Policy Uncertainty as a Catalyst: Global Evidence on Industrial Robotics Adoption*

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Abstract

This study examines the impact of economic policy uncertainty on industrial robotic automation from a global perspective. Leveraging a cross-country panel dataset from 2004 to 2022, we analyze how different industries respond to uncertainty by investing in automation across different economies. Our findings suggest that the industrial adoption of robotics is positively associated with higher EPU, particularly in capital-intensive sectors such as automotive, electronics, and basic metals. However, this relationship varies across industries and countries due to differences in labor market structures, financial constraints, and institutional environments. We identify key moderating factors, including profitability, volatility, leverage, and capital market development, which influence firms' automation decisions under uncertainty. Additionally, demographic characteristics — such as population growth, aging, and employment structures — play a significant role in shaping automation responses. Using panel OLS estimation and instrumental variable (IV) analysis, we establish a robust dynamic between EPU and automation, demonstrating that uncertainty acts as a catalyst for firms to substitute labor with technology. These findings have critical implications for policymakers and businesses, highlighting the need to balance technological advancement with labor market policies in uncertain economic environments.

Keywords: Robotics, Economic Policy Uncertainty, Labor Economics, Investment Decisions, Industrial Transformation, Technological Adoption
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1 Introduction

Why do firms invest in automation precisely when uncertainty looms? In 2022, the second year of the COVID-19 pandemic, global installations of industrial robots reached a record high—517,385 units, representing a 31% increase from 2020—even as firms faced COVID-related disruptions, geopolitical tensions, and volatile economic policy. This remarkable growth surpassed the previous peak of 423,321 units set in 2018 by 22%, underscoring the accelerated adoption of automation across industries.[1] This trend challenges traditional investment theory, which predicts cautious behavior during uncertain times. Yet, firms around the world responded with a surge in automation.

This paper investigates the diffusion of automation by examining how economic policy uncertainty (EPU) shapes the adoption of industrial robots across 25 economies and 19 industries from 2004 to 2022. We argue that uncertainty acts as a strategic catalyst, prompting firms—especially in capital-intensive sectors—to substitute labor with technology to hedge against future uncertainty. We provide international empirical evidence showing that automation can not only be viewed as a function of technological feasibility or labor costs but also as a forward-looking instrument and strategy shaped by macroeconomic uncertainty and structural conditions.

Technological innovation has been a fundamental driver of economic transformation, shaping productivity, financing, labor markets, and industrial efficiency (Brynjolfsson and McAfee (2014); Acemoglu and Restrepo (2018a); Bates et al. (2024); McElheran et al. (2024)). The Fourth Industrial Revolution, characterized by robotics, artificial intelligence, and digitalization, is rapidly transforming global industries. Industrial robotics, in particular, is traditionally viewed as a means of enhancing efficiency, reducing production costs, and substituting for routine labor tasks and has become central to modern production processes,

[1] The expansion in robotic installations was widespread across key manufacturing and service sectors, despite ongoing supply chain disruptions, resource constraints, and regional economic challenges that impeded production. By 2021, the total operational stock of industrial robots had climbed to 3,477,127 units, reflecting a 15% year-over-year increase (IFR (2023)).

enabling firms to enhance efficiency, reduce costs, and improve competitiveness (Autor et al. (2003) and Autor (2015)).

This rapid expansion of automation aligns with a well-documented trend in the literature linking the rise of automation- and AI-driven technologies to shifting labor market dynamics and growing wage inequality. Automation reduces employment and labor shares, particularly in middle-skill occupations that are most vulnerable to technological displacement (Acemoglu and Restrepo (2018b); Acemoglu and Restrepo (2020); Acemoglu and Restrepo (2022); Acemoglu et al. (2022); Autor (2015)). At the same time, automation stimulates the creation of new jobs, particularly in high-skill, non-routine, and technology-intensive sectors, where human expertise remains indispensable. This process contributes to labor market polarization, with high-skilled workers benefiting from rising wages while middle-class jobs face increasing downward pressure. These dual effects underscore the complex and uneven implications of automation, influencing income distribution, workforce transitions, and broader economic inequality in the evolving labor landscape.

Figure 1 presents the long-term trend of industrial robotics adoption from 2004 to 2021, highlighting the steady rise in automation across industries. The time-series plot captures the broader structural transformation where firms have increasingly integrated robotics into production processes. Notably, the trajectory of automation adoption accelerates around major economic disruptions, such as the 2008 financial crisis and the recent periods of geopolitical and trade policy uncertainty. This pattern suggests that firms do not adopt automation at a constant rate but rather respond to external pressures, including economic policy uncertainty. The surge in robotic installations post-2015 further indicates that as uncertainty in global markets increased, firms proactively invested in automation, possibly as a hedge against labor market risks, rising production costs, and potential policy changes.

Place Figure 1 Here

As the United States is the leading economy globally, Figure 2 zooms into the case of the United States, exploring how automation responds to fluctuations in domestic economic policy uncertainty. This suggests that firms in the U.S. leverage automation not only for productivity gains but also as a risk management strategy in times of economic unpredictability. The 2008 financial crisis serves as a clear inflection point, with a sharp rise in automation following the economic downturn. Similarly, the post-2016 trade policy uncertainty, triggered by tariff disputes and shifting global supply chain policies, corresponds with a notable increase in robotic adoption. These trends reinforce the notion that automation is not simply driven by technological feasibility but is also shaped by the broader policy environment in which firms operate.

Place Figure 2 Here

While much of the literature has examined automation through the lens of labor substitution, productivity gains, and technological advancements, the role of macroeconomic uncertainty in shaping firms' automation decisions remains underexplored and less empirically established. Existing research has extensively documented how automation replaces routine and repetitive tasks, leading to shifts in labor demand, wage structures, and occupational polarization (Acemoglu and Restrepo (2018b); Autor (2015); Bresnahan et al. (2002)). Scholars have also highlighted the role of technological feasibility, declining capital costs, and improvements in AI and robotics as primary drivers of automation adoption (Brynjolfsson and McAfee (2014) and Acemoglu and Restrepo (2020)). However, firms do not operate in isolation from broader economic conditions.

Macroeconomic uncertainty—arising from policy shifts, financial instability, trade disruptions, and geopolitical tensions—can have a profound impact on corporate investment strategies, particularly for capital-intensive technologies like automation (Baker et al. (2016); Gulen and Ion (2016); Bloom (2009)). In uncertain environments, firms may hesitate to make irreversible automation investments due to the unpredictability of future returns, consistent with real options theory (Bernanke (1983); Pindyck (1993)). Alternatively, uncertainty may accelerate automation adoption as firms seek to hedge against regulatory risks, labor market fluctuations, and supply chain disruptions (Davis (2016); Jaimovich et al. (2021)). Despite these theoretical possibilities, empirical evidence on how uncertainty influences automation adoption remains scarce, especially from a cross-country and industry-level perspective. This gap in the literature calls for a deeper investigation into how firms navigate automation investment decisions under different economic conditions, institutional settings, and policy environments.

This study provides empirical global evidence on the relationship between Economic Policy Uncertainty and industrial automation adoption across different economies, focusing on how firms respond to heightened uncertainty through investments in robotics. While prior research has extensively examined automation from the perspectives of technological progress, labor substitution, and firm productivity, the role of macroeconomic uncertainty in shaping automation decisions remains underexplored. This paper addresses this gap by systematically investigating how uncertainty affects automation adoption across different countries, industries, and institutional settings.

The analysis is based on a unique panel dataset covering 25 emerging and developed economies across the globe from 2004 to 2021, combining data on industrial robotics adoption with measures of economic policy uncertainty, macroeconomic conditions, and firm-level financial constraints. The empirical strategy employs a panel OLS estimation framework with country, industry, and year fixed effects to account for unobserved heterogeneity and isolate the impact of EPU on automation. The primary dependent variables include both robotic stock (cumulative automation adoption) and robotic flow (new annual installations), allowing us to capture the extensive and intensive margins of automation investment. To address concerns of endogeneity and reverse causality, we implement an instrumental variable (IV) approach leveraging the 2014 oil price crash as an exogenous shock to EPU. Given that oil-exporting economies experienced significant economic disruptions following the price collapse, leading to increased policy uncertainty independent of firms' automation decisions, this instrument provides a robust strategy for establishing causal inference.

The results consistently show that higher levels of EPU are associated with a significant increase in both the stock and flow of industrial robots, supporting the hypothesis that firms respond to uncertainty by accelerating automation investments. However, the magnitude of this effect varies across industries and economic contexts. The findings suggest that automation adoption in response to uncertainty is highly heterogeneous and shaped by multiple mechanisms, including financial constraints, labor market rigidity, capital intensity, and institutional differences. The empirical analysis explores these mechanisms in depth, identifying how firms' automation responses differ based on their access to financial resources, labor market structures, and industry-specific characteristics.

One key channel through which uncertainty influences automation is firms' financial characteristics. The results indicate that firms with strong profitability, stable cash flows, and low leverage are more likely to increase automation investment when faced with uncertainty. In contrast, financially constrained firms, particularly those with high debt burdens and limited access to credit, exhibit weaker automation responses. This finding aligns with theories of investment behavior under uncertainty, suggesting that firms with greater financial flexibility are better positioned to undertake long-term capital expenditures such as robotics adoption in uncertain environments.

Motivated by Acemoglu and Restrepo (2021), Abeliansky and Prettner (2023), and Díaz Pavez and Martínez-Zarzoso (2024), we further explore a crucial dimension, the role of demographics and labor supply factors. Our results indicate that countries with aging populations and declining labor force participation rates exhibit stronger automation responses to uncertainty, suggesting that demographic pressures reinforce firms' incentives to invest in robotics. In economies where the working-age population is shrinking, firms increasingly turn to automation as a long-term strategy to mitigate labor shortages and sustain productivity. However, in countries with high unemployment rates, the EPU-automation relationship is significantly weaker, as firms in these economies have access to a surplus of labor, reducing the urgency to automate. These findings suggest that automation adoption is not purely a function of uncertainty but is also contingent on structural labor market conditions.

We also examine how financial market conditions and borrowing costs influence firms' ability to automate under uncertainty. The results confirm that in economies with well-developed financial markets, firms exhibit a stronger automation response to EPU, as they have greater access to external financing to support capital-intensive investments in robotics. The findings show that firms operating in markets with low borrowing costs and high credit availability are more likely to invest in automation as a strategic response to uncertainty. In contrast, firms facing higher lending rates and constrained credit access tend to delay automation adoption, as financial uncertainty exacerbates investment risk. This highlights the critical role of financial infrastructure in enabling firms to automate in response to economic policy uncertainty.

This study makes several key contributions to the literature on technology diffusion, economic policy uncertainty, labor economics, and industry investment behavior. While existing research has extensively explored the determinants of automation adoption—including technological advancements, labor market dynamics, and capital investment decisions—this paper is among the first to systematically investigate the role of economic policy uncertainty as a driving force behind industrial robotics adoption across a broad set of economies and industries. First, our research extends the growing body of literature on economic uncertainty and investment decisions (Bloom (2009); Baker et al. (2016); Gulen and Ion (2016)) by providing empirical evidence that heightened policy uncertainty accelerates firms' adoption of automation technologies. While prior studies have largely focused on the impact of uncertainty on aggregate investment and hiring decisions, our findings highlight a novel channel through which firms respond to uncertainty—by substituting labor with capital-intensive automation technologies.

Second, our study builds upon the automation literature (Acemoglu and Restrepo (2018b); Acemoglu and Restrepo (2020); Autor (2015), etc.) by demonstrating that firms do not merely adopt automation as a response to labor market conditions or technological feasibility, but also as a strategic response to macroeconomic uncertainty. The findings suggest that in uncertain policy environments, firms increase investment in robotics to mitigate risks associated with labor costs, regulatory volatility, and financial instability. This expands existing theoretical models by incorporating uncertainty as a key determinant of automation adoption.

Third, our cross-country analysis enriches the literature on automation and economic structure by providing one of the first comprehensive global examinations of how firms respond to uncertainty through automation across both emerging and developed economies. While prior research has primarily focused on automation trends within individual countries—most notably the United States and Germany—our study leverages a unique panel dataset spanning 25 economies from 2004 to 2022, offering an expansive, cross-national perspective on automation under uncertainty. By capturing heterogeneity across diverse economic contexts, our analysis highlights how policy uncertainty interacts with industry characteristics, financial constraints, and institutional environments to shape firms' automation decisions worldwide. Importantly, our findings underscore that while automation serves as a strategic response to uncertainty globally, the magnitude and mechanisms of this effect vary considerably based on economic development, industrial composition, and institutional frameworks. By filling this critical gap in the literature, our study provides robust empirical evidence that advances our understanding of automation as a global economic phenomenon rather than a trend confined to a few technologically advanced nations.

The remainder of this paper is structured as follows: Section 2 describes the data sources and sample, including EPU indices and industrial robotics adoption measures. Section 3 outlines the empirical strategy, detailing the panel regression model and IV approach. Section 4 explores the mechanisms driving the EPU-automation relationship, including financial constraints, labor substitution, and industry characteristics. Section 5 addresses endogeneity concerns and presents robustness checks using alternative uncertainty indices. Section 6 concludes.

2 Data and Sample

2.1 Global EPU Data

Our country-level economic policy uncertainty measure follows the seminal work by Baker et al. (2016) and the index is a text-based measure constructed from newspaper archives, capturing the frequency of articles that discuss economic policy-related uncertainty. The index is derived by searching major national newspapers for terms related to economic uncertainty, government policies, and regulation, ensuring that it reflects policy-driven economic risks rather than general economic volatility.

Our EPU dataset provides country-level indices for 25 economies and are aggregated to the annual level to be consistent with our industrial robotic sample. The dataset spans 2004-2021[2]. One limitation of the measure is that media coverage intensity varies across countries, which may lead to differences in how uncertainty is quantified. To address this, country fixed effects are included in the subsequent analysis.

In our robustness analysis, we also adopt alternative EPU measures, Global Economic Policy Uncertainty (GEPU). This index aggregates national EPU indices using GDP-weighted averages, providing a broad measure of global uncertainty trends. The dataset is updated regularly and publicly available, making it a key resource for analyzing the impact of policy uncertainty on economic behavior, including investment and automation decisions.

2.2 Industrial Robotics Data

The International Organization for Standardization (ISO) defines robots as self-directed apparatus capable of autonomous operation along two or more axes, and the two categories in which are industrial robots and service robots. Specifically, industrial robots are characterized by at least three axes (directions used to design the movement of the robot either in a straight-line or rotational manner), and they are manipulators that operate automatically,

[2] Our sample period is restricted by the IFR sample period.

are reprogrammable, multipurpose, and can be either stationary or mobile. However, relying solely on the mechanical kinematics of a robot is inadequate to differentiate between these two types of robots. The classification between industrial and service robots is determined based on their intended use. Industrial robots are designed for applications within industrial automation, while a service robot is defined as one that carries out beneficial tasks for humans or equipment, excluding applications related to industrial automation.

This study focuses on industrial robotics, and its data is obtained through the International Federation of Robotics which contains the operational stock of robots that measures the number of robots currently deployed in each industry across the globe. IFR Statistical Department calculates the operational stock assuming an average service life of 12 years with an immediate withdrawal from service afterward IFR (2023).[3] Here in this study, we follow the IFR industry classification, which is derived from the International Standard Industrial Classification of All Economic Activities (ISIC) revision 4 scheme. Specifically, we have data on the use of robotics in 19 industries, and the industry distribution of robotics can be found in Figure 3.

Place Figure 3 Here

2.3 Industry decomposition of the robotic adoption

As presented in Figure 3, our sample shows a clear divergence in automation intensity, with capital-intensive industries—such as automotive, electronics, and basic metals—exhibiting a much stronger relationship between EPU and robotic adoption compared to labor-intensive sectors. This finding aligns with theoretical expectations: industries where production relies heavily on capital investments are more likely to accelerate automation when uncertainty rises, as they seek to stabilize operations and reduce reliance on fluctuating labor costs. In

[3]This assumption was investigated in a UNECE/IFR pilot study, carried out in 2000 among some major robot companies (see World Robotics 2001). This investigation suggested that an assumption of 12 years of average life span might be too conservative and that the average service life was closer to 15 years. Presumably, there are substantial differences depending on industry, application, and type of robot. In the meantime, the operational stock is calculated as the sum of robot installations over 12 years.

contrast, labor-intensive industries, such as textiles and hospitality, display a more muted response, likely due to the difficulty of substituting human labor with technology in these sectors. This heterogeneity underscores that automation is not a universal response to uncertainty but rather a strategic adaptation more commonly employed in industries where technology is a viable and cost-effective alternative to labor.

2.4 Cross-Country and Cross-Industry Correlation Between EPU and Robotic Adoption

Figure 4 presents the relationship between EPU and robotic adoption across different countries and industries. Countries are sorted by the magnitude of correlation, highlighting those where the relationship is strongest, whether positive or negative. We do capture the country-level heterogeneity where several countries, including China, Canada, Russia, France, Singapore, and Germany, exhibit strong positive correlations across multiple industries. Industries such as Basic Metals, Automotive, and Electrical/Electronics frequently show strong positive correlations with EPU, indicating that firms in these capital-intensive sectors may accelerate automation in times of uncertainty to ensure stable operations. In contrast, some countries, including Mexico, Italy, and Sweden, exhibit negative correlations in certain industries. There is considerable variation across industries, with some showing consistent trends across countries while others exhibit more diverse patterns. The Automotive and Electronics industries, for example, tend to display strong positive correlations in many economies, reflecting a broader trend where firms in these sectors may be more inclined to invest in automation when faced with policy uncertainty. On the other hand, industries such as Mining & Quarrying and Textiles show mixed results, indicating that automation decisions in these sectors are likely influenced by country-specific economic conditions. Evidence presented in Figure 4 underscore the importance of understanding how uncertainty shapes automation trends, motivating further investigation into the economic and institutional factors driving this dynamic.

Place Figure 4 Here

This variation is further confirmed in Figure 5. Countries such as China, Croatia, and Russia exhibit the strongest positive correlations, suggesting that firms in these nations actively turn to automation in response to rising uncertainty. The economic structure of these countries, often characterized by policy volatility, shifting regulatory landscapes, and labor market constraints, may drive firms to adopt robotics as a safeguard against unpredictability. In contrast, India and Japan show weak or even negative correlations, indicating that automation adoption in these economies is not primarily driven by uncertainty. This could reflect differences in labor market adaptability, industrial strategies, or the availability of alternative risk-mitigation mechanisms, such as state interventions or financial market stability. The divergence in automation responses underscores how national institutions, financial environments, and labor policies shape firms' strategic decisions under uncertainty.

Turning to industry-level correlations between EPU and robotic adoption, our data shows that some sectors are far more responsive to uncertainty than others. The electricity, gas, and water supply sector leads in correlation strength, likely reflecting the industry's emphasis on automation for reliability and efficiency amid regulatory and economic shifts. Education and research also rank high, suggesting that automation investment in these fields may be linked to broader government funding cycles and policy reforms rather than immediate labor substitution. Industrial machinery and electronics, on the other hand, demonstrate strong positive correlations, reinforcing the idea that capital-intensive industries with global supply chains turn to automation in uncertain times to stabilize production. Meanwhile, the mining and paper industries show much weaker correlations, implying that automation in these sectors is either constrained by high capital costs or less reactive to short-term policy uncertainty. The variation across industries suggests that the automation response to uncertainty is highly dependent on structural factors such as capital intensity, labor substitutability, and regulatory exposure.

Place Figure 5 Here

2.5 Cross-Industry Trends in Robotics Adoption Over Time

Figure 6 and Figure 7 present the evolution of robotic installations across industries over time, providing insights into how different sectors have adopted automation. The data has been normalized within each industry, meaning the values reflect deviations from the industry's own average rather than absolute installation levels.

The method used to construct the heatmap begins with aggregating robotics adoption by industry and year. The total robotic adoption for industry i in year t is calculated as:

$$X_{i,t} = \sum_{j \in i} \text{Robotics}_{j,t} \tag{2.1}$$

where the summation aggregates across all firms or observations within an industry. This step ensures that the data reflects the overall automation trends at the industry level.

To emphasize relative changes over time within each industry rather than absolute differences in robotic adoption levels, the data is demeaned by subtracting each industry's mean over all years. The transformation is given by:

$$\tilde{X}_{i,t} = X_{i,t} - \frac{1}{T} \sum_{t=1}^{T} X_{i,t} \tag{2.2}$$

where $\tilde{X}_{i,t}$ represents the demeaned robotic adoption for industry i in year t, and T is the total number of years in the sample. The term $\frac{1}{T}\sum_{t=1}^{T} X_{i,t}$ represents the industry-specific mean robotic adoption, ensuring that each industry's values are centered around zero.

$\boxed{\text{Place Figures 6 and 7 Here}}$

The heatmap visualizes $\tilde{X}_{i,t}$ to highlight temporal shifts in automation trends within industries. Regions in red indicate periods when robotic adoption was above the historical average for that industry, while regions in blue indicate periods when adoption was below the historical average. This approach removes biases due to structural differences in automation levels across industries and enables a clearer interpretation of how industries experience automation growth over time. The results suggest that while some industries have steadily increased their automation, others have seen rapid changes in more recent years.

This approach highlights relative trends and allows for easier comparison across industries that may have different baseline levels of robotic adoption. Figure 6 suggests that automation has increased across most industries, with a more pronounced surge after 2015. Industries such as automotive, electrical/electronics, and basic metals display the strongest upward trends, indicating that these sectors have consistently led in robotic adoption. Toward the later years, some industries, particularly "all other non-manufacturing branches," exhibit a sharp increase in robotic installations, as indicated by the deep red shading. This suggests a more recent acceleration of automation in previously lower-adopting sectors. An alternative approach we employ is to use the percentage-scaled based sorting, which presents consistent evidence.

Place Figure 6 Here

The data consistently indicate that industries strategically increase automation investments in times of heightened uncertainty, but this response varies across countries and industries based on structural and financial conditions. By illustrating both temporal trends and cross-sectional differences, the data and sample reinforce the core argument that automation is not just a function of technological progress but also a deliberate adaptation to economic volatility.

Our final sample employed in the analysis consists of a panel of 25 countries with 19 industries over the sample period of 2003 to 2021. Our automation proxies are from the International Federation of Robotics, following the preprocessing procedure documented in Acemoglu and Restrepo (2020). All the industry characteristics are aggregated from COMPUSTAT-GLOBAL, and country-level economics variables are acquired and constructed using data from World Bank indicators (WDI). Table 1 presents the summary statistics of the main variables used in the paper.

3 Empirical Design

3.1 Panel OLS Estimation

The baseline model investigates the relationship between EPU and industrial automation adoption, measured as either robotic stock or robotic flow at the country-industry-year level. The inclusion of fixed effects is crucial in controlling for unobserved heterogeneity across different economies, industries, and time, ensuring that the estimated relationship between policy uncertainty and automation is not driven by structural differences or common time trends.

The empirical specification is presented below:

$$\text{Robotics}_{c,i,t} = \beta_0 + \beta_1 \text{EPU}_{c,t-1} + \mathbf{X}_{c,i,t-1}\mathbf{\Gamma} + \lambda_c + \lambda_i + \lambda_t + \epsilon_{c,i,t} \tag{3.1}$$

where $\text{Robotics}_{c,i,t}$ represents industrial automation adoption in country c, industry i, and year t, measured either as robotic stock, which captures the accumulated number of industrial robots, or robotic flow, which measures new installations. The key explanatory variable, $\text{EPU}_{c,t-1}$, is the lagged value of EPU, ensuring that uncertainty is measured before automation adoption, thereby aligning with firms' decision-making processes, which typically involve planning periods.

The vector $\mathbf{X}_{c,i,t-1}$ includes a set of lagged control variables designed to account for key economic and industry-level factors that influence automation decisions. Given the long-term nature of automation investments, firms' choices are shaped not only by immediate uncertainty but also by broader financial and market conditions. Foreign direct investment ($\text{FDI}_{c,i,t-1}$) plays a crucial role in technology diffusion and capital availability, enabling firms to adopt automation more readily. Imports growth ($\text{Imports Growth}_{c,i,t-1}$) reflects firms' exposure to global competition and foreign technological advancements, both of which can push industries toward automation.

Since automation investments require substantial upfront costs, inflation ($\text{Inflation}_{c,i,t-1}$) is included to capture fluctuations in capital costs, while GDP growth ($\text{GDP Growth}_{c,i,t-1}$) serves as a broad measure of economic conditions that can either encourage or limit investment capacity. Government-related factors such as tax revenue ($\text{Tax Revenue}_{c,i,t-1}$) and government expenditure ($\text{Government Expenditure}_{c,i,t-1}$) help gauge the state's ability to provide fiscal incentives and infrastructure support for automation adoption.

Turning to other industry characteristics aggregated from firm-level variables, financial constraints are critical determinants. Leverage ($\text{Leverage}_{c,i,t-1}$) measures firms' reliance on debt, which may restrict their ability to undertake capital-intensive automation projects. Meanwhile, profitability ($\text{Profitability}_{c,i,t-1}$) is a key factor, as more profitable firms are better positioned to invest in automation even during uncertain times. Market structure considerations also play a role: market concentration ($\text{HHI}_{c,i,t-1}$) determines the level of competition within an industry, where firms in more concentrated markets may have greater pricing power and thus more flexibility in adopting automation. Labor intensity ($\text{Labor Intensity}_{c,i,t-1}$) captures the extent to which firms rely on human labor, influencing their incentives to automate, while asset tangibility ($\text{Tangibility}_{c,i,t-1}$) reflects the capital structure of firms, as industries with high tangible assets may find it easier to transition toward automation.

By incorporating these controls, the analysis aims to isolate the impact of EPU on automation, ensuring that observed relationships are not driven by broader economic or industry-specific conditions. Our industry-level characteristics in the sample are aggregated from COMPUSTAT-GLOBAL from WRDS and the country-level characteristics are sourced from the WDI World Bank indicators. Detailed variable definitions can be located in the appendix table.

The model includes country fixed effects (λ_c), industry fixed effects (λ_i), and year fixed effects (λ_t). Country fixed effects control for all time-invariant national characteristics that could influence both economic policy uncertainty and automation adoption. These include differences in labor market regulations, unionization rates, long-term industrial policies, legal frameworks, and institutional quality, which shape firms' investment environments. By including λ_c, the model effectively compares changes in automation within the same country over time, rather than across countries with different baseline institutional conditions.

Industry fixed effects (λ_i) control for sector-specific characteristics that remain constant over time, such as the inherent technological feasibility of automation, sectoral capital intensity, and industry-specific regulatory environments. Some industries, such as manufacturing, have historically been more automation-intensive due to the nature of production processes, while others, such as services, face more barriers to automation. By accounting for λ_i, the model ensures that the estimated effect of policy uncertainty on automation is not confounded by pre-existing technological differences across different industries.

Year fixed effects (λ_t) capture global macroeconomic shocks, technological advancements, and worldwide economic fluctuations that might influence automation adoption trends. This is particularly important given the rapid evolution of automation technologies and fluctuations in global economic conditions, such as financial crises, recessions, or expansions that affect all industries and countries simultaneously. The inclusion of λ_t ensures that the estimated relationship between EPU and automation is not driven by common global trends but rather reflects within-country and within-industry variation.

By structuring the model with lagged explanatory variables and incorporating fixed effects at multiple levels, this specification isolates the dynamic impact of policy uncertainty on industrial automation adoption. This approach provides a framework for analyzing how past uncertainty affects automation decisions while controlling for structural economic and institutional factors that might otherwise bias the estimated effects. The error term $\epsilon_{c,i,t}$ captures idiosyncratic shocks that are not accounted for by the included variables.

3.2 Empirical Results of the EPU-Automation Panel Estimation

The results presented in Table 2 provide a preliminary examination of the relationship between EPU and industrial automation adoption, measured by robotic stock and robotic flow across countries and industries. The baseline model employs a panel OLS estimation, controlling for industry fixed effects, country fixed effects, and year fixed effects to account for unobserved heterogeneity. The findings offer key insights into how uncertainty influences automation, as well as the role of various economic factors.

Place Table 2 Here

Across all model specifications, EPU consistently exhibits a positive and statistically significant effect on both robotic stock and robotic flow. This suggests that firms increase their automation investments in response to higher levels of uncertainty, likely as a strategic response to mitigate future labor cost volatility or disruptions in economic conditions. The magnitude of the coefficient, while varying slightly across weighting schemes, remains highly significant across unweighted, employment-weighted, and GDP-weighted specifications.

Unweighted models (Panel A) show that a one-unit increase in EPU leads to an increase in robotic stock by approximately 0.363 and robotic flow by 0.332 (Columns 1-2). Employment-weighted models (Panel B) suggest a weaker but still significant effect (Columns 5-6), implying that industries with larger employment bases exhibit more moderated automation responses to EPU.

GDP-weighted models (Panel C) show that higher-GDP economies exhibit a slightly weaker response to uncertainty in automation adoption compared to unweighted models, suggesting that wealthier economies may have better capacity to absorb uncertainty shocks through other means rather than immediate automation.

The inclusion of weighted specifications is crucial for understanding how automation responses to uncertainty differ based on economic scale and labor intensity. Employment-weighted regressions help account for the fact that larger workforces may influence firms' automation decisions differently than industries with smaller employment bases, where labor-saving automation may be more immediately necessary. Similarly, GDP-weighted specifications highlight how economic size affects firms' ability to respond to uncertainty, as wealthier economies often have greater financial flexibility, institutional stability, and alternative risk-mitigation strategies beyond automation. By presenting results across these weighting schemes, we ensure that the analysis captures the heterogeneous responses to uncertainty across different economic contexts.

4 Mechanisms

To examine the interaction effect of EPU with industry- and country-level characteristics on automation adoption, we estimate the following regression model:

$$Y_{c,i,t} = \alpha + \beta \mathrm{EPU}_{c,t-1} + \theta Z_{c,i,t-1} + \eta(\mathrm{EPU}_{c,t-1} \times Z_{c,i,t-1}) + X_{c,i,t-1}\mathbf{\Gamma} + \lambda_c + \lambda_i + \lambda_t + \varepsilon_{c,i,t} \quad (4.1)$$

where:

- $Y_{c,i,t}$ represents industrial automation adoption (measured as robotic stock or flow) in country c, industry i, and year t.
- $\mathrm{EPU}_{c,t-1}$ is the lagged economic policy uncertainty, ensuring that uncertainty is measured before automation adoption.
- $Z_{c,i,t-1}$ is the moderating variable, which varies based on the model specification:
  - Industry-level: Financial characteristics, leverage, market structure.
  - Country-level: Demographics, labor market conditions, financial development.
- $\mathrm{EPU}_{c,t-1} \times Z_{c,i,t-1}$ captures the interaction effect, examining how Z influences the impact of policy uncertainty on automation adoption.
- $X_{c,i,t-1}$ represents a vector of control variables, including factors that are adopted in the baseline model (Eq. (3.1)).

- $\mathbf{\Gamma}$ is the vector of coefficients corresponding to the control variables.
- λ_c, λ_i, and λ_t denote country, industry, and year fixed effects, respectively, to control for unobserved heterogeneity.
- $\varepsilon_{c,i,t}$ is the error term, capturing idiosyncratic shocks.

The results presented in Table 3 analyze how EPU influences industrial automation adoption across different industry characteristics. The inclusion of interaction terms (EPU $\times$ Z) allows us to assess whether the effect of uncertainty on automation adoption is amplified or mitigated by industry-specific or country-level factors.

Place Table 3 Here

4.1 The Role of Profitability, Volatility, Debt Structure, Capital Intensity and Market Structure

Panel A of Table 3 investigate the role of profitability and volatility in shaping the effect of EPU on industrial automation. Profitability indicators such as operating profit margin and net profit margin provide insight into firms' financial health and investment capacity, while earnings volatility and cash flow volatility capture firms' financial risk exposure.

Minton and Schrand (1999) finds that a higher level of firm's cash flow volatility leads to lower capital expenditure and R&D investments on average. Moreover, firms facing cash flow shortfalls in a given year, whether in comparison to their industry peers or to their own historical performance, tend to engage in significantly lower levels of discretionary investment during that year than firms that do not face such shortfalls (Minton and Schrand (1999)). Automation and industrial robot adoption have the characteristics of improving production efficiency and can be seen as a form of corporate R&D investment. Therefore, it is legitimate to consider the role of profitability and volatility on the EPU-automation dynamic.

The results indicate that EPU has a direct positive effect on automation adoption, as seen in the significant coefficients on EPU across all specifications ($\beta > 0$). However, the interaction effects with profitability and volatility (η) suggest that this relationship is highly contingent on firms' financial stability. The interaction term between EPU and profitability (Z = Operating Profit Margin, Net Profit Margin) is positive and statistically significant ($\eta > 0$), implying that firms with stronger profitability are more likely to increase automation in response to uncertainty. This finding aligns with the notion that financially healthy firms are better positioned to invest in capital-intensive technologies, even in the face of policy uncertainty.

Conversely, firms experiencing higher earnings and cash flow volatility exhibit a negative interaction effect ($\eta < 0$), suggesting that greater financial instability weakens the EPU-automation relationship. This result highlights the importance of liquidity constraints in shaping firms' strategic responses to uncertainty. Firms with high earnings volatility may struggle to finance automation investments due to uncertainty in future revenues, making them more reluctant to engage in capital-intensive projects. Similarly, industries with high cash flow volatility face greater financing constraints, which reduces their ability to invest in automation as a hedge against uncertainty.

These findings underscore that the ability to leverage automation in uncertain times depends on financial resilience. While profitable firms view uncertainty as an opportunity to invest in automation and strengthen long-term competitiveness, financially unstable firms may lack the capacity to make similar investments and may instead opt for short-term cost-cutting measures.

Giroud and Mueller (2017) documents that firms with higher leverage faced notably greater employment losses when local consumer demand declined during the Great Recession, and the magnitude of this leverage effect is considerable. Since firms' leverage has been proven to be negatively correlated with human capital investment in times of high uncertainty, our results complement the literature by showing whether such a relationship also exists in non-human capital, such as automation during periods of uncertainty.

Panel B of Table 3 shifts focus to the role of financial leverage and debt structure in moderating the EPU-automation relationship. The leverage characteristics examined net leverage, long-term debt, and short-term debt, which capture firms' financial obligations and liquidity constraints. The results indicate that firms with higher net leverage (Z = Net Leverage) are less likely to automate in response to EPU, as evidenced by a significant negative interaction effect ($\eta < 0$). This suggests that highly indebted firms face greater financial constraints, making them less responsive to uncertainty-driven automation incentives. Unlike firms with strong balance sheets, leveraged firms may prioritize debt repayment over capital expenditures during periods of heightened uncertainty, leading to lower automation investments.

Interestingly, the interaction between long-term debt (Z = LT Debt) and EPU is positive ($\eta > 0$), implying that firms that rely more on long-term financing are better able to sustain automation investments even when faced with policy uncertainty. This result suggests that access to long-term capital provides firms with financial stability, allowing them to invest in automation as a strategic response to uncertainty. In contrast, firms with high short-term debt burdens (Z = ST Debt) show a negative interaction effect ($\eta < 0$), indicating that those with substantial short-term obligations are more constrained in their ability to allocate resources toward automation.

These findings highlight the role of financial flexibility in enabling automation investments during uncertain times. Firms with stable, long-term financing are better positioned to pursue automation, while those facing short-term liquidity constraints prioritize immediate financial obligations over capital investment.

Panel C of Table 3 examines how capital intensity and market structure influence firms' automation responses to policy uncertainty. The capital-labor ratio, tangibility of assets, and market concentration (HHI) are used as moderating variables to assess how industry structure and capital investment levels affect automation adoption under uncertainty.

We find that industries with higher asset tangibility respond less to EPU shocks in terms of automation investment. This contrasts with prior work by Almeida and Campello (2007), who show that tangibility eases financing frictions and facilitates investment.[4] Our results suggest that in the context of automation, high tangibility may instead reflect structural constraints: these industries are already capital-intensive and may face higher adjustment costs or technological rigidity, limiting their ability to expand automation in response to uncertainty. Additionally, the negative interaction between EPU and the capital-labor ratio reinforces this mechanism: industries that are less capital-intensive—those with greater reliance on labor—have more scope and incentive to automate when faced with policy uncertainty. Together, these findings highlight that the real response to uncertainty is shaped not just by financing capacity, but by the technological flexibility and marginal returns to automation inherent to an industry's capital intensity structure.

Market structure also plays a crucial role in shaping firms' automation responses. The interaction effect for market concentration ($Z = HHI$) is negative and significant ($\eta < 0$), indicating that firms operating in more concentrated industries (with fewer competitors) are less responsive to EPU-driven automation incentives. This finding suggests that in industries where market power is highly concentrated, dominant firms may have less pressure to adopt automation as a competitive strategy. By contrast, firms in more competitive industries (low HHI) may view automation as a crucial tool for maintaining cost efficiency and competitiveness under uncertainty.

The findings presented in Table 3 demonstrate that the relationship between EPU and

[4] Intangible assets differ from tangible assets in several ways: First, intangible capital has a high degree of "scalability", meaning that although their development often requires substantial upfront investment, they can be reused multiple times at little or no additional cost once created (Kaus et al. (2023)); Moreover, since intangible investment projects often involve complicated coordination and management efforts, they typically require additional investments in a firm's organizational structure or workforce skills such as organizational capital or human capital to be effectively implemented (Brynjolfsson et al. (2021)); In addition, while intangible investment projects may yield positive returns on average, they are usually associated with a high level of uncertainty (Kaus et al. (2023)); Finally, if an investment fails, intangible assets are generally harder to convert into cash compared to physical assets like machinery or equipment, making them less effective as collateral (Hall and Lerner (2010)). Kaus et al. (2023) finds that intangible capital contributes positively to firm-level total factor productivity (TFP). While its overall effect is modest on average, the contribution becomes significantly larger in firms with greater intangible capital intensity. This paper intends to study the impact of the level of tangibility of assets on automation adoption under economic policy uncertainty. Our result indicates a negative interaction effect tangibility of assets ($Z =$ Tangibility) and EPU.

automation adoption is not uniform across industries. Instead, the effect of EPU on automation is highly contingent on firms' financial strength, leverage constraints, capital intensity, and market competition. Industries characterized by higher profitability and financial stability are more likely to automate in response to uncertainty, whereas firms with high earnings volatility, cash flow instability, or high short-term leverage are less responsive. The ability to invest in automation as a strategic response to uncertainty is therefore strongly tied to firms' access to long-term financing and their ability to withstand financial volatility.

Moreover, the capital intensity and market structure of an industry shape how firms respond to policy uncertainty. Highly capital-intensive industries exhibit weaker automation responses to uncertainty, suggesting that firms that have already invested in automation are less sensitive to additional uncertainty-driven investments. Meanwhile, firms in highly concentrated industries are less responsive to EPU, likely because dominant firms face less competitive pressure to adapt. In contrast, firms in more competitive industries respond more aggressively to uncertainty by increasing automation.

4.2 Demographic and Labor Market Forces in the EPU-Automation Dynamic

The role of demographic and labor market characteristics in the automation response to EPU is complex. Understanding how firms respond to economic policy uncertainty through automation requires looking beyond financial factors. Labor markets and demographic structures are fundamental drivers of automation adoption, as they shape firms' incentives and constraints in deploying technology. While automation is often framed as a response to uncertainty-driven cost pressures or productivity concerns, the availability and characteristics of labor fundamentally alter these dynamics.

The dynamic between various demographic characteristics and labor supply or technology advancement has been widely studied. Endogenous technological growth literature suggests that population growth causes an increase in technological changes (Aghion and

Howitt (1992), Grossman and Helpman (1993)). The integrated model of population growth and technological change in Kremer (1993) predicts that during the historical period when technology constrained population size, population growth would be roughly proportional to the existing population level, which is supported by empirical evidence. Next, fertility rate has been found to have a direct impact on family labor supply. Although Angrist and Evans (1998), Bronars and Grogger (1994) and Lundborg et al. (2017) show that fertility is negatively correlated with maternal labor supply, Aaronson et al. (2020) and Agüero and Marks (2008) argue that this inverse relationship is present only in more economically developed countries. That is, there is heterogeneity among countries in the fertility–labor supply relationship. Moreover, population aging is an important factor. New technology adoption is very costly and requires workers' effort to learn; as noted by Jovanovic (1997), the cost of adoption of technology is approximately 20 to 30 times higher than its cost of invention. In an aging society, the high learning costs for older workers may hinder the development of automation technology. As evidenced in Chari and Hopenhayn (1991), the vintage-specific human capital that older individuals build up through learning-by-doing in their youth can slow down the adoption of new technology—especially when the skills of newly unskilled workers are highly complementary to the existing human capital of the older generation. In addition, Acemoglu et al. (2023) point out that in general, fast-growing firms with a large number of employees are the ones that self-select to adopt more technologies like robotics, automation, and artificial intelligence, which means that employment size positively influences the level of advanced technology adoption.

In rapidly growing labor markets, firms may automate to maintain efficiency despite labor expansion, whereas in aging economies, automation may be a necessity due to workforce shortages. At the same time, labor market characteristics, such as employment size and unemployment rates, dictate whether firms view automation as a complement to or a substitute for labor. In tight labor markets with limited workforce availability, firms may accelerate automation to mitigate hiring challenges. Conversely, in economies with high unemployment, firms may have less incentive to automate if labor remains an accessible and cost-effective alternative. By integrating these demographic and labor market dimensions into the analysis, one can better understand why automation responses to uncertainty are highly heterogeneous across countries and industries. This perspective allows us to assess whether automation serves as a strategic response to labor constraints, a reaction to shifting workforce compositions, or a reflection of broader structural transformations in the economy.

Place Table 4 Here

Table 4 presents evidence that population growth and fertility rates have opposing moderating effects on the EPU-automation relationship, highlighting the nuanced ways in which demographic trends influence firms' strategic decisions regarding technology adoption. The interaction between EPU and population growth (Z = Population Growth) is positive and statistically significant, suggesting that in economies experiencing rapid labor force expansion, uncertainty accelerates robotic adoption, which supports the evidence in Kremer (1993). This effect likely reflects firms' anticipation of long-term shifts in workforce composition. A growing labor force introduces uncertainty regarding future employment structures, wage dynamics, and labor availability, prompting firms to preemptively integrate automation to maintain operational stability. In such contexts, automation serves not only as a hedge against short-term volatility but also as a long-term strategic adaptation to evolving labor market conditions. Firms operating in expanding economies may view automation as a way to counteract potential future labor market frictions, particularly in industries where skill mismatches, labor shortages in specialized fields, or rising wage pressures are expected to emerge over time. This result underscores that firms do not merely respond to present labor conditions when making automation investments but also factor in expectations about future labor market shifts when uncertainty is high.

By contrast, the interaction between EPU and fertility rate (Z = Fertility) is negative and statistically significant, indicating that higher fertility rates weaken the automation response to uncertainty. This result is consistent with the findings in Aaronson et al. (2020) and

Agüero and Marks (2008). Unlike immediate population growth, which signals a near-term expansion of the workforce, fertility rates represent a more delayed increase in labor supply, shaping firms' automation incentives differently. In economies with high fertility rates, firms may anticipate a long-term surplus of workers, reducing the urgency to substitute labor with automation in response to uncertainty. In these cases, rather than investing heavily in technology as a stabilizing mechanism, firms may continue to rely on human labor, given the expectation that labor costs will remain manageable in the future. This finding suggests that automation adoption in response to uncertainty is not purely a reaction to demographic size but is also contingent on the timing and structure of labor market expansion. When firms perceive that future labor markets will remain relatively abundant and flexible, the incentive to accelerate automation diminishes, even in periods of economic policy uncertainty.

The results also reveal that age dependency ratios and aging populations further weaken the automation response to uncertainty, reinforcing the idea that demographic shifts toward older populations slow down firms' technological adaptation. While an aging workforce could, in principle, create stronger incentives for automation by reducing the available labor pool, the empirical evidence suggests otherwise. In economies with high age dependency ratios, firms may face institutional, financial, and economic constraints that limit their ability to automate aggressively.

Taken together, these findings highlight that the EPU-automation relationship is fundamentally shaped by workforce composition and demographic transitions. While population growth strengthens firms' incentives to automate under uncertainty by introducing concerns over labor supply expansion and employment volatility, higher fertility rates and aging populations weaken this effect, suggesting that firms delay or dampen automation investments when they anticipate stable or declining labor costs over the long term. These results underscore that automation in response to uncertainty is not simply a function of technological feasibility or immediate economic conditions but is also a forward-looking strategy shaped by firms' expectations about labor market evolution. Additionally, poverty levels (Z = Poverty) influence automation adoption, with high-poverty economies exhibiting a more muted response to uncertainty. Financial constraints limit firms' ability to leverage automation as a hedge against macroeconomic volatility, reinforcing the notion that a baseline level of capital accessibility is essential for automation investments.

Beyond demographic factors, labor market conditions significantly shape how firms respond to uncertainty through automation. Industries with larger employment bases ($Z =$ Employment Size) tend to exhibit stronger automation responses to EPU, which is consistent with Acemoglu et al. (2023). Firms in these environments may integrate automation preemptively to manage labor risks, particularly in sectors with high turnover or skill shortages. In contrast, high unemployment rates ($Z =$ Unemployment) weaken the effect of EPU on automation. The rationale is straightforward—when surplus labor is readily available, firms have little incentive to substitute workers with automation. Instead, they rely on the existing workforce, postponing investments in technology-driven efficiency improvements.

These findings underscore that automation choices are shaped not only by technological feasibility but also by the economic realities of labor supply. Where labor is abundant and inexpensive, automation remains a lower priority. However, in tighter labor markets, automation emerges as a logical response to mitigate hiring risks and wage pressures.

4.3 Financial Market Development, Borrowing Costs, and Their Influence on EPU-Driven Automation

Firms' ability to respond to economic policy uncertainty with automation investments is not solely dictated by labor dynamics or industry characteristics—it is also deeply influenced by overall financial conditions.

Automation is a capital-intensive process, requiring substantial upfront investment and access to long-term financing. Firms operating in financially developed economies with well-functioning credit markets may find it easier to invest in automation, even under uncertainty. In contrast, firms facing high borrowing costs or constrained credit access may delay or forgo automation investments, particularly in uncertain economic environments where liquidity preservation becomes a priority. Financial development in a country provides a platform and foundation for robotics adoption. Industries exhibiting higher growth rates in countries with more developed financial systems tend to have higher R&D intensity and more irregular investment patterns (Ilyina and Samaniego (2011)). Deeper financial markets accelerate the diffusion of capital-intensive technologies, particularly during periods shortly after these technologies have been invented (Comin and Nanda (2019)). Therefore, financial development characteristics should exhibit positive correlations with technology transformation and adoption. On the other hand, a drop in real interest rates results in a notable decline in sectoral total factor productivity, as capital inflows are inefficiently directed toward firms with greater net worth rather than those that are more productive (Gopinath et al. (2017)). Given the negative relationship between real interest rate and productivity, a firm might increase its investment in robotics to help sustain stable productivity during periods of economic uncertainty.

Place Table 5 Here

Table 5 examines how financial market characteristics influence the relationship between EPU and automation adoption. Panel A explores the role of financial market development, while Panel B focuses on the cost of borrowing, including lending rates and credit risk premiums.

Panel A examines how the broader development of financial markets influences firms' ability to invest in automation in response to economic policy uncertainty. The availability of external financing is crucial for automation adoption, as robotics and other capital-intensive technologies require significant upfront investment. In well-functioning financial markets, firms can access various funding channels, reducing liquidity constraints and allowing them to pursue long-term investment strategies, even in uncertain economic environments. Conversely, in economies where financial markets are less developed, firms may struggle to secure funding for automation projects, particularly in periods of heightened uncertainty when risk aversion increases.

One of the strongest effects in Panel A comes from stock market activity, captured by the volume of stocks traded. Economies with higher stock market activity exhibit a stronger positive relationship between EPU and automation adoption. This suggests that firms operating in more liquid financial environments can more easily raise capital through public markets, mitigating financing constraints that might otherwise deter long-term investment. Stock liquidity not only allows larger firms to expand automation but may also provide mid-sized enterprises with alternative funding options beyond traditional debt markets.

Market capitalization, which reflects the total value of publicly traded firms relative to GDP, presents a slightly different dynamic. A high market capitalization indicates a deep financial market with well-established corporate financing mechanisms. The results suggest that firms in economies with larger market capitalization are better positioned to sustain automation investments under uncertainty, likely because capital-rich financial systems allow for more patient investment strategies. However, unlike stock liquidity, market capitalization does not necessarily translate into immediate automation activity for all firms—it primarily benefits those with strong access to capital markets, potentially favoring large corporations over smaller businesses.

The role of public listing density—measured as the number of listed firms per capita—offers yet another perspective. Economies with a greater density of publicly traded firms tend to show a more widespread automation response to uncertainty. This suggests that, beyond a few dominant corporations, a well-distributed access to capital markets helps mid-sized firms engage in automation investments even when uncertainty is high. In contrast, in economies where public listings are concentrated among a few major firms, automation investment may be restricted to a handful of large players, while smaller firms remain constrained by financing limitations.

Taken together, these findings highlight that financial market development is not a uniform facilitator of automation—different aspects of financial infrastructure contribute in distinct ways. Stock market activity appears to be the most immediate enabler, offering liquidity for firms seeking to finance automation in uncertain environments. Market capitalization provides a long-term foundation for automation investment, benefiting firms with strong financial access but potentially leaving others behind. Public listing density broadens automation engagement across firms, ensuring that automation is not just a strategy for the largest corporations.

The results in Panel B of Table 5 highlight a crucial determinant of automation adoption under uncertainty: the cost of borrowing. With real interest rates, lending rates, and lending premiums serving as the moderating variables, the findings suggest that financial frictions significantly alter the way firms react to EPU.

When credit is expensive, firms become hesitant to commit to large-scale investments, particularly those involving automation and capital-intensive technologies. The interaction between EPU and real interest rates (Z = Real Interest Rate) is significantly negative ($\eta < 0$), indicating that the uncertainty-induced increase in automation is dampened in high-interest-rate environments. This implies that when borrowing costs are elevated, firms may delay automation investments or opt for alternative, less capital-intensive strategies to cope with uncertainty.

A similar trend emerges for lending rates (Z = Lending Rate), where the negative interaction term suggests that firms operating in environments with high borrowing costs are less likely to automate in response to uncertainty. High lending rates create liquidity constraints, limiting firms' access to capital for automation investment. Instead of making costly technology upgrades, firms in such conditions may resort to labor adjustments or operational cost-cutting as a response to uncertainty.

Perhaps the most striking result is the interaction between EPU and the lending premium (Z = Lending Premium). The large, negative, and highly significant coefficient ($\eta < 0$) indicates that firms in markets with high credit risk premiums are particularly constrained in their ability to pursue automation strategies under uncertainty. This suggests that financial risk amplifies firms' hesitation to commit to long-term technology investments, reinforcing the notion that automation adoption requires stable and predictable financing conditions.

A higher lending premium means that firms with less collateral or weaker credit standings face disproportionately high borrowing costs. Under such circumstances, firms may refrain from capital-intensive investments, further delaying automation adoption even in the face of rising uncertainty. This finding underscores the role of credit accessibility in determining whether uncertainty translates into automation investments or stagnation in technological upgrading.

Results from Panel B jointly highlight the pivotal role of financial conditions in shaping firms' automation responses to economic uncertainty. While uncertainty may push firms toward automation as a risk-mitigating strategy, tight financing conditions can substantially limit their ability to act on this impulse.

5 Endogeneity Tests: The 2014 Oil Price Crash as an Exogenous Shock

To address concerns of endogeneity in the relationship between economic policy uncertainty and automation adoption, we employ an instrumental variable (IV) approach, leveraging the 2014 oil price crash as an exogenous shock. An oil price shock refers to the unanticipated or surprise part of a change in oil prices (Baumeister and Kilian (2016)). The short-run price elasticity of gasoline demand is of immediate relevance to policymakers. For instance, the sharp drop in gasoline prices in the latter half of 2014 has renewed interest in understanding how U.S. gasoline consumption might react to lower retail gasoline prices (Coglianese et al. (2017)). This event provides a unique opportunity to isolate external fluctuations in economic uncertainty that are independent of firms' internal decisions regarding automation investment.

The 2014 oil price collapse was one of the most dramatic and unexpected commodity market disruptions in recent history. Similar to the Great Recession, the oil price crash involved a rapid and dramatic decline in asset prices (Wang (2021)). Over the course of six months, global crude oil prices dropped by more than 50 percent, falling from approximately $110 per barrel in mid-2014 to below $50 per barrel by early 2015. This decline was driven by a combination of supply and demand forces that reshaped global energy markets. The rapid expansion of U.S. shale oil production significantly increased supply, while the Organization of the Petroleum Exporting Countries (OPEC) opted not to reduce output, leading to persistent oversupply. Simultaneously, this action slowed global demand, particularly from major energy consumers such as China and the Eurozone, exacerbating downward price pressures. A strengthening U.S. dollar further intensified the price drop by making oil more expensive in local currencies for non-dollar economies. Unlike the Great Recession, which was a broad-based, systemic crisis that impacted the entire economy, the oil shock was more localized, affecting primarily the oil and gas sector. As a result, its impact was concentrated in specific regions of the country, while other areas remained largely unchanged and showed a continuous upward trend (Wang (2021)).

This episode stood out from other oil price shocks in recent decades due to four distinct characteristics: First, the drop in prices was swift and widely perceived as long-lasting, with prices remaining well below their pre-shock levels for years afterward; Second, different from some past declines driven by demand, this one was primarily the result of increased supply; Third, in contrast to the 2008–2009 price fall, which coincided with the global financial crisis, this shock occurred in a relatively stable global economic environment, free from other major disruptions that might have influenced outcomes in oil-exporting countries; Fourth, the prolonged period of high oil prices before the shock may have led some exporters to grow accustomed to elevated revenues, complicating their adjustment to the downturn (Grigoli et al. (2019)).

For oil-exporting economies, this price collapse triggered a wave of economic instability.

For many oil exporters, oil rents serve as the primary source of foreign exchange earnings and government revenues, which finance public expenditures, infrastructure projects, and social programs. Oil also makes up a significant part of the real economy, not only through direct production but also through related sectors like refining and distribution. As a result, many oil exporters experienced an economic slowdown due to the 2014–16 oil price crash (Grigoli et al. (2019)). The sudden loss of revenue forced many oil-dependent economies to revise fiscal policies, cut government spending, and adjust economic forecasts, leading to heightened policy uncertainty. Exchange rate volatility intensified as capital flows responded to shifting macroeconomic conditions, adding further unpredictability to financial markets. In contrast, oil-importing economies benefited from lower energy costs, but the overall global economic slowdown limited the extent of their gains.

The unique features and its asymmetric impact make the 2014 oil price crash a compelling instrument for economic policy uncertainty. Oil-exporting economies experienced a sharp, externally driven increase in uncertainty, independent of domestic policy choices or firm-level investment decisions. Unlike endogenous sources of uncertainty—such as regulatory changes, financial crises, or political instability—the oil price shock was a global event, externally imposed on oil-dependent economies. Firms operating in these economies faced heightened uncertainty not because of industry-specific disruptions or endogenous technological trends, but due to broad macroeconomic conditions beyond their control. This ensures that the variation in uncertainty we capture is exogenous to firm-level automation choices.

By leveraging this differential exposure, we create a setting where economic uncertainty is induced by an external shock, rather than by firms' expectations or internal dynamics. If EPU influences automation adoption, we should observe a stronger automation response in economies where the oil price collapse led to heightened uncertainty. This approach allows us to assess the causal impact of uncertainty on automation while mitigating concerns that automation investment decisions themselves may be shaping perceptions of uncertainty.

The plausibility of this IV rests on two core arguments. First, the oil price crash was exogenous to automation decisions, meaning it was not triggered by firms' investment strategies but rather by global supply and demand dynamics in the energy market. Second, it provides a strong first-stage relationship with EPU, as the fiscal and economic instability induced by the price collapse translated into real policy uncertainty, particularly in oil-dependent economies. Because automation investments are long-term capital expenditures, firms must assess uncertainty at the macroeconomic level before committing to such projects. If heightened uncertainty stemming from the oil price shock leads to increased automation adoption, it supports the argument that uncertainty acts as a driver of automation, rather than merely correlating with it.

This strategy also helps distinguish the substitutive role of automation in uncertain environments. When firms in affected economies face volatility in government policy, exchange rates, and demand conditions, automation may emerge as a stabilization mechanism, reducing reliance on labor costs and mitigating exposure to future policy risks. However, in economies less affected by the oil shock, where uncertainty remains stable, firms may not feel the same urgency to accelerate automation. This contrast strengthens the causal interpretation, as we can observe automation responses varying systematically with an externally driven source of uncertainty. By employing the 2014 oil price crash as an instrumental variable, we ensure that uncertainty-driven automation responses are not confounded by reverse causality or omitted variables. This approach provides a robust framework for understanding how firms adjust investment strategies when faced with external economic shocks, contributing to a deeper understanding of the mechanisms linking uncertainty and technological transformation.

To classify countries as oil exporters, we rely on a three-step methodology that ensures we only include economies that are genuinely impacted by global oil price fluctuations. The three criteria used are:

1. Economic Dependence on Oil, measured as Oil Rents as a percentage of GDP. This helps identify economies that rely on oil revenues to sustain government expenditures

and overall economic activity.

2. Net Oil Exporter Status, which ensures that the country exports more oil than it imports, indicating that oil price fluctuations directly affect its economic stability.

3. Oil Production Volume, ensuring that the country produces more than 1 million barrels per day (bpd), thus filtering out small exporters that are less affected by oil price movements.

These criteria allow us to select countries where economic shocks from oil price volatility strongly impact national policy uncertainty, making them suitable for our IV approach.

5.1 Economic Dependence on Oil (Oil Rents as % of GDP)

Economic dependence on oil is measured using Oil Rents as a percentage of GDP, which quantifies the contribution of crude oil extraction to a country's overall economy. This measure captures the economic value of oil extraction after deducting production costs, and it is provided by the World Bank's World Development Indicators (WDI) database[5].

The oil rents metric is calculated as:

$$\text{Oil Rents} = \frac{\text{Value of Oil Production} - \text{Production Costs}}{\text{GDP}} \times 100 \tag{5.1}$$

where the Value of Oil Production is derived from global crude oil prices multiplied by the quantity extracted, and Production Costs include exploration, extraction, and operational expenses.

A high percentage of oil rents in GDP indicates that oil revenues are a major component of national income, implying that economic fluctuations in global oil markets will have a direct impact on the country's fiscal health and EPU. Countries where oil contributes significantly

[5] We employ the variable Oil Rents (% of GDP) - NY.GDP.PETR.RT.ZS. It measures oil rents as a percentage of GDP, where oil rents are the difference between the value of crude oil production at world prices and the total cost of production. It represents the economic reliance of a country on oil revenues in relation to its total economic output (GDP).

to GDP tend to rely on oil-related revenues for government budgets, public services, and infrastructure investments. When oil prices collapse, these governments often face severe budgetary constraints, forcing them to implement fiscal adjustments, subsidy reductions, or policy shifts, which increase uncertainty in the business environment.[6]

To apply this criterion, we extract Oil Rents as % of GDP from the World Bank WDI database for 2014-2015. The choice of this period aligns with a major global oil price crash (2014-2015), ensuring that we capture the direct impact of oil price shocks on EPU. Countries that exceed the 5% threshold are classified as oil-dependent economies, making them eligible for further classification as oil exporters.

5.2 Net Oil Exporter Status

Even if a country has high oil rents, it is essential to ensure that it is a net exporter of crude oil, meaning it sells more oil to international markets than it imports. This distinction is necessary because net oil importers, even if they produce oil domestically, often benefit from lower oil prices rather than suffer from them. For example, China and India are large oil producers but remain net importers, meaning they do not experience the same fiscal stress as countries that export oil.

To classify countries as net oil exporters, we use data from the U.S. Energy Information Administration (EIA, 2015) on total crude oil exports and imports. The key equation used for classification is:

$$\text{Net Oil Exports} = \text{Total Oil Exports} - \text{Total Oil Imports} \tag{5.2}$$

A country is classified as a net oil exporter if:

$$\text{Net Oil Exports} > 0 \tag{5.3}$$

[6]For this classification, we set a threshold of 5% of GDP for oil rents. Countries exceeding this threshold are considered economically dependent on oil, as a drop in oil prices would lead to immediate economic distress, increased uncertainty, and a potential policy response.

If net oil exports are positive, it means that the country sells more crude oil than it buys on international markets, making its export revenues highly sensitive to oil price volatility.

To implement this classification, we extract export and import data for crude oil from the EIA's 2015 energy statistics database. We then compute net oil exports for each country and classify countries where net exports are positive as net oil exporters. Only these economies are expected to experience economic downturns and policy uncertainty when oil prices collapse. By including only net oil exporters, we ensure that our IV strategy accurately captures the impact of oil price shocks on EPU. This step also helps exclude economies that might have high oil rents but do not experience revenue instability from oil price fluctuations.

5.3 Oil Production Volume (Crude Oil Production > 1M bpd)

Even if a country is economically dependent on oil and a net exporter, we need to verify that it produces a significant amount of crude oil. This ensures that we are not including small oil exporters whose economies are less structurally tied to global oil markets.

To classify major oil producers, we use data from the BP Statistical Review of World Energy (2015), which reports crude oil production in barrels per day (bpd) for each country. We apply a threshold of 1 million bpd, meaning:

$$\text{Crude Oil Production} > 1,000,000 \text{ bpd} \tag{5.4}$$

Countries exceeding this threshold are classified as major oil producers, ensuring that our analysis focuses on economies where oil extraction is a significant industrial activity. This criterion is necessary to avoid misclassifying countries like Denmark or the Netherlands, which export refined petroleum products but do not have significant crude oil extraction operations. Additionally, some refining hubs like Singapore may be classified as oil exporters but do not produce crude oil domestically. By applying the 1M bpd threshold, we exclude economies that do not experience strong economic linkages to crude oil price shocks. To apply this criterion, we extract crude oil production data from BP's 2015 review, filter for countries producing more than 1 million barrels per day, and flag them as major oil producers.

Based on the above classification methodology, we construct a rigorous classification that captures oil exporter and non-oil exporter economies as presented in Table 6.

Place Table 6 Here

In classifying oil-exporting countries for our instrumental variable (IV) approach, we include South Korea, Singapore, and the Netherlands as oil exporters (trading hubs) despite their lack of significant crude oil production. These countries are major refining and distribution centers that play a crucial role in the global oil trade, re-exporting refined petroleum products at significant volumes. Unlike traditional oil-exporting nations that rely on crude oil extraction, these economies import crude oil, process it in large-scale refineries, and export higher-value refined petroleum products such as gasoline, diesel, and petrochemicals.[7] Since refining-based economies rely on stable crude oil imports and consistent demand for refined products, volatility in global oil prices impacts their fiscal policies, trade balances, and economic uncertainty, much like crude oil producers. As a result, classifying them as oil exporters (trading hubs) ensures that our analysis captures all economies where oil market dynamics significantly influence macroeconomic stability and policy uncertainty.

To implement our IV identification, the first stage models the endogenous regressor $\text{EPU}_{c,i,t}$, which represents economic policy uncertainty for country c, industry i, and year t. The instrumental variable (IV), denoted as $\text{OilShock}_{c,t}$ ($OilExporter_c \times Post\text{-}2014_t$), captures the exposure of oil-exporting countries to the oil price crash. The first-stage equation is:

[7] South Korea, for instance, is home to some of the largest oil refineries in the world, including SK Energy Ulsan and GS Caltex Yeosu, with capacities exceeding 800,000 barrels per day. The country consistently ranks among the top global exporters of refined petroleum products, supplying markets in China, Japan, and Southeast Asia. Similarly, Singapore serves as Asia's primary oil trading hub, refining and redistributing vast quantities of oil products despite having no domestic crude oil reserves. The Netherlands, through the Port of Rotterdam, acts as Europe's largest oil refining and transit hub, facilitating energy trade between major markets.

$$\text{EPU}_{c,i,t} = \alpha + \gamma_1(OilExporter_c \times Post\text{-}2014_t) + \mathbf{X}_{c,i,t-1}\boldsymbol{\delta} + \lambda_c + \lambda_i + \lambda_t + \epsilon_{c,i,t} \tag{5.5}$$

where: $\text{EPU}_{c,i,t}$ is the economic policy uncertainty for country c, industry i, and year t. $\text{OilShock}_{c,t}$ is the instrumental variable, capturing the effect of the oil price crash on oil-exporting countries. $OilExporter_c$ is an indicator variable for oil-exporting countries. $Post\text{-}2014_t$ is an indicator for the post-2014 period. $\mathbf{X}_{c,i,t}$ is a vector of control variables employed in the baseline model (Eq. (3.1)). λ_c, λ_i, and λ_t are country, industry, and year fixed effects. $\epsilon_{c,i,t}$ is the error term.

Using the predicted values $\widehat{\text{EPU}}_{c,i,t}$ from the first stage, we estimate the impact of policy uncertainty on automation on the second stage:

$$\text{Robotics}_{c,i,t} = \beta + \theta_1\widehat{\text{EPU}}_{c,i,t-1} + \mathbf{X}_{c,i,t-1}\boldsymbol{\eta} + \lambda_c + \lambda_i + \lambda_t + \nu_{c,i,t} \tag{5.6}$$

where:

- $\text{Robotics}_{c,i,t}$ represents industrial automation, measured as:
  - Robotic Stock ($\text{Stock}_{c,i,t}$): cumulative number of industrial robots.
  - Robotic Flow ($\text{Flow}_{c,i,t}$): number of newly installed robots.
- $\widehat{\text{EPU}}_{c,i,t}$ is the instrumented value of EPU obtained from the first stage.
- $\mathbf{X}_{c,i,t}$, λ_c, λ_i, and λ_t are the same control variables and fixed effects as in the first-stage equation.
- $\nu_{c,i,t}$ is the second-stage error term.

Place Table 7 Here

Table 7 reports the results based on the second stage of the instrumental variable estimation from the above specification. The strong first-stage results confirm that oil price shocks significantly impact EPU in oil-exporting countries. The relevance condition (oil shocks drive EPU) and exogeneity condition (oil shocks do not directly affect robot adoption) seem reasonably satisfied based on your classification criteria. The coefficient on the predicted EPU variable is positive and statistically significant across all specifications. In the unweighted regressions, the coefficient for robotic stock is 3.595 with a t-statistic of 6.55, and for robotic flow, it is 0.917 with a t-statistic of 2.41. These results indicate that an increase in EPU is associated with higher levels of both accumulated robotic adoption and new robot installations. This confirms that policy uncertainty not only contributes to an increase in the overall stock of robots but also drives firms to make immediate investments in new automation technologies In the employment-weighted regressions, the coefficients remain positive and significant, though slightly smaller in magnitude, with 1.613 for robotic stock (t-statistic of 4.77) and 0.400 for robotic flow (t-statistic of 2.63). This suggests that the effect of EPU on automation is somewhat stronger in industries with smaller employment bases, potentially because larger industries have higher labor adjustment costs that slow down automation responses.

Overall, the results strongly support the hypothesis that economic policy uncertainty accelerates automation adoption. The positive and significant EPU coefficients across all specifications indicate that firms respond to uncertain policy environments by investing in automation, likely to reduce reliance on human labor and mitigate risks associated with economic instability. The robustness of these findings, even when controlling for key economic and industry-specific factors, underscores the importance of policy stability in shaping technological adoption patterns.

6 Robustness Checks: Alternative Uncertainty Measures and Expanded Global Coverage

To assess the robustness of our findings, we complement our baseline economic policy uncertainty measure with two alternative indicators: the Global Economic Policy Uncertainty (GEPU) index by Davis (2016) and the World Uncertainty Index (WUI) by Ahir et al. (2022). Each measure provides a distinct perspective on economic uncertainty, and its inclusion allows us to validate whether our core results are sensitive to different conceptualizations of uncertainty.

6.1 Global Economic Policy Uncertainty (GEPU)

The GEPU index is a GDP-weighted average of national EPU indices across 16 major economies that collectively represent a significant portion of global economic output (Davis (2016)). The key difference between GEPU and national-level EPU measures lies in its aggregation approach. While national EPU indices capture country-specific economic policy uncertainty based on local newspaper sources, the GEPU index reflects global uncertainty trends, accounting for spillover effects from major geopolitical and economic events.

One potential concern with national EPU (Baker et al. (2016)) measures is that differences in media coverage and journalistic intensity across countries may lead to inconsistencies in the magnitude of reported uncertainty. A country with highly active political discourse in its media may exhibit higher measured EPU levels than another with less coverage, even if actual uncertainty levels are similar. While our model controls for country fixed effects to mitigate this issue, GEPU provides an additional advantage by smoothing out country-level idiosyncrasies through GDP-weighted aggregation.

The construction of GEPU involves several steps: First, national EPU indices are normalized to a mean of 100 for comparability across countries. Then, missing values for certain countries (such as Australia and India before 2003) are imputed using regression-based methods. Finally, GEPU is computed as a GDP-weighted average of these national EPU indices.

Place Table 8 Here

Empirical results using GEPU, presented in Table 8, show that the positive relationship between uncertainty and automation remains robust, albeit with slightly attenuated coefficients compared to national EPU. This suggests that firms respond more strongly to domestic policy uncertainty rather than global uncertainty, possibly because national policies more directly impact firms' operating environments, taxation, and regulation. However, the persistence of significance under GEPU reinforces the idea that uncertainty—whether local or global—encourages automation investment as firms hedge against economic volatility.

6.2 World Uncertainty Index (WUI)

The World Uncertainty Index (WUI) by Ahir et al. (2022) differs fundamentally from EPU in both scope and data construction. While the EPU of Baker et al. (2016) is based on newspaper coverage of policy-related uncertainty, the WUI is constructed from Economist Intelligence Unit (EIU) country reports that provide standardized economic and political assessments. This methodological distinction significantly reduces the risk of media-driven biases or inconsistencies arising from differences in newspaper intensity across countries.

Another major distinction is that WUI covers over 140 economies, making it far broader in scope than EPU, which primarily focuses on advanced economies. The WUI dataset includes a mix of advanced, emerging, and developing economies, capturing a wider range of uncertainty experiences across different economic systems. The list of countries includes major economies like the United States, China, and Germany, but also extends to smaller economies such as Chile, South Africa, and Hungary, providing a more representative global measure of uncertainty.

Table 9 presents the results using WUI. It confirms a positive relationship between uncertainty and automation but exhibit a weaker effect compared to EPU (For example, Column

5 and 6 present marginal significance of WUI measures' impact on the robotic flow.). This difference may arise because WUI captures a broader definition of uncertainty, encompassing both economic and political uncertainties, whereas EPU is more narrowly focused on economic policy. Political uncertainty—such as election cycles, governance changes, and diplomatic tensions—may not always have direct implications for automation decisions, which are often more sensitive to regulatory and economic uncertainty.

Another interpretation is that firms in developing economies, which are more heavily represented in WUI, may face structural constraints (such as weak financial markets or labor market rigidities) that limit their ability to respond to uncertainty through automation. In contrast, firms in advanced economies, where EPU is more concentrated, may have greater capacity to adapt through technological investments.

Place Table 9 Here

7 Conclusion

This paper explores the impact of EPU on industrial automation, motivated by the growing relevance of automation in mitigating policy-driven risks. Firms face increasing uncertainty due to factors such as regulatory changes, trade disruptions, and macroeconomic instability, prompting them to seek technological solutions to maintain stability and efficiency. While automation has traditionally been viewed as a response to labor costs and productivity needs, this research highlights its role as a strategic investment under uncertainty, filling a gap in the literature that has primarily focused on capital investment and employment effects separately.

To analyze this dynamic, we compile a cross-country panel dataset that integrates industrial robotics adoption, macroeconomic conditions, financial conditions, and labor market and demographic characteristics. The study employs panel OLS estimation with fixed effects to control for unobserved heterogeneity across countries, industries, and time. Recognizing potential endogeneity concerns, we use an instrumental variable (IV) approach, leveraging oil-exporting countries' exposure to oil price fluctuations as an exogenous shock to EPU. Additionally, we investigate moderating effects, considering factors such as profitability, leverage, labor market structure, and demographic trends, to capture the diverse influences shaping automation decisions across different economic environments.

Our findings establish a positive and significant link between EPU and automation adoption, indicating that firms increase their reliance on robotics when faced with policy uncertainty. However, this effect varies based on industry characteristics, financial constraints, and labor market conditions. (1) Industries with high capital intensity and automation feasibility—such as automotive, electronics, and basic metals—are more likely to invest in automation during uncertain times, while labor-intensive sectors show mixed responses. (2) Financially stable industries, particularly those with higher profitability and access to long-term capital, are more responsive to EPU, whereas firms with high short-term debt burdens and borrowing costs exhibit weaker automation adoption. (3) Countries with aging populations and declining labor supply show stronger automation responses, whereas those with high unemployment rates exhibit a dampened effect due to labor availability. (4) Firms in competitive markets automate more aggressively under uncertainty than those in highly concentrated industries, where dominant firms face less pressure to adapt. (5) Firms in economies with well-developed financial markets and low borrowing costs exhibit a stronger automation response to uncertainty. Conversely, high lending rates and credit risk premiums significantly dampen automation investments, suggesting that financial constraints limit firms' ability to adopt robotics as a strategic response to policy uncertainty.

This study contributes to the literature by bridging the gap between policy uncertainty and automation research, offering a cross-country and industry-level perspective that enhances understanding of how institutional and market conditions influence automation decisions. By incorporating financial and labor market dynamics, the research provides deeper insights into why some firms and industries respond more aggressively to uncertainty-driven automation incentives than others. The findings also have important policy implications, suggesting that governments should design targeted policies to support automation investment while ensuring labor market stability, particularly in economies experiencing high policy volatility.

In an era of increasing economic uncertainty, automation will continue to reshape global industries and labor markets. While firms leverage robotics as a stabilization strategy, the degree of adoption depends on financial constraints, workforce demographics, and competitive pressures. Future research should examine the long-term labor market effects of uncertainty-driven automation, including its influence on employment, wage structures, and economic inequality, to better inform policy responses and business strategies in a rapidly evolving economic landscape.

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Table 1: Summary Statistics. This Table provides the summary statistics of the main variables we employ in the paper. The sample period is from 2003 to 2021 for 25 countries. All the variables are constructed at the annual level. Detailed variable definitions are presented in the Appendix.

	(1)	(2)	(3)	(4)	(5)
Variable	Obs	Mean	Std. Dev.	Min	Max
Robotic Stock	7733	2893.915	16061.38	0	454000
Robotic Flow	7733	409.417	2831.324	0	111000
log(1+Robotic Stock)	7733	3.767	3.175	0	13.027
log(1+Robotic Flow)	7733	2.097	2.611	0	11.619
FDI	7258	24.089	1.523	17.368	27.322
Imports Growth	7391	0.044	0.082	-0.204	0.406
Inflation	7733	0.027	0.026	-0.046	0.164
GDP Growth	7733	0.027	0.038	-0.109	0.246
Tax Revenue	6327	0.188	0.072	0.079	0.365
Gov Expenditure	6327	0.307	0.102	0.121	0.623
Leverage	7733	0.23	0.04	0.116	0.385
HHI	7733	0.334	0.107	0.128	0.622
Labor Intensity	7733	-1.777	0.334	-2.783	-0.382
Tangibility	7733	0.318	0.071	0.188	0.501
Sales Growth	7733	0.173	0.139	-0.165	0.86
Earnings Volatility	7733	0.7	2.765	0.032	24.207
Liquidity	7733	4.797	8.949	1.571	77.541
Net Leverage	7733	0.296	0.816	-0.144	5.829
Capital-Labor	7733	9.883	1.362	7.585	15.148
Population Growth	7733	0.008	0.008	-0.042	0.053
Fertility	7733	1.766	0.507	0.772	4.297
Age Dependency	7733	21.599	9.097	6.655	46.034
Aging	7733	14.271	5.65	3.821	27.512
Poverty	5472	6.295	13.328	0	77.5
Employment Size	6878	2.878	1.687	0.491	6.684
Unemployment	7733	7.174	3.699	0.653	26.094
Legal Rights	3059	6.441	3.133	2	12
MarketCap	6764	1.246	2.194	0.141	12.545
Stocks Traded	6726	83.964	123.141	0.603	660.259
Public Listing Density	6878	1435.464	1682.946	41	7499

Table 2: Baseline Model - Economic Policy Uncertainty and Industrial Automation Adoption. This table reports panel OLS regressions of the cross-country industry level of robotics stocks on the EPU, with a sample period of 2003 to 2021. The covariate set includes the FDI, import growth, inflation, employment to population ratio, GDP growth rate, tax revenue, government expenditure, industry leverage, industry profitability, HHI, labor intensity, and industry tangibility. All explanatory variables are lagged by one period. Country, Industry, and Year fixed effects are controlled in all specifications. t-statistics are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	Panel A.				Panel B.				Panel C.			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Unweighted				Weighted by Employment Size				Weighted by GDP			
	Robotic Stock	Robotic Flow	Robotic Stock	Robotic Flow	Robotic Stock	Robotic Flow	Robotic Stock	Robotic Flow	Robotic Stock	Robotic Flow	Robotic Stock	Robotic Flow
EPU	0.363***	0.332***	0.235**	0.273***	0.119***	0.105***	0.114*	0.132***	0.342***	0.297***	0.160**	0.188***
	(5.59)	(6.31)	(2.76)	(3.46)	(3.01)	(3.59)	(2.00)	(3.13)	(6.39)	(7.28)	(2.37)	(3.14)
FDI			0.131***	0.076***			0.034**	0.020			0.097***	0.054***
			(4.34)	(3.56)			(2.19)	(1.71)			(3.66)	(3.11)
Imports Growth			-1.019***	0.748*			0.425***	0.398***			-0.832***	0.538*
			(-4.64)	(2.09)			(4.74)	(2.97)			(-4.51)	(1.86)
Inflation			-1.468*	-1.360*			0.615*	0.065			-1.169*	-1.131*
			(-2.00)	(-1.87)			(1.83)	(0.19)			(-1.96)	(-2.05)
Employment to Population			-2.368	-0.572			-0.075	0.200			-3.049**	-1.130
			(-1.37)	(-0.52)			(-0.05)	(0.21)			(-2.28)	(-1.31)
GDP Growth			0.772	-0.042			0.123	-0.631*			0.692**	0.031
			(1.69)	(-0.07)			(0.40)	(-2.07)			(2.18)	(0.06)
Tax Revenue			-3.966**	6.360**			-4.259***	3.576**			-1.731	5.353***
			(-2.19)	(2.80)			(-3.27)	(2.44)			(-1.21)	(3.27)
Gov Expenditure			-0.135	0.644			0.268	0.888***			-0.062	0.449
			(-0.25)	(1.05)			(0.69)	(2.93)			(-0.16)	(1.12)
Leverage			0.523	-1.035			-0.431	0.123			-0.141	-0.831
			(0.41)	(-0.54)			(-0.34)	(0.13)			(-0.11)	(-0.57)
Profitability			-0.005	-0.012*			-0.005	-0.008**			-0.006	-0.011*
			(-0.56)	(-2.01)			(-0.59)	(-2.27)			(-0.76)	(-2.04)
HHI			0.773	-0.686			0.225	-0.540			0.447	-0.695
			(0.66)	(-0.55)			(0.25)	(-0.88)			(0.45)	(-0.76)
Labor Intensity			-0.379	0.303			-0.036	0.176			-0.198	0.282
			(-1.27)	(0.79)			(-0.15)	(0.88)			(-0.77)	(0.99)
Tangibility			2.329	3.795			0.840	1.709			1.897	2.783
			(1.30)	(1.07)			(0.44)	(0.81)			(1.00)	(0.93)
Constant	2.076***	0.537**	-0.412	-2.452*	1.207***	0.263*	0.870	-1.435*	1.307***	0.134	0.531	-1.303
	(6.72)	(2.15)	(-0.33)	(-1.98)	(6.53)	(1.92)	(0.83)	(-1.83)	(5.14)	(0.69)	(0.55)	(-1.32)
N	8398.000	8398.000	5548.000	5548.000	7163.000	7163.000	5244.000	5244.000	8056.000	8056.000	5548.000	5548.000
Adjusted R-Square	0.884	0.795	0.895	0.788	0.919	0.800	0.922	0.790	0.895	0.816	0.909	0.813
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Industry Heterogeneity in EPU-Automation Relationship: Role of Profitability, Volatility, Leverage, and Capital Intensity and Market Structure. This table reports panel OLS regressions of the cross-country industry level of robotics on the interaction between EPU and a set of industry characteristics, denoted as Z, with a sample period of 2003 to 2021. In Panel A, Z represents a set of variables that captures industrial profitability and volatility. In Panel B, Z represents a set of leverage characteristics. In Panel C, Z represents capital distribution and market structure. All explanatory variables are lagged by one period. Country, Industry, and Year fixed effects are controlled in all specifications. t-statistics are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Variable definitions are presented in the Appendix.

	Panel A. Z = Profitability and Volatility					Panel B. Z = Leverage Characteristics			Panel C. Z = Capital Intensity and Market Structure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Sales Growth	Operating Profit Margin	Net Profit Margin	Earnings Volatility	CF Volatility	Net Leverage	LT Debt	ST Debt	Capital-Labor	Tangibility	HHI
EPU	0.392**	0.299*	0.392**	0.291***	0.263***	0.289*	0.241	0.291*	1.171**	1.135***	0.654**
	(2.49)	(1.92)	(2.49)	(3.58)	(2.95)	(1.92)	(1.61)	(1.93)	(2.79)	(3.12)	(2.31)
EPU * Z	-0.758**	0.120**	0.117**	-0.030**	-0.008**	-0.110***	0.083**	-0.137***	-0.092**	-2.761**	-1.197*
	(-2.88)	(2.49)	(2.52)	(-2.14)	(-2.79)	(-3.12)	(2.74)	(-4.45)	(-2.57)	(-2.88)	(-1.88)
Z	3.540**	-0.489**	-0.485**	0.138*	0.050***	0.585***	-0.294*	0.723***	0.421**	15.297***	6.639**
	(2.69)	(-2.37)	(-2.33)	(1.93)	(3.40)	(3.22)	(-1.90)	(5.02)	(2.45)	(3.02)	(2.18)
Constant	-1.527	-1.985	-1.995	-0.880	-2.155**	-1.810	-1.641	-1.781	-5.970**	-6.146**	-3.825
	(-1.01)	(-1.27)	(-1.20)	(-1.16)	(-2.22)	(-1.12)	(-1.02)	(-1.10)	(-2.50)	(-2.45)	(-1.73)
N	5548.000	5852.000	5852.000	5548.000	5852.000	5852.000	5852.000	5852.000	5852.000	5852.000	5852.000
Adjusted R-Square	0.904	0.894	0.894	0.904	0.894	0.895	0.895	0.895	0.894	0.895	0.894
Country - level Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry - level Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Country-Level Moderation in EPU-Automation Relationship: Role of Demographics and Labor Market Characteristics. This table reports panel OLS regressions of the cross-country industry level of robotics on the interaction between EPU and a set of demographic and labor characteristics, denoted as Z, with a sample period of 2003 to 2021. In Panel A, Z represents a set of variables that captures the demographic characteristics. In Panel B, Z represents a set of labor characteristics. All explanatory variables are lagged by one period. Country, Industry, and Year fixed effects are controlled in all specifications. t-statistics are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Variable definitions are presented in the Appendix.

	Panel A. Z = Demographic Characteristics					Panel B. Z = Labor Characteristics	
	(1) Population Growth	(2) Fertility	(3) Age Dependency	(4) Aging	(5) Poverty	(6) Employment Size	(7) Unemployment
EPU	1.050***	2.111***	1.157***	0.868***	1.397***	0.467***	1.603***
	(8.27)	(5.95)	(6.58)	(4.77)	(9.61)	(3.64)	(7.96)
EPU* Z	20.080***	-0.609***	-0.029***	-0.026**	-0.021***	0.151***	-0.057**
	(4.03)	(-3.80)	(-4.36)	(-2.39)	(-3.91)	(4.70)	(-2.74)
Z	-90.661***	0.472	0.385***	0.575***	0.034	5.745***	0.262**
	(-3.52)	(0.70)	(9.88)	(9.61)	(1.18)	(8.49)	(2.56)
Constant	-3.397*	-3.673*	-11.366***	-10.790***	-2.710*	-16.980***	-6.103***
	(-1.75)	(-1.75)	(-7.00)	(-6.81)	(-1.78)	(-6.31)	(-3.03)
N	5852.000	5852.000	5852.000	5852.000	4389.000	5548.000	5852.000
Adjusted R-Square	0.866	0.874	0.882	0.883	0.881	0.881	0.866
Country - level Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry - level Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Financial Market Development, Borrowing Costs, and EPU-Automation Relationship. This table reports panel OLS regressions of the cross-country industry level of robotics on the interaction between EPU and a set of country-level macroeconomic characteristics, denoted as Z, with a sample period of 2003 to 2021. In Panel A, Z represents a set of variables that captures financial development characteristics. In Panel B, Z represents a set of financing characteristics. All explanatory variables are lagged by one period. Country, Industry, and Year fixed effects are controlled in all specifications. t-statistics are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Variable definitions are presented in the Appendix.

	Panel A. Z = Financial Development Characteristics				Panel B. Z = Financing Characteristics		
	(1) Stocks Traded	(2) MarketCap	(3) Public Listing Density	(4) Domestic Credit	(5) Real Interest Rate	(6) Lending Rate	(7) Lending Premium
EPU	0.725***	0.438***	0.746***	0.682***	1.343***	1.344***	1.649***
	(5.56)	(3.53)	(5.90)	(4.48)	(10.24)	(10.03)	(8.88)
EPU* Z	0.009***	0.894***	0.000***	0.004**	-2.429***	-1.510**	-4.404***
	(5.90)	(7.68)	(6.16)	(2.38)	(-3.16)	(-2.31)	(-4.61)
Z	-0.041***	-3.621***	-0.001***	-0.014	3.860	-0.590	18.607***
	(-5.61)	(-6.49)	(-8.01)	(-1.66)	(0.83)	(-0.15)	(3.41)
Constant	-2.786	-1.431	-2.425	2.035	-6.589**	-6.409**	-5.843*
	(-1.35)	(-0.68)	(-1.02)	(0.84)	(-2.32)	(-2.26)	(-1.79)
N	4978.000	4921.000	5092.000	5301.000	3648.000	3648.000	1957.000
Adjusted R-Square	0.869	0.872	0.868	0.572	0.546	0.546	0.540
Country - level Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry - level Control?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Classification of Oil-Exporting Countries Based on World Bank and EIA Data

Country	Oil Rents $> 5\%$ GDP (WDI)	Net Oil Exporter (EIA)	Oil Production $> 1M$ bpd (BP/EIA)	Final Classification
Australia	× (0.9%)	×	× (400K bpd)	Non-Oil Exporter
Belgium	× (0.1%)	×	× (No data)	Non-Oil Exporter
Brazil	✓ (7.2%)	✓	✓ (2.6M bpd)	**Oil Exporter**
Canada	✓ (7.9%)	✓	✓ (4.3M bpd)	**Oil Exporter**
China	× (2.1%)	×	✓ (3.8M bpd)	Non-Oil Exporter
Colombia	✓ (5.8%)	✓	✓ (1.0M bpd)	**Oil Exporter**
Croatia	× (1.2%)	×	× (15K bpd)	Non-Oil Exporter
Denmark	× (3.2%)	✓	× (200K bpd)	**Oil Exporter (small-scale)**
France	× (0.1%)	×	× (No data)	Non-Oil Exporter
Germany	× (0.2%)	×	× (100K bpd)	Non-Oil Exporter
Hong Kong	× (0.0%)	×	× (No data)	Non-Oil Exporter
India	× (1.3%)	×	✓ (1.0M bpd)	Non-Oil Exporter
Ireland	× (0.1%)	×	× (No data)	Non-Oil Exporter
Italy	× (0.3%)	×	× (80K bpd)	Non-Oil Exporter
Japan	× (0.0%)	×	× (No data)	Non-Oil Exporter
Mexico	✓ (6.1%)	✓	✓ (2.4M bpd)	**Oil Exporter**
Netherlands	× (2.5%)	✓ (Refining hub)	× (small crude production)	**Oil Exporter (trading hub)**
New Zealand	× (0.5%)	×	× (No data)	Non-Oil Exporter
Pakistan	× (0.7%)	×	× (No data)	Non-Oil Exporter
Singapore	× (0.1%)	✓ (Refining hub)	× (No production)	**Oil Exporter (trading hub)**
Spain	× (0.2%)	×	× (No data)	Non-Oil Exporter
Sweden	× (0.1%)	×	× (No data)	Non-Oil Exporter
United States	✓ (6.4%)	✓	✓ (12M bpd)	**Oil Exporter**
Russia	✓ (15.0%)	✓	✓ (10.8M bpd)	**Oil Exporter**
South Korea	× (0.3%)	✓ (Refining hub)	× (No crude production)	**Oil Exporter (trading hub)**

Notes: Oil Rents data from World Bank (2014-2015), Net Oil Exports and Production data from EIA and BP Statistical Review of World Energy.
Thresholds: Oil rents $> 5\%$ GDP, Net Oil Exports > 0, Oil Production $> 1M$ bpd.

Table 7: Instrumental Variable Estimation. This table reports the second stage results of 2-stage estimation of the IV regressions of the cross-country industry level of robotics on the EPU. On the first stage, the EPU is regressed on the instrumental variable of oil exporter, whereas the predicted EPU is adopted to explain the robotics adoption on the second stage. All explanatory variables are lagged by one period. Country, Industry, and Year fixed effects are controlled in all specifications. t-statistics are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Variable definitions are presented in the Appendix.

	(1)	(2)	(3)	(4)	(5)	(6)
	Unweighted		Weighted by Empolyment Size		Weighted by GDP	
	Robotic Stock	Robotic Flow	Robotic Stock	Robotic Flow	Robotic Stock	Robotic Flow
$\widehat{EPU}$	3.894***	0.885*	1.626***	0.407**	3.153***	0.947***
	(5.79)	(1.93)	(4.60)	(2.52)	(5.92)	(3.15)
FDI	0.186**	0.053**	0.062**	0.003	0.131**	0.034**
	(2.46)	(2.41)	(2.72)	(0.31)	(2.29)	(2.82)
Imports Growth	-1.336	0.960*	-0.271	0.461**	-1.091	0.628
	(-1.46)	(1.76)	(-0.65)	(2.47)	(-1.49)	(1.59)
Inflation	-4.562	1.470	-1.100	0.948*	-3.342	0.486
	(-1.55)	(1.04)	(-0.82)	(1.85)	(-1.39)	(0.53)
Employment to Population	-5.240	-2.086	-1.059	-0.641	-5.859	-2.845
	(-0.87)	(-0.63)	(-0.56)	(-0.44)	(-1.17)	(-1.06)
GDP Growth	10.054**	-0.870	3.544**	-0.589	7.871**	0.448
	(2.75)	(-0.59)	(2.88)	(-1.18)	(2.60)	(0.38)
Tax Revenue	10.572	4.990	1.946	3.528*	10.326	6.079*
	(1.34)	(1.16)	(0.55)	(1.95)	(1.61)	(1.98)
Gov Expenditure	-5.164*	1.440	-1.986	0.809	-4.554*	0.177
	(-1.97)	(1.10)	(-1.73)	(1.32)	(-2.11)	(0.20)
Leverage	-23.578***	-16.261***	-15.824***	-8.061***	-20.558***	-12.871***
	(-8.37)	(-7.89)	(-7.42)	(-6.54)	(-8.39)	(-7.71)
Profitability	0.052*	0.026	0.030	0.019	0.045*	0.026
	(1.97)	(1.00)	(1.48)	(1.05)	(1.88)	(1.17)
HHI	-7.598***	-6.371***	-5.909***	-3.560***	-6.910***	-5.231***
	(-10.26)	(-9.75)	(-9.98)	(-8.90)	(-10.60)	(-9.77)
Labor Intensity	-1.385***	-0.834***	-0.850***	-0.414***	-1.192***	-0.657***
	(-4.79)	(-3.19)	(-4.15)	(-3.16)	(-4.71)	(-3.16)
Tangibility	0.455	-0.266	0.861	0.526	0.617	0.012
	(0.27)	(-0.19)	(0.70)	(0.67)	(0.42)	(0.01)
N	5548.000	5548.000	5244.000	5244.000	5548.000	5548.000
Adjusted R-Square	0.156	0.198	0.215	0.165	0.161	0.186
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Additional Evidence from Global Policy Uncertainty (GEPU). This table reports panel OLS regressions of the cross-country industry level of robotics on the global policy uncertainty (GEPU) with a sample period of 2003 to 2021. $GEPU^{GDP}$ is the GDP-weighted average of national EPU indices for 16 countries that account for two-thirds of global output, following Davis (2016). $GEPU^{PPP}$ is the PPP-adjusted GEPU index based on the same sample. Country and Industry fixed effects are controlled in all specifications. t-statistics are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Variable definitions are presented in the Appendix.

	(1) Robotic Stock	(2) Robotic Stock	(3) Robotic Flow	(4) Robotic Flow
$GEPU^{GDP}$	0.009***		0.003***	
	(5.37)		(3.11)	
$GEPU^{PPP}$		0.009***		0.003***
		(5.41)		(3.03)
Constant	-0.451	-0.337	-1.709	-1.655
	(-0.18)	(-0.13)	(-0.98)	(-0.95)
N	5852.000	5852.000	5852.000	5852.000
Adjusted R-Square	0.872	0.872	0.782	0.782
Country - level Control?	Yes	Yes	Yes	Yes
Industry - level Control?	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No

Table 9: Evidence From a Broader Economy Using World Uncertainty Index (WUI). This table reports panel OLS regressions of the cross-country industry level of robotics on the world uncertainty indexes with a sample period of 2003 to 2021. WUI is computed by counting the frequency of the world uncertainty (or its variant) in EIU country reports. WUI^{3QWMA} is the three-quarter weighted moving average of the World Uncertainty Index. WTU is the world trade uncertainty following Ahir et al. (2022). Country, Industry, and Year fixed effects are controlled in all specifications. t-statistics are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Variable definitions are presented in the Appendix.

	(1) Robotic Stock	(2) Robotic Stock	(3) Robotic Stock	(4) Robotic Flow	(5) Robotic Flow	(6) Robotic Flow
WUI	5.813***			2.596**		
	(4.02)			(2.42)		
WUI^{3QWMA}		2.318***			1.034**	
		(3.91)			(2.49)	
WTU			0.506**			0.306*
			(2.12)			(1.77)
Constant	2.142***	2.106***	2.382***	1.037***	1.021***	1.127***
	(24.38)	(21.14)	(42.91)	(16.03)	(14.75)	(28.39)
N	22344.000	22344.000	22344.000	22458.000	22458.000	22458.000
Adjusted R-Square	0.282	0.283	0.281	0.197	0.198	0.199
Country - level Control?	Yes	Yes	Yes	Yes	Yes	Yes
Industry - level Control?	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1: Time Series Property of Operational Industrial Robotics Adoption. This figure presents the relationship between Economic Policy Uncertainty and industrial robotic adoption over time, measured as operational stock of robots. The blue solid line represents the average EPU index, while the green dashed line represents the mean operational stock of robots. The data is based on our 25-economy global sample and aggregated annually, covering the period from 2003 to 2021.

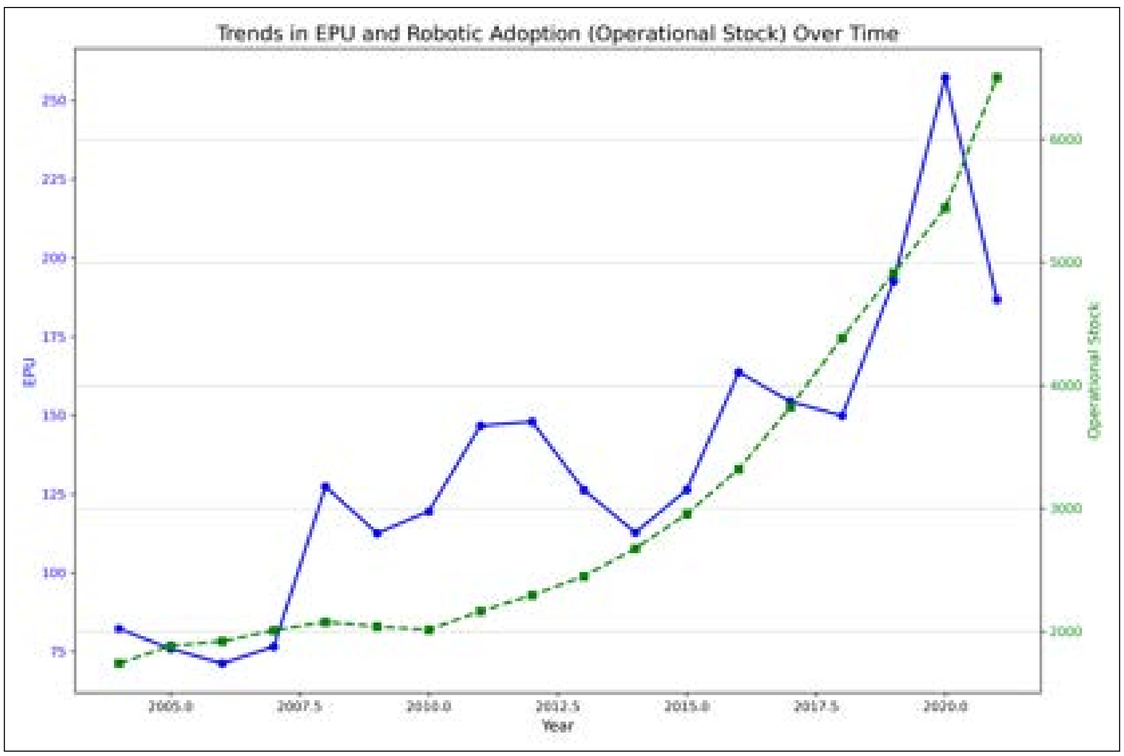


Figure 2: EPU vs. Robotic Adoption (United States). This figure presents the relationship between Economic Policy Uncertainty and industrial robotic adoption over time, measured as operational stock of robots. The data is based on the US sample and aggregated annually, covering the period from 2003 to 2021.

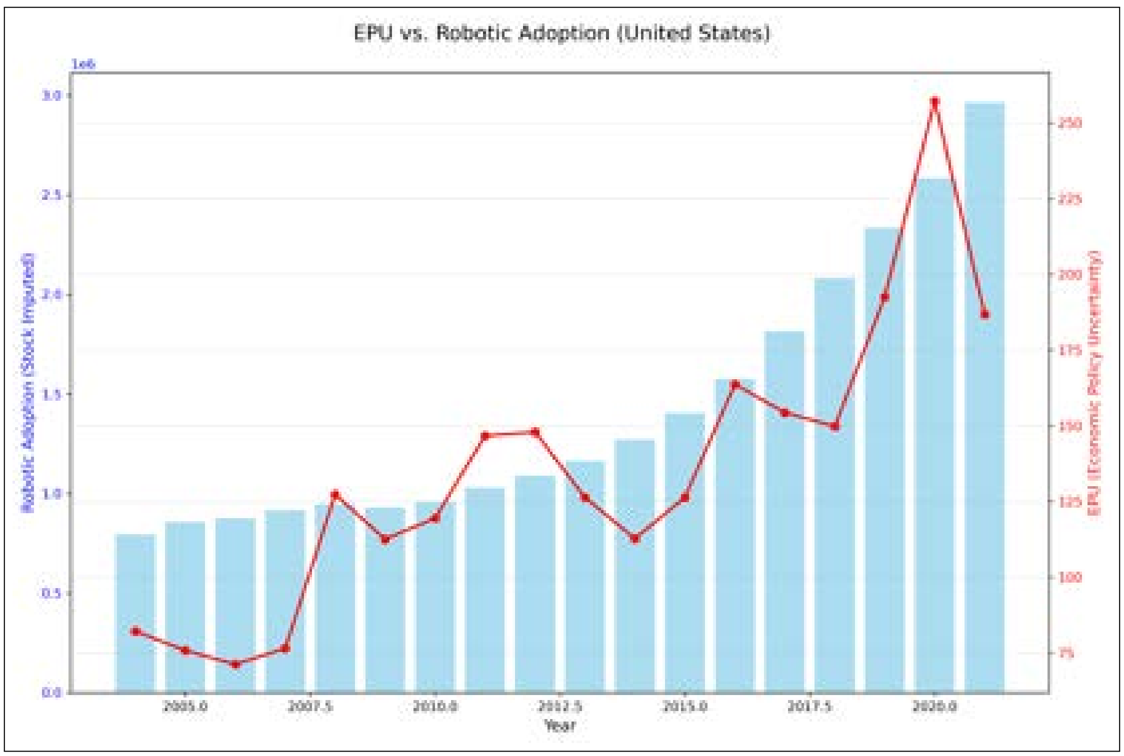


Figure 3: Industry Distribution of Robotic Adoption. This figure presents a stacked bar chart of robotic adoption by industry, displaying the total operational stock of robots from 2004 to 2021, over 19 industries, aggregated annually. The data is grouped by industry, with each color representing a distinct sector. The height of each stacked bar reflects the cumulative robotic adoption across all industries in a given year. The data is processed by summing the operational stock of robots within each industry and year. Missing values are filled with zeros to maintain consistency across time. The figure highlights industry-level heterogeneity in automation adoption, with some sectors consistently leading in robotics deployment while others exhibit lower adoption rates. The plotted values provide insight into how different industries contribute to overall automation growth and how their adoption rates have evolved over time.

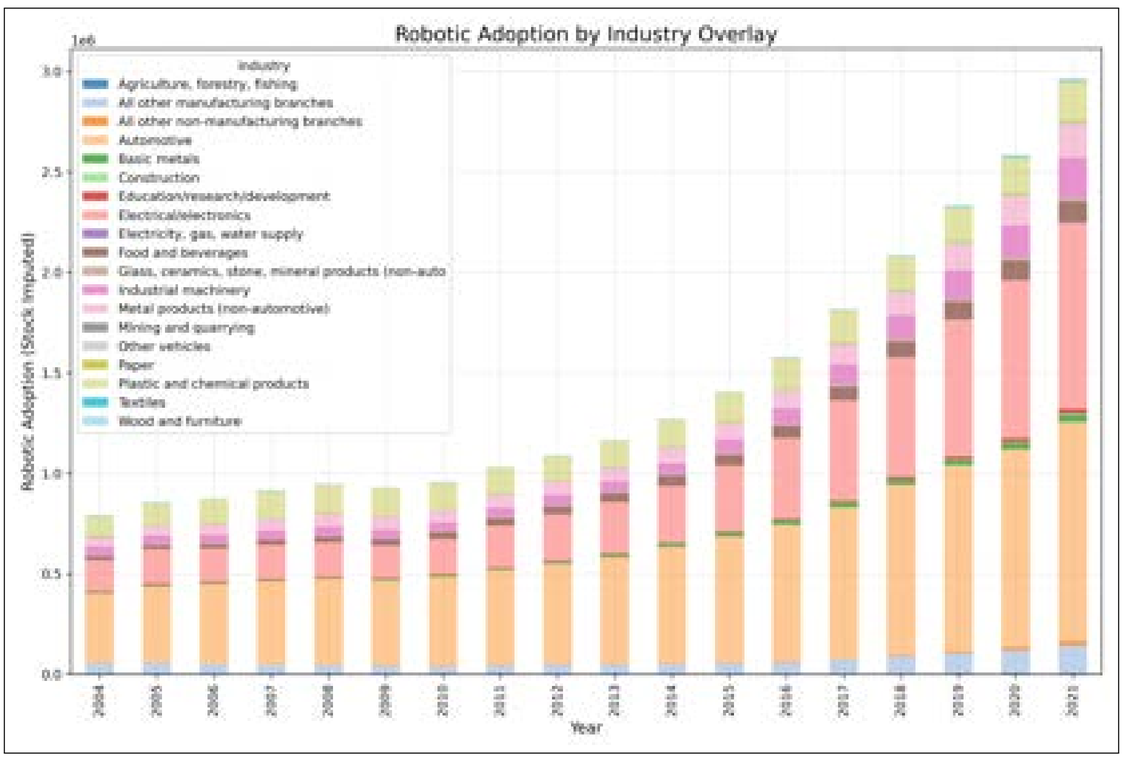


Figure 4: Heatmap Sorted by Correlation Magnitude. This heatmap visualizes the correlation between Economic Policy Uncertainty and robotic adoption (measured by operational stock of robotics) across countries and industries. Each cell represents the correlation coefficient between EPU and robotic adoption for a given country-industry pair, with values ranging from negative (blue) to positive (red). The data is sorted by the absolute magnitude of the correlations, ensuring that countries with stronger overall correlations—whether positive or negative—appear at the top. The correlation values are computed by aggregating EPU and robotic adoption at the country-industry level and then calculating Pearson correlations for all country-industry pairs with sufficient data points. Countries exhibiting consistently high positive correlations suggest that firms in those economies respond to uncertainty by increasing automation, whereas negative correlations may indicate different labor market dynamics, policy responses, or industry structures that dampen the automation-uncertainty relationship. The heatmap helps identify systematic patterns in how uncertainty affects automation across various national and industrial contexts.

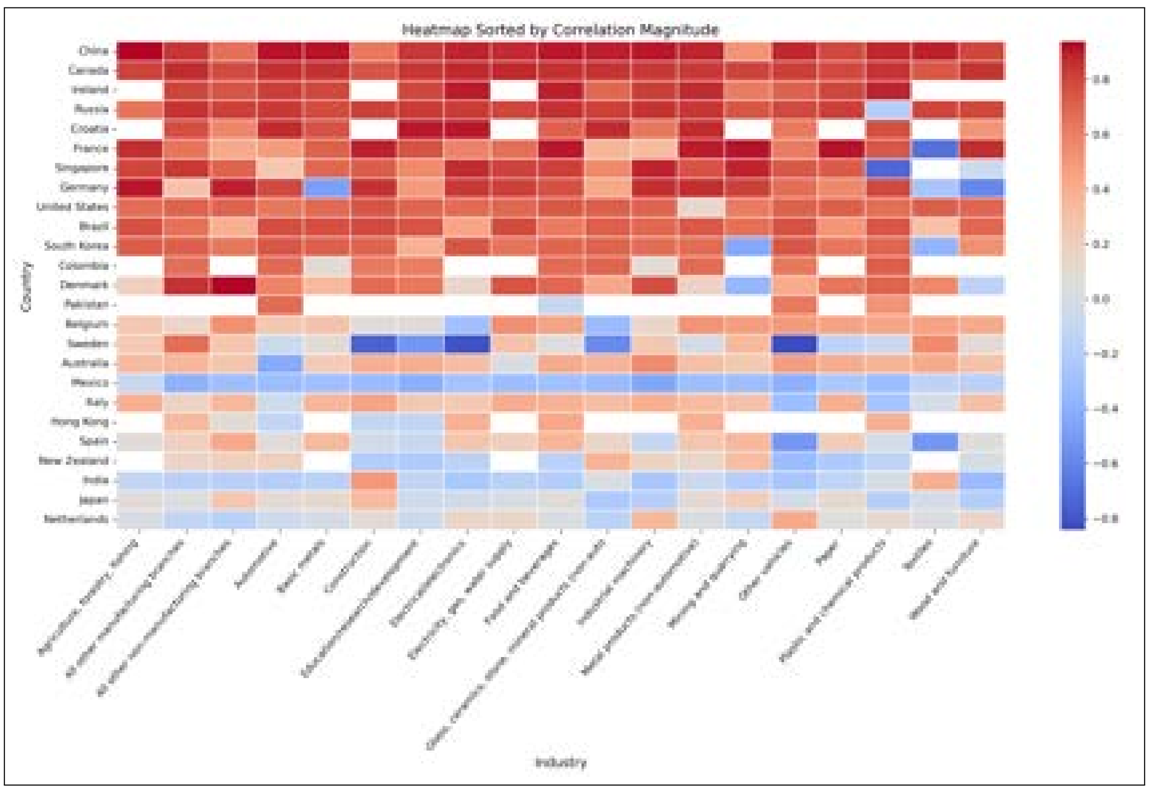
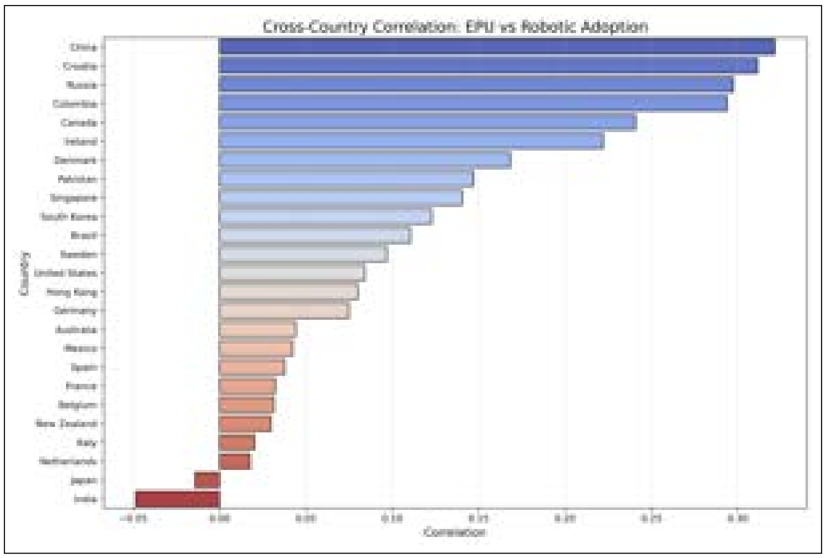


Figure 5: Cross-Country Correlation: EPU vs Robotic Adoption. This bar chart presents the correlation between Economic Policy Uncertainty and robotic adoption (measured by operational stock of robotics) for each country. The correlation coefficients are computed based on country-level data from 2003 to 2021, capturing the relationship between policy uncertainty and automation trends. The data is processed by grouping observations at the country level, calculating the Pearson correlation between EPU and robotic stock, and filtering for countries with sufficient data points. The countries are then ranked in descending order based on their correlation values, with China, Croatia, and Russia exhibiting the strongest positive associations between uncertainty and automation. Countries with negative or near-zero correlations, such as India and Japan, suggest that automation adoption in these economies is influenced by factors other than policy uncertainty. The visualization provides insight into how firms in different national contexts respond to uncertainty through automation investment.



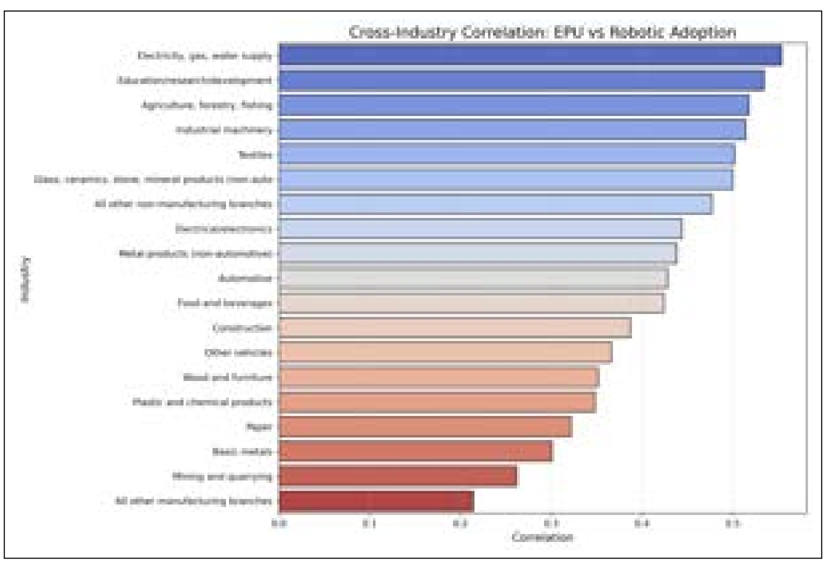
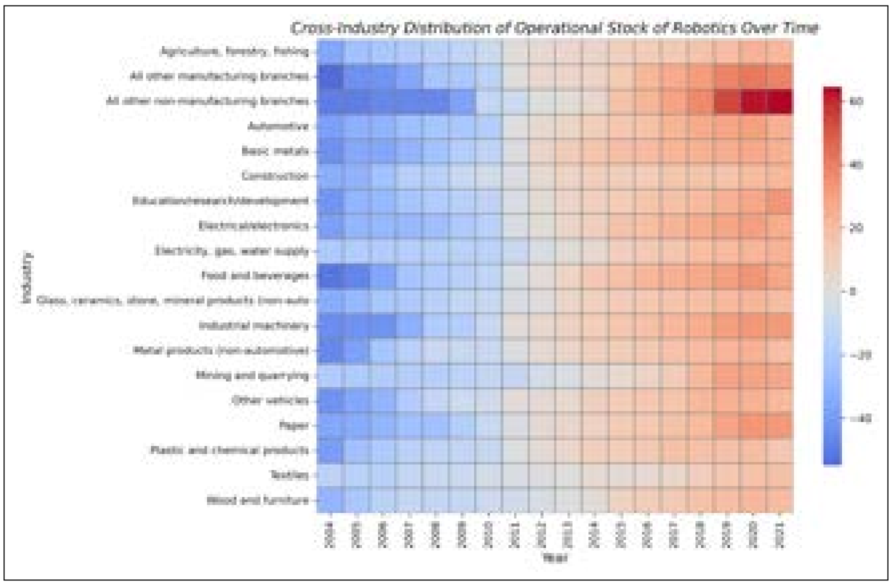


Figure 6: Cross-Industry Pattern of Robotics Over Time. This heatmap presents the evolution of the total operational stock of robots across industries from 2004 to 2021, reflecting the cumulative adoption of robotics over time. Each row represents an industry, and the colors indicate relative changes in robotic stock compared to the industry's historical average. The visualization is created by aggregating log-transformed operational stock (and flow) data and normalizing within industries to highlight periods of accelerated automation expansion. Red-shaded areas indicate years where industries expanded their robotic workforce at a faster rate than their historical trend, while blue-shaded areas reflect slower adoption periods. The figure provides insight into how automation has diffused across different sectors over time and which industries have experienced sustained growth in robotic adoption.



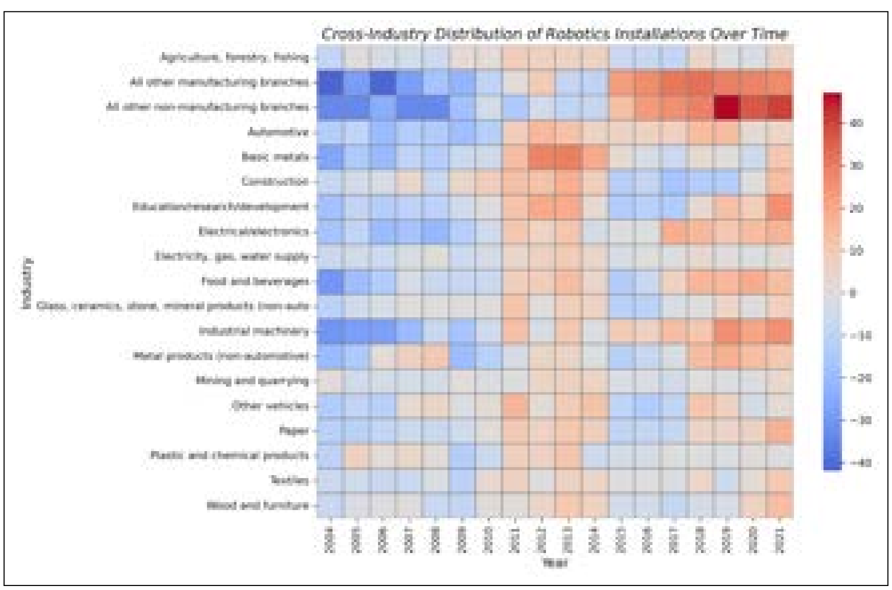
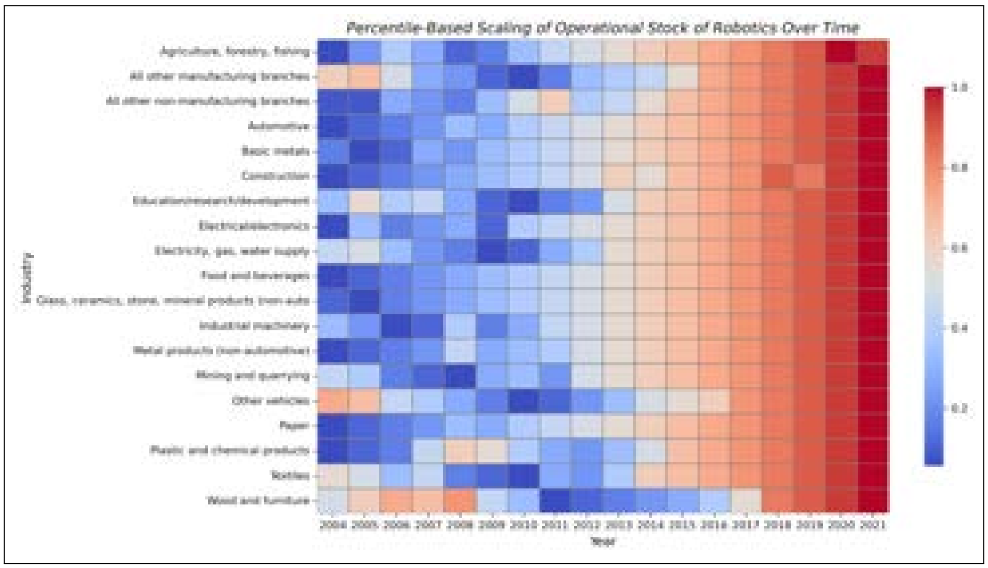
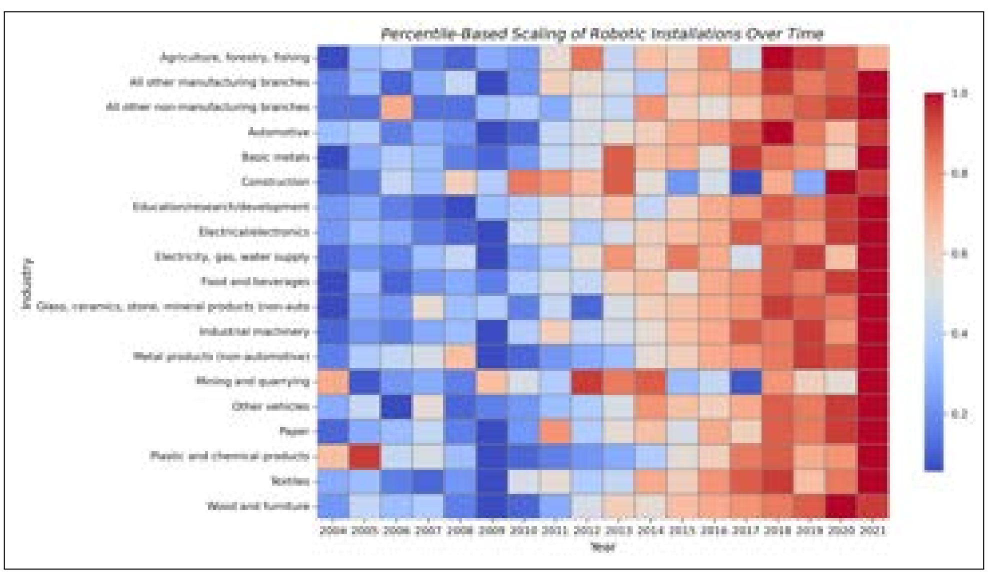


Figure 7: Percentile-Based Scaling of Robotic Operational Stock Over Time. This heatmap visualizes the percentile-based scaling of robotic installations and operational stock across industries from 2004 to 2021, offering a comparative view of how automation adoption has evolved relative to historical industry trends. Each row represents an industry, and colors indicate the percentile ranking of robotic adoption within that industry, rather than absolute values. The visualization is constructed by aggregating raw installation and operational stock data, applying a log transformation, and normalizing values within each industry to derive percentile ranks. This approach highlights periods of relative acceleration in automation adoption while controlling for industry-specific differences in baseline adoption levels. Red-shaded areas represent years where robotic adoption was in the upper percentiles relative to an industry's historical trend, while blue-shaded areas indicate periods of slower adoption.





Appendix

Variable Definitions

- Robotic Stock: The stock of industrial robots represents the total number of robots currently deployed in a given country, industry, and year. The International Federation of Robotics (IFR) calculates the operational stock assuming an average service life of 12 years, with robots being immediately withdrawn from service after their lifespan ends. The stock measures cumulative robotic adoption over time (IFR defines the raw operational stock to be the sum of robot installations over 12 years). (Country-Industry-Year, Source: International Federation of Robotics)

- Robotic Flow: The annual number of newly installed industrial robots in a given country and industry. (Country-Industry-Year, Source: International Federation of Robotics)

- Foreign Direct Investment (FDI): The net inflow of foreign direct investment (FDI) in current U.S. dollars, including equity capital, reinvestment of earnings, and intra-company loans. FDI represents cross-border investments made by firms and investors to establish or expand businesses. (Country-Year, Source: WDI, Indicator Code: BX.KLT.DINV.CD.WD)

- Imports Growth: Measures the annual percentage growth of total imports of goods and services, adjusted for inflation. (Country-Year, Source: WDI, Indicator Code: NE.IMP.GNFS.KD.ZG)

- Inflation: Annual percentage change in the GDP deflator, which accounts for the changes in the price levels of all newly produced goods and services within an economy. (Country-Year, Source: WDI, Indicator Code: NY.GDP.DEFL.KD.ZG)

- GDP Growth: Measures the annual percentage change in real Gross Domestic Product (GDP). (Country-Year, Source: WDI, Indicator Code: NY.GDP.MKTP.KD.ZG)

- Tax Revenue: The total tax revenue collected by the government, expressed as a percentage of GDP. It includes income taxes, corporate taxes, sales taxes, and other levies imposed by the government to finance public services. (Country-Year, Source: WDI, Indicator Code: GC.TAX.TOTL.GD.ZS)

- Government Expenditure: Total government spending as a percentage of GDP, covering expenditures on goods and services, social programs, infrastructure, and other public sector investments. (Country-Year, Source: WDI, Indicator Code: GC.XPN.TOTL.GD.ZS)

- Leverage: The book leverage ratio is calculated as:

  (Total Long-Term Debt + Current Debt)/Total Assets, indicating the level of financial risk and dependency on debt financing. Firm-level data is aggregated to the industry level. (Country-Industry-Year, Source: Compustat Global)

- Herfindahl-Hirschman Index (HHI): A measure of market concentration, computed as the sum of the squared market shares of firms within an industry. The HHI is calculated as: $HHI = \sum(\text{Market Share}_i)^2$, where Market Share_i is the sales of firm i divided by total industry sales. Higher values indicate greater market concentration. (Country-Industry-Year, Source: Compustat Global)

- Labor Intensity: A measure of how labor-intensive an industry is calculated as

  log(SGA Expenses/Sales). This reflects the relative reliance on human labor versus automation. (Country-Industry-Year, Source: Compustat Global)

- Tangibility: The proportion of tangible fixed assets (such as property, plant, and equipment) relative to total assets, calculated as PP&E/Total Assets. (Country-Industry-Year, Source: Compustat Global)

- Sales Growth: The year-over-year percentage increase in sales revenue, calculated as $(\text{Sales}_t - \text{Sales}_{t-1})/\text{Sales}_{t-1}$. (Country-Industry-Year, Source: Compustat Global)

- Operating Profit Margin: The ratio of operating income before depreciation and amortization to revenue, calculated as OIBDP/Revenue. (Country-Industry-Year, Source: Compustat Global)

- Net Profit Margin: The ratio of net income to revenue, calculated as Net Income/Revenue. (Country-Industry-Year, Source: Compustat Global)

- Earnings Volatility: The standard deviation of return on assets (ROA) over the past five years, where ROA is calculated as Net Income/Total Assets. (Country-Industry-Year, Source: Compustat Global)

- Cash Flow Volatility: The standard deviation of cash flow relative to total assets over a rolling five-year period. Cash flow is calculated as:

  $$\text{Cash Flow} = (\text{OIBDP} - \text{Interest} - \text{Taxes} - \text{Dividends})/\text{Total Assets}$$

  (Country-Industry-Year, Source: Compustat Global)

- Net Leverage: A measure of financial leverage adjusted for liquidity, calculated as:

  $$\text{Net Working Capital}/\text{Total Assets}$$

  where Net Working Capital = (Working Capital−Cash Equivalents). (Country-Industry-Year, Source: Compustat Global)

- Capital-Labor Ratio: A measure of capital intensity, calculated as:

  $$\text{PP\&E}/\text{Employees}$$

  indicating the amount of fixed capital available per worker. (Country-Industry-Year, Source: Compustat Global)

- Population Growth: The annual percentage growth rate of the total population. (Country-Year, Source: WDI, Indicator Code: SP.POP.GROW)
- Fertility Rate: The average number of children a woman is expected to have in her lifetime. (Country-Year, Source: WDI, Indicator Code: SP.DYN.TFRT.IN)
- Real Interest Rate: The lending interest rate adjusted for inflation, capturing the real cost of borrowing. (Country-Year, Source: WDI, Indicator Code: FR.INR.RINR)
- Lending Interest Rate: The annual interest rate charged by banks on loans. (Country-Year, Source: WDI, Indicator Code: FR.INR.LEND)
- Lending Premium: The risk premium on lending, reflecting additional interest charged due to borrower risk. (Country-Year, Source: WDI, Indicator Code: FR.INR.RISK)

Appendix Table

Appendix Table: Matrix of Correlations. This table provides the correlation coefficients of the main variables we employ in the paper. The sample period is from 2003 to 2021 of 25 countries. All the variables are constructed at the annual level.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Robotic Stock	1.00											
(2) Robotic Flow	0.85	1.00										
(3) FDI	0.30	0.28	1.00									
(4) Imports Growth	-0.13	-0.06	0.06	1.00								
(5) Inflation	-0.17	-0.11	0.01	0.37	1.00							
(6) GDP Growth	-0.16	-0.12	0.09	0.72	0.30	1.00						
(7) Tax Revenue	-0.02	-0.10	-0.43	-0.04	-0.25	-0.11	1.00					
(8) Gov Expenditure	0.17	0.10	-0.20	-0.21	-0.30	-0.37	0.62	1.00				
(9) Leverage	-0.19	-0.17	-0.02	-0.06	-0.00	-0.05	-0.00	0.01	1.00			
(10) HHI	-0.31	-0.28	-0.02	0.02	0.01	0.00	0.01	-0.00	-0.10	1.00		
(11) Labor Intensity	-0.09	-0.06	0.00	-0.04	-0.03	-0.04	-0.01	0.00	-0.33	0.20	1.00	
(12) Tangibility	-0.24	-0.21	-0.02	-0.00	-0.00	-0.01	0.00	-0.01	0.57	0.15	0.10	1.00