Legacies of Globalization and the Role of the State in the AI Economy*

Leonardo Baccini   Katja Kleinberg   Stephen Weymouth

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Abstract

Globalization restructured labor markets, and now artificial intelligence (AI) threatens a new wave of displacement. How do these shocks shape attitudes about the government's role in the economy? We develop a theory of sequential disruption in which attitudes about the state's economic role depend on the employment legacies of globalization. We argue that globalization shaped beliefs about whether markets deliver secure work and fair pay, and those beliefs condition how citizens interpret AI displacement risk and the appropriate government response. Cross-national survey evidence shows that support for government responsibility is stronger where manufacturing employment declined, with effects concentrated among low-skilled workers. Exploiting variation in exposure to the NAFTA shock, we find that demand for a larger government role increased among low-skilled Americans and declined among low-skilled Mexicans. Survey experiments show that AI displacement information increases support for government involvement in the United States and Mexico, but weakens beliefs that markets provide economic security only in the U.S., where globalization had previously eroded them. Unlike trade, AI displacement does not activate the same skill-based cleavages, suggesting that citizens evaluate automation risk less through individual labor-market position than through broader national experience. These findings recast the politics of AI as dependent on the legacies of globalization.

*Baccini: Professor of Political Science, McGill University. Email: leonardo.baccini@mcgill.ca. Kleinberg: Associate Professor of Political Science, Binghamton University. Email: kkleinbe@binghamton.edu. Weymouth: Dean's Professor of International Political Economy, McDonough School of Business, Georgetown University. Email: stephen.weymouth@georgetown.edu.
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Introduction

AI-driven automation is reopening a central political question in democratic capitalism. When jobs become more insecure, do citizens turn toward a larger government role in the economy? Globalization and technological change have already disrupted employment and weakened confidence that markets deliver secure work and fair pay in many advanced economies (Boix, 2019; Milner, 2021a; Wolf, 2023). Yet this erosion of confidence is not universal. In labor-abundant developing countries, where globalization expanded employment and income opportunities, support for market-oriented policies has remained comparatively strong (Rudra et al., 2021; Mansfield et al., 2021; Gaikwad and Suryanarayan, 2019; Pew Research Center, 2014). We explain this divergence, and whether it persists under AI, by showing how globalization legacies shape perceived market legitimacy and condition support for government involvement in the economy. The central argument is that the political effects of AI-driven displacement risk depend on the employment legacies created by globalization.

Our paper examines successive technological shocks and their effects on perceived market legitimacy—the belief that markets deliver secure work and fair pay. The first shock, globalization driven by advances in information and communication technologies (ICT), reorganized production across borders according to comparative advantage (Baldwin, 2016). In capital-abundant economies, offshoring and import competition displaced low-skilled manufacturing workers, eroding confidence in markets and fueling a backlash against globalization (Autor et al., 2013, 2020; Baccini and Weymouth, 2021; Bisbee et al., 2020; Colantone and Stanig, 2018; Milner, 2021b; Margalit, 2011; Jensen et al., 2017; Broz et al., 2021; Mansfield and Rudra, 2021; Rommel and Walter, 2018; Walter, 2021; Baccini et al., 2025). In labor-abundant economies, globalization expanded manufacturing employment and strengthened the view that markets were delivering (Mayda and Rodrik, 2005; Rudra et al., 2021; Mansfield et al., 2021; Dolan and Milner, 2023). These divergent experiences generated durable beliefs about whether market integration provides economic security. These beliefs form the baseline against which citizens evaluate the next disruption. When AI displacement risk becomes salient, it compounds existing doubts where globalization weakened confidence in markets.

This argument shifts focus from views about trade to broader attitudes about the government's role in the economy. Whereas prior studies examine support for trade liberalization (Bisbee and Rosendorff, 2024; Rho and Tomz, 2017; Scheve and Slaughter, 2001; Mayda and Rodrik, 2005), we study whether repeated disruptions change views about whether government should take greater responsibility for ensuring jobs and a decent standard of living, or leave individuals to provide for themselves. In our account, globalization influenced market legitimacy, and that legitimacy conditions how individuals view the role of the state when AI threatens employment.

The empirical analysis proceeds in three steps. First, we use cross-national data from the World Values Survey (WVS) to assess whether country-level trade exposure explains variation in perceived market legitimacy and support for government involvement in the economy. We find that legitimacy declines and support for government involvement is stronger where manufacturing employment eroded, and that this pattern is more pronounced among low-skilled workers in countries experiencing trade-induced deindustrialization. Second, we leverage policy variation in the case of NAFTA to study changes in attitudes in the capital-abundant United States and labor-abundant Mexico. We exploit pre-NAFTA variation in industry composition, interacted with the post-NAFTA shock, to estimate how trade reallocation affected attitudes toward government responsibility in both countries. The results show that NAFTA shifted demand for state intervention in opposite directions: upward among low-skilled Americans in exposed industries and downward among low-skilled Mexicans in industries where manufacturing employment expanded.

Third, we field original, preregistered survey experiments in the United States and Mexico that randomly assign respondents to information about worker displacement by AI. These experiments test whether the same displacement information affects perceived market legitimacy and support for government involvement differently across the two countries. We find a clear divergence in legitimacy, with the AI treatment reducing market legitimacy in the United States but not in Mexico. The treatment increases support for government involvement in both countries, but the U.S. effect operates in part through legitimacy while the Mexico effect does not. Together, these results support the argument that globalization legacies shape how individuals interpret AI displacement risk and, in turn, how they think about the government's economic role.

Our globalization legacy framework helps explain a striking divergence in attitudes toward AI across countries. Respondents in the United States and other industrialized nations tend to view AI more negatively than those in countries where globalization expanded manufacturing employment and trade (Figure 1). The economic gains or losses from the earlier shock shape how citizens interpret the next one.

Our paper builds on research examining how trade and automation shape political attitudes. Existing work shows that automation anxiety can generate anti-globalization sentiment and that these responses depend in part on whether automation is attributed to foreign competition (Wu, 2021; Chaudoin and Mangini, 2024). Magistro et al. (2025) compares reactions to automation and globalization

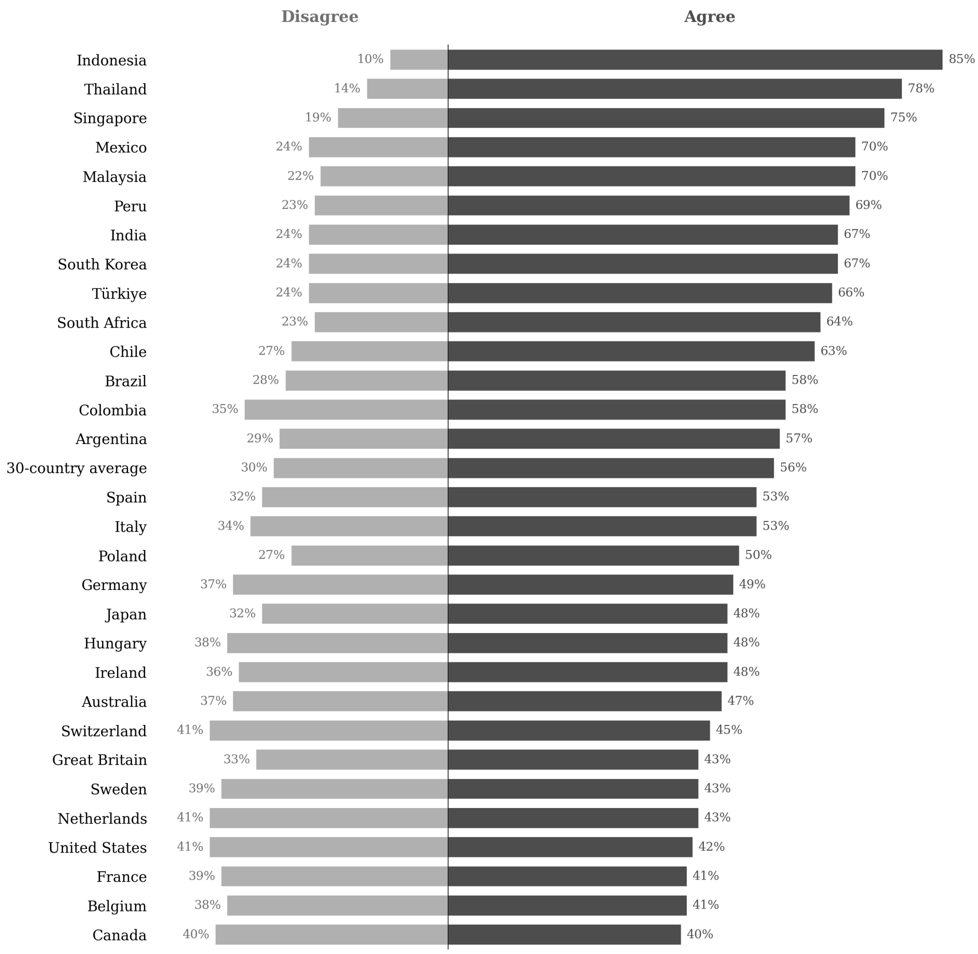

Figure 1: Cross-national variation in AI optimism. Percentage of respondents who agree or disagree with the statement: "Products and services using artificial intelligence have more benefits than drawbacks." (Source: Ipsos 2025 Survey)

directly by examining support for firms' offshoring and AI adoption. Other work links automation risk to demand for government action to mitigate its negative effects (Ehret, 2022; Gallego et al., 2021; Haslberger et al., 2025; Magistro et al., 2024; Menon and Zhang, 2025). We extend this literature by asking how the two shocks interact over time: globalization legacies shape perceived market legitimacy and thereby condition political responses to AI displacement risk. Where globalization left scars, AI threatens to deepen them.

Theoretical Framework

We explain attitudes toward the government's role in the economy. By "role," we mean the scope of the state's responsibility for protecting citizens against economic insecurity. Our focus is narrow and economic: whether government should take greater responsibility for ensuring jobs and a decent standard of living, or whether individuals should largely be left to provide for themselves. These views capture what citizens think the state ought to do, not whether they approve of current leaders or believe government has performed well.

Our theory links these attitudes to sequential technological shocks through perceived market *legitimacy*. By legitimacy, we mean sociotropic judgments about whether the economy delivers secure work and fair compensation. These judgments are shaped by collective economic experience and by the national narratives that emerge from it, rather than by individual experience alone.[1] Legitimacy therefore differs from economic expectations, which are forward-looking beliefs about personal circumstances and can change quickly as new information arrives.

As legitimacy is relatively durable, it conditions how citizens respond to subsequent shocks. Where earlier experience has already weakened legitimacy, new displacement risk is more likely to increase concern about whether markets will continue to provide economic security and to raise support for government involvement.[2] Where earlier experience has reinforced legitimacy, the same shock should be less destabilizing. In this sense, legitimacy is the mechanism linking economic shocks to attitudes about the government's role in the economy.

With this concept in mind, we turn to the two shocks that influenced market legitimacy in our framework. The first shock, ICT-enabled globalization, reshaped employment trajectories across countries according to comparative advantage. In capital-abundant economies, offshoring and import competition reduced manufacturing employment; in many labor-abundant economies, trade integration expanded it. These divergent experiences generated distinct national accounts of whether globalization delivered broad-based opportunity or instead produced insecurity. We use the term narratives to refer to widely shared understandings of whether globalization brought broad-based opportunity or instead generated insecurity, rooted in collective economic experience and reinforced by elite discourse and media (Ballard-Rosa et al., 2024; Boucher and Thies, 2019; Kim, 2023; Menon and Osgood, 2024; Wolak and Peterson, 2020).[3] Where manufacturing employment expanded, political debate reinforced the view that markets were delivering; where it contracted, the prevailing account emphasized dislocation and insecurity. The resulting narratives

[1] We also distinguish legitimacy from economic anxiety and from downstream policy attitudes. Economic anxiety refers to personal insecurity, while support for redistribution or trade protection refers to policy preferences.

[2] While declining legitimacy could in principle be blamed on governments, our expectation is that worsening employment conditions will generally increase demands for government action. When markets fail, citizens are more likely to expect state intervention, even if confidence in government is limited.

[3] We highlight narratives that are national in scope. Citizens may receive and interpret them differently, according to their values and material circumstances (Ballard-Rosa et al., 2024), and the ways in which elites and media reinforce them (Kim, 2023).

shape how citizens well beyond those directly affected understand globalization's distributive consequences, including who the winners and losers are (Ballard-Rosa et al., 2024; Menon and Osgood, 2024).

These narratives form the market legitimacy baseline against which citizens interpret the second shock, AI-driven automation. When automation risk becomes salient, it is more likely to weaken perceived market legitimacy where the prevailing narrative already casts markets as failing to provide secure work and fair compensation. As perceived legitimacy declines, individuals become more supportive of an expanded government role to shield against risk and provide economic security, rather than letting people fend for themselves. We refer to this as a compounding process: globalization legacies shape how individuals interpret AI displacement risk and the government's role in responding to it.

Factor Endowments, Trade, and the Government's Economic Role

We begin with how ICT-enabled globalization reshaped employment across countries and skill groups. Classic trade theory implies that openness shifts gains toward the abundant factor and losses toward the scarce one (Stolper and Samuelson, 1941). In the globalization era, these distributional effects appeared most clearly in manufacturing. Advances in information and communication technologies made it easier to fragment production across borders and build global supply chains (Baldwin, 2016; Mansfield and Rudra, 2021). Firms in capital-abundant economies increasingly offshored labor-intensive stages of production to labor-abundant economies, in line with comparative advantage.

The political consequences differed across national economies. In many capital-abundant economies, this process reduced manufacturing employment through import competition and offshoring (see, e.g., Autor et al., 2013; Broz et al., 2021; Fort et al., 2018; Pierce and Schott, 2016). Concentrated losses in tradable industries fueled electoral backlash against incumbents seen as having failed to protect workers (Baccini and Weymouth, 2021; Jensen et al., 2017; Margalit, 2011; Colantone and Stanig, 2018). In many labor-abundant countries, by contrast, trade liberalization expanded manufacturing employment (Erten and Leight, 2021; McCaig and Pavcnik, 2018) and increased support for trade among low-skilled workers (Dolan and Milner, 2023; Milner and Kubota, 2005).

These differential employment legacies gave rise to distinct narratives about whether markets delivered opportunity and security. Changes in manufacturing employment became a highly visible signal trade's consequences. Globalization's distributional effects proved durable, shaping national economic narratives that have persisted into the AI era. Where industry declined, confidence that markets would provide secure work and fair compensation eroded (Walter, 2017; Beramendi et al., 2015).

Trade should therefore influence support for government involvement through its effects on market legitimacy. Where globalization strengthened perceived legitimacy, support for an expanded government role should be lower. Where globalization weakened it, support for a more active government role should be higher.

Hypothesis 1 (Trade Shocks and the Government's Economic Role)**.** *Support for government involvement in the economy is stronger (weaker) where trade shocks decreased (increased) manufacturing employment.*

Globalization gave rise to national narratives, but its distributional effects varied within countries. In line with Stolper–Samuelson logic, trade integration benefited the locally abundant factor and harmed the scarce one. In many labor-abundant economies, export-oriented manufacturing expansion improved employment prospects for less-skilled workers; in many capital-abundant economies, import competition and offshoring reduced manufacturing employment for less-skilled workers. The result is a skill-based difference in how individuals experience globalization, shaping whether it is perceived as increasing or decreasing employment security.

These experiences matter because they shape how citizens evaluate whether markets are working and the degree to which the state should intervene. When individuals' own labor-market opportunities improve, their assessments of market legitimacy improve; when opportunities deteriorate, they are more likely to conclude that markets are not reliably providing economic security. These evaluations shape attitudes about the role of government in the economy.

Table 1: Predicted Effects of Trade Exposure on Market Legitimacy and Support for Government Involvement

Worker Type/ Country Endowment	**Market Legitimacy**	**Support for Gov't Involvement**
Low skilled, capital abundant	Negative	Positive
Low skilled, labor abundant	Positive	Negative
High skilled, capital abundant	Positive	Negative
High skilled, labor abundant	Negative	Positive

Table 1 summarizes the resulting predictions. In capital-abundant economies, low-skilled workers who faced the clearest employment losses from trade should assess lower market legitimacy and higher support for government involvement than high-skilled workers. In labor-abundant economies, the sign flips for low-skilled workers because export-oriented manufacturing expansion improved their employment prospects, raising legitimacy and reducing demand for government involvement. Among high-skilled workers, legitimacy should increase less because the employment gains from manufacturing expansion are more concentrated among the less-skilled, and it may be unchanged or even decline relative to less-skilled workers. These implications motivate our next hypothesis.

Hypothesis 2 (Trade and Worker Skill Levels)**.** *Trade shocks have a more positive effect on support for increased government involvement in the economy among low-skilled workers in capital-abundant economies and a more negative effect among low-skilled workers in labor-abundant economies; the reverse pattern holds for high-skilled workers.*

In what follows, we argue that AI automation is evaluated through these inherited assessments of market legitimacy, shaping support for government involvement across countries.

Automation, Employment Security, and the Government's Economic Role

Trade displaced workers along predictable factor lines, making individual skill a strong predictor of who experienced insecurity and who did not. AI-driven automation operates differently. AI systems increasingly substitute for labor across occupations and sectors, automating tasks that appear in both routine and non-routine work, including in non-tradable occupations (Acemoglu and Restrepo, 2020; Frey and Osborne, 2017; Webb, 2020; Eloundou et al., 2023; Eisfeldt et al., 2023). AI can also enhance productivity and generate employment in complementary activities, producing new patterns of economic winners and losers (Babina et al., 2024; Hui et al., 2024). But while the precise labor-market effects remain uncertain, a central concern is that AI could displace large numbers of workers by automating tasks they currently perform (Frey and Osborne, 2017). Because exposure is task-based rather than sector-based, the disruption is more likely to be perceived as economy-wide.

This difference in the structure of exposure has an important implication for the theory. Trade sorted citizens into winners and losers along fairly visible lines of skill and sector, making individual education or industry of employment a basis for political attitudes. AI disruption does not yet divide individuals as cleanly. When people lack a clear basis for assessing their own exposure, they are more likely to rely on broader assessments of whether markets deliver economic security. Those assessments are shaped by national experience with globalization. The implication is that the compounding effect of AI displacement risk should appear primarily at the country level, through cross-national differences in legitimacy baselines, more so than through skill-based responses within countries.

AI automation shapes attitudes toward the government's economic role by shifting perceived market legitimacy. When AI-driven displacement risk becomes salient, it weakens assessments of whether the economy will continue to deliver employment opportunities. Even though most AI-related displacement has not yet materialized, public debate and information about projected job loss can still erode confidence in markets. As that confidence declines, support for government involvement increases. Although AI will likely affect some occupations more than others, public debate often frames automation risk in sociotropic terms, as a threat to the economy's capacity to provide work.

Hypothesis 3 (Automation Risk—Main Effect)**.** *The threat of AI-driven automation increases support for government involvement in the economy.*

The political impact of automation depends on prior exposure to ICT-enabled globalization. Trade legacies sustain national economic narratives that shape baseline perceived market legitimacy. The compounding effect operates through these inherited assessments: AI displacement risk shifts political attitudes more where globalization undermined confidence in markets, because legitimacy is already low and the marginal effect of further decline is larger.[4] Where globalization strengthened legitimacy, the same displacement risk should produce smaller changes in support for more government responsibility.

This logic suggests systematic variation across countries with different factor endowments. In capital-abundant countries, globalization generated visible dislocation among low-skilled workers, contributing to weaker baseline legitimacy. Concentrated manufacturing losses became politically salient, reinforcing narratives that globalization had not delivered secure work and fair pay (Ballard-Rosa et al., 2024). In labor-abundant economies, globalization was more often associated with employment expansion in export-oriented manufacturing, contributing to stronger baseline legitimacy. The effect of AI displacement risk on support for government involvement should therefore be larger in capital-abundant economies.

Hypothesis 4 (Automation Risk in Capital- vs. Labor-Abundant Economies)**.** *AI-driven displacement increases support for government involvement in the economy more in capital-abundant economies than in labor-abundant economies.*

We also evaluate a more demanding skill-based hypothesis as a direct test of whether factor-based distributional politics from trade carry over to automation.

[4]This builds on the argument that macroeconomic crisis can "catalyze" the political consequences of long-run economic decline in particular places (Broz et al., 2021). The Appendix formalizes this implication.

Trade created within-country winners and losers, which can translate into different baseline market legitimacy across skill groups. In capital-abundant economies, low-skilled workers were more exposed to trade dislocation and may therefore respond more strongly to information about automation risk. In labor-abundant economies, low-skilled workers gained more from globalization, so the same automation risk may produce a smaller shift in support for government involvement.

Hypothesis 5 (Compounding by Skill)**.** *AI-driven displacement increases support for government involvement in the economy more among low-skilled workers in capital-abundant economies (e.g., the United States) than among low-skilled workers in labor-abundant economies (e.g., Mexico).*

For this prediction to hold, individuals would need to map AI displacement risk onto the same factor- or industry-based cleavages that trade produced. That may be less likely if AI risk is perceived in sociotropic rather than individual terms (Haslberger et al., 2025). One reason is that some low-skilled workers may believe AI primarily threatens higher-skilled occupations, weakening any straightforward extension of trade-based legitimacy patterns. Another is that automation risk is task-based and harder to assign to particular industries than trade exposure, which may lead citizens to rely more on national narratives than on their own labor market position.

Our examination of H5 will adjudicate between these contending possibilities, and a null result would be informative. If country-level compounding holds but skill-level compounding does not, the evidence points toward sociotropic evaluation over factor-based distributional politics as the main channel through which AI shapes demand for government involvement. This could be either because citizens evaluate automation risk through national-level legitimacy baselines, or because perceived AI displacement does not track the skill cleavages that trade created. It will be important to assess our results alongside H4: if country-level compounding through legitimacy beliefs holds but skill-level compounding does not, the evidence points toward sociotropic evaluation over factor-based distributional politics as the main channel through which AI shapes demand for government involvement.[5] We propose mediation analyses to shed additional light.

Figure 2 summarizes the argument. Trade legacies shape perceived market legitimacy, which in turn influences support for government involvement (H1, H2). AI displacement risk increases support for government involvement in the economy (H3), but its effect depends on the legitimacy baseline that globalization established. Where globalization weakened legitimacy, AI displacement risk produces a larger

[5]We return to this distinction when discussing the experimental results.

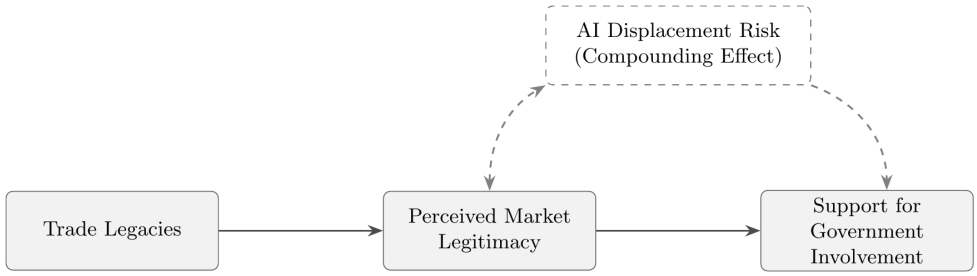

Figure 2: Theoretical Framework

response in favor of government; where it strengthened legitimacy, the response is smaller (H4, H5).

Observational Analysis

The observational analysis evaluates whether globalization created the employment legacies that anchor baseline views about the state's economic role. We first use the WVS to test whether support for government responsibility is higher where manufacturing employment declined during the era of trade integration (H1), and whether this relationship is stronger among lower-skilled workers (H2). We then use the policy shock of NAFTA to examine the same logic, using pre-NAFTA industry composition to measure local exposure to the trade shock in the United States and Mexico. These analyses examine the baseline attitudes that condition responses to AI in the experimental analysis.

Data

We begin with a cross-country analysis to examine H1. Our final dataset includes more than 220,000 respondents surveyed in four WVS waves: 1994–1998, 1999–2004, 2005–2009, and 2010–2014.

To build our main independent variable, we use data on tariff cuts in *all* preferential trade agreements (PTAs) signed by the following trading entities: Australia, Canada, China, Japan, New Zealand, the United States, and the EU. In short, the data include all North–South PTAs plus all PTAs signed by China. The time span is 1995 to 2014. For each agreement, the data record the identity of partners, the year of signature and implementation, sector coverage, depth of commitments, and compliance tools. The dataset provides information on baseline tariffs and the stipulated reductions over time during the implementation period for each product at the level of 6-digit Harmonized System (HS) code, up to 12 years after implementation. Tariff schedules are extracted from the officially negotiated schedules listed in the appendices of the PTAs.[6] Since agriculture products are often carved out from tariff schedules and services are mostly non-tradable, these tariff cuts are overwhelmingly in manufacturing. The dataset comes from Baccini et al. (2018).

We use these preferential tariff cuts (PRF) to build our measure of trade exposure. In particular, we estimate the following:

$$Trade\ Exposure_i = \sum_{jk}^{n} PRF_{ijk} \times \frac{Import_{ijk}}{GDP_j}, \tag{1}$$

where PRF_{ijk} is the preferential tariff cut implemented by country i with country j in product k. PRF is the difference between the MFN tariff (i.e., the pre-PTA tariff) and the preferential tariff in year zero of each PTA, i.e., when PTAs enter into force. $\frac{Import_{ijk}}{GDP_j}$ is the total volume of imports from country j to country i in product k (weighted by the size of country j's economy). Both imports and GDP are pre-PTA values. For each country i, we then take the sum of Equation 1 across preferential trade partners j and products k. Intuitively, *Trade Exposure* has high values when country i implements large tariff cuts in products in which it imports large volumes, i.e., in comparative-disadvantage products. This variable is our main proxy for exposure to the first wave of technological shock.[7]

Moreover, we merge these data with International Labour Organization (ILO) statistics[8] measuring the growth of manufacturing employment as a share of total employment. Changes in manufacturing employment provide an alternative proxy for trade exposure since manufacturing concentrated the most visible dislocation and expansion associated with ICT-enabled offshoring and import competition. For each country, we take the average share of manufacturing employment in 1990–1994 and in 1995–2014, then compute the difference (post- minus pre-share of manufacturing employment). Countries with a positive value experienced growth in manufacturing employment, whereas those with a negative value experienced a decline during this period. We label this variable *Growing Manufacturing*.[9]

The correlation between *Trade Exposure* and *Growing Manufacturing* is negative and large, i.e., $\rho \approx -0.5$, which validates our proxy for exposure to globalization.

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[6] The tariff cuts we consider are *de jure* and not *de facto*, since countries can still set applied tariffs that differ from the negotiated ones.

[7] We standardize this variable, which has a very large range. Results are not affected by standardization.

[8] This dataset measures the share of industry employment, which includes construction, mining and quarrying, electricity, and gas and water supply in addition to manufacturing. More information is available at `https://ilostat.ilo.org/methods/concepts-and-definitions/classification-economic-activities/` and `https://databank.worldbank.org/metadataglossary/world-development-indicators/series/SL.IND.EMPL.ZS`.

[9] Table B1 in Appendix B lists countries with growing manufacturing and countries with declining manufacturing.

Countries that cut tariffs in comparative-disadvantage products have experienced a decline in manufacturing.

To explore how trade affects cross-country attitudes toward the government's economic role across skill levels (H2), we interact our main independent variable (*Trade Exposure*) with a dummy capturing whether respondents have a college degree (our measure of skill level).

Outcome Variables

We measure attitudes toward the government's role in the economy using the following question available in the WVS: "Some people argue that people should take more responsibility to provide for themselves. Suppose those people are on one end of a scale, at point 1. Others argue that government should take more responsibility to ensure that everyone is provided for. Suppose those people are on the other end of the scale, at point 10. Where would you place yourself on this scale?" This measure captures preferences regarding the state's role in providing economic security. We label this variable *Government Involvement*.

Empirical Strategy

We use the following model specification to test H1:

$$Y_{i,t} = \alpha_0 + \beta_1 \mathit{Trade\ Exposure}_c + \beta_2 \mathit{College}_i + \beta_3 \mathbf{X}_i + \epsilon_{i,t}, \tag{2}$$

where $Y_{i,t}$ represents our measure of attitudes toward the government's economic role. *Trade Exposure* is the main independent variable capturing the impact of the first technological shock. *College* denotes respondents' skill level, included as an additive covariate. The key coefficient of interest is β_1, which we expect to be positively correlated with demand for government involvement in the economy. $\mathbf{X}_i$ is a matrix of individual-level controls (age and gender). $\epsilon_{i,t}$ are the residuals. We estimate ordinary least squares (OLS) models with robust standard errors, weighting all regressions to correct for sample bias.

To test H2, we estimate:

$$\begin{aligned} Y_{i,t} = &\alpha_0 + \beta_1 \mathit{Trade\ Exposure}_c + \beta_2 \mathit{College}_i \\ &+ \beta_3 \mathit{Trade\ Exposure}_c \times \mathit{College}_i + \beta_4 \mathbf{X}_i + \epsilon_{i,t}. \end{aligned} \tag{3}$$

This equation interacts *Trade Exposure* with *College*. The coefficient of interest, β_3, captures how the effect of trade exposure varies by skill group. Consistent with our theory, we expect this interaction to be negative: In capital-abundant economies, where globalization eroded employment prospects, low-skilled respondents (without a college degree) should demand state involvement more than high-skilled respondents (with a college degree) do. Symmetrically, in labor-abundant economies, where globalization improved employment prospects, low-skilled respondents (without a college degree) should demand state involvement less than high-skilled respondents (with a college degree) do. This specification exploits variation across individuals only.

Results

Table 2 reports the results of both the additive and the interaction models, which support H1 and H2. The coefficient of *Trade Exposure* is positive and significant in Model 1. As expected, respondents exposed to globalization, which has led to a decline in manufacturing over the past three decades, are more likely to demand state involvement. The magnitude of the effect is sizable: Moving the value of *Trade Exposure* from one standard deviation below the mean to one standard deviation above the mean increases support for government involvement by 10%. This finding validates H1.

	(1)	(2)
	OLS	
	Favoring Government Involvement	
Trade Exposure	0.365***	0.394***
	(0.013)	(0.014)
College	-0.311***	-0.307***
	(0.019)	(0.019)
Trade Exposure*College		-0.131***
		(0.017)
Constant	10.433***	10.425***
	(0.181)	(0.181)
Country-level controls	Yes	Yes
Individual-level controls	Yes	Yes
Observations	151,815	151,815

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2: Trade Exposure and Support for Government Involvement

Figure 3 shows the graphical results of Model 2, which validate H2. In countries with high exposure to trade and declining manufacturing, respondents without a college degree are *more* likely to demand state involvement than low-skilled respondents in countries with low trade exposure (and growing manufacturing). While low-skilled workers tend to favor state involvement more than high-skilled workers in every country, the difference in demand for state involvement widens significantly in countries with high trade exposure (and declining manufacturing). The magnitude of the effect is large: Moving the value of *Trade Exposure* from one standard deviation below the mean to one standard deviation above the mean decreases the marginal effect by 14%.

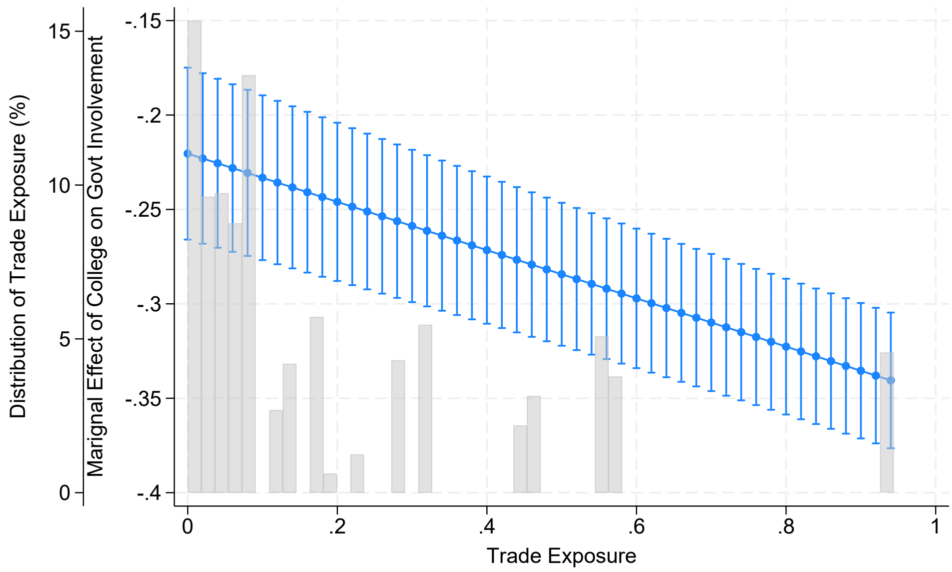

Figure 3: Government Involvement, Trade Exposure, and Individuals' Skills

We perform three additional tests to corroborate our analysis, which we report in Appendix B.1. First, we show that our results are similar if we limit our variable *Trade Exposure* to manufacturing (Table B2). This finding is not surprising, since North–South PTAs liberalize mainly the manufacturing sector. Second, we re-run our main models using respondents from WVS waves prior to 1995. Results show that we observe the opposite patterns compared to post-1995 waves (Table B3). This finding is in line with our theory: Prior to globalization, winners and losers are the scarce factor of production, which benefits from protectionism, echoing Rogowski (1989). The first wave of technological shock reversed this pattern and produced a defining structural transformation in both developed economies and emerging markets. Third, we re-run the interaction models including country fixed effects. Note that we are unable to include *Trade Exposure*, whose coefficient is absorbed by country fixed effects. Results remain unchanged (see Table B4 and Figure B1).

Cohort Analysis

We implement further tests of H1 and H2. Following Besley et al. (2025), we build a variable capturing the manufacturing decline (or growth) experienced by different cohorts of respondents in the WVS. Specifically, we measure cohort experiences with manufacturing decline (or growth) within countries using the following equation:

$$\bar{g}_{ibcts} = \frac{\sum_{k=1}^{\text{age}_{ibct}-1} w_{ibct}(k,\lambda)\, g_{bct-k}}{\sum_{k=1}^{\text{age}_{ibct}-1} w_{ibct}(k,\lambda)}, \tag{4}$$

where $w_{ibct}(k,\lambda) = (\text{age}_{ibct} - k)^{\lambda}$. For individual i in birth cohort b in country c up to survey year t in survey s, we take a weighted average of all past manufacturing decline realizations, $g_{bc,t-k}$, across the individual's lifetime since birth. This measure varies at the country $\times$ birth–cohort level. The weights in Equation 4, $w_{ibct}(k,\lambda)$, are a function of age, and the parameter λ determines how manufacturing decline realizations at different points in an individual's lifetime are weighted up to the year before they are surveyed (i.e., $t-1$). Following Besley et al. (2025), we set $\lambda = 1$ so that manufacturing decline experiences are linearly related to past growth realizations over the life cycle. We label this variable *Declining Manufacturing Experience*.

To test H1, we regress our measure of support for state involvement on *Declining Manufacturing Experience*, adding individual-level controls (education, gender, and race/ethnicity) in addition to country-wave fixed effects. Moreover, we interact *Declining Manufacturing Experience* with *College* to test H2. We run OLS regressions with standard errors clustered at the country–cohort level, as in Besley et al. (2025).

Results are reported in Table 3. Model 1 shows that the coefficient of *Declining Manufacturing Experience* is positive, as expected, and statistically significant. In short, individuals who have experienced declining (growing) manufacturing over their life span are more (less) likely to demand state involvement to guarantee jobs and a good standard of living. The magnitude of the effect is sizable: Moving the value of *Declining Manufacturing Experience* from one standard deviation below the mean to one standard deviation above the mean increases support for government involvement by 7%. This finding validates H1.

Figure 4 shows that the interaction effect validates H2. The slope of the marginal effect is negative, implying that low-skilled workers demand *more* state involvement in countries/cohorts that have experienced declining manufacturing compared to low-skilled workers in countries/cohorts that have experienced growing manufacturing. For large values of *Declining Manufacturing Experience*, the marginal effect crosses zero, i.e., there is no significant difference between low- and high-skilled workers in terms of favoring state involvement.[10] The magnitude of the effect is very large: Moving the value of *Declining Manufacturing Experience* from one stan-

[10]Results are similar if we include experience with economic growth by cohort in our models (see Table B5) in Appendix B.2.

dard deviation below the mean to one standard deviation above the mean decreases the marginal effect by 50%.

	(1)	(2)	(3)	(4)
	OLS			
	Favoring Government Involvement			
Declining Manufacturing Experience	0.541**	0.468*	0.478*	0.495*
	(0.224)	(0.280)	(0.283)	(0.281)
College			-0.276***	-0.269***
			(0.023)	(0.022)
Declining Manufacturing Experience*College			-0.145***	-0.150***
			(0.048)	(0.048)
Constant	6.204***	6.288***	6.315***	6.283***
	(0.034)	(0.090)	(0.056)	(0.090)
Country-wave FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	381,546	270,465	270,608	270,465

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3: Government Involvement and Experience with Declining Manufacturing

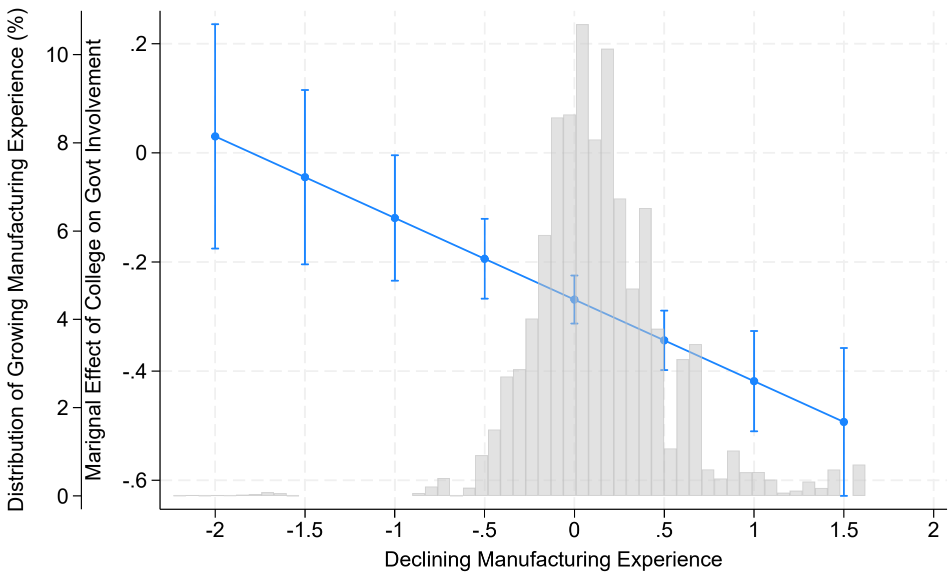

Figure 4: Government Involvement, Experience with Declining Manufacturing, and Individuals' Skills

The Case of NAFTA

We next examine NAFTA as a case study. NAFTA is an informative case because its implementation led to a dramatic increase in exports from Mexico (a labor-abundant country) to the United States (a capital-abundant country), with Mexico's trade surplus with the United States roughly quadrupling by 2008 (Choi et al., 2024).

NAFTA coincided with dramatic reductions in wage growth for U.S. blue-collar workers in the most affected industries (Hakobyan and McLaren, 2016) and an expansion in manufacturing jobs in Mexico (Trachtenberg, 2019). These contrasting employment effects made NAFTA a central episode in how each country understood the gains and losses of globalization. Mexico is also a relatively conservative test of the argument: its broader post-NAFTA growth record was modest, even if trade integration expanded manufacturing employment in exposed regions.

Data. Following Choi et al. (2024), we build the following variable to capture trade exposure:

$$Trade\ Exposure_{s,1990} = \frac{\sum_{j=1}^{J} L_{1990}^{sj} RCA_{1990}^{j} \tau_{j,1990}}{\sum_{j=1}^{J} L_{1990}^{sj} RCA_{1990}^{j}} \tag{5}$$

where L_{1990}^{sj} is employment in industry j in state s in 1990 for the US and in region s in 1990 for Mexico.[11] RCA_{1990}^{j} captures Mexico's "revealed comparative advantage" (RCA) in industry j in 1990. RCA is a standard index in international economics that captures a country's relative advantage or disadvantage in a particular sector based on trade flows.[12] It is based on the Ricardian concept of comparative advantage and is calculated as the share of a country's exports in a given sector, $\frac{E_{cp}}{\sum_{p'} E_{cp'}}$, divided by the share of world exports in that sector, $\frac{\sum_{c'} E_{c'p}}{\sum_{c',p'} E_{c'p'}}$, where E_{cp} is country c's exports in product p, c' indexes all other countries, and p' indexes all other products. A comparative advantage is "revealed" if the RCA value exceeds 1; otherwise, the country is considered to have a comparative disadvantage. $\tau_{j,1990}$ is the ad-valorem equivalent tariff rate of industry j in 1990.[13]

L_{1990}^{sj} is the only component of Equation 5 that differs between the US and Mexico. Our measure of *Trade Exposure* captures an opportunity for Mexico, especially in areas with high employment in industries protected by high US tariffs pre-NAFTA and in which Mexico has an RCA. Indeed, the highest values of this variable for Mexico are in Mexican states near the US border (see Figure B3 in Appendix B). In contrast, *Trade Exposure* captures a vulnerability for the US, especially in areas

[11] Employment data come from IPUMS for Mexico [accessed in November 2025] and from Choi et al. (2024) for the US (the original source is the County Business Patterns from the US Census). In the WVS, we can only geolocate Mexican respondents in large regions: *Norte* (North), *Centro* (Center), *Sur* (South), and *Zona Metropolitana* (Metropolitan Zone). States belonging to the *Norte* region are the following: Baja California, Baja California Sur, Sonora, Chihuahua, Coahuila, Nuevo León, Tamaulipas, Durango, and Sinaloa. States belonging to the *Centro* region are the following: Aguascalientes, Guanajuato, Querétaro, San Luis Potosí, Zacatecas, Jalisco, Colima, Michoacán, Hidalgo, Puebla, and Tlaxcala. States belonging to the *Sur* region are the following: Chiapas, Oaxaca, Guerrero, Veracruz, Tabasco, Campeche, Yucatán, and Quintana Roo. States belonging to the *Zona Metropolitana* region are the following: Distrito Federal, Hidalgo, Mexico City, Morelos, and Tlaxcala.

[12] RCA data are drawn from the Comtrade database [accessed in October 2025].

[13] Tariff data come from Choi et al. (2024) (the original source is Feenstra et al. (2002)).

with high employment in industries protected by high tariffs pre-NAFTA and in which Mexico has an RCA. Indeed, the highest values of this variable for the US are in the *Rust Belt* and in southern states close to the Mexican border (see Figure B4 in Appendix B).

There are a few things to note about this measure. First, it uses only pre-NAFTA measures of both Mexican RCA and state-level industrial composition, and thus does not pick up any endogenous reaction to NAFTA itself. Second, since the large majority of tariffs go to zero in 1994, there is an extremely high correlation between 1990 tariffs and the 1990 to 2000 change in tariffs (Choi et al., 2024). In other words, protection in the 1990–1993 window becomes aggressive liberalization in the 1994–2000 window, which mirrors a trade shock. Unlike other shift-share instruments (e.g., (Autor et al., 2013)), ours is based on a policy (preferential tariffs) rather than on actual flows (imports). Thus, if anything, our measure is less endogenous to economic confounders than China Trade Shock-like measures.

We merge *Trade Exposure* with the WVS survey (for Mexico) and with the ANES (for the US) to obtain our outcome variables capturing attitudes toward state involvement. For the WVS, we rely on the second (1989–1993) and third (1994–1998) waves. For the ANES, we rely on the 1990 and 1992 waves for the pre-NAFTA period and the 1994, 1996, 1998, and 2000 waves for the post-NAFTA period. Therefore, we are left with only two periods for both Mexico and the US, i.e., pre- and post-NAFTA.[14] We do not include waves after 2000 because we are interested in the short-term effect of NAFTA, i.e., a local treatment effect, which is easier to identify. We are also concerned about the China Trade Shock post-2000, which is likely to correlate with our measure of trade exposure.

Empirical strategy. Armed with this dataset, we estimate the following model:

$$\begin{aligned} Y_{is,t} =& \alpha + \beta_1 \, \text{Trade Exposure}_s \times \text{PostNAFTA}_t + \beta_2 \, \text{Trade Exposure}_s \times \text{College}_{is,t} \\ & + \beta_3 \, \text{College}_{is,t} \times \text{PostNAFTA}_t + \beta_4 \, \text{Trade Exposure}_s \times \text{PostNAFTA}_t \times \text{College}_{is,t} \\ & + X'_{is,t}\beta_5 + \delta_s + \tau_t + \epsilon_{is,t} \end{aligned} \tag{6}$$

where $Y_{is,t}$ is our outcome capturing individual-level support for state involvement. We rely on the same variable as above for the WVS. For the ANES, we use the following question: "Some people argue that the government should let each person get ahead. Suppose those people are on one end of a scale, at point 1. Others argue that the government should see to it that every person has a job and a good standard of living. Suppose those people are on the other end of the scale, at point 7. Where would you place yourself on this scale?" $PostNAFTA_t$ is a dummy that scores 1 after 1994 and $College_{is,t}$ is a variable scoring 1 if respondents have

[14]Concretely, we collapse pre- and post-NAFTA waves by individuals and states in the ANES to end up with two periods.

a college degree. We include individual-level controls in $X_{is,t}$, i.e., age, gender, ideology, and race/ethnicity. We also include state (US) or region (Mexico) fixed effects and a dummy for the post-treatment period (period fixed effects). Note that the coefficients of *Trade Exposure* and *PostNAFTA* are absorbed by state/region and period fixed effects, respectively. We run OLS estimates. For the US analysis, we double-cluster the standard errors by both state and period. For Mexico, we use (jackknife) bootstrap standard errors, given the very low number of units (i.e., four regions).

Results. We show the results graphically in Figures 5 and 6.[15] Remember that for both countries, high values of the outcome imply higher support for state involvement. Both figures report the marginal effect of *College* in the pre- and post-NAFTA period for different values of *Trade Exposure*.

We begin with Mexico (Figure 5). Recall that *Trade Exposure* captures trade potential in the US market for Mexico. In the pre-NAFTA period, low-skilled workers demand more state involvement in regions with high employment in RCA industries compared to high-skilled workers. These industries are still protected in the US and therefore there are no gains from trade for Mexican low-skilled workers (blue). The pattern is reversed in the post-NAFTA period, in which exports from Mexico to the US have boomed as preferential tariffs go to zero. As they gain from access to the US market, low-skilled workers demand *less* state involvement in regions with high employment in RCA industries compared to high-skilled workers after 1994 (red line). The magnitude of the effect is very large: Moving the value of *Trade Exposure* from one standard deviation below the mean to one standard deviation above the mean increases the marginal effect by 50% in the post-NAFTA period.

We turn now to the US (Figure 6). Before NAFTA, US industries in which Mexico has an RCA are protected by high tariffs. As a result, losses from trade are limited for low-skilled Americans, who demand less state involvement than high-skilled Americans. In the post-NAFTA period, preferential tariffs go to zero and low-skilled Americans feel the heat of import competition from Mexico. Hence, low-skilled workers employed in industries in which Mexico has an RCA start demanding more state involvement than high-skilled workers, who are largely unaffected by NAFTA.[16] The magnitude of the effect is very large: Moving the value of *Trade Exposure* from one standard deviation below the mean to one standard deviation above the mean decreases the marginal effect by 60% in the post-NAFTA period.

[15] Table B6 in Appendix B.3 reports the results of the two models.

[16] Figures B5 and B6 in Appendix B.3 show that our results are similar if we limit our measure of trade exposure to manufacturing.

All in all, the case of NAFTA largely corroborates the results from previous analyses and strongly supports H2.

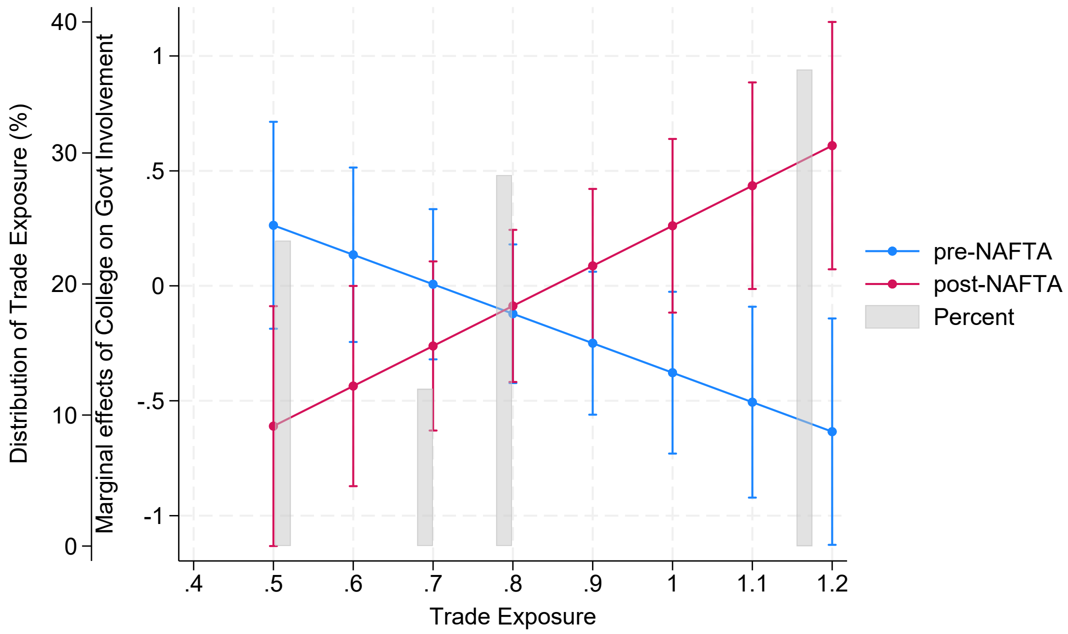

Figure 5: Mexico: Government Involvement, Trade Exposure, and Individuals' Skills

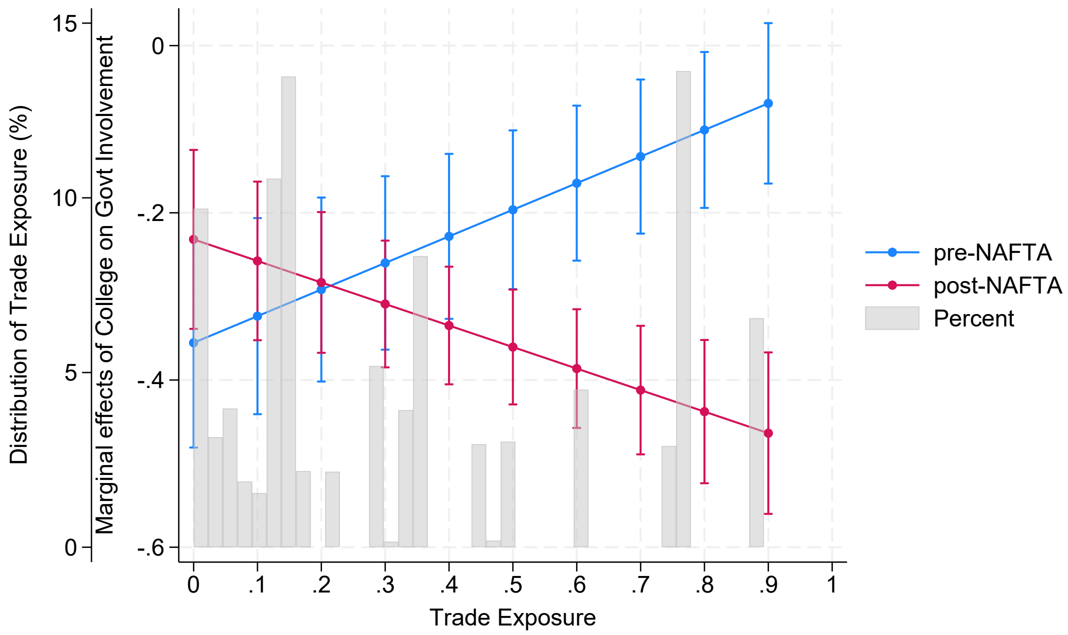

Figure 6: US: Government Involvement, Trade Exposure, and Individuals' Skills

Experimental Analysis

To test our hypotheses linking AI automation to support for government involvement in the economy (H3–H5), we conducted original, pre-registered surveys with embedded experiments in Mexico and the United States. Because our theory predicts variation across countries with different factor endowments, we compare a relatively labor-abundant country (Mexico) with a relatively capital-abundant one (the United States), as we do in the observational analysis. We selected these cases for two main reasons, which are evident from the NAFTA case presented above. First, our observational analysis shows that manufacturing employment has expanded in Mexico but declined in the United States over the past 30 years (see Table B1). Second, the two countries share a long border and have deeply integrated economies, first through NAFTA and now under the United States–Mexico–Canada Agreement. Trade integration has benefited low-skilled Mexican workers while disadvantaging low-skilled American workers (Jensen and Rosas, 2007). In short, there is a clear link between ICT-enabled globalization and manufacturing growth (decline) in Mexico (the US).

The experimental analysis has two overarching goals. First, the experimental design allows us to estimate the causal effect of exposure to salient information about AI-driven job displacement on support for government involvement in the economy. Second, the survey experiment allows us to test the causal effect of that information on perceived market legitimacy, which mediates the effect of technological shocks on support for government involvement in the economy, and are not readily available in most existing surveys. Figure 7 clarifies the empirical tests that we run in this part of the analysis.

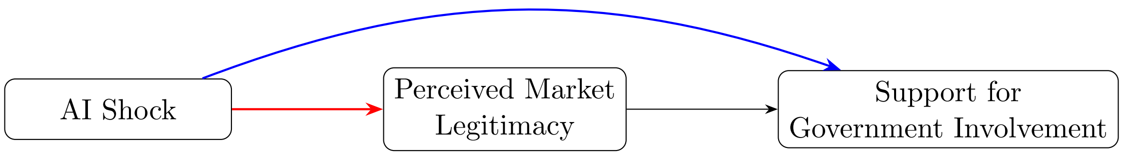

Figure 7: Direct (blue) and mediated (red) effects.

Research Design

The surveys were administered by Bilendi in Mexico and Forthright in the United States. Both companies fielded large online samples (3,017 and 4,196 respondents, respectively) with age, gender, and regional distributions similar to those of the adult population. The samples are drawn from non-probability online panels used primarily for market research. Participation is voluntary and requires a double opt-in registration. The surveys were conducted simultaneously from August 14 to August 25, 2025.[17]

After providing informed consent, participants answered screening questions (age, gender, ideology, and state) as well as questions about their familiarity with and use of AI. We also collected measures of personal economic optimism and life satisfaction.[18] To test H5, respondents were block-randomized by education level (college degree versus no college). In both countries, we oversampled respondents with a college degree (comprising 50% of each sample) to ensure sufficient power for the interaction tests. While block randomization is not required for H3 and H4, it does not affect the design's internal validity.[19]

The survey included a between-subject informational experiment. Participants were randomly assigned to one of two groups: (1) a treatment providing information about AI-related job displacement risk or (2) a control group that received no information about AI. We expect the treatment to reduce confidence in market self-regulation and increase support for government involvement by making large-scale displacement risk more salient.

AI Treatment. The treatment provides respondents with a scenario of AI displacement risk, anchored in each country's prior globalization experience by design. Because our theory predicts that automation risk is interpreted against inherited legitimacy baselines, the relevant contrast is not attitudes toward AI displacement in the abstract but responses to the same displacement information among citizens whose confidence in markets has already been shaped by globalization.

Participants in the treatment group received information indicating that AI could automate roughly 45% of each country's projected 2035 workforce.[20]

According to U.S. Bureau of Labor Statistics projections, total U.S. employment in 2035 will be approximately 178 million, so a 45% automation rate implies a loss of 80 million jobs (U.S. Bureau of Labor Statistics, 2024). In Mexico, the National Institute of Statistics and Geography (INEGI) recorded 60.7 million employed in early

[17] The study was pre-registered and adheres to the American Political Science Association Principles and Guidance for Human Subjects Research. The anonymized pre-analysis plan is available at https://aspredicted.org/xh7j-xkfj.pdf. The survey complies with APSA Principles and Guidance. Appendix D details ethical considerations.

[18] Appendix F reports the exact question wording.

[19] Respondents had to pass an attention check to proceed. We excluded those who failed it, those who completed the survey in less than half the median completion time, and those who provided uniform responses across all outcomes. More details are provided in Appendix E.

[20] This estimate synthesizes several prominent forecasts, including Frey and Osborne (2017), which predicts that 47% of U.S. jobs are at high risk of computerization; McKinsey Global Institute's estimate that 30% of U.S. work hours could be automated by 2030 (Ellingrud et al., 2023); PwC's projection that 38–44% of jobs in OECD countries are at high risk by the 2030s (PricewaterhouseCoopers, 2018); Banxico's task-based estimate that 57–65% of Mexican jobs face high automation risk (Cebreros et al., 2020); and the IMF's global assessment that roughly 40% of jobs are exposed to AI (Cazzaniga et al., 2024).

2025. Assuming 0.8–0.9% annual growth yields an estimated 66 million workers by 2035, so a 45% automation rate equates to about 30 million jobs lost (Instituto Nacional de Estadística y Geografía, 2025). The treatment was designed to present a high salience displacement scenario rather than a forecast about the most likely employment path under AI.

Participants in the AI treatment were shown a figure charting projected job losses due to AI. For U.S. respondents, Figure 8 plots employment losses rising from 2 million in 2025 to 30 million in 2030 and 80 million in 2035, consistent with high-end projections (ET Online, 2025). For Mexican respondents, the same trajectory was scaled by 0.375, showing losses increasing from 0.8 million to 11 million to 30 million by 2035. The experiment identifies the effect of exposure to a severe AI job-loss scenario.

Each figure incorporated data on prior manufacturing job losses (U.S.) or gains (Mexico) to anchor the AI displacement scenario in each country's globalization experience. This framing underscored the sequential nature of technological shocks: for U.S. respondents, AI displacement dwarfs prior manufacturing decline; for Mexican respondents, automation threatens to undo earlier employment gains.[21]

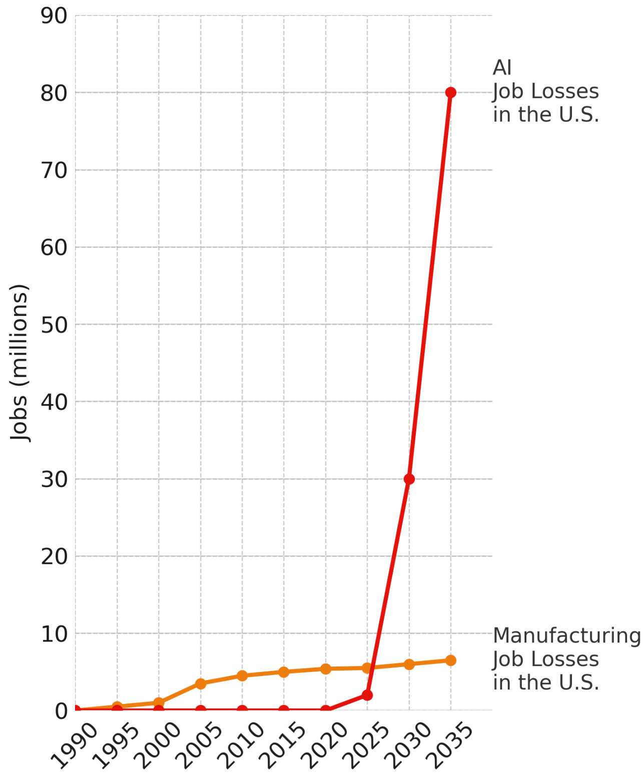

Figure 8: AI Treatment (U.S.)

[21]Tables C1 and C2 in Appendix C.2 show evidence of balance checks for key socio-demographic variables across experimental conditions in both Mexico and the US.

The accompanying treatment text for U.S. participants states: "AI is replacing workers by automating complex tasks once performed by humans. Jobs once considered secure are being eliminated as AI surpasses human capabilities. These AI job losses are expected to far exceed the jobs lost in U.S. manufacturing over the past several decades." The final sentence of the Mexico treatment was modified to reference prior job *gains* in manufacturing. We interpret this treatment as a test of how respondents react to information about large-scale AI displacement, not as a test of attitudes toward AI in general.

Control Group. Respondents in the control condition received no information and no figure.

Attention Checks and Manipulation Tests

Our surveys included three attention and manipulation checks to verify that respondents understood and retained the treatment information and that it influenced their perceptions of AI's impact on employment.

First, we asked respondents to recall the exact number of job losses shown in Figure 8. Over 90% of participants correctly recalled the figure presented in the treatment, confirming strong attention to the stimulus.

Second, we asked: "Based on the information you saw earlier in the graph, which of the following is true? [AI will lead to job losses / AI will not lead to job losses]." As expected, respondents exposed to the AI treatment were overwhelmingly more likely to state that AI will lead to job losses compared to those in the control group (Figure 9).

Third, we asked: "How concerned are you that AI will replace millions of human workers over the next decade? [1 = not concerned, 7 = very concerned]." Figure 10 shows that treated respondents express substantially greater concern about AI-driven job displacement than those in the control group in both countries. Together, these results confirm that respondents understood and internalized the treatment message and that it effectively shaped perceptions of AI-related labor risks.

Outcome Variables

Our theory predicts that information about AI job loss increases support for government involvement (H3–H5) and does so, in part, by weakening perceived market legitimacy. We therefore examine two outcomes: market legitimacy and support for government involvement. If the AI treatment reduces legitimacy in the United States but not in Mexico, this would indicate that displacement risk deepens existing doubts about markets. The measures of support for government involvement

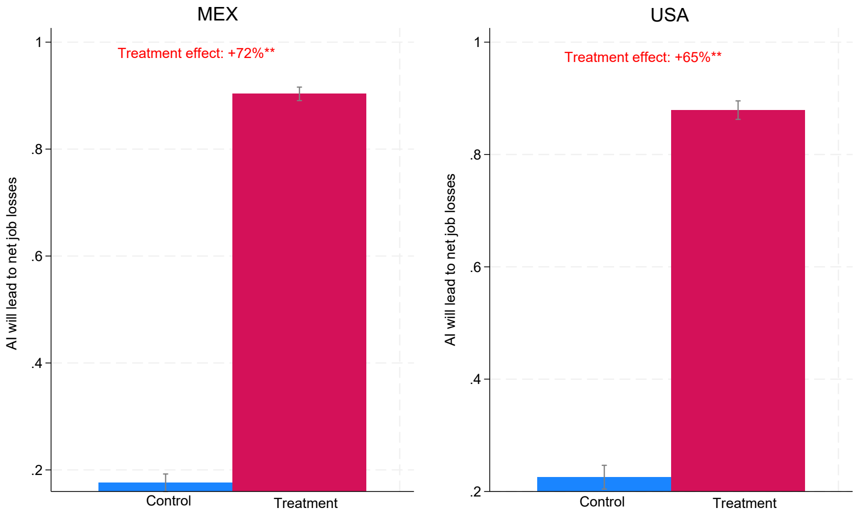

Figure 9: Attention Check: Perceived AI Impact on Employment (Control vs. Treatment)

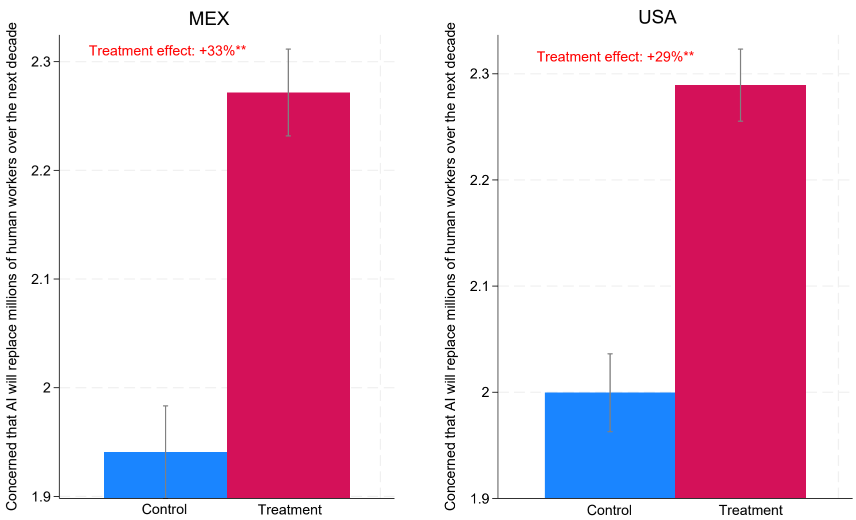

Figure 10: Manipulation Check: Concern About AI Replacing Human Workers

parallel those used in the observational analysis, while the legitimacy items allow us to test the mechanism directly.

To capture beliefs about legitimacy, we use two questions:

1. Do you agree or disagree with the following statement? "In the next decade, the Mexican/American economy will provide job opportunities for those who want to work." [1 = strongly disagree, 7 = strongly agree]

2. Do you agree or disagree with the following statement? "In the next decade, the Mexican/American economy will fairly compensate workers for their labor." [1 = strongly disagree, 7 = strongly agree]

We then use principal component analysis (PCA) to combine these two correlated items into a single standardized index. We label this outcome *Market Legitimacy.*

To capture support for government involvement in the economy—more precisely, preferences for an interventionist mode of market governance rather than leaving outcomes primarily to markets—we rely on the following three questions, two of which are the same as in the observational analysis:

1. As our main measure of support for government involvement in the economy, we use the same question as in the WVS: "Some people argue that people should take more responsibility to provide for themselves. Suppose those people are on one end of a scale, at point 1. Others argue that government should take more responsibility to ensure that everyone is provided for. Suppose those people are on the other end of the scale, at point 7. Where would you place yourself on this scale?"

2. We also use the same question as in the ANES: "Some people feel that the government should just let each person get ahead on their own. Suppose those people are on one end of a scale, at point 1. Others think the government should see to it that every person has a job and a good standard of living. Suppose those people are on the other end of the scale, at point 7. Where would you place yourself on this scale?"

3. Finally, to capture the same underlying orientation without explicitly invoking government—which can cue evaluations of incumbents—we include a trade-off item contrasting market-determined outcomes with arrangements that prioritize job security: "Some people prefer an economy with high potential earnings but also high risk of job loss. Suppose these people are on one end of a scale, at point 1. Others prefer an economy where earnings are more limited but job security is high. Suppose those people are on the other end of the scale, at point 7. Where would you place yourself on this scale?"[22]

We then create a standardized index, which we label *Government Involvement*, using the PCA of these correlated questions. These questions capture attitudes toward market governance and the state's role in managing economic risk.

[22] This question gets at a more abstract preference over economic governance rather than attitudes toward "the government". A preference for security over higher-risk, higher-reward outcomes reflects support for institutions and policies that mitigate market risk even when respondents are not prompted to think explicitly about government. Consistent with this interpretation, the three items load closely on a common factor in both countries (see Table C3 in Appendix C).

Factor analysis confirms that the two sets of outcome items load onto two factors corresponding to legitimacy and government involvement in both countries (see Table C3 in Appendix C).

To complement these measures, we also include two questions capturing possible policy responses to AI:

1. Would you favor government restrictions on AI use? [1 = strongly disagree, 7 = strongly agree]

2. To what extent do you agree or disagree with the following statement: "The government should support workers displaced by AI." [1 = strongly disagree, 7 = strongly agree]

We create a standardized index, which we label *Government AI Intervention*, using the PCA of these correlated questions.

Moreover, we include two open-ended questions on AI benefits and risks: "What concerns you most about AI?" and "What excites you most about AI?" We analyze these responses to corroborate the experimental patterns.

Empirical Strategy

We estimate the following model to test H3 and H4:

$$Y_i = \alpha_0 + \beta_1 AI\ \ Treatment_i + \epsilon_i, \tag{7}$$

where Y_i captures perceived market legitimacy and individual attitudes toward the government's economic role. $AI\ \ Treatment_i$ is the main independent variable. The coefficient β_1 captures the causal effect of AI job-loss information on these attitudes; we expect it to be positive for support for government involvement (and negative for confidence in markets). In some specifications, we include a matrix of individual-level controls (e.g., age, education, gender, and ideology); ϵ_i denotes the residuals. We estimate ordinary least squares (OLS) regressions with robust standard errors.

To test H5, we modify Equation 7 to include an interaction term with education (our measure of skill):

$$Y_i = \alpha_0 + \beta_1 AI\ \ Treatment_i + \beta_2 College_i + \beta_3 AI\ \ Treatment_i \times College_i + \epsilon_i. \tag{8}$$

The key coefficient of interest is β_3, which captures how the effect of AI exposure varies by skill level. If trade-era skill cleavages carry over to responses to AI displacement risk, β_3 to be negative in the United States and positive in Mexico. As before, we include the same set of individual-level controls in some model specifications and estimate OLS regressions with robust standard errors.

Results

Figures 11 and 12 show the results of the additive models from Equation 7. We begin with perceived market legitimacy (Figure 11). The average treatment effect (ATE) of the AI treatment is negative and significant in the US. When exposed to the AI treatment, American respondents are less likely to perceive the market as legitimate compared to the control group. The effect is large: a 20% drop in the legitimacy index. In contrast, the ATE is not significant for Mexican respondents. The difference between the two treatment effects (i.e., US–MEX) is negative and significant. This cross-national divergence in legitimacy responses is the clearest evidence for the paper's compounding logic.

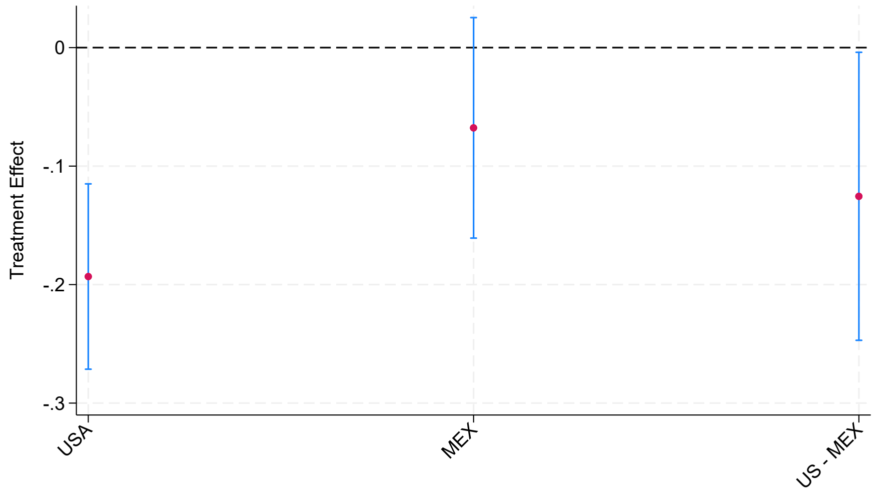

Figure 11: AI Treatment and Market Legitimacy

For support for government involvement, Figure 12 shows that the ATE of the AI treatment is positive and significant for both Mexico and the US. When exposed to the AI treatment, American respondents are roughly 20% more likely to support government involvement in the economy compared to the control group. The effect is about half as large for Mexican respondents, i.e., 10%. The difference between the two treatment effects (i.e., US–MEX) is positive, but not significant.

Taken together, the findings in Figures 11 and 12 support H3 and provide qualified support for H4. In particular, the fact that the same treatment erodes legitimacy in the United States but not in Mexico is consistent with the logic of H4.

Appendices C.1 and C.2 report several additional results. The AI treatment also increases support for AI-specific government responses in both countries. Alternative constructions of the outcome indexes yield similar substantive patterns,

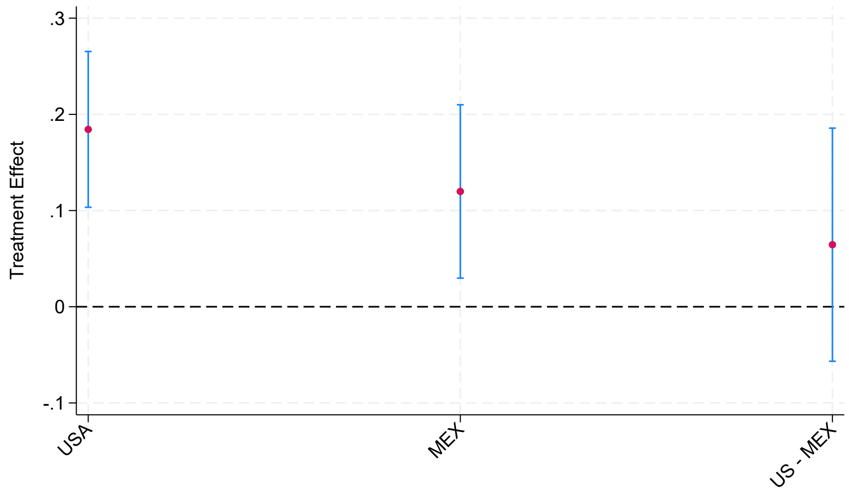

Figure 12: AI Treatment and Support for Government Involvement

although the clearest and most consistent cross-national difference appears for market legitimacy rather than for the total effect on government involvement.[23]

Table 4 presents results from the interaction models in Equation 8 to evaluate H5. The interaction effects are not statistically significant predictors of attitudes toward the government's economic role (see also Figures C9–C14 in Appendix C.1). Overall, we find little evidence for H5.[24]

The absence of skill-based compounding is substantively informative. The observational findings show how trade formed legitimacy baselines differently across skill groups. The experimental results show that exposure to AI displacement information does not activate those legitimacy baselines along the same skill lines. This pattern suggests that AI is judged less through personal skill-based exposure than trade was.[25]

This difference follows from the structure of the two shocks. Trade exposure created clearer winners and losers across skill groups and sectors, giving individuals a basis for evaluating both their own position and the national experience. AI,

[23]Figure C2 shows positive and significant treatment effects on *Government AI Intervention* in both Mexico and the United States. Tables C4–C7 report results for the individual components of the three indexes. In Mexico, the estimated effect on *Government Involvement* is driven mainly by the WVS-style item. Using simple standardized averages instead of PCA yields similar results (Figures C6–C8). Dropping the other two components of the government-involvement index does not change the main findings (Figures C4 and C5).

[24]Results are similar if we use a simple average rather than PCA to construct our indexes (Table C8).

[25]We find little evidence of other heterogeneous effects, including by ideology, age, gender, AI usage, and individual optimism or pessimism (Tables C9 and C11 in Appendix C.2). The main exception is *Government AI Intervention* in the U.S. sample, where treated respondents without a college degree are more likely than treated respondents with a college degree to support AI restrictions and compensation for AI-induced job losses. The corresponding interaction is not significant in Mexico (Figure C14).

	(1)	(2)	(3)	(4)
	Mexico		US	
	Market Legitimacy	Government Involvement	Market Legitimacy	Government Involvement
AI Treatment	-0.119*	0.143**	-0.204***	0.160***
	(0.066)	(0.064)	(0.055)	(0.058)
College	-0.330***	-0.237***	-0.137**	-0.051
	(0.065)	(0.064)	(0.056)	(0.058)
AI Treatment*College	0.091	-0.049	0.024	0.048
	(0.094)	(0.092)	(0.080)	(0.083)
Constant	0.196***	0.057	0.166***	-0.067
	(0.046)	(0.045)	(0.039)	(0.041)
Observations	3,002	2,956	4,195	4,171

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4: AI Treatment and Skill Levels

by contrast, is harder to map onto skill or sectoral cleavages. Its distributional effects remain uncertain, and early evidence points to a task-based disruption that cuts across occupations and skill levels.[26] In the absence of clear distributional consequences, citizens may rely more on national narratives shaped by globalization.

Taken together, these results suggest that cross-country differences matter more than the skill cleavages associated with trade politics in shaping responses to AI displacement information. Unlike trade, AI does not sort people as clearly by skill or sector. That makes it harder for respondents to interpret the shock through their own labor-market position, which may help explain why we find little evidence of skill-based compounding. Responses instead appear to be shaped more by broader national narratives than by group cleavages.

Mediation Analysis

The political effects of automation may operate, in part, through market *legitimacy*—individuals' beliefs that the economy delivers secure work and fair compensation. Where globalization weakened employment prospects, citizens may interpret AI displacement as confirming a pattern of market failure, making the legitimacy channel more salient. Where globalization strengthened confidence, the same displacement risk may increase support for government involvement without eroding legitimacy beliefs. Mediation analysis allows us to assess whether the same shock shifts policy demand through different channels in the U.S. and Mexico.

We estimate nonparametric mediation models using the `mediation` package in R with 5,000 quasi-Bayesian simulations, following Imai et al. (2010). The mediator is *Market Legitimacy*. The outcome is *Government Involvement*. We estimate a

[26] Eloundou et al. (2023). Future research could build on Owen and Johnston (2017) to map task-based AI exposure to political responses.

mediator model regressing *Market Legitimacy* on the treatment indicator, and an outcome model regressing *Government Involvement* on both the treatment and the mediator.

Causal mediation requires the sequential ignorability assumption—that no unobserved confounders jointly influence the mediator and the outcome—which is untestable. Following Keele (2015), we evaluate whether the empirical patterns are consistent with the hypothesized mechanism rather than claiming definitive causal identification (p. 510). Our theory predicts that the legitimacy channel should operate where globalization eroded confidence in markets. In our data, the treatment significantly lowers legitimacy in the United States but has no effect in Mexico, consistent with that expectation.

Figure 13 presents the results as a path diagram. Each panel displays estimates from two regressions: the first regresses the legitimacy index on the treatment indicator (yielding the a path), and the second regresses the government involvement index on both the treatment and legitimacy (yielding the b and c' paths). The indirect effect is the product $a \times b$, and the direct effect c' captures the remaining treatment effect that bypasses legitimacy.

In the United States, the AI treatment significantly reduces perceived market legitimacy ($a = -0.147$, $p < 0.01$), and lower legitimacy in turn predicts greater support for government involvement ($b = -0.302$, $p < 0.01$). The resulting indirect effect is 0.044 standard deviations, accounting for approximately 32% of the total treatment effect. The direct effect remains significant ($c' = 0.094$, $p < 0.01$), indicating that legitimacy is an important but not exclusive channel.[27]

In Mexico, the treatment does not significantly reduce market legitimacy ($a = -0.047$, $p > 0.10$); the indirect effect is indistinguishable from zero. The treatment nonetheless increases support for government involvement—consistent with H3—but does so entirely through the direct path ($c' = 0.101$, $p < 0.01$). This suggests that Mexican respondents view AI displacement as a policy challenge warranting a government response rather than as evidence of declining market legitimacy.

Notably, the b path differs in sign across the two countries, negative in the United States (-0.302) but positive in Mexico (0.128). In the United States, market confidence and demand for government involvement are substitutes, with those who trust markets wanting less state intervention. In Mexico, they are complements: confidence in markets coexists with support for an active state. One possible explanation is that respondents view the state as having facilitated Mexico's globalization gains.

[27]Sensitivity analyses using `medsens` indicate that an unobserved confounder would need to produce a correlation of approximately $\rho = -0.31$ between the mediator and outcome residuals to reduce the U.S. indirect effect to zero, suggesting that the estimated mediation is robust to plausible levels of unmeasured confounding.

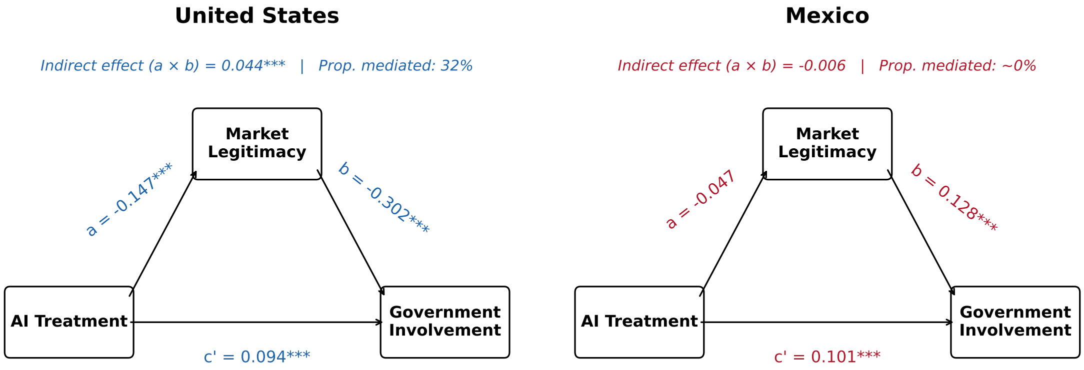

Figure 13: **Mediation of AI Job-Loss Treatment Effects through Market Legitimacy.**
Notes: The a path is the coefficient from regressing the legitimacy index on the treatment indicator. The b and c' paths are coefficients from regressing the government involvement index on both the treatment and legitimacy. The indirect effect is the product $a \times b$. All variables are standardized first principal components. Estimated using the `mediation` package in R with 5,000 quasi-Bayesian simulations. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

While both countries show significant treatment effects consistent with H3, the cross-country difference in total effects is not statistically significant. The mediation results clarify why: the direct effects are nearly identical across countries ($c' = 0.094$ in the U.S. and $c' = 0.101$ in Mexico), and the U.S. total treatment effect is larger (0.138 vs. 0.095) because it operates through an additional channel—the erosion of market legitimacy—that is absent in Mexico. We interpret this pattern as consistent with the paper's core compounding argument: the same AI displacement information increases support for government involvement in both countries, but only in the United States does it operate through an erosion of market legitimacy.

Text Analysis

We further assess how respondents interpret the benefits and risks of AI using two open-ended survey questions: "What excites you most about AI?" and "What concerns you most about AI?" We analyze responses using structural topic models and report the five most prevalent topics in each country (Figure 14).

The AI benefit responses show two patterns. Americans are more likely to describe AI in aspirational terms—*innovation* and *creativity*—but they are also more likely to report *nothing* that excites them. Mexicans, by contrast, emphasize concrete usefulness: *solving problems* is more prevalent in Mexico than in the United States.

The AI risk responses show an even sharper contrast. Americans disproportionately associate AI with *unemployment*, making employment displacement the dominant concern. Mexican respondents focus less on job loss and more on misuse

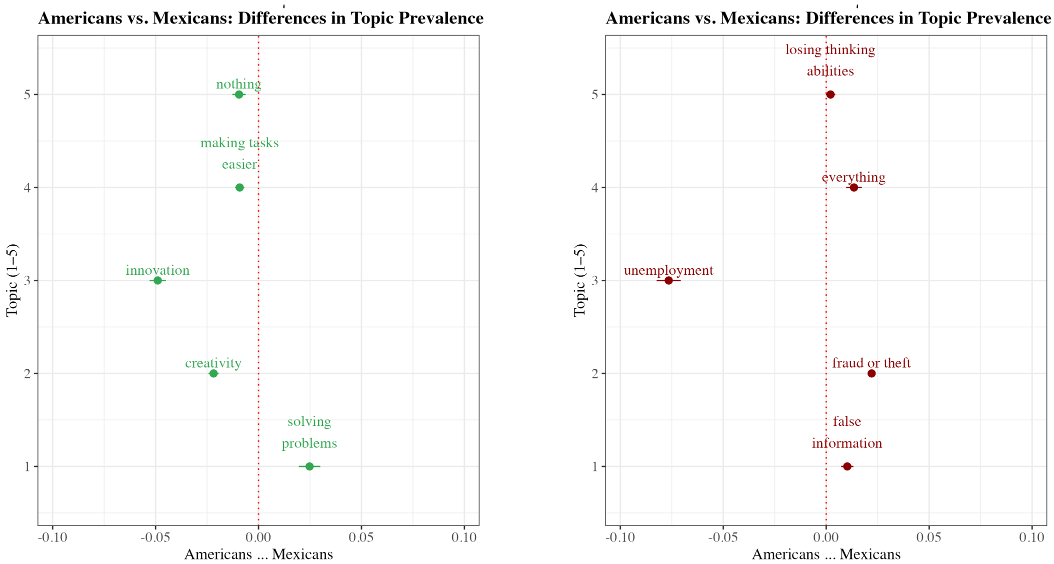

Figure 14: Open-Ended Questions: AI Benefits (Left) and AI Risks (Right)

and social harms—*fraud or theft* and *false information*—along with broader worries (e.g., *everything* and *losing thinking abilities*). This split lines up with the mediation results: the AI treatment reduces market legitimacy in the United States but not in Mexico, even as support for government involvement increases in both countries. Overall, the open-ended responses are consistent with the claim that globalization legacies shape how individuals interpret AI displacement risk, especially whether it is experienced as a threat to employment security and market legitimacy.

Conclusion

This paper shows that technological disruptions to labor markets reshape support for government involvement in the economy, and that these effects unfold sequentially across shocks. The first disruption, ICT-enabled globalization, reallocated employment globally according to comparative advantage. Where manufacturing expanded, confidence that markets deliver secure work and fair pay strengthened. Where manufacturing employment declined, confidence eroded and citizens became more likely to look to government for economic security.

AI-driven automation is interpreted against country-level baselines of market legitimacy. Those baselines were shaped by ICT-enabled globalization and the employment gains and losses it produced. In our account, globalization set the baseline and information about AI displacement updates attitudes against it.

We find that AI differs from trade in how its distributional effects map onto politics. The effects of trade exposure on support for government involvement follow factor endowments and skill. AI's distributional consequences remain uncertain: we do not yet know which jobs and tasks will be displaced at scale or how firms will reorganize work in response. In that setting, exposure does not sort citizens cleanly by skill or occupation. Consistent with this implication, we find little evidence that AI displacement risk activates the same skill-based cleavages that drive trade politics. Our findings caution against mechanically extending factor-based trade politics to the politics of AI.

At the same time, our experiments show that support for a more active government role rises in both the United States and Mexico when respondents are exposed to information about large-scale AI displacement. What differs is the mechanism: in the United States, the response operates partly through reduced market legitimacy, whereas in Mexico it does not. Even where globalization previously strengthened confidence in markets, large-scale AI displacement can still increase demand for government involvement.

Our paper suggests several avenues for future research. First, what is the scope of globalization legacies beyond the attitudes examined here? If trade exposure reshapes beliefs about market legitimacy, it may also influence political behavior. Second, how general is the sequential logic we identify? It may extend beyond AI to other disruptions that shift employment risk, such as the green energy transition. Third, as the labor-market effects of AI become clearer, politics may sort more cleanly along skill- or occupation-based lines rather than through the sociotropic narratives we emphasize here, with implications for political coalitions and voting (Antoniades et al., 2025; Borwein et al., 2025, 2024). Finally, our analysis leaves open the question of how legitimacy beliefs translate into policy outcomes. It will be important to examine how party competition and elite messaging shape which narratives about markets and the state prevail as AI displacement arrives.

References

Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy*, 128(6):2188–2244.

Antoniades, A., Balcazar, C. F., Chatzikonstantinou, M., and Kern, A. (2025). The electoral consequences of ai adoption: Evidence from us elections. *Available at SSRN 5975634*.

Autor, D., Dorn, D., Hanson, G., and Majlesi, K. (2020). Importing political polarization? the electoral consequences of rising trade exposure. *American Economic Review*, 110(10):3139–3183.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, 103(6):2121–2168.

Babina, T., Fedyk, A., He, A., and Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151:103745.

Baccini, L., Ciobanu, C., and Krzysztof, P. (2025). The source of economic shocks matters for their political outcomes. *Research & Politics*, 12(3).

Baccini, L., Dür", A., and Elsig, M. (2018). Intra-industry trade, global value chains, and preferential tariff liberalization. *International Studies Quarterly*, 62(2):329–340.

Baccini, L. and Weymouth, S. (2021). Gone for good: Deindustrialization, white voter backlash, and us presidential voting. *American Political Science Review*, 115(2):550–567.

Baldwin, R. (2016). *The great convergence: Information technology and the new globalization*. Harvard University Press.

Ballard-Rosa, C., Goldstein, J. L., and Rudra, N. (2024). Trade as villain: belief in the american dream and declining support for globalization. *The Journal of Politics*, 86(1):274–290.

Beramendi, P., Häusermann, S., Kitschelt, H., and Kriesi, H. (2015). *The politics of advanced capitalism*. Cambridge University Press.

Besley, T., Dann, C., and Dray, S. (2025). Growth experiences and trust in government. *Quarterly Journal of Economics*.

Bisbee, J., Mosley, L., Pepinsky, T. B., and Rosendorff, B. P. (2020). Decompensating domestically: The political economy of anti-globalism. *Journal of European Public Policy*, 27(7):1090–1102.

Bisbee, J. and Rosendorff, B. P. (2024). Antiglobalization sentiment: Exposure and immobility. *American Journal of Political Science*.

Boix, C. (2019). *Democratic Capitalism at the Crossroads: Technological Change and the Future of Politics*. Princeton University Press.

Borwein, S., Bonikowski, B., Loewen, P., Magistro, B., and Lee-Whiting, B. (2024). Who can assert ownership over automation? workplace technological change, populist and ethno-nationalist rhetoric, and candidate support. *Political Behavior*, 46(4):2191–2214.

Borwein, S., Bonikowski, B., Loewen, P. J., Lee-Whiting, B., and Magistro, B. (2025). Perceived technological threat and vote choice: evidence from 15 european democracies. *West European Politics*, 48(3):534–561.

Boucher, J.-C. and Thies, C. G. (2019). "i am a tariff man": The power of populist foreign policy rhetoric under president trump. *The Journal of Politics*, 81(2):712–722.

Broz, J. L., Frieden, J., and Weymouth, S. (2021). Populism in place: The economic geography of the globalization backlash. *International Organization*, 75(2):464–494.

Cazzaniga, M., Jaumotte, F., Li, L., Melina, G., Panton, A. J., Pizzinelli, C., Rockall, E., and Tavares, M. M. (2024). Gen-ai: Artificial intelligence and the future of work. Staff Discussion Note SDN/2024/001, International Monetary Fund.

Cebreros, A., Heffner-Rodríguez, A., Livas, R., and Puggioni, D. (2020). Automation technologies and employment at risk: The case of mexico. Working Paper 2020-11, Banco de México.

Chaudoin, S. and Mangini, M.-D. (2024). Robots, foreigners, and foreign robots: Policy responses to automation and trade. *Journal of Politics*.

Choi, J., Kuziemko, I., Washington, E., and Wright, G. (2024). Local economic and political effects of trade deals: Evidence from nafta. *American Economic Review*, 114(6):1540–1575.

Colantone, I. and Stanig, P. (2018). The trade origins of economic nationalism: Import competition and voting behavior in western europe. *American Political Science Review*, 112(2):201–218.

Dolan, L. R. and Milner, H. V. (2023). Low-skilled liberalizers: Support for free trade in africa. *International Organization*, 77(4):848–870.

Ehret, S. (2022). Public preferences for governing ai technology: Comparative evidence. *Journal of European Public Policy*, 29(11):1779–1798.

Eisfeldt, A. L., Jin, A. L., Kepler, C., and Wittenberg-Moerman, R. (2023). Generative ai, firm-level impacts, and labor market dynamics. *NBER Working Paper*. Working Paper.

Ellingrud, K., Sanghvi, S., Madgavkar, A., Dandona, G. S., Chui, M., White, O., and Hasebe, P. (2023). Generative ai and the future of work in america.

Eloundou, T., Manning, A., Rock, D., and Brynjolfsson, E. (2023). Gpts are gpts: An early look at the labor market impact potential of large language models. *arXiv preprint arXiv:2303.10130*.

Erten, B. and Leight, J. (2021). Exporting out of agriculture: The impact of wto accession on structural transformation in china. *Review of Economics and Statistics*, 103(2):364–380.

ET Online (2025). Think your job is safe from ai? these 4 careers are already on the chopping block.

Feenstra, R. C., Romalis, J., and Schott, P. K. (2002). Us imports, exports, and tariff data, 1989-2001.

Fort, T. C., Pierce, J. R., and Schott, P. K. (2018). New perspectives on the decline of us manufacturing employment. *Journal of Economic Perspectives*, 32(2):47–72.

Frey, C. B. and Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerization? *Technological Forecasting and Social Change*, 114:254–280.

Gaikwad, N. and Suryanarayan, P. (2019). Attitudes toward globalization in ranked ethnic societies. *Available at SSRN 3398262*.

Gallego, A., Manzano, D., and Fernández-Albertos, J. (2021). Technological risk and policy preferences. *Comparative Political Studies*, 55(1):60–92.

Hakobyan, S. and McLaren, J. (2016). Looking for local labor market effects of nafta. *Review of Economics and Statistics*, 98(4):728–741.

Haslberger, M., Gingrich, J., and Bhatia, J. (2025). Rage against the machine? generative ai exposure, subjective risk, and policy preferences. *Journal of European Public Policy*.

Hui, X., Reshef, O., and Zhou, L. (2024). The short-term effects of generative artificial intelligence on employment: Evidence from an online labor market. *Organization Science*, 35(6):1977–1989.

Imai, K., Keele, L., and Tingley, D. (2010). A general approach to causal mediation analysis. *Psychological methods*, 15(4):309.

Instituto Nacional de Estadística y Geografía (2025). Encuesta nacional de ocupación y empleo (enoe): Indicadores de ocupación y empleo, febrero 2025. https://www.inegi.org.mx/contenidos/saladeprensa/boletines/2025/iooe/ioe2025_03.pdf. Accessed 23 July 2025.

Jensen, J. B., Quinn, D. P., and Weymouth, S. (2017). Winners and losers in international trade: The effects on us presidential voting. *International Organization*, 71(3):423–457.

Jensen, N. M. and Rosas, G. (2007). Foreign direct investment and income inequality in mexico, 1990–2000. *International Organization*, 61(3):467–487.

Keele, L. (2015). Causal mediation analysis: warning! assumptions ahead. *American Journal of Evaluation*, 36(4):500–513.

Kim, E. (2023). Entertaining beliefs in economic mobility. *American Journal of Political Science*, 67(1):39–54.

Magistro, B., Borwein, S., Alvarez, R. M., Bonikowski, B., and Loewen, P. J. (2025). Attitudes toward artificial intelligence (ai) and globalization: Common microfoundations and political implications. *American Journal of Political Science*.

Magistro, B., Loewen, P., Bonikowski, B., Borwein, S., and Lee-Whiting, B. (2024). Attitudes toward automation and the demand for policies addressing job loss: The effects of information about trade-offs. *Political Science Research and Methods*, 12(4):783–798.

Mansfield, E. D., Milner, H. V., and Rudra, N. (2021). The globalization backlash: Exploring new perspectives. *Comparative Political Studies*, 54(13):2267–2285.

Mansfield, E. D. and Rudra, N. (2021). Embedded liberalism in the digital era. *International Organization*, 75(2):558–585.

Margalit, Y. (2011). Costly jobs: Trade-related layoffs, government compensation, and voting in us elections. *American Political Science Review*, 105(1):166–188.

Mayda, A. M. and Rodrik, D. (2005). Why are some people (and countries) more protectionist than others? *European Economic Review*, 49(6):1393–1430.

McCaig, B. and Pavcnik, N. (2018). Export markets and labor allocation in a low-income country. *American Economic Review*, 108(7):1899–1941.

Menon, A. and Osgood, I. (2024). The wrong winners: Anti-corporate animus and attitudes towards trade. *British Journal of Political Science*, 54(4):1180–1197.

Menon, A. and Zhang, B. (2025). Future shock or future shrug? public responses to varied artificial intelligence development timelines. *The Journal of Politics*. Forthcoming.

Milner, H. V. (2021a). Is global capitalism compatible with democracy? inequality, insecurity, and interdependence. *International Studies Quarterly*, 65(4):1097–1110.

Milner, H. V. (2021b). Voting for populism in europe: Globalization, technological change, and the extreme right. *Comparative Political Studies*, 54(13):2286–2320.

Milner, H. V. and Kubota, K. (2005). Why the move to free trade? democracy and trade policy in the developing countries. *International organization*, 59(1):107–143.

Owen, E. and Johnston, N. P. (2017). Occupation and the political economy of trade: Job routineness, offshorability, and protectionist sentiment. *International Organization*, 71(4):665–699.

Pew Research Center (2014). Emerging and developing economies much more optimistic than rich countries about the future. Published October 9, 2014.

Pierce, J. R. and Schott, P. K. (2016). The surprisingly swift decline of us manufacturing employment. *American economic review*, 106(7):1632–1662.

PricewaterhouseCoopers (2018). Will robots really steal our jobs? an international analysis of the potential long term impact of automation.

Rho, S. and Tomz, M. (2017). Why don't trade preferences reflect economic self-interest? *International Organization*, 71(S1):S85–S108.

Rogowski, R. (1989). *Commerce and Coalitions: How Trade Affects Domestic Political Alignments*. Princeton University Press.

Rommel, T. and Walter, S. (2018). The electoral consequences of offshoring: how the globalization of production shapes party preferences. *Comparative political studies*, 51(5):621–658.

Rudra, N., Nooruddin, I., and Bonifai, N. (2021). Globalization backlash in developing countries: Broadening the research agenda. *Comparative Political Studies*, 54(13):2416–2441.

Scheve, K. F. and Slaughter, M. J. (2001). What determines individual trade-policy preferences? *Journal of International Economics*, 54(2):267–292.

Stolper, W. F. and Samuelson, P. A. (1941). Protection and real wages. *The Review of Economic Studies*, 9(1):58–73.

Trachtenberg, D. (2019). Local labor-market effects of nafta in mexico: Evidence from mexican commuting zones. Technical report, IDB Working Paper Series.

U.S. Bureau of Labor Statistics (2024). Employment projections: 2023–2033. https://www.bls.gov/news.release/pdf/ecopro.pdf. Accessed 23 July 2025.

Walter, S. (2017). Globalization and the demand-side of politics: How globalization shapes labor market risk perceptions and policy preferences. *Political Science Research and Methods*, 5(1):55–80.

Walter, S. (2021). The backlash against globalization. *Annual Review of Political Science*, 24(1):421–442.

Webb, M. (2020). The impact of artificial intelligence on the labor market. *SSRN Working Paper*.

Wolak, J. and Peterson, D. A. (2020). The dynamic american dream. *American Journal of Political Science*, 64(4):968–981.

Wolf, M. (2023). *The crisis of democratic capitalism*. Penguin.

Wu, N. (2021). Misattributed blame? attitudes toward globalization in the age of automation. *Political Science Research and Methods*, 9(3):510–526.

Contents

Appendix

A Model

This appendix provides a simple formulation underlying the theory. The goal is to formalize how trade and automation shape support for government involvement in the economy through their effects on perceived market legitimacy. In the main text, legitimacy beliefs are shaped by globalization-era employment legacies and the national economic narratives they sustain; here we treat that mapping in reduced form.

Setup

Support for government involvement is a function of perceived market legitimacy and other characteristics:

$$G_i = G(L_i, X_i),$$

where L_i denotes individual i's assessment of whether the economy delivers secure work and fair compensation.

We assume:

$$\frac{\partial G_i}{\partial L_i} < 0, \quad \frac{\partial^2 G_i}{\partial L_i^2} > 0.$$

The first condition captures that support for government involvement rises as perceived market legitimacy declines. The curvature assumption allows the marginal effect of declining legitimacy to be larger when legitimacy is already low.

Trade exposure (T) and automation displacement risk (P_i^{displace}) influence support through their effects on legitimacy beliefs:

$$L_i = g(P_i^{\text{displace}}, T, X_i).$$

We interpret T as summarizing globalization-era legacies, and the narratives they produced, that shape baseline legitimacy beliefs.

We interpret P_i^{displace} as *perceived* displacement risk, which may be sociotropic (common across individuals) or mapped unevenly across skill groups depending on beliefs about which occupations AI will affect.

Trade and Automation as Indirect Effects

Focusing on the legitimacy channel, we apply the chain rule.

Trade.

$$\frac{\partial G_i}{\partial T} = \frac{\partial G_i}{\partial L_i} \cdot \frac{\partial L_i}{\partial T}.$$

Automation.

$$\frac{\partial G_i}{\partial P_i^{\text{displace}}} = \frac{\partial G_i}{\partial L_i} \cdot \frac{\partial L_i}{\partial P_i^{\text{displace}}}.$$

If automation risk weakens legitimacy beliefs, $\frac{\partial L_i}{\partial P_i^{\text{displace}}} < 0$, then automation increases support for government involvement because $\frac{\partial G_i}{\partial L_i} < 0$.

Compounding Effect

Define:

$$f_i(T, P_i^{\text{displace}}) \equiv \frac{\partial G_i}{\partial L_i}, \qquad g_i(T, P_i^{\text{displace}}) \equiv \frac{\partial L_i}{\partial P_i^{\text{displace}}}.$$

The total effect of automation on support is:

$$h_i(T, P_i^{\text{displace}}) \equiv f_i(T, P_i^{\text{displace}}) \cdot g_i(T, P_i^{\text{displace}}) = \frac{\partial G_i}{\partial P_i^{\text{displace}}}.$$

To see how this effect depends on trade exposure, differentiate with respect to T:

$$\frac{\partial h_i}{\partial T} = \frac{\partial f_i}{\partial T}\, g_i(T, P_i^{\text{displace}}) + f_i(T, P_i^{\text{displace}})\, \frac{\partial g_i}{\partial T}.$$

Cross-Partial Derivative

Equivalently,

$$\frac{\partial h_i}{\partial T} = \frac{\partial}{\partial T}\left(\frac{\partial G_i}{\partial P_i^{\text{displace}}}\right) = \frac{\partial^2 G_i}{\partial P_i^{\text{displace}}\, \partial T}.$$

Expanding each term:

Step 1. Since $f_i = \frac{\partial G_i}{\partial L_i}$, it depends on T only through L_i. By the chain rule:

$$\frac{\partial f_i}{\partial T} = \frac{\partial^2 G_i}{\partial L_i^2} \cdot \frac{\partial L_i}{\partial T}.$$

Step 2. Since $g_i = \frac{\partial L_i}{\partial P_i^{\text{displace}}}$, differentiating with respect to T gives a mixed partial:

$$\frac{\partial g_i}{\partial T} = \frac{\partial^2 L_i}{\partial P_i^{\text{displace}}\, \partial T}.$$

Step 3. Substituting yields:

$$\frac{\partial^2 G_i}{\partial P_i^{\text{displace}}\,\partial T} = \left(\frac{\partial^2 G_i}{\partial L_i^2} \cdot \frac{\partial L_i}{\partial T} \cdot \frac{\partial L_i}{\partial P_i^{\text{displace}}}\right) + \left(\frac{\partial G_i}{\partial L_i} \cdot \frac{\partial^2 L_i}{\partial P_i^{\text{displace}}\,\partial T}\right). \tag{9}$$

Interpretation

- *Term 1 (baseline-legitimacy/curvature channel):* curvature of support in legitimacy beliefs × trade's effect on baseline legitimacy × automation's effect on legitimacy.
- *Term 2 (trade–automation interaction channel):* marginal effect of legitimacy beliefs on support × the cross-partial showing how trade exposure changes the sensitivity of legitimacy beliefs to automation risk.

The cross-partial derivative $\frac{\partial^2 G_i}{\partial P_i^{\text{displace}}\,\partial T}$ formalizes the theory's central claim: the political consequences of AI-driven automation depend systematically on prior globalization shocks, insofar as those shocks shape baseline market legitimacy and condition how displacement risk is interpreted.

B Observational Analysis

B.1 Trade Exposure

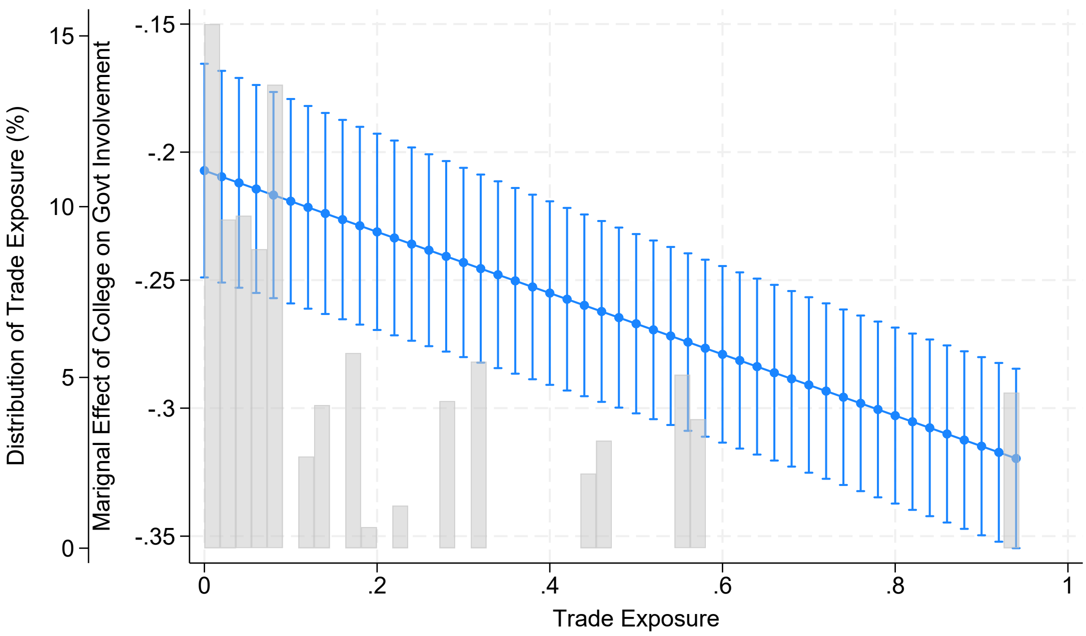

Figure B1: Government Responsibility, Trade Exposure, and Individuals' Skills (with country fixed effects)

Declining Manufacturing	Growing Manufacturing
ARG	ALB
ARM	BFA
AUS	CHN
AZE	EGY
BGR	ETH
BRA	GHA
CAN	IDN
CHE	IND
CHL	JOR
COL	KAZ
CYP	MAR
CZE	MEX
DEU	NGA
ECU	PER
ESP	PHL
EST	QAT
FIN	THA
FRA	TTO
GBR	TUN
GEO	TUR
HKG	TZA
HUN	VNM
ISR	ZMB
ITA	
JPN	
KGZ	
KOR	
LBN	
LTU	
LVA	
MDA	
MKD	
MYS	
NLD	
NOR	
NZL	
POL	
ROU	
SGP	
SLV	
SRB	
SVK	
SVN	
SWE	
UKR	
URY	
USA	
ZAF	
ZWE	

Table B1: Growing vs. Declining Manufacturing (WVS)

	(1)	(2)
	OLS	
	Favoring Government Involvement	
Trade Exposure	0.356***	0.384***
	(0.013)	-0.014
College	-0.311***	-0.305***
	(0.019)	(0.019)
Trade Exposure*College		-0.123***
		(0.016)
Constant	10.305***	10.134***
	(0.183)	(0.177)
Country-level controls	Yes	Yes
Individual-level controls	Yes	Yes
Observations	151,815	151,815

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B2: Trade Exposure (manufacturing) and Attitudes Toward the Government's Economic Role

	(1)	(2)
	OLS	
	Favoring Government Involvement	
Trade Exposure	-49.500***	-50.717***
	(5.608)	(5.602)
College	-0.496***	0.853***
	(0.081)	(0.297)
Trade Exposure*College		2.200***
		(0.464)
Constant	-239.495***	-242.462***
	(29.812)	(29.776)
Country-level controls	Yes	Yes
Individual-level controls	Yes	Yes
Observations	6,728	6,728

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B3: Placebo: Trade Exposure and Attitudes Toward the Government's Economic Role (pre-1995)

	(1)
	OLS
	Favoring Govt Involvement
College	-0.207***
	(0.021)
Trade Exposure*College	-0.120***
	(0.017)
Constant	6.349***
	(0.030)
Country-level controls	Yes
Individual-level controls	Yes
Country Fixed Effects	Yes
Observations	151,815

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B4: Trade Exposure and Attitudes Toward the Government's Economic Role (country fixed effects)

B.2 Cohort Analysis

	(1)	(2)
	OLS	
	Favoring Government Involvement	
Declining Manufacturing Experience	0.437**	0.395
	(0.222)	(0.282)
College		-0.273***
		(0.022)
Declining Manufacturing Experience*College		-0.146***
		(0.048)
Constant	6.244***	6.345***
	(0.035)	(0.056)
Country-wave FE	Yes	Yes
Controls	Yes	Yes
Experience with Economic Growth	Yes	Yes
Observations	381,546	270,608

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B5: Government Responsibility and Experience with Declining Manufacturing

B.3 The Case of NAFTA

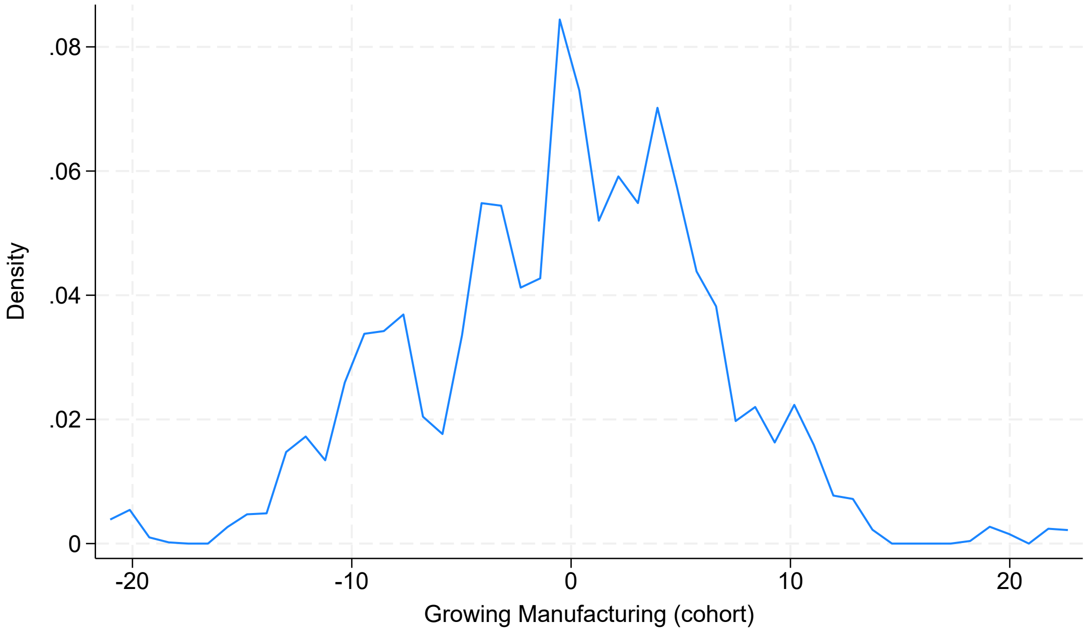

Figure B2: Distribution of Growing Manufacturing (cohort).

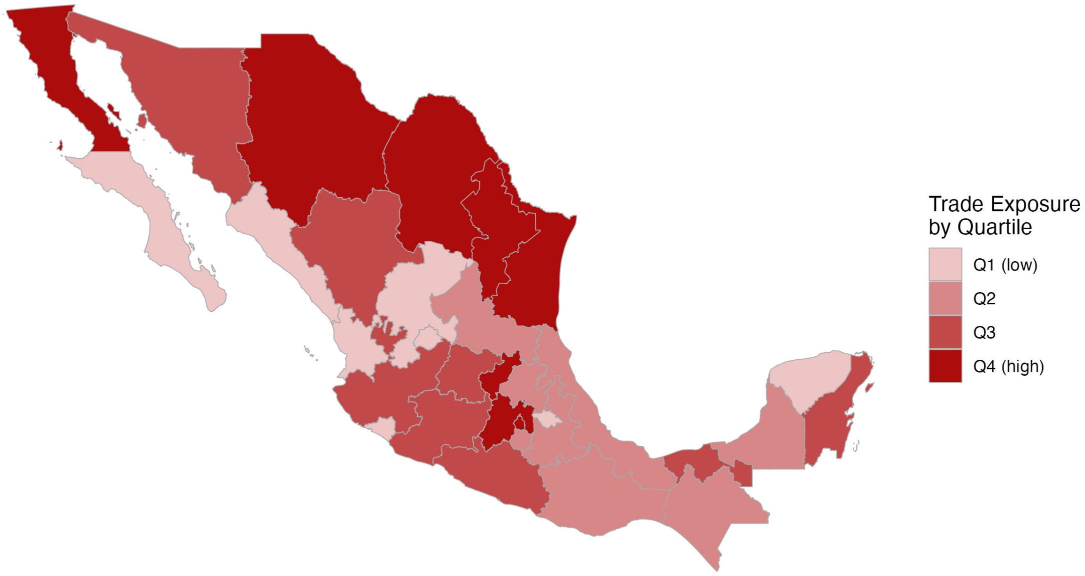

Figure B3: Distribution of Trade Exposure across Mexican States.

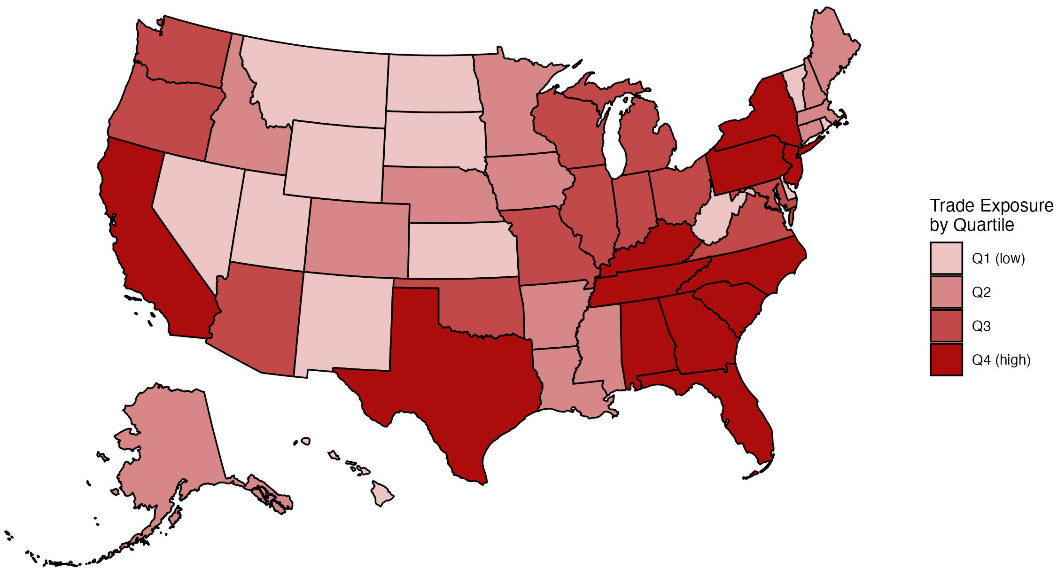

Figure B4: Distribution of Trade Exposure across US States.

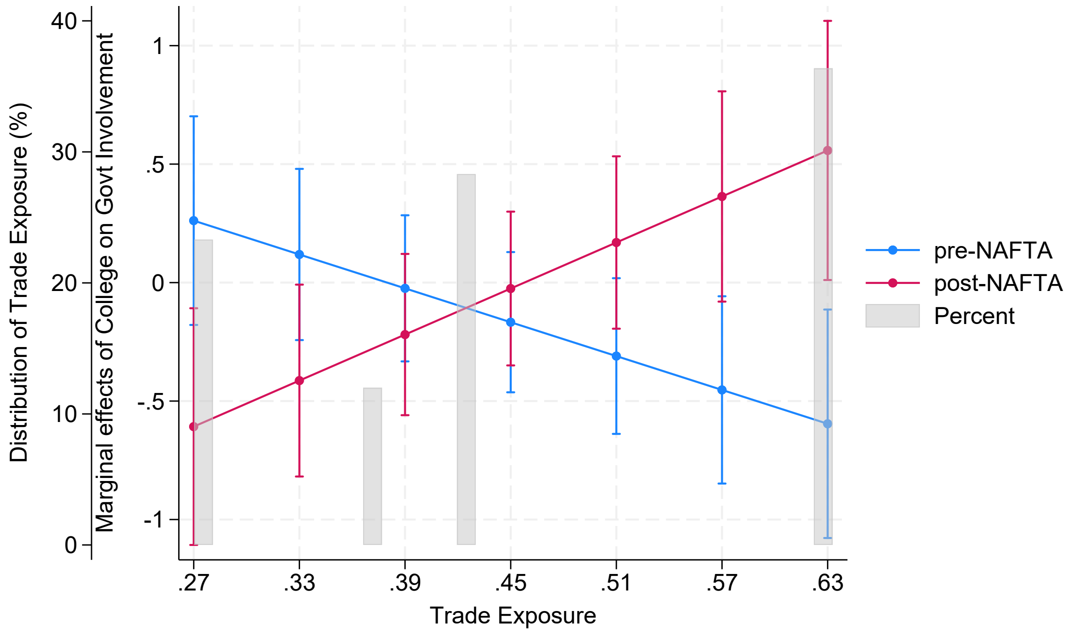

Figure B5: Mexico: Government Responsibility, Trade Exposure (manufacturing), and Individuals' Skills

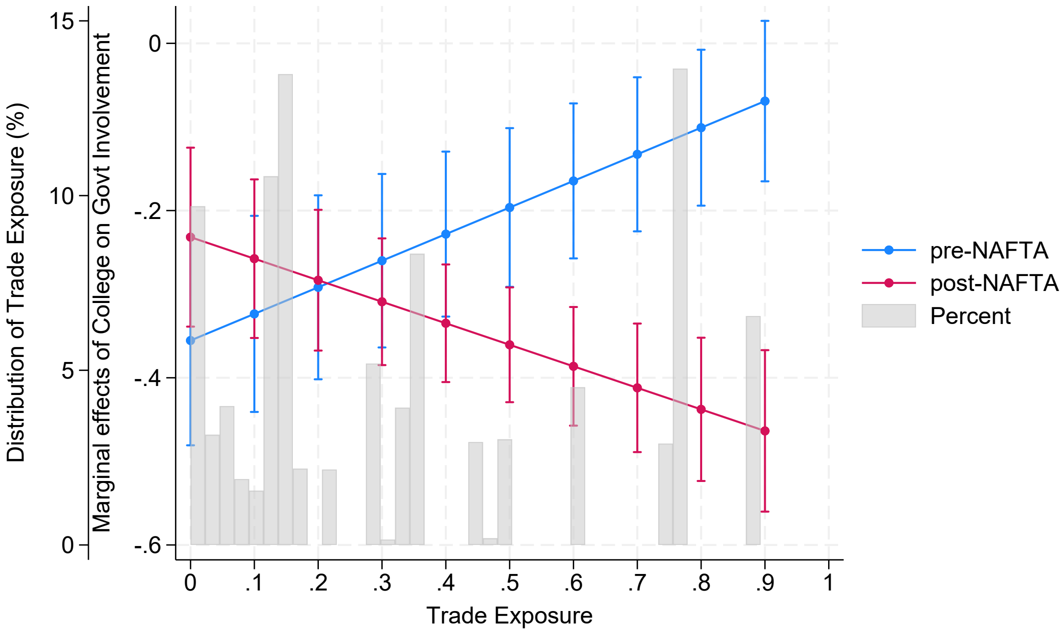

Figure B6: US: Government Responsibility, Trade Exposure (manufacturing), and Individuals' Skills

	(1)	(2)
	OLS	
	Mexico	US
	Favoring Govt Involvement	
Trade Exposure*PostNAFTA	1.342***	-0.133
	(0.496)	(0.184)
Trade Exposure*College	1.283*	-0.318
	(0.655)	(0.076)
College*PostNAFTA	1.482**	0.232
	(0.640)	(0.065)
Trade Exposure*PostNAFTA*College	3.026***	-0.576*
	(0.999)	(0.058)
Constant	-164.549*	-4.782***
	(98.098)	(0.070)
Region FE	Yes	No
State FE	No	Yes
Period FE	Yes	Yes
Controls	Yes	Yes
Observations	2,681	6,791

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table B6: The Case of NAFTA

C Experimental Analysis

C.1 Figures

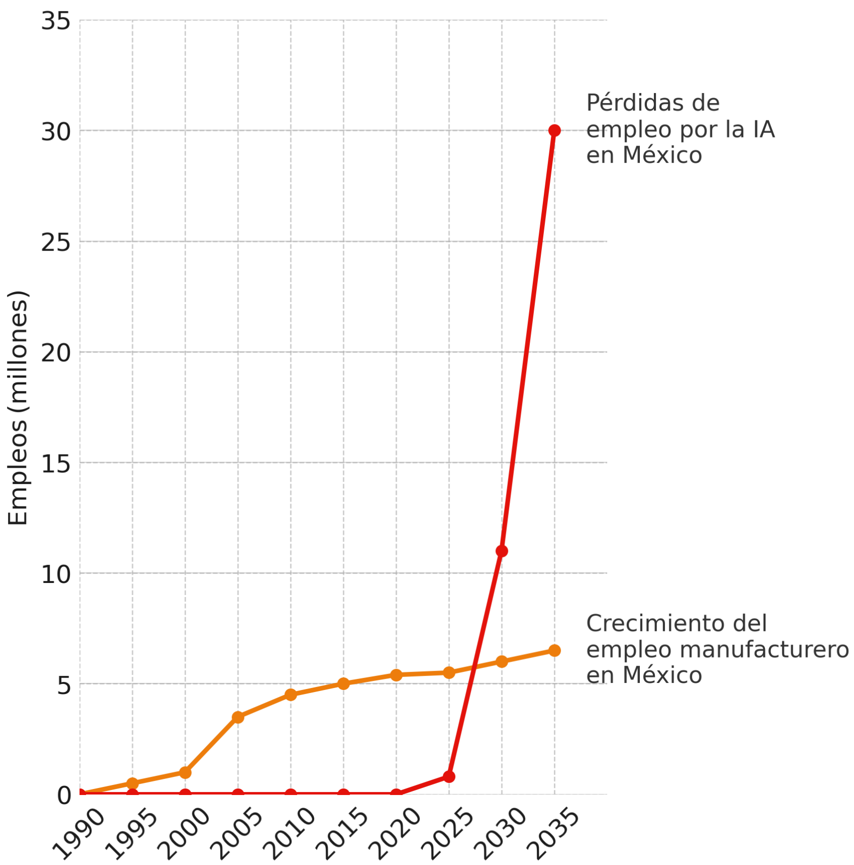

Figure C1: AI Treatment (Mexico)

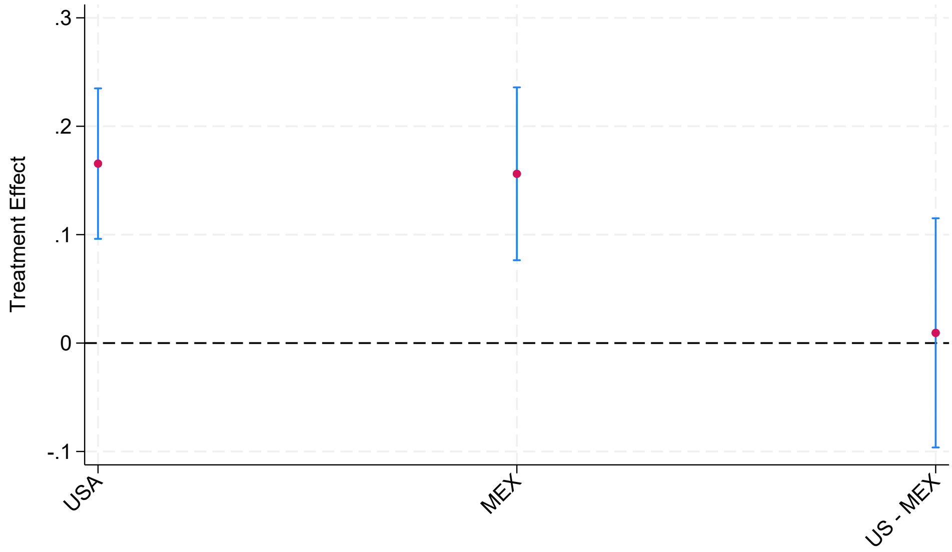

Figure C2: AI Treatment and Support for AI Restrictions and Compensation

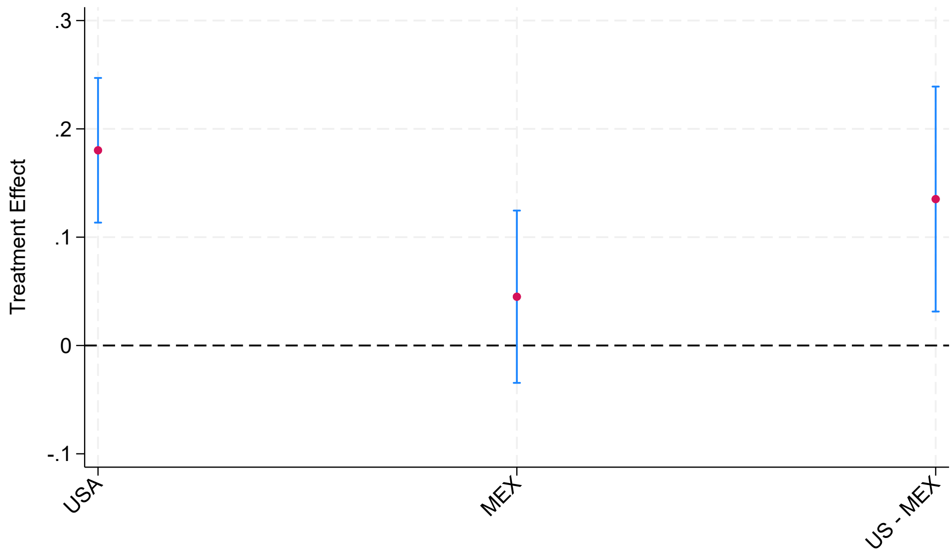

Figure C3: AI Treatment and Support for Government Involvement (without the WVS question)

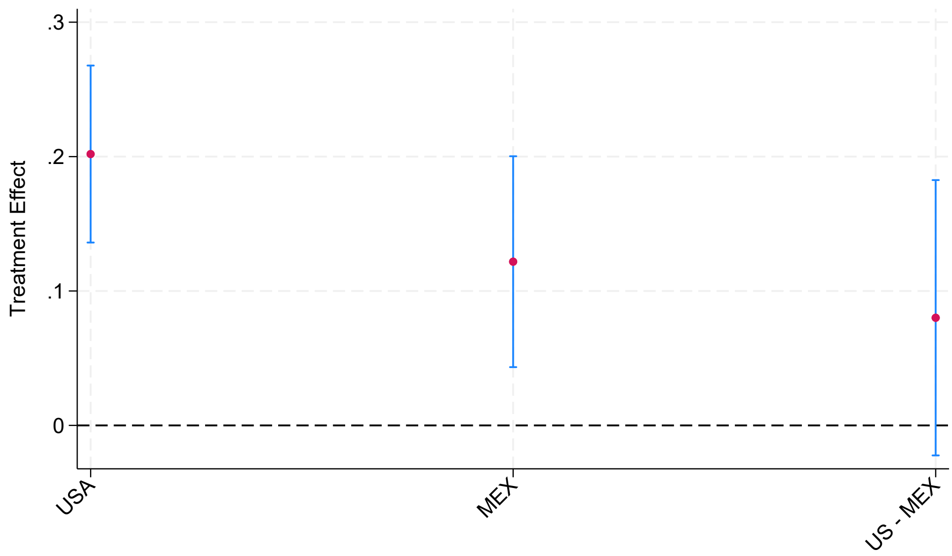

Figure C4: AI Treatment and Support for Government Involvement (without the ANES question)

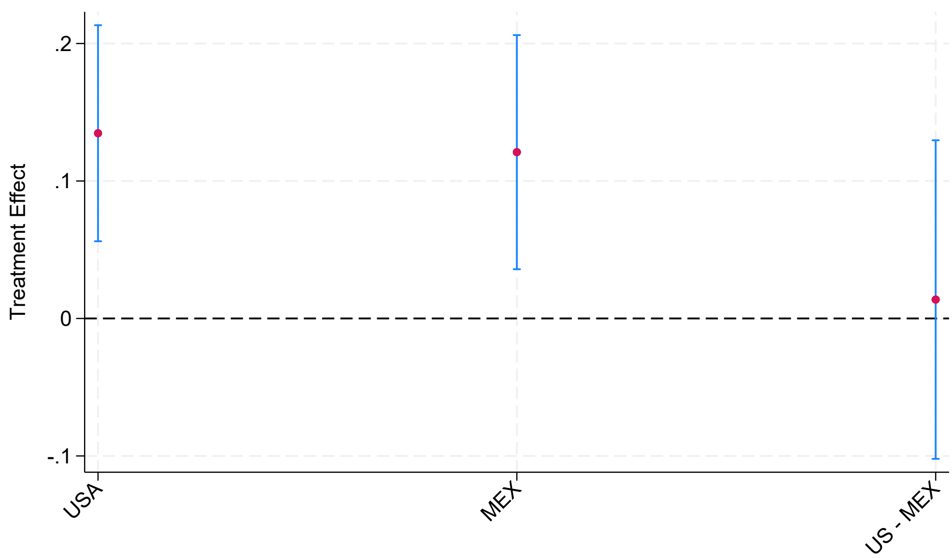

Figure C5: AI Treatment and Support for Government Involvement (without the Job Security question)

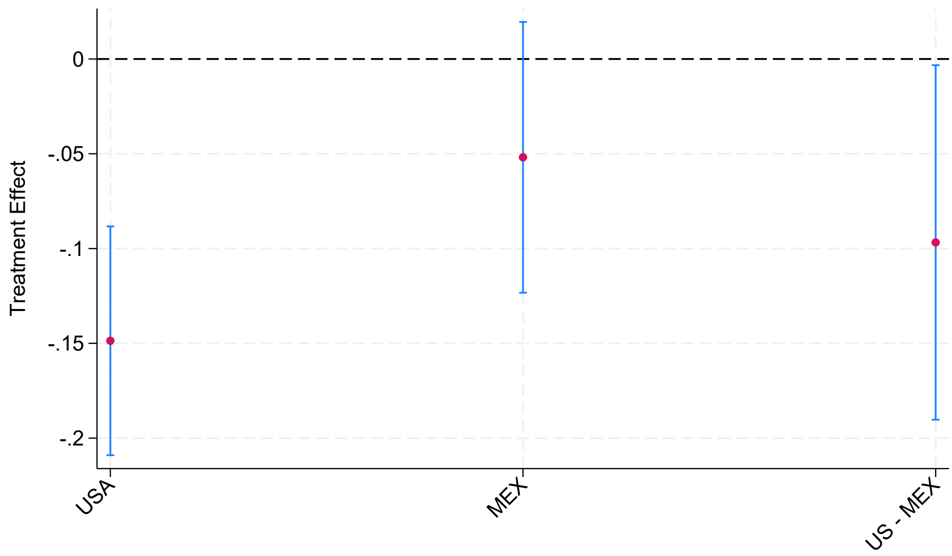

Figure C6: AI Treatment and Perceived Market Legitimacy (mean)

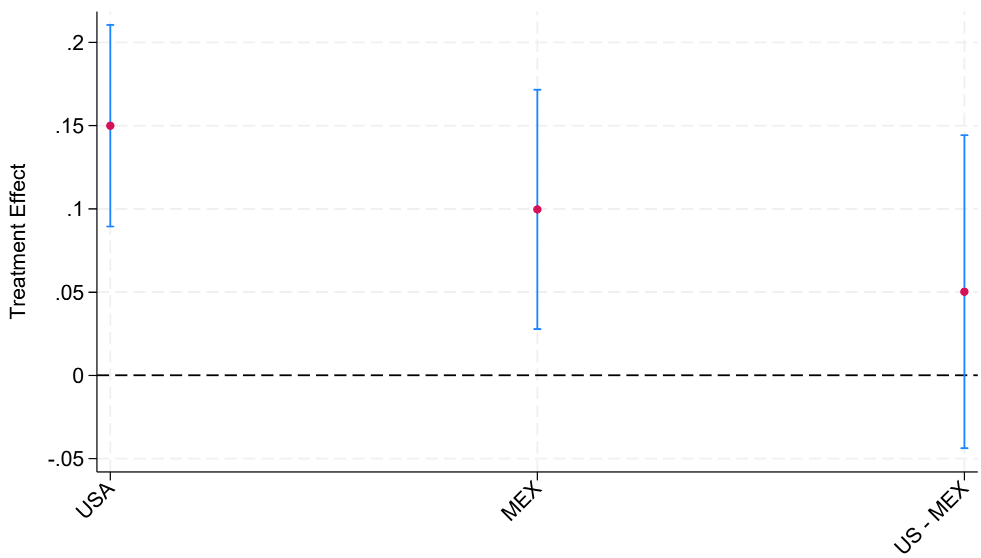

Figure C7: AI Treatment and Support for Government Involvement (mean)

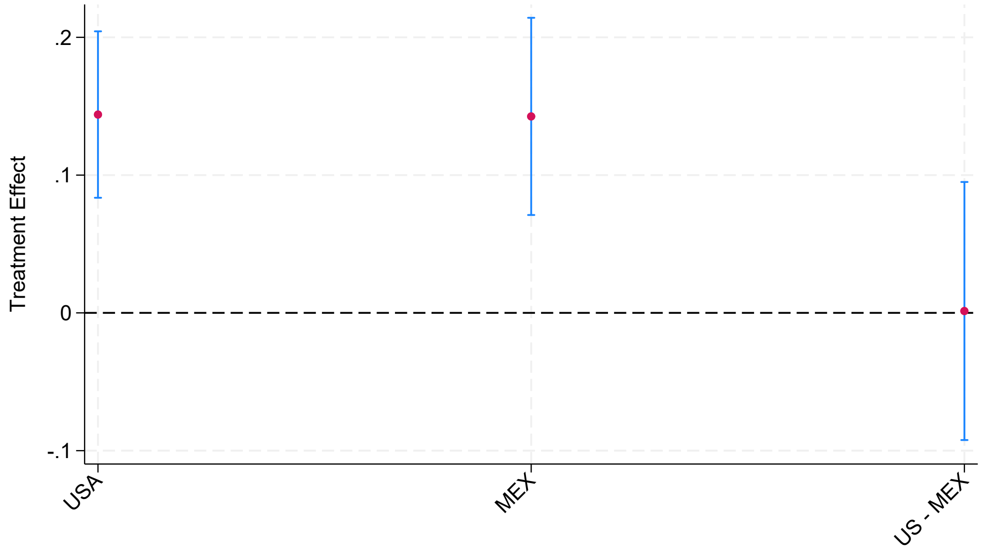

Figure C8: AI Treatment and Support for AI Restrictions and Compensation (mean)

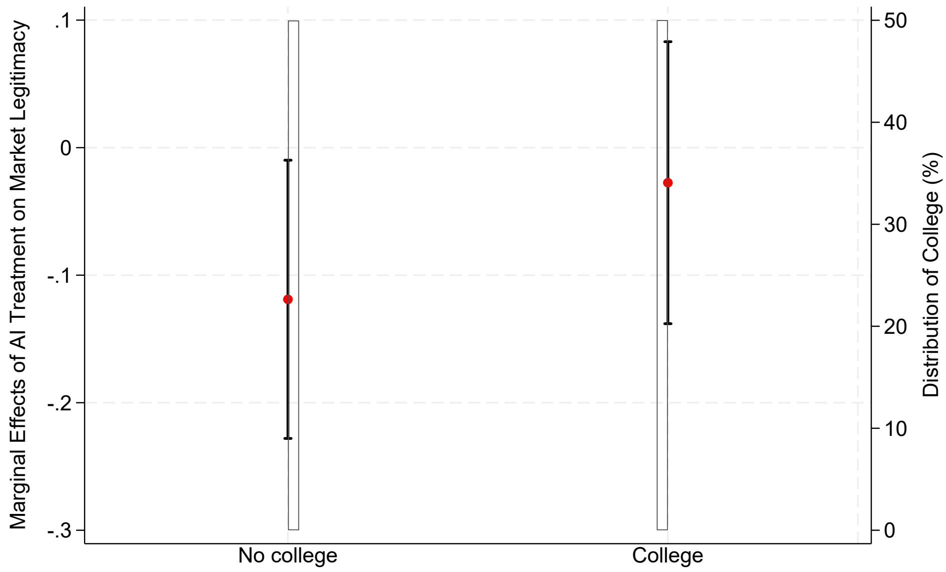

Figure C9: Predictions about Market Legitimacy, by Skill Level (Mexico)

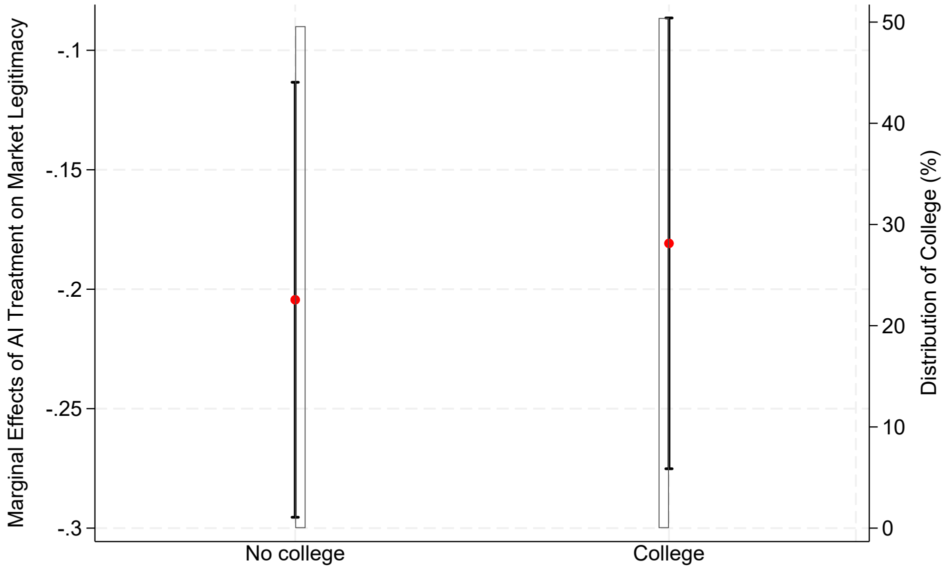

Figure C10: Predictions about Market Legitimacy, by Skill Level (US)

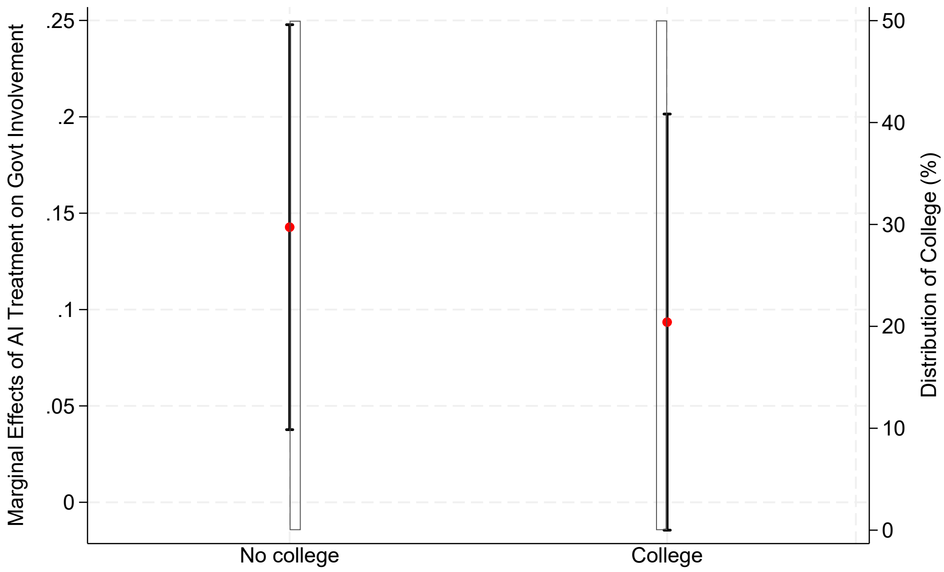

Figure C11: Predictions about Government Involvement, by Skill Level (Mexico)

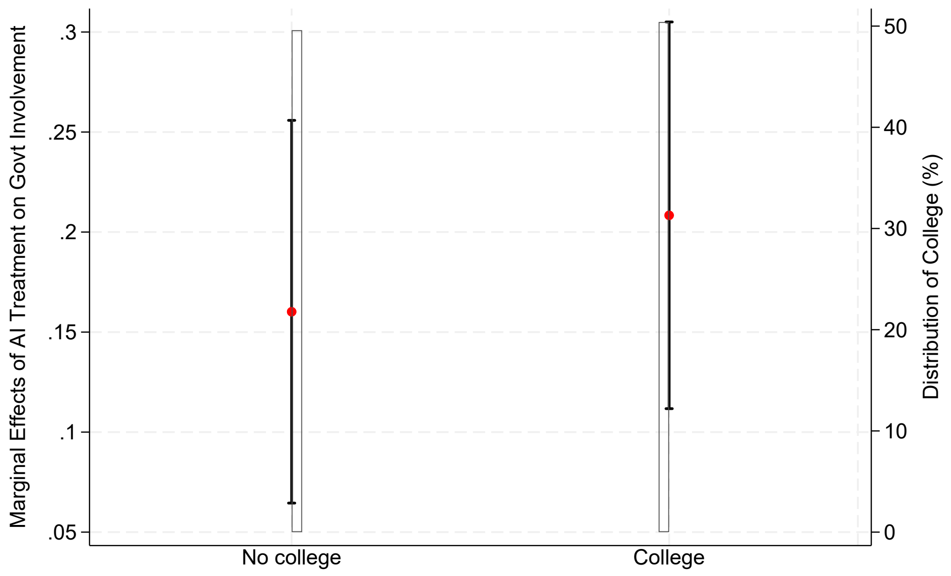

Figure C12: Predictions about Government Involvement, by Skill Level (US)

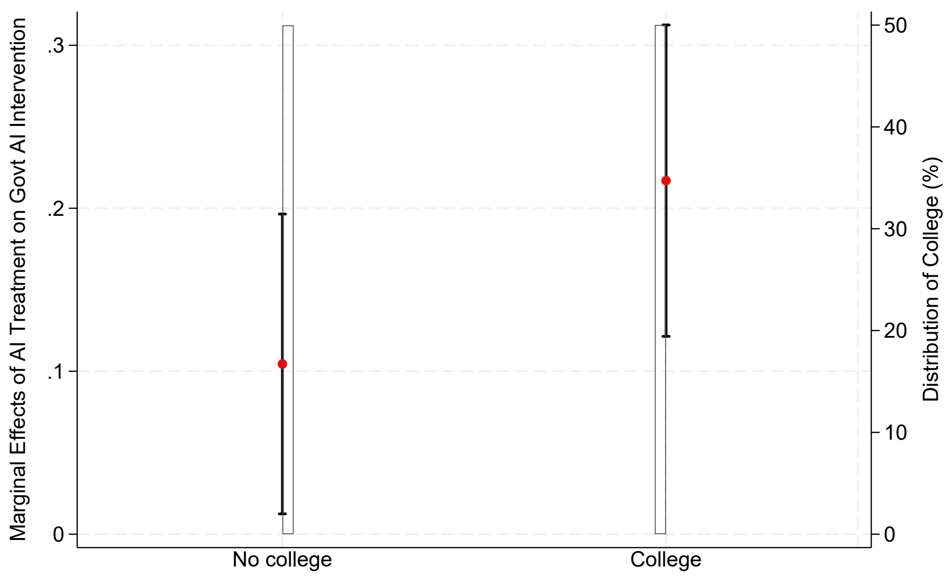

Figure C13: Predictions about Government AI Intervention, by Skill Level (Mexico)

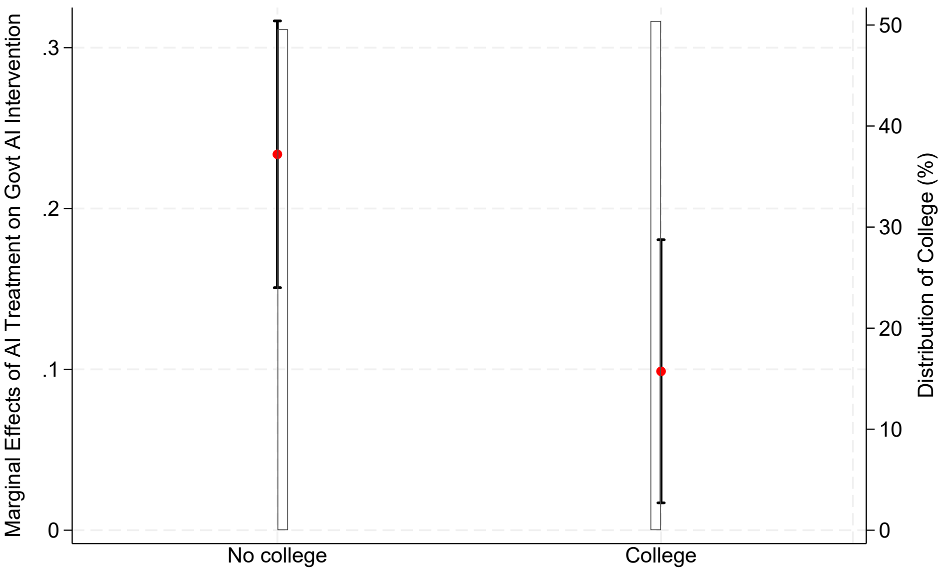

Figure C14: Predictions about Government AI Intervention, by Skill Level (US)

C.2 Tables

Variable	Experiment	p_value
Working	AI Treatment	0.48
Annual income under 50k	AI Treatment	0.47
Female	AI Treatment	0.91
Age under 36	AI Treatment	0.45
Region	AI Treatment	0.34

Table C1: Balance Checks (Analysis of Variance) – Mexico

Variable	Experiment	p_value
White (Hispanics excluded)	AI Treatment	0.44
Big city residence	AI Treatment	0.47
Working	AI Treatment	0.66
Annual income under 50k	AI Treatment	0.42
Female	AI Treatment	0.93
Age under 36	AI Treatment	0.29
Region	AI Treatment	0.38
High political interest	AI Treatment	0.65

Table C2: Balance Checks (Analysis of Variance) – US

	Mexico		US	
Questions	Factor 1	Factor 2	Factor 1	Factor 2
Fairly compensate workers	0.77		0.75	
Provide job opportunities	0.77		0.78	
More security		0.34		0.25
Everyone provided for (ANES)		0.58		0.79
Government responsibility (WVS)		0.64		0.77

Table C3: Factor Analysis of Outcome Questions

	(1)	(2)	(3)	(4)	(5)
	Market Legitimacy			Government Involvement	
	More job opportunities	Fairly compensate workers	More job security	Everyone has a job (ANES)	Everyone provided for (WVS)
AI Treatmen	-0.075*	-0.038	0.048	0.044	0.276***
	(0.042)	(0.043)	(0.053)	(0.059)	(0.069)
Constant	2.218***	1.946***	4.325***	5.035***	4.173***
	(0.029)	(0.029)	(0.037)	(0.042)	(0.049)
Observations	3,017	3,014	2,998	3,002	3,004

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table C4: AI Treatment and Single Components, Main Outcomes (Mexico)

	(1)	(2)	(3)	(4)	(5)
	Market Legitimacy		Government Involvement		
	More job opportunities	Fairly compensate workers	More job security	Everyone has a job (ANES)	Everyone provided for (WVS)
AI Treatmen	-0.194***	-0.114***	0.242***	0.139**	0.212***
	(0.034)	(0.035)	(0.042)	(0.055)	(0.058)
Constant	2.287***	1.858***	4.352***	4.318***	3.858***
	(0.024)	(0.025)	(0.030)	(0.039)	(0.042)
Observations	4,196	4,195	4,183	4,187	4,190

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table C5: AI Treatment and Single Components, Main Outcomes (US)

	(1)	(2)
	Govt's restrinctions of AI use	Govt's support workers displaced by AI
AI Treatment	0.259***	0.129**
	(0.067)	(0.058)
Constant	3.721***	5.033***
	(0.048)	(0.042)
Observations	3,001	3,004

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table C6: AI Treatment and Single Components, AI Outcomes (Mexico)

	(1)	(2)
	Govt's restrinctions of AI use	Govt's support workers displaced by AI
AI Treatment	0.214***	0.184***
	(0.052)	(0.053)
Constant	4.720***	4.729***
	(0.037)	(0.038)
Observations	4,190	4,196

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table C7: AI Treatment and Single Components, AI Outcomes (US)

	(1)	(2)	(3)	(4)
	Mexico		US	
	Market Legitimacy	Government Involvement	Market Legitimacy	Government Involvement
AI Treatment	-0.091*	0.115**	-0.157***	0.136***
	(0.051)	(0.051)	(0.043)	(0.043)
College	-0.253***	-0.195***	-0.106**	-0.038
	(0.050)	(0.051)	(0.043)	(0.043)
AI Treatment*College	0.071	-0.034	0.018	0.029
	(0.072)	(0.073)	(0.062)	(0.062)
Constant	0.151***	0.046	0.128***	-0.057*
	(0.035)	(0.036)	(0.030)	(0.031)
Observations	3,002	2,956	4,195	4,171

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table C8: AI Treatment and Skill Levels (mean)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Market Legitimacy	Govt Involvement	Market Legitimacy	Govt Involvement	Market Legitimacy	Govt Involvement	Market Legitimacy	Govt Involvement	Market Legitimacy	Govt Involvement
AI Treatment	-0.068	0.183***	-0.061	0.209***	-0.111*	0.108*	-0.112	0.135	-0.009	-0.097
	(0.056)	(0.057)	(0.089)	(0.081)	(0.066)	(0.062)	(0.101)	(0.102)	(0.165)	(0.212)
Republican	0.714***	0.549***								
	(0.066)	(0.064)								
AI Treatment*Morena	0.005	-0.196**								
	(0.097)	(0.094)								
Age<30			-0.161**	-0.127*						
			(0.073)	(0.072)						
Age[30,59]			-0.230*	-0.105						
			(0.132)	(0.126)						
AI Treatment*Age<30			-0.022	-0.114						
			(0.107)	(0.100)						
AI Treatment*Age[30,59]			0.099	-0.154						
			(0.185)	(0.179)						
Male					0.074	-0.184***				
					(0.066)	(0.065)				
AI Treatment*Male					0.088	0.033				
					(0.095)	(0.092)				
AI User							0.207	0.124		
							(0.171)	(0.154)		
AI Treatment*AI User							0.150	-0.033		
							(0.235)	(0.211)		
Pessimisitc									2.104***	0.498***
									(0.158)	(0.178)
AI Treatment*Pessimisitc									0.124	0.027
									(0.218)	(0.268)
Constant	-0.191***	-0.234***	0.157**	0.030	-0.002	0.027	-0.023	-0.068	-1.311***	4.132***
	(0.039)	(0.040)	(0.061)	(0.059)	(0.045)	(0.043)	(0.071)	(0.071)	(0.120)	(0.138)
Observations	3,012	2,965	3,012	2,965	3,004	2,957	2,904	2,859	3,003	2,988

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table C9: Other Heterogeneous Effects (Mexico)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Market Legitimacy	Govt Involvement	Market Legitimacy	Govt Involvement	Market Legitimacy	Govt Involvement	Market Legitimacy	Govt Involvement	Market Legitimacy	Govt Involvement
AI Treatment	-0.180***	0.161***	-0.231**	0.133	-0.273***	0.245***	-0.139	0.046	-0.039	0.524**
	(0.047)	(0.046)	(0.117)	(0.113)	(0.058)	(0.062)	(0.092)	(0.097)	(0.208)	(0.259)
Republican	0.897***	-0.896***								
	(0.053)	(0.061)								
AI Treatment*Republican	-0.025	0.064								
	(0.078)	(0.088)								
Age<30			0.260***	-0.342***						
			(0.090)	(0.089)						
Age[30,59]			0.493***	-0.829***						
			(0.096)	(0.099)						
AI Treatment*Age<30			0.047	0.097						
			(0.129)	(0.124)						
AI Treatment*Age[30,59]			0.033	-0.011						
			(0.136)	(0.137)						
Male					-0.207***	0.265***				
					(0.056)	(0.058)				
AI Treatment*Male					0.164**	-0.131				
					(0.080)	(0.083)				
AI User							0.344***	0.249**		
							(0.119)	(0.119)		
AI Treatment*AI User							-0.029	0.042		
							(0.163)	(0.165)		
Pessimisitc									1.831***	-0.440**
									(0.164)	(0.205)
AI Treatment*Pessimisitc									-0.037	-0.335
									(0.224)	(0.274)
Constant	-0.178***	0.182***	-0.199**	0.346***	0.210***	-0.241***	-0.040	-0.168**	-1.218***	0.289
	(0.033)	(0.033)	(0.083)	(0.081)	(0.042)	(0.043)	(0.068)	(0.071)	(0.154)	(0.196)
Observations	4,195	4,171	4,195	4,171	4,145	4,121	4,043	4,019	4,194	4,170

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table C10: Other Heterogeneous Effects (US)

	(1)	(2)
	Mexico	US
	Govt AI Intervention	
AI Treatment	0.104*	0.234***
	(0.056)	(0.050)
College	-0.385***	0.054
	(0.057)	(0.050)
AI Treatment*College	0.112	-0.135*
	(0.081)	(0.071)
Constant	0.112***	-0.111***
	(0.040)	(0.036)
Observations	2,977	4,190

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table C11: AI Treatment and Skill Levels (Government AI Intervention)

D Ethical Considerations

Our research has received ethics clearance from the Research Ethics Board of [anonymized information] (REB File #22-06-055-04). Furthermore, our research adheres to the APSA Principles and Guidance for Human Subjects Research.

We conducted our original surveys with the survey companies *Bilendi* and *Forthright*. The sample was drawn from an online panel used only for market research and for which membership and participation are voluntary and follow a double opt-in registration process. The respondents were able to take the survey only after reading the consent form and agreeing to it. The consent form clearly stated key details such as the following: 1) the study was an academic survey; 2) who conducted the study and who funded it; 3) the general goal of the study; 4) how the data will be used; 5) how the subjects can end the survey at any point by simply closing their browser; 6) how the data will be protected; and 7) how the respondent can contact the Research Ethics Board or the researchers.

The study did not involve at-risk or vulnerable populations. Our sample is representative (in terms of age, gender, and region) of the US adult population.

The study did not use deception.

The study did not intervene in the political process.

The study protects the confidentiality of the respondents. We, as researchers, did not collect data that would make the respondents identifiable.

The respondents were compensated for their work by Forthright. Specifically, each respondent received $2 for their answers. This represents approx. 32% of the fee we paid to Forthright for an interview. The payment is in line with what other similar platforms offer to respondents (if not higher).

E Quality Control

We excluded three problematic groups from the sample. The first is straightliners, those who consistently picked the same response options by position despite the randomized order of the answer choice position. We exclude those who selected 0, 5, or 10 on scales for more than 80% of the outcome variable slider questions, implying that they merely picked the ends or the default starting point rather than fully evaluating the question. The second group is speeders, those who answered 2 standard deviations faster than the median response time. Finally, low-attention respondents failed a simple attention check unrelated to the survey content prior to the treatments.

We removed these respondents before they filled the quotas of our survey respondent groups to preserve the sample size. Those who failed the attention check immediately had their responses terminated and dropped from our sample. However, the other two groups completed the survey before being terminated; their responses are excluded from the data. These respondents were not included in the sample count, thus we continued to fill the quotas for respondents until the sample was filled with fully attentive, non-speeding and non-straightlining respondents.

F Questionnaire

On the next page, we reproduce the questionnaire administered to Mexican respondents. The document was originally in Spanish and it has been translated into English. The graph presented with the treatment is excluded, but reported in Appendix C.

Start of Block: Consent

Q1_consent Study Title: Views on the Economy in Mexico Sponsor: Social Sciences and Humanities Research Council - SSHRC 430-2021-00079 and SSHRC 430-2023-00126 and Carnegie Corporation of New York G-22-59412. Researchers: Professor Leonardo Baccini (McGill University, email: leonardo.baccini@mcgill.ca), Professor Katja Kleinberg (Binghamton University, SUNY, email: kkleinbe@binghamton.edu), and Professor Stephen Weymouth (Georgetown University, Stephen.Weymouth@georgetown.edu).   Dear Participant, You are being invited to take part in a research study conducted by the researchers above. Below is detailed information for you to consider when determining whether or not to participate. Carefully consider all this information and ask any questions you may have about it before deciding whether to participate or not.   **Key Information for You to Consider Voluntary Consent:** You are being asked to volunteer for a research study. It is your choice whether to participate or not. There will be no penalty or loss of benefits to which you are otherwise entitled if you choose not to participate or to discontinue participation. **Purpose:** The purpose of this research is to better understand Mexicans' opinions on economic transformations in general, and on Artificial Intelligence in particular. It is expected that approximately 500 individuals will be participating in this research. **Procedures and Activities:** If you choose to participate, you will be asked to answer a number of questions about your views. You can skip any question that makes you feel uncomfortable, and you can end your participation at any time by simply closing your browser. **Duration:** Your time commitment will be approximately 5 minutes. **Risks:** Some of the foreseeable risks or discomforts of your participation include concerns about privacy and confidentiality. We will take measures to protect your privacy and the security of your personal information. **Benefits:** No direct benefits may be expected but the researchers hope to learn more about the public's views on capitalism in the United States. **Alternatives:** Participation is voluntary, and the only alternative is not to participate.   **What happens to the information collected for this research?** Your answers will not be judged or evaluated in any way. Answers to the survey are converted into numeric entries in a spreadsheet. Researchers call this a database. This database will then be analyzed, and the results reported in academic articles that will be published in scientific journals. Identifiers might be removed from identifiable private information and/or identifiable specimens and, after such removal, the information and/or specimens could be used for future research studies or distributed to another investigator for future research studies without additional informed consent from you.   **How will my privacy and data confidentiality be protected?** All information will be kept on password-protected storage that only the researchers can access. Identifiers will be removed from identifiable private information and after such removal, the information could be used for future research studies or distributed to other investigators for future research studies without additional informed consent from you. Please note that the survey is being conducted with the help of Forthright, a company not affiliated with McGill University, Binghamton University, or Georgetown University, and with its own privacy and security policies that you can find at its website: https://www.beforthright.com/.   **Will I be paid for participation in this research? [FIX WITH NEW PROPER INFORMATION FOR BILENDI]** You will receive a monetary compensation for participating in the survey through your Forthright account. You can expect to be paid $1.00 plus 1 loyalty credit; you can request payout in your member account or as instant online payments through PayPal, Amazon, Tango Card, or Bitcoin.   **What if I want to stop participating in this research?** Taking part in this research study is your decision. Your participation is voluntary. You do not have to take part in this study, but if you do, you can end your participation at any time by simply closing your browser and no data will be collected. If there are questions you do not want to answer, you will have the option to do so. Note that data may not be withdrawn once anonymous responses have been submitted. Your decision whether or not to participate will not affect your relationship with the researchers or Binghamton University, or Georgetown University, or McGill University.   **Who can answer questions about this research?** If you have questions or concerns regarding your rights or welfare as a participant in this research study please contact the McGill Ethics Manager at +1-514-398-6831 or lynda.mcneil@mcgill.ca. Should you have questions about the project, do not hesitate to contact Leonardo Baccini via e-mail at leonardo.baccini@mcgill.ca.   **Statement of consent** I have had the opportunity to read and consider this information. I have asked any questions necessary to make a decision about my participation. I understand that I can ask additional questions throughout my participation. I understand that by clicking 'YES' below, I volunteer to participate in this research. I understand that I am not waiving any legal rights. I confirm that I am at least 18 years of age.   I consent to participating in this study.

○ Yes (1)

○ No (2)

End of Block: Consent

Start of Block: Pre

pre_opt Do you agree or disagree with the following statements? Looking ahead, I am optimistic about...

	Strongly agree (1)	Agree (2)	Neither agree nor disagree (3)	Disagree (4)	Strongly disagree (5)
The future of the Mexican economy (2)	○	○	○	○	○
My personal life (3)	○	○	○	○	○

Page Break

pre_usage How often do you use artificial intelligence (AI) tools such as chatbots, image generation, or LLMs like ChatGPT?

○ Multiple times per day (1)

○ Daily (2)

○ Multiple times per week (3)

○ Weekly (4)

○ Multiple times per month (5)

○ Monthly (9)

○ Less frequently than monthly (6)

○ Never (8)

○ Not sure (7)

pre_educ Please confirm your highest level of educational attainment

- ◯ Less than high school graduate (1)
- ◯ High school graduate, diploma or the equivalent (for example: GED) (10)
- ◯ Some college credit, no degree (11)
- ◯ Trade/technical/vocational training (12)
- ◯ Associate degree (13)
- ◯ Bachelor's degree (14)
- ◯ Master's degree (15)
- ◯ Professional degree (16)
- ◯ Doctorate degree (17)

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pre_age What is your age?

▼ 17 or younger (4) ... 76+ (62)

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pre_gender What is your gender?

▼ Male (4) ... Prefer not to say (7)

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pre_close Which ONE of the following political parties do you feel CLOSEST to? (Please select the option that best applies)

- Movimiento Regeneración Nacional (MORENA) (1)
- Partido Acción Nacional (PAN) (2)
- Partido Revolucionario Institucional (PRI) (3)
- Partido del Trabajo (PT) (7)
- Partido Verde Ecologista de México (PVEM) (8)
- Movimiento Ciudadano (MC) (9)
- None of the above (6)

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attention_check You probably have a favorite color, but we just want to make you sure you are paying attention so just pick the color blue.

- Blue (1)
- Red (2)
- Green (3)
- Yellow (4)
- Orange (5)

End of Block: Pre

Start of Block: t1_neg

t1_neg AI is replacing workers by automating complex tasks once performed by humans. Jobs once considered secure are being eliminated as AI surpasses human capabilities. These AI job losses are expected to far exceed the job gains in Mexican manufacturing over the past several decades.

t1_neg_attention The figure shows that AI will eliminate approximately how many jobs by 2035?

- 5 Million (1)
- 10 Million (4)
- 20 Million (5)
- 30 Million (6)

End of Block: t1_neg

Start of Block: Manipulation

manipulation_1 How concerned are you that AI will replace millions of human workers over the next decade?

- Very concerned (1)
- Concerned (2)
- Not concerned (3)
- Not at all concerned (4)
- Not sure (5)

recall_1 Based on the information you saw earlier on the graph, which of the following is true?

- AI will lead to net job losses (1)
- AI will lead to net job gains (2)
- I did not see a graph earlier in the survey (5)

End of Block: Manipulation

Start of Block: post_percep_cap

JS

post_percep_cap Do you agree or disagree with the following statements? In the next decade…

	Strongly disagree (1)	Disagree (2)	Neither agree nor disagree (6)	Agree (7)	Strongly agree (8)
The Mexican economy will provide job opportunities for those who want to work. (1)	○	○	○	○	○
The Mexican economy will fairly compensate workers for their labor. (2)	○	○	○	○	○

End of Block: post_percep_cap

Start of Block: post_rel_parents

post_rel_parents In the next decade, do you believe that it will be harder or easier for individuals to do better economically than their parents?

- Much harder (1)
- Harder (2)
- About the same as now (4)
- Easier (5)
- Much easier (6)
- Don't know (7)

End of Block: post_rel_parents

Start of Block: post_uncertainty

post_uncertainty Some people prefer an economy with **high potential earnings but also high risk of job loss**. Suppose these people are on the end of a scale, at point 1. Others prefer an economy where **earnings are more limited, but job security is high.** Suppose those people are on the other end of the scale, at point 7. Where would you place yourself on this scale?

	High earnings potential but low job security					Lower earnings potential but high job security.	
	1	2	3	4	5	6	7
()							

End of Block: post_uncertainty

Start of Block: post_ensure

post_ensure Some people argue that the American economy should ensure **equal opportunities for everyone**. Suppose those people are on one end of a scale, at point 1. Others argue it should ensure **equal outcomes for everyone**. Suppose those people are on the other end of the scale, at point 7. Where would you place yourself on this scale?

Equal opportunities for everyone	Equal outcomes for everyone

	1	2	3	4	5	6	7
()							

End of Block: post_ensure

Start of Block: post_anes_job_sol

post_anes_job_sol Some people feel that the government should just let each person get ahead on their own. Suppose those people are on one end of a scale, at point 1. Others think the government should see to it that every person has a job and a good standard of living. Suppose those people are on the other end of the scale, at point 7. Where would you place yourself on this scale?

	Let each person get ahead on their own				See to it that everyone has a job		
	1	2	3	4	5	6	7
()							

End of Block: post_anes_job_sol

Start of Block: post_wvs

post_wvs_q2 How would you place your views on this scale?

	People should take more responsibility to provide for themselves				Government should take more responsibility to ensure that everyone is provided for		
	1	2	3	4	5	6	7
()							

End of Block: post_wvs

Start of Block: post_gov_resp

post_gov_resp On the whole, do you think it should or should not be the government's responsibility to provide a job for everyone who wants one?

	Definitely *not* the government's responsibility				Definitely the government's responsibility		
	1	2	3	4	5	6	7
()							

End of Block: post_gov_resp

Start of Block: Open

open_1 What concerns you most about AI?

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open_2 What excites you most about AI?

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End of Block: Open

Start of Block: post_gov_rest

post_gov_rest Would you favor government restrictions of AI use?

	Not at all favor				Completely favor		
	1	2	3	4	5	6	7
()							

End of Block: post_gov_rest

Start of Block: post_gov_workers

post_gov_workers To what extent do you agree or disagree with the following statement: *The government should support workers displaced by AI.*

	Completely disagree				Completely agree		
	1	2	3	4	5	6	7
()							

End of Block: post_gov_workers