynamic treatment effects, illustrated in Figure 4, reveal that the negative impact of economic sanctions on AI diffusion via industrial robots is not only persistent but also amplifies over time, extending up to eight years after the imposition of sanctions. This temporal pattern suggests that, rather than fading, the constraints generated by sanctions intensify

[13]We verify the distribution of weights in our setting and find that they range from 0.0147 to 1.988, suggesting that negative weighting is not an issue in our design.

Figure 4: Effects of Economic Sanctions over time



as technological gaps widen, supply chains remain disrupted, and access to advanced robotics becomes increasingly constrained. Such findings indicate that adaptation mechanisms, whether through technological substitution, institutional adjustments, or external partnerships, are insufficient to offset the effects of sanctions on AI diffusion. Lastly, a Wald test (P-value = 0.41) conducted to assess the parallel trends assumption indicates no significant pre-treatment differences in AI diffusion trends between sanctioned and non-sanctioned countries, thereby reinforcing the credibility of our identification strategy.

8 Beyond Sanctions: Do Tariffs also Matter?

While the baseline analysis focuses on U.S economic sanctions, it is equally important to consider the broader spectrum of trade restrictions, particularly tariffs, which have become a central instrument of US economic statecraft in recent years (Ignatenko et al., 2025). Tariffs, much like sanctions, restrict market access and alter the incentives for firms to invest in advanced production technologies, including industrial robots. For example, the U.S.–China trade war that escalated in 2018 resulted in average tariff rates on bilateral trade rising from less than 3 percent to over 20 percent (Bown, 2021). Recent evidence suggests that such tariffs disrupted global value chains, reduced productivity, and in some cases delayed technology adoption in manufacturing sectors heavily exposed to international trade (Amiti et al., 2019). Extending the analysis to tariffs allows us to examine whether the negative effects observed for sanctions reduced diffusion of industrial robots also apply to broader trade restrictions that are less politically targeted but economically significant. This comparison enriches the analysis by situating sanctions within a continuum of protectionist and coercive trade policies, thereby providing a more comprehensive picture of how external shocks to trade and technology access shape automation trajectories in the global economy.

To extend the analysis to tariffs, we use a continuous treatment framework consistent with the empirical strategy used for economic sanctions. Specifically, we rely on a country-level measure of average applied tariffs faced in a given year applied by USA. To address potential selection bias, we apply the continuous entropy balancing approach using the same set of macroeconomic, structural, and institutional covariates as in the sanctions analysis. This ensures that countries with different levels of tariff exposure are comparable along observable characteristics that jointly influence trade policy and automation outcomes. By preserving the same covariate structure across sanctions and tariffs, our empirical design guarantees consistency in identification and facilitates a direct comparison of the effects of different us economic measures. The reweighting procedure balances the distribution of covariates across varying levels of tariff exposure, thereby mitigating concerns that observed differences in industrial robot diffusion reflect pre-existing heterogeneity rather than differences in trade policy intensity. This unified continuous framework allows us to isolate the association between tariffs and the diffusion of industrial robots while accounting for the endogenous nature of trade policy adoption.

As shown in Table 4, before entropy balancing, the R-squared is equal to 0.021, indicating that the covariates explain about 2.1% of the variation in tariff exposure. Although this explanatory power is lower than in the sanctions analysis, the F-statistic is equal to 2.976 with a p-value of 0.007, leading us to reject the null hypothesis that the covariates jointly have no explanatory power over the treatment variable. This suggests that tariff exposure is not randomly distributed across countries but is partially driven by observable macroeconomic and institutional characteristics, implying the presence of selection into different levels of trade protection. After applying entropy balancing, the R-squared falls to zero, and the F-statistic also drops to zero, with an associated p-value of 1.000. This indicates that, after reweighting, the covariates no longer explain any variation in tariff exposure. In other words, the distribution of observable characteristics is fully balanced across different levels of tariffs, and the balancing property is satisfied. These results confirm the effectiveness of the continuous entropy balancing procedure

in addressing selection on observables in the tariff analysis. By eliminating the systematic relationship between country characteristics and tariff exposure, the reweighting approach strengthens the causal interpretation of the estimated effects of tariffs on industrial robot diffusion. The results presented in Table **??** indicate that tariff have a negative and statistically significant effect on the deployment of industrial robots. In particular, an increase in tariffs above 1% is associated with a larger decline in robot adoption compared to the effect of sanctions alone. This finding highlights the broader mechanism through which external trade restrictions whether politically motivated sanctions or more general protectionist measures constrain firms' access to advanced technologies and weaken incentives for automation. The result is consistent with recent evidence that higher tariffs disrupt global value chains and reduce firms' technological upgrading (see Amiti et al. (2019)).

These findings imply that sanctions and tariff alike can slow down industrial modernization, but tariff appear particularly detrimental because they directly inflate the cost of acquiring capital goods indispensable for automation.

Table 4: Balancing quality of US. Tariffs

	Treatment variable: Average U.S. Tariffs	
	Before Balancing	**After Balancing**
R-squared	0.021	0.000
F-statistic	2.976	0.000
P-value	0.007	1.000

Table 5: Tariff and AI Deployment

	(1) AI	(2) AI	(3) AI	(4) AI	(5) AI
US Tariffs	-5.029**	-10.060***	-3.872*	-6.743**	-7.792***
	(2.375)	(2.845)	(2.192)	(2.665)	(2.718)
Observation	882	882	882	882	811
Country FE	NO	YES	NO	YES	YES
Year FE	NO	NO	YES	YES	YES
Controls	NO	NO	NO	NO	YES
R-squared	0.015	0.765	0.072	0.815	0.853

Notes : This table reports estimates of the impact of average Tariff applied by USA on Industrial Robots Deployment. The control variables included in the second step are Patents, Control of corruption, GDP, CO2 emissions and Human capital. All regressions include the constant, not reported in the table. Robust standard errors are shown in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

9 Empirical evidence of Channels

Since the beginning of this study, we have provided consistent evidence that economic sanctions hinder the diffusion of artificial intelligence, as proxied by the deployment of industrial robots. In this section, we investigate the potential transmission channels through which sanctions may exert this negative effect. As discussed earlier, we hypothesize that sanctions reduce the adoption of industrial robots through three main mechanisms: (i) by amplifying macroeconomic uncertainty, (ii) by constraining technology transfer and (iii) Economic recession. The first mechanism emphasizes that heightened uncertainty discourages firms from undertaking irreversible investments in automation. Macroeconomic uncertainty is proxied using both perception-based and outcome-based indicators. The perception-based measure is a textual indicator capturing the frequency of uncertainty-related terms in economic publications, reflecting agents' sentiment and expectations. The outcome-based measures are the volatilities of the real effective exchange rate and inflation, which capture the degree of macroeconomic instability stemming from fluctuations in key nominal and real variables following (Nandnaba, 2025).[14] The second mechanism reflects the fact that industrial robots are often imported capital goods, whose diffusion depends critically on cross-border technology transfers. This channel is proxied by indicators of trade openness and foreign direct investment inflows. The last mechanism economic recession is proxied by a dummy variable that takes the value 1 during periods of negative GDP per capita growth.

To empirically assess the relevance of these channels, we proceed in two steps following the recent trend in literature (Nandnaba, 2025). First, we examine the correlation between each potential transmission mechanism and robot deployment. Second, we apply our baseline entropy balancing specification to estimate the causal impact of sanctions on these channels Apeti and Edoh (2024) and Combes et al. (2025). Figure 5 presents the correlations between the identified channels and industrial robot adoption. The results show that greater macroeconomic uncertainty, measured through textual indicators as well as exchange rate, inflation volatility and recession, are significantly and negatively associated with robot deployment. By contrast, improved access to international technology transfer, reflected in higher trade flows and stronger FDI inflows is positively correlated with automation. Table 6 reports the estimated effects of sanctions on each channel. The findings indicate that sanctions significantly increase macroeconomic instability and simultaneously reduce both trade openness and FDI inflows, thereby constraining technology transfer and also reduce GDP growth. These results suggest that the adverse impact of sanctions on industrial robot deployment operates through multiple reinforcing mechanisms: heightened uncertainty that discourages investment, reduced access to foreign technologies that are essential for automation and caused economic recession.

[14] Volatility is measured by the standard deviation of the level of over a 3-year moving window following (Nandnaba, 2025)

Table 6: Transmission channels

Channels	(1) Inflation Vol.	(2) Real Exchange Rate vol.	(3) Uncertainty Index	(4) Trade	(5) FDI	(6) Recession
Economic Sanctions	1.879**	4.015**	0.079*	-5.237***	-0.216**	0.193**
	(0.870)	(2.010)	(0.048)	(1.712)	(0.107)	(0.092)
Observation	793	705	726	842	785	839
Controls	YES	YES	YES	YES	YES	YES
Country & Year FE	YES	YES	YES	YES	YES	YES

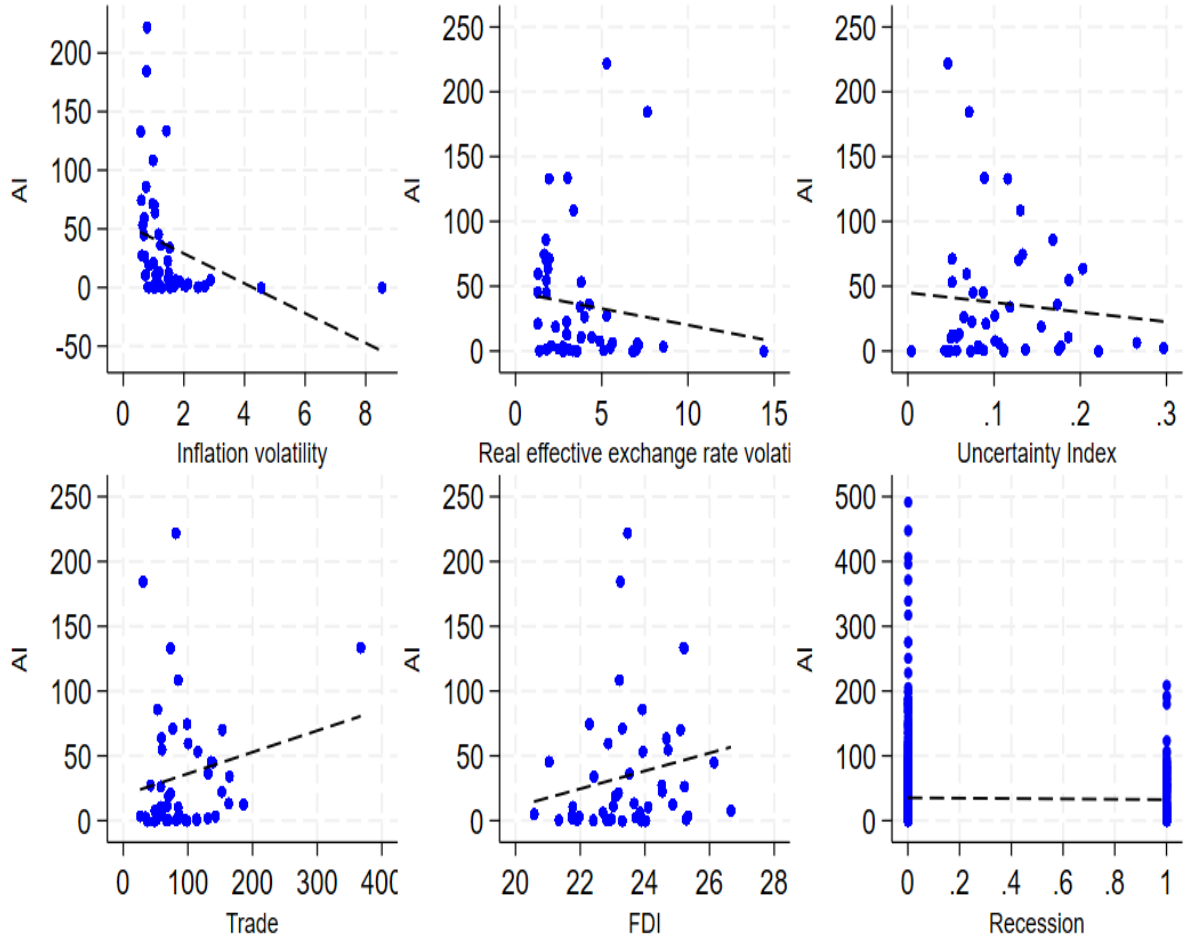
Notes: In this Table, we re-estimate our baseline model using entropy balancing and replacing our outcome variable with the potential channel. All regressions include the constant and the baseline model controls, not reported in the table. Robust standard errors are shown in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

10 Conclusion

This paper has examined how U.S. economic measures specifically sanctions and tariffs, affect the global diffusion of artificial intelligence, proxied by the deployment of industrial robots. Using panel data for 49 countries from 2002 to 2019 and employing the Entropy Balancing method, we provide robust evidence that these measures significantly hinder technological diffusion. Both sanctions and tariffs exert adverse effects, but the magnitude is larger for tariffs, which directly disrupt trade networks, raise production costs, and slow investment in automation. Sanctions, by contrast, operate primarily through restrictions on finance, trade, and technology transfer. Our findings also reveal strong heterogeneity: countries with low GDP levels and high trade openness are more vulnerable to external restrictions, while resource-rich or industrialized economies show greater resilience. Furthermore, we identify three main mechanisms: economic recession, macroeconomic and geopolitical uncertainty, and technology transfer constraints, through which economic measures curtail the diffusion of AI. These results align with existing evidence showing that geopolitical tensions and economic coercion can weaken technological progress and international collaboration (Góes and Bekkers, 2022; Luo and Van Assche, 2023; Charpin et al., 2024).

From a policy perspective, our results underscore a key paradox. Artificial intelligence and automation hold vast potential for productivity gains, innovation, and inclusive growth (Agrawal et al., 2019; Brynjolfsson et al., 2021). Yet, the proliferation of geopolitical and protectionist measures risks fragmenting the global innovation landscape and reinforcing technological divides between advanced and developing economies. Restrictive trade and financial policies can limit access to essential hardware, data, expertise and critical inputs for AI development, thereby slowing the diffusion of general-purpose technologies that could benefit all nations. Three policy recommendations emerge at the end of this study. First, international coordination on technology governance should be strengthened. Multilateral institutions such as the WTO, OECD, and WIPO could facilitate mechanisms for technology sharing and safeguard exemptions for AI-related components, even under sanction regimes. Second, investment in domestic innovation ecosystems through R&D incentives, skills training, and digital infrastructure can enhance technological resilience and reduce dependency on foreign technologies. Third, geoeconomic policies

Figure 5: Correlation between Channels and AI



Notes: The Figure plots the correlation between Channels and Industrial Robots diffusion.

must balance security concerns with long-term innovation goals. Policymakers should design targeted rather than broad-based restrictions, ensuring that national security measures do not inadvertently undermine global technological progress.

In conclusion, while U.S. economic measures have become central tools of geopolitical strategy, their broader economic implications extend far beyond their immediate targets. By constraining AI diffusion and automation, such measures risk slowing productivity growth and deepening technological inequalities. A more cooperative international framework is therefore essential to reconcile security objectives with the shared benefits of technological innovation.

Limits and future research

This study is subject to several limitations that open promising avenues for future research. First, our empirical analysis relies on data from the International Federation of Robotics, which restricts the sample to 49 countries over the period 2002–2019 due to data availability. While

this dataset provides the most authoritative and internationally comparable measure of industrial robot diffusion, it primarily covers countries with established manufacturing sectors and reporting capacity. As a result, the analysis may underrepresent low-income and fragile economies, where automation and artificial intelligence adoption remain more difficult to observe but may nonetheless be affected by trade restrictions. Second, although industrial robots constitute a key and economically relevant application of artificial intelligence, they capture only one dimension of AI diffusion. Our measure focuses on embodied, production-oriented AI adoption and does not fully account for advances in software-based or service-oriented artificial intelligence. Future research could therefore extend the analysis to alternative indicators, including generative AI models, cloud-based AI services, firm-level AI adoption surveys, or data on computational capacity and digital infrastructure. Third, data constraints prevent us from examining more recent developments in artificial intelligence, particularly the rapid diffusion of generative AI technologies after 2019. As trade restrictions increasingly target data access, advanced chips, and cloud computing, future studies could explore how sanctions and tariffs affect newer forms of AI that are less dependent on physical capital but more reliant on digital ecosystems and cross-border data flows. Finally, extending the analysis to firm-level or sector-level data would allow for a deeper investigation of heterogeneous responses to trade policies, including differences across industries, firm sizes, and positions in global value chains. Such extensions would further improve our understanding of how trade restrictions reshape not only the level but also the composition and direction of artificial intelligence diffusion.

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Appendix

Alternative Methods

In this section, we also use alternative methods to check that our results are robust. We, therefore, use PSM methods, the Two-step system-GMM method to address endogeneity bias and Oster's Method to confirm that omitted variables don't affect our results.

PSM estimates. First, we test the robustness of our results using the PSM, which is part of an impact analysis methodology. It allows us to correct for endogeneity problems, especially selection bias. The results in columns [1], [2] and [3] of Table A2 summarise the estimation of sanctions. The conclusions are consistent with our baseline results: sanctions reduce Industrial Robots.

IV-GMM estimates. As an additional alternative method, we rely on the instrumental variables generalized method of moments (IV-GMM) estimator to address potential endogeneity concerns in the relationship between sanctions and industrial robot adoption. This approach is particularly suitable when the treatment variable, in this case, sanctions, may be correlated with unobserved determinants of automation, leading to biased estimates in conventional panel models. The IV-GMM framework allows us to exploit internal instruments derived from the data itself, thereby alleviating the challenge of identifying fully exogenous external instruments (Nguea, 2024). Moreover, it improves efficiency relative to standard two-stage least squares (2SLS) by optimally weighting the moment conditions. The results, reported in column [4] of Table A2, remain consistent with the baseline findings, showing that sanctions exert a negative and statistically significant effect on robot adoption. Furthermore, the Hansen J-test of overidentifying restrictions suggests that the instruments used are valid, while the difference-in-Hansen test confirms the robustness of the exclusion restrictions.

Oster's Method. Finally, while our models include an extensive set of control variables, as detailed in the previous section, the potential influence of unobserved confounders cannot be entirely ruled out. To evaluate the robustness of our estimates to such omitted variable bias, we employ the sensitivity analysis framework developed by Oster (2019). This method quantifies the extent to which selection on unobservables would need to exceed selection on observables in order to reduce the estimated average treatment effect on the treated (ATT) to zero. Following the empirical strategies of (Galletta and Giommoni, 2022; Combes et al., 2025), we report the corresponding Delta statistic in column [5] of Table A2. A value of Delta greater than one implies that unobserved factors would need to be more influential than the observed covariates to eliminate the estimated treatment effect. In our analysis, the delta for Industrial robots is 4.72, indicating that unobserved selection would have to be more than 4 times stronger than the observed selection to invalidate our main result. These results lead us to conclude that our model is unlikely to suffer from omitted variable bias severe enough to generate endogeneity concerns. In other words, the influence of unobserved confounders appears insufficient to overturn our findings. Therefore, we provide robust evidence that economic sanctions have a detrimental

effect on AI deployment.[15]

Table A1: Robustness check: Adding Controls and Covariates.

	Inflation	Public investment	Unemployment	Rule of Law	Property Rights
AI	[1]	[2]	[3]	[4]	[5]
Economic sanctions	-5.875***	-6.186***	-6.804***	-5.136***	-5.892***
	(1.5850)	(1.7000)	(1.746)	(1.5546)	(1.6141)
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Main controls	Yes	Yes	Yes	Yes	Yes
Observations	811	811	811	811	811

	Manufact Value.	Log.Pop.	Stability	Trade Openness	All additional controls
AI	[6]	[7]	[8]	[9]	[10]
Economic sanctions	-6.030***	-6.774***	-5.633***	-5.800***	-6.583***
	(1.7320)	(1.6732)	(1.562)	(1.6017)	(2.112)
Country FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Main Controls	Yes	Yes	Yes	Yes	Yes
Observations	811	811	811	811	811

Notes : This table displays the robustness of our results using additional control variables and covariates. All regressions include the constant not reported in the table. Robust standard errors are shown in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1 .

[15] Although alternative estimators such as IV-GMM and PSM also yield negative and statistically significant coefficients, their magnitudes are substantially larger than those obtained with entropy balancing. This discrepancy likely reflects the limitations of these methods in the presence of sample heterogeneity and weak instrument concerns. IV-GMM relies heavily on the availability of strong and valid instruments, which are difficult to identify in the context of economic sanctions; weak instruments tend to inflate coefficient magnitudes and reduce reliability (see (Stock and Yogo, 2002)). Similarly, PSM balances only on a one dimensional propensity score, which may fail to eliminate imbalances across the covariate distribution. By contrast, entropy balancing directly reweights the control group such that the treatment and control groups match exactly on the covariate means. Even when limited to mean balancing, this approach ensures that observable differences in baseline characteristics do not confound the estimated treatment effect. See Hainmueller (2012) for a detailed discussion of its advantages over conventional matching methods.

Table A2: Alternative Methods

AI	PSM Nearest-Neighbors Matching	PSM Radius Matching	PSM Kernel Matching	IV-GMM	Oster's Method
Economic sanctions	-17.219***	-18.77*	-21.504***	-19.34***	-5.875***
	(5.9483)	(11.048)	(3.2433)	(4.034)	(1.589)
Treated observations	84	84	84		
Control observations	727	727	727		
Pseudo R^2/Rosenbaum bounds tests	0.073/1.3	0.036/1.2	0.074/1.3		
Control Variables	YES	YES	YES	YES	YES
Kleibergen-Paap F-stat				80.078	
Hansen Test P-value				0.127	
Numpber of instruments/countries				60/96	
Delta					4.72
Total observations	811	811	811	779	811

Notes: This table displays the effects of IT on REP using alternative methods. All regressions include the constant not reported in the table. Robust standard errors are shown in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Descriptive Statistics of the Main Variables

	mean	sd	min	max
AI	34.83	56.18	0	491.98
US sanctions	0.09	0.29	0	1
US Tariffs	3.29	1.41	0.01	7.96
Inflation (annual %)	3.25	3.99	-4.44	48.69
GDP growth (annual %)	2.94	3.52	-16.04	24.61
Democracy Control	5.11	1.21	1	6
Coups	0.003	0.05	0	1
Trade (% of GDP)	91.34	57.23	20.44	437.32
Debt	58.40	37.85	3.76	235.44
Patents(Log)	7.09	2.12	2.89	14.14
Corruption Control	3.39	1.22	1	6
GDP(Log)	9.69	0.98	7.41	11.37
CO2 emission(Log)	1.73	0.61	-0.23	2.91
Human capital	3.07	0.46	1.59	4.35
Observations	882	882	882	882

Table 4: List of Countries

Country	Full country-year obs.	country-year obs. with sanctions	Country	Full country-year obs.	country-year obs. with sanctions
Argentina	18	18	Australia	18	18
Austria	18	18	Belgium	18	18
Brazil	18	18	Bulgaria	18	18
Chile	18	18	China*	18	03
Colombia*	18	10	Croatia	18	18
Czech Republic	18	18	Denmark	18	18
Egypt, Arab Rep*	18	03	Estonia	18	18
Finland	18	18	France*	18	16
Germany	18	18	Greece*	18	07
Hungary	18	18	Iceland	18	18
Ireland*	18	13	Israel	18	18
Italy	18	18	Japan	18	18
Korea, Rep	18	18	Latvia*	18	01
Lithuania	18	18	Malaysia	18	18
Morocco	18	18	Netherlands	18	18
New Zealand	18	18	Norway	18	18
Peru	18	18	Philippines*	18	18
Poland	18	18	Portugal	18	18
Russian Federation*	18	05	Serbia	18	18
Singapore	18	18	Slovak Republic	18	18
Slovenia	18	18	South Africa*	18	01
Spain	18	18	Sweden	18	18
Switzerland	18	18	Tunisia	18	18
Turkey*	18	01	Ukraine*	18	06
United Kingdom	18	18			

*Note: * refers to countries under US sanctions.*

Table 5: Summary of data sources and variable definitions

Variable	Definition	Source
Dependent Variable		
AI	Stock of Industrial Robots per 10,000 Manufacturing workers	IFR Data
Variables of Interest		
US economic sanctions	Dummy equal to one if a country is under US trade or financial sanctions in year t and zero otherwise.	Kirikakha et al. (2021).
US trade sanctions	Dummy equal to one if a country is under US trade sanctions in year t and zero otherwise.	Kirikakha et al. (2021).
US financial sanctions	Dummy equal to one if a country is under US financial sanctions in year t and zero otherwise.	Kirikakha et al. (2021).
EU sanctions	Dummy variable taking one if a country is subject to EU economic sanctions in year t and zero otherwise.	Kirikakha et al. (2021).
All sanctions	Dummy variable taking one if a country is subject to US economic sanctions or EU economic sanctions.	Kirikakha et al. (2021).
US Tariffs	Average Tariffs rates applied by USA (%)	WITS
Covariates & Controls		
Real GDP growth	Annual percentage growth rate of real GDP.	WDI, World Bank.
Inflation	Inflation, average consumer prices (% change).	WDI, World Bank.
Foreign Direct Investment	net inflows of investment as a % of GDP.	WDI, World Bank.
Trade openness	Sum of exports and imports of goods and services as a % of GDP.	WDI, World Bank.
Democracy	Index ranging from 0 to 6.	ICRG.
Innovation	Patent applications, residents	WDI, World Bank.
Property Rights	Property Rights Index (higher value = fewer Property Rights).	Teorell et al. (2016).
Unemployment	Unemployment, total (% of total labor force)	WDI, World Bank.
Public Investment	Gross fixed capital formation (% of GDP) (% of GDP)	WDI, World Bank.
Manufact Value.	Manufacturing, value added (% of GDP)	WDI, World Bank.
Political Stability	Political Stability and Absence of Violence/Terrorism: Estimate	WGI, World Bank.
Rule of Law	Rule of Law: Estimate	WGI, World Bank.
Population (Log)	Total population.	WDI, World Bank.
Coups d'État	Number of coups d'état in a country.	Bjørnskov and Rode (2020).
Real exchange rate	Real effective exchange rate.	PWT, Feenstra et al. (2015).
Public debt	Government total public debt as a percentage of GDP.	PFMHD, International Monetary Fund.
Economic recession	Dummy during negative growth using annual growth in %	Authors construction
Uncertainty Index	World uncertainty Index	WUI, Ahir et al. (2022)
Inflation Rate Vol.	standard deviation of the level of inflation over a 3-year moving window	Authors construction
Exchange Rate Vol.	standard deviation of the level of REER over a 3-year moving window	Authors construction