

The Decline of Manufacturing Employment and the Rise of the Far-Right in Austria

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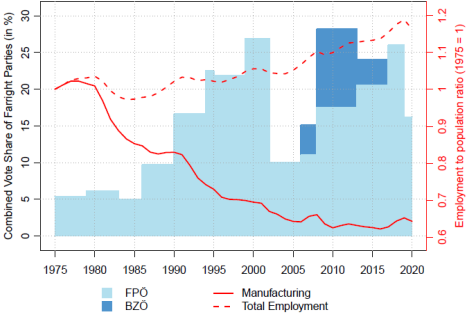
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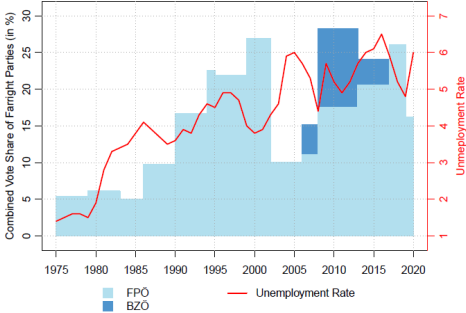
August 29th 2023

Manufacturing Decline & Far-Right Voting

(a) Employment/population ratio



(b) Unemployment rate



Manufacturing Decline & Far-Right Voting

Structural employment shocks:

- ◇ Trade Shocks: Dippel et al. (2022); Autor et al. (2020); Rodrik (2018); Colantone and Stanig (2018a, 2018b), Margalit (2011)
- ◇ Automation Shocks: Anelli et al. (2019, 2021), or Frey et al. (2018)

→ Trade and technology are the causes of the manufacturing decline

→ Reduced firm relationships

→ Only tell part of the story

Temporary employment shocks:

- ◇ Great Recession, Euro-Crisis & Austerity: Algan et al. (2017); Fetzner (2019)
- ◇ Financial Crises: Funke et al. (2016)
- ◇ Mass Layoffs: Dehdari (2021)

The Role of Immigration

Large Literature on the effects of immigration

- ◇ Austria: Steinmayr (2021), Halla et al. (2017)
- ◇ International: Barone et al. (2016), Brunner et al. (2011), Dustmann et al. (2019). Edo et al. (2019),...

Generally finds that (in particular low-skilled) immigration increases far-right voting.

- Effect not independent of employment conditions
- Low-skilled migrants exacerbate labor market competition in manufacturing

This paper:

- ◇ Connection between manufacturing decline and far-right voting in Austria
- ◇ Assessing the role of trade and technology
- ◇ Investigational period: 1995-2017

Data:

- ◇ Employment Data: Austrian Social Security Database (ASSD)
Covers the universe of Austrian employees between 1975-2018
- ◇ Voting Data: Austrian Ministry of the Interior (BMI)
- ◇ Trade Data: UN Comtrade Database
- ◇ Robotics Data: International Federation of Robotics (IFR)

Estimation:

I estimate the following equation on the regional level:

$$\% \Delta \text{Voteshare}_{rt} = \gamma \% \Delta \text{Manuf. Emp.}_{rt} + X_{rt} \beta + \rho_r + \tau_t + \epsilon_{rt}$$

With:

- ◇ X : Set of Control Variables
- ◇ τ_t, ρ_r : Period and Region Fixed-Effects
- ◇ Regional Units: Clustered Commuting Zones [▶ Appendix 1](#)
- ◇ Four Panel periods:
 - 1995-2002, 2002-2008, 2008-2013 and 2013-2017
 - Not of equal length because elections take place irregularly
 - Elections of 1999 and 2006 skipped to avoid very short intervals and be able to isolate (more) long run trends
 - Robot data is not available prior to 2002
- ◇ Weighted by eligible population

Control Variables:

- ◇ Demographic controls of the native voting age population:
 - Shares of females, 3 educational groups, 3 age groups
- ◇ Regional Characteristics:
 - $\log(\text{gross regional product})$
 - $\log(\text{unemployment rate})$
 - Degree of urbanization (Share of population in urban areas)
- ◇ Structure of the local economy
 - Detailed industry structure
- ◇ Immigration Controls:
 - Migrant shares
 - Change in migrant shares
 - Separately for high-, medium- and low-skilled immigrants

The Bartik Instrument:

The Bartik Instrument is based on two accounting identities:

- ◇ Regional employment growth can be expressed as a weighted sum of industry-region growth rates (weighted by the size of each industry)

$$\% \Delta Emp_{rt} = \sum_i \frac{Emp_{irt}}{Emp_{rt}} \times \% \Delta Emp_{irt}$$

- ◇ Regional employment growth in industry i can be decomposed into the industry level growth rate and an idiosyncratic regional term

$$\% \Delta Emp_{irt} = \% \Delta Emp_{it} + \tilde{g}_{irt}$$

whereby $i \in \text{Manufacturing Industries}$ and $\sum_i \frac{Emp_{irt}}{Emp_{rt}} = 1$

The Bartik Instrument:

Combining these two accounting identities gives:

$$\begin{aligned}\% \Delta Emp_{rt} &= \sum_i \frac{Emp_{irt}}{Emp_{rt}} \times \% \Delta Emp_{irt} \\ &= \sum_i \frac{Emp_{irt}}{Emp_{rt}} \times \% \Delta Emp_{it} + \underbrace{\sum_i \frac{Emp_{irt}}{Emp_{rt}} \times \tilde{g}_{irt}}_{\text{Endogenous!}}\end{aligned}$$

The Bartik Instrument is constructed from this by:

- Lagging the *exposure shares* into the past
- Using growth rates from other geographical regions

$$Bartik_{rt}^{IV} = \sum_i \frac{Emp_{irt-15}}{Emp_{rt-15}} \times \% \Delta Emp_{it}^{OtherRegions}$$

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Identifying Assumptions:

$$Bartik_{rt}^{IV} = \sum_i \frac{Emp_{irt-15}}{Emp_{rt-15}} \times \% \Delta Emp_{it}^{OtherRegions}$$

(1) Exogenous shares condition

- Goldsmith-Pinkham et al. (2020)
- Sufficient (but not necessary) condition
- Requires $\frac{Emp_{irt-15}}{Emp_{rt-15}}$ to be exogenous
- not really plausible that industry composition is unrelated to voting beyond impact on employment growth (e.g. compositional effects)

(2) Exogenous shocks condition

- Borusyak et al. (2022) and Adao et al. (2019)
- Sufficient and necessary condition
- Requires $\% \Delta Emp_{it}^{OtherRegions}$ to be exogenous
- **more plausible in this setting**

The Bartik Instrument:

The shocks $\% \Delta Emp_{it}$ are computed from **other European countries**:

- from EuroStats Structural Business Statistics
- Belgium, Czechia, Finland, France, Hungary, Italy, Netherlands, Norway, Portugal, Spain and Sweden

$$Bartik_{rt}^{IV} = \sum_i \frac{Emp_{irt-15}}{Emp_{rt-15}} \times \% \Delta Emp_{it}^{OtherCountries}$$

Results

Main Results:

Table 1: Manufacturing Employment and far-right voting (1995-2017)

	Dependent Variable: %Δ Voteshare Far-Right Parties					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS Estimations:						
%Δ Manufacturing Emp.:	-0.382 (0.149)**	-0.3 (0.105)***	-0.274 (0.102)***	-0.284 (0.103)***	-0.277 (0.103)***	-0.294 (0.104)***
Panel B: 2SLS Estimations:						
%Δ Manufacturing Emp.:	-0.967 (0.214)*** [0.283]***	-1.235 (0.267)*** [0.241]***	-1.159 (0.401)*** [0.272]***	-1.325 (0.443)*** [0.289]***	-1.437 (0.483)*** [0.285]***	-1.181 (0.418)*** [0.23]***
Panel C: First Stage Estimations:						
Bartik ^{IV} :	0.214 (0.015)*** [0.01]***	0.184 (0.02)*** [0.008]***	0.155 (0.024)*** [0.009]***	0.153 (0.023)*** [0.01]***	0.145 (0.023)*** [0.012]***	0.157 (0.022)*** [0.011]***
First-Stage F-Statistic:	207.67	85.71	42.46	42.61	39.77	51.3
Period Fixed Effects	x	x	x	x	x	x
Commuting Zone Fixed Effects	x	x	x	x	x	x
Industry Structure	x	x	x	x	x	x
Regional Characteristics		x	x	x	x	x
Demographic Characteristics			x	x	x	x
Lagged employment changes				x	x	x
Migrant shares (by skill groups)					x	x
%Δ Migrant shares						x
Commuting Zones	100	100	100	100	100	100
Periods	4	4	4	4	4	4
Observations	400	400	400	400	400	400

Notes: * < 0.10, ** < 0.05, *** < 0.01. Heteroskedasticity robust standard errors are reported in round brackets, while industry structure clustered standard errors from [Adao, Kolesár, and Morales \(2019\)](#) are reported in square brackets.

Main Results:

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Commuting Zone Fixed Effects	x	x	x	x	x	x
Industry Structure	x	x	x	x	x	x
Regional Characteristics		x	x	x	x	x
Demographic Characteristics			x	x	x	x
Lagged employment changes				x	x	x
Migrant shares (by skill groups)					x	x
%Δ Migrant shares						x
Commuting Zones	100	100	100	100	100	100
Periods	4	4	4	4	4	4
Observations	400	400	400	400	400	400

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Commuting Zone Fixed Effects	x	x	x	x	x	x
Industry Structure	x	x	x	x	x	x
Regional Characteristics		x	x	x	x	x
Demographic Characteristics			x	x	x	x
Lagged employment changes				x	x	x
Migrant shares (by skill groups)					x	x
%Δ Migrant shares						x
Commuting Zones	100	100	100	100	100	100
Periods	4	4	4	4	4	4
Observations	400	400	400	400	400	400

Notes: * < 0.10, ** < 0.05, *** < 0.01. Heteroskedasticity robust standard errors are reported in round brackets, while industry structure clustered standard errors from [Adao, Kolesár, and Morales \(2019\)](#) are reported in square brackets.

Main Results:

- ◇ Second Stage:
 - Negative relationship between changes in manufacturing employment and changes in far-right voting
 - Declines in manufacturing employment thus increase support for the far-right

- ◇ First Stage:
 - Bartik IV is sufficiently strong and appears relevant
 - First stage coefficient has expected sign
 - Around 16% of manufacturing employment growth in Austria is explained by common industry level trends with the IV countries

Additional Results:

- ◇ Effect is entirely mediated through increases in natives unemployment rates [▶ Appendix 2](#)
- ◇ Increases in far-right voting come primarily at the expense of the center-left Social Democratic Party [▶ Appendix 3](#)
- ◇ The far-left Communist Party also benefited from the manufacturing decline (albeit to a much smaller extent) [▶ Appendix 3](#)

The role of trade and technology:

To assess the relative contributions of trade and robot exposure I estimate:

$$\% \Delta \text{Voteshare}_{rt} = \gamma \Delta \text{Shock}_{rt} + X_{rt} \beta + \rho_r + \tau_t + \epsilon_{rt}$$

where ΔShock_{rt} corresponds to a regional measure of either net-import or robot-exposure. Following Autor et al. (2013) and Acemoglu and Restrepo (2020), these measures are calculated as shift share variables

$$\Delta \text{Net-Imports}_{rt} = \sum_i \frac{\text{Emp}_{irt}}{\text{Emp}_{rt}} \times \frac{\Delta \text{Net-Imports}_{it}}{\text{Emp}_{it}}$$

$$\Delta \text{Robots}_{rt} = \sum_i \frac{\text{Emp}_{irt}}{\text{Emp}_{rt}} \times \frac{\Delta \text{Robots}_{it}}{\text{Emp}_{it}}$$

The role of trade and technology:

To obtain causal estimates, the measures of net-import and robot exposure are instrumented with respective shift-share instruments:

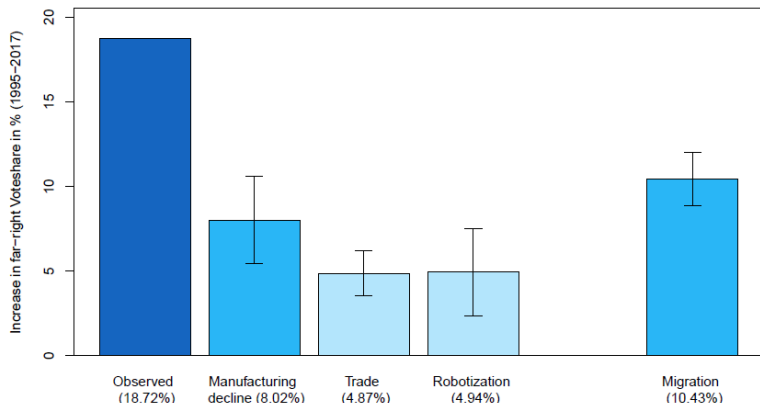
$$\Delta Net-Imports_{r,t}^{IV} = \sum_i \frac{Emp_{i,r,t-15}}{Emp_{r,t-15}} \times \frac{\Delta Net-Imports_{i,t}^{OtherCountries}}{Emp_{i,t-15}}$$

$$\Delta Robots_{r,t}^{IV} = \sum_i \frac{Emp_{i,r,t-15}}{Emp_{r,t-15}} \times \frac{\Delta Robots_{i,t}^{OtherCountries}}{Emp_{i,t-15}}$$

The role of trade and technology:

	Δ Net-Imports	Δ Robots
	(1)	(2)
Panel A: OLS Estimations:		
	2.974 (1.866) [0.886]***	3.071 (1.484)** [1.057]***
Panel B: 2SLS Estimations:		
	9.175 (3.431)*** [2.106]***	6.421 (3.09)** [2.033]***
Panel C: First-Stage Estimations		
	0.014 (0.004)*** [0.002]***	0.006 (0.001)*** [0.001]***
First-Stage F-Statistic:	15.36	27.94
<hr/>		
Full Controls	x	x
<hr/>		
	1995-2017	2002-2017
<hr/>		
Commuting Zones	100	100
Periods	4	3
Observations	400	300

Benchmarking Effect Size:



Notes: The contribution of the decline in manufacturing employment is calculated using the estimated effect of manufacturing employment on the far-right vote-share from Table 1 (panel B, column 6) and multiplying it with the observed percentage-change in manufacturing employment. Similarly, the contributions of trade-exposure (robot-exposure) is calculated by multiplying the estimated coefficients from Table 4, column 8 (table 5, column 7) and multiplying it with the observed change in net-imports per worker (robots per 1000 workers). Since the robotization effect can only be estimated on the timeframe 2002-2017, it is assumed that the same effect size also applies to the period 1995-2002. The contribution of migration to the increase in the far-right vote-share is calculated using the estimated effect of the migrant-share on far-right vote-shares for Austrian municipalities from [Halla, Wagner, and Zweimüller \(2017\)](#) (Table 8, column 2) and multiplying it with observed increases in the migrant share from the Austrian census data (1991-2011) and the Austrian Labor Market Statistics (2012 onwards).

Robustness Checks:

- ◇ Pre-Trend Tests
- ◇ Balance Tests
- ◇ Outliers & Influential Observations [▶ Appendix 6](#)
- ◇ Fixing exposure shares at common base year [▶ Appendix 7](#)
- ◇ Changes in voter turnout [▶ Appendix 7](#)
- ◇ Internal migration responses [▶ Appendix 7](#)
- ◇ Alternative definitions of regional units [▶ Appendix 8](#)

Pre-Trend Tests

	1986 – 1995		N
	(1)	(2)	(3)
<i>Bartik</i> ^{IV}	0.985 (0.09)*** [4.069]	0.058 (0.093) [0.098]	400
Δ <i>Net-Imports</i> ^{IV}	-0.014 (0.21) [1.289]	-0.078 (0.057) [0.191]	400
<i>ΔRobots</i> ^{IV}	-0.089 (0.034)*** [2.114]	0.019 (0.025) [0.049]	300
Period Fixed Effects	x	x	
Industry Structure		x	
Regional Characteristics		x	
Demographic Characteristics		x	
Shift-Share Controls		x	
Migrant share (by skill groups)		x	
Δ Migrant shares		x	

Summary of Main Findings:

- ▶ Declines in manufacturing employment lead to increases in far-right voting
- ▶ This increase is entirely mediated through increases in natives unemployment rates [▶ Appendix 2](#)
- ▶ The increase of far-right voting coincides with a decrease in the vote shares of the Social Democratic Party and of small fringe parties [▶ Appendix 3](#)
- ▶ Increases in the exposure to international trade and robotization are of roughly equal importance
- ▶ While the positive (exports) and negative (imports) employment effects of trade exposure are of roughly equal size, the electoral effects are highly asymmetric with the increasing effect of imports strongly dominating the offsetting effect of exports [▶ Appendix 5](#)

Thank you for your attention!

Appendix Quick Links:

- ▶ Commuting Zones [▶ Appendix 1](#)
- ▶ Causal Mediation Model [▶ Appendix 2](#)
- ▶ Inter-party dynamics [▶ Appendix 3](#)
- ▶ Employment effects of trade and automation [▶ Appendix 4](#)
- ▶ Separate electoral effects of imports and exports [▶ Appendix 5](#)
- ▶ Robustness checks [▶ Appendix 6-9](#)

Literature: I

- Acemoglu, Daron and Pascual Restrepo**, "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 2020, 128 (6), 2188–2244.
- Adao, Rodrigo, Michal Kolesár, and Eduardo Morales**, "Shift-Share Designs: Theory and Inference," *The Quarterly Journal of Economics*, 2019, 134 (4), 1949–2010.
- Algan, Yann, Sergei Guriev, Elias Papaioannou, and Evgenia Passari**, "The European trust crisis and the rise of populism," *Brookings Papers on Economic Activity*, 2017, 2017 (2), 309–400.
- Anelli, Massimo, Italo Colantone, and Piero Stanig**, "We Were the Robots: Automation and Voting Behavior in Western Europe," *IZA Working Paper 12485*, 2019.
- , —, and —, "Individual vulnerability to industrial robot adoption increases support for the radical right," *Proceedings of the National Academy of Sciences*, 2021, 118 (47), e2111611118.
- Autor, David, David Dorn, and Gordon Hanson**, "The China syndrome: Local labor market effects of import competition in the United States," *American Economic Review*, 2013, 103 (6), 2121–68.

Literature: II

—, —, —, and **Kaveh Majlesi**, “Importing political polarization? The electoral consequences of rising trade exposure,” *American Economic Review*, 2020, *110* (10), 3139–83.

Barone, Guglielmo, Alessio D’Ignazio, Guido de Blasio, and Paolo Naticchioni, “Mr. Rossi, Mr. Hu and politics. The role of immigration in shaping natives’ voting behavior,” *Journal of Public Economics*, 2016, *136*, 1–13.

Bartik, Timothy J, “Who benefits from state and local economic development policies?,” 1991.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, “Quasi-Experimental Shift-Share Research Designs,” *Review of Economic Studies*, 2022, *89* (1), 181–213.

Brunner, Eric, Stephen L Ross, and Ebonya Washington, “Economics and policy preferences: causal evidence of the impact of economic conditions on support for redistribution and other ballot proposals,” *Review of Economics and Statistics*, 2011, *93* (3), 888–906.

Colantone, Italo and Piero Stanig, “The Trade Origins of Economic Nationalism: Import Competition and Voting Behavior in Western Europe,” *American Journal of Political Science*, 2018a, *62* (4), 936–953.

Literature: III

— and — , “Global Competition and Brexit,” *American Political Science Review*, 2018b, 112 (2), 201–218.

Dehdari, Sirus, “Economic Distress and Support for Far-Right Parties - Evidence from Sweden,” *Comparative Political Studies*, 2021, 55 (2), 191–221.

Dippel, Christian, Robert Gold, Stephan Hebllich, and Rodrigo Pinto, “The effect of trade on workers and voters,” *The Economic Journal*, 2022, 132 (641), 199–217.

Dustmann, Christian, Anna Piil Damm, and Kristine Vasiljeva, “Refugee Migration and Electoral Outcomes,” *Review of Economic Studies*, 2019, 86 (5), 2035–91.

Edo, Anthony, Yvonne Giesing, Jonathan Öztunc, and Panu Poutvaara, “Immigration and electoral support for the far-left and the far-right,” *European Economic Review*, 2019, 115, 99–143.

Fetzer, Thiemo, “Did Austerity Cause Brexit,” *American Economic Review*, 2019, 109 (11), 3849–3886.

Frey, Carl Benedikt, Thor Berger, and Chinchih Chen, “Political machinery: did robots swing the 2016 US presidential election?,” *Oxford Review of Economic Policy*, 2018, 34 (3), 418–442.

Literature: IV

- Funke, Manuel, Moritz Schularick, and Christoph Trebesch**, "Going to extremes: Politics after financial crises, 1870–2014," *European Economic Review*, 2016, 88, 227–260.
- Goldsmith-Pinkham, Isaac Paul Sorkin, and Henry Swift**, "Bartik instruments: What, When, Why, and Wow," *American Economic Review*, 2020, 110 (8), 2586–2624.
- Halla, Martin, Alexander F Wagner, and Josef Zweimüller**, "Immigration and voting for the far right," *Journal of the European Economic Association*, 2017, 15 (6), 1341–1385.
- Margalit, Yotam**, "Costly jobs: Trade-related layoffs, government compensation, and voting in US elections," *American Political Science Review*, 2011, 105 (1), 166–188.
- Rodrik, Dani**, "Populism and the Economics of Globalization," *Journal of International Business Policy*, 2018, pp. 1–22.
- Steinmayr, Andreas**, "Contact versus Exposure: Refugee Presence and Voting for the Far Right," *The Review of Economics and Statistics*, 2021, 103 (2), 310–327.
- Tolbert, Charles M. and Molly Sizer**, "US Commuting Zones and Labor Market Areas: A 1990 Update," *Economic Research Service Staff Paper 9614*, 1996.

Appendix 1: Commuting Zones

Because of regional spillovers, these estimations cannot be performed using the 2.095 Austrian municipalities as units of observation.

Possible Solutions:

- ◇ Political Districts
- ◇ Commuting Zones (following Tolbert and Sizer, 1996)
 - Idea: Cluster municipalities according to the strength of their commuting-ties
 - Implementation: Horizontal Clustering Algorithm
 - Data on commuting flows: Statistik Austrias registry based census (since 2011)
 - Extensively used in the literature on trade- and automation based labor market shocks

Appendix 1: Commuting Zones

Estimation of Commuting Zones:

The Horizontal Clustering Algorithm

- ◇ Municipalities are clustered according to their distance $0 \leq D_{ij} \leq 1$
- ◇ D_{ij} is computed from the commuting flow data (for a detailed description see Tolbert & Sizer, 1996)
- ◇ The smaller D_{ij} is, the stronger are the commuting ties between two communities
- ◇ "Closest" communities are clustered
- ◇ Algorithm stops when the average between cluster distance is equal to h ("tuning constant")
- ◇ Tolbert and Sizer (1996) tune the algorithm to $h = 0.98$

Appendix 1: Commuting Zones

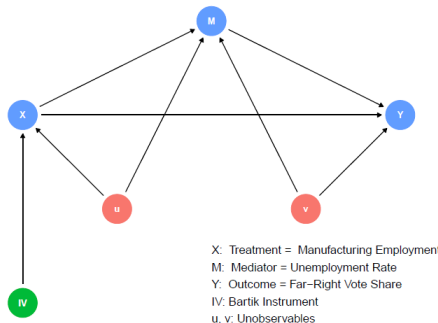
Table: Comparison of different "Local Labor Market" definitions

LLM	Commuters within LLM	N
Municipalities:	47.30%	2090
Political Districts:	65.62%	94
Commuting Zones:		
$h = 0.98$	70.07%	238
$h = 0.9825$	71.57%	197
$h = 0.985$	72.75%	158
$h = 0.9875$	74.18%	124
$h = 0.99$	75.31%	100

- ◇ Commuting Zones capture Commuting Flows much better
- ◇ They thus control better for spatial employment spillovers
- ◇ I use a baseline definition of $h = 0.99$
- ◇ Morans I: districts and lower configurations fail to capture spatial spillovers

Appendix 2: Causal Mediation Model

Causal mediation model in single instrument settings from Dippel et al. (2022)



	<u>%Δ Vote-Share</u> (1)	<u>pptΔ Vote-Share</u> (2)
Total Effect:	-0.917 (0.326)*** [0.237]***	-0.248 (0.044)*** [0.017]***
Direct Effect:	-0.099 (0.173) [0.034]***	0.055 (0.034) [0.003]***
Indirect Effect:	-0.819 (0.369)** [0.239]***	-0.303 (0.056)*** [0.018]***

▶ Text

▶ Summary

▶ Appendix Overview

Appendix 3: Inter-party dynamics

	Established Parties						(7) Non-Voters
	(1) Communists	(2) Social Democrats	(3) Greens	(4) Conservatives	(5) Far-right	(6) Other	
Avg. Manifesto Right-Left Score	-21.83	-15.3	-11.71	3.09	7.32		
%Δ Manufacturing Emp.:	-0.014 (0.004)*** [0.001]***	0.151 (0.043)*** [0.03]***	0.02 (0.024) [0.011]*	-0.029 (0.059) [0.044]	-0.272 (0.058)*** [0.023]***	0.163 (0.044)*** [0.011]***	-0.019 (0.071) [0.063]
First-Stage F-Statistic:	51.3	51.3	51.3	51.3	51.3	51.3	51.3
Period Fixed Effects	x	x	x	x	x	x	x
Commuting Zone Fixed Effects	x	x	x	x	x	x	x
Regional Characteristics	x	x	x	x	x	x	x
Demographic Characteristics	x	x	x	x	x	x	x
Industry Structure	x	x	x	x	x	x	x
Lagged employment changes	x	x	x	x	x	x	x
Migrant share (by skill groups)	x	x	x	x	x	x	x
%Δ Migrant Shares	x	x	x	x	x	x	x
Commuting Zones	100	100	100	100	100	100	100
Periods	4	4	4	4	4	4	4
Observations	400	400	400	400	400	400	400

Notes: * < 0.10, ** < 0.05, *** < 0.01. Heteroskedasticity robust standard errors are reported in round brackets, while industry structure clustered standard errors from [Adao, Kolesár, and Morales \(2019\)](#) are reported in square brackets. Units of observation are 100 clustered commuting zones.

▶ Text

▶ Summary

▶ Appendix Overview

Appendix 4: Trade & Robots - Employment Effects (Overall)

	1995-2017		2002-2017	
	Manuf. (1)	Non-Manuf. (2)	Manuf. (3)	Non-Manuf. (4)
Panel A: Net-Import Exposure				
Δ Net-Imports	-3.026 (2.624)	-0.528 (0.995)	-3.534 (1.873)*	-0.758 (1.143)
	[1.052]***	[0.498]	[0.779]***	[0.69]
First-Stage F-Statistic:	15.36	15.36	29.99	29.99
Panel B: Import- & Export-Exposure separately				
Δ Imports	-3.096 (3.367)	-1.225 (1.628)	-3.55 (2.526)	-1.391 (1.709)
	[1.115]***	[0.626]*	[1.397]**	[0.974]
First-Stage F-Statistic:	18.85	18.85	12.16	12.16
Δ Exports	2.973 (2.18)	-0.002 (0.911)	3.515 (1.503)**	-0.027 (1.064)
	[0.942]***	[0.441]	[0.797]***	[0.51]
First-Stage F-Statistic:	20.05	20.05	9.78	9.78
Panel C: Robot-Exposure				
Δ Robots			-3.244 (1.548)**	-0.919 (1.273)
			[1.116]***	[0.734]
First-Stage F-Statistic:			27.94	27.94
Full Controls	x	x	x	x
Commuting Zones	100	100	100	100
Periods	4	4	3	3
Observations	400	400	300	300

Notes: * < 0.10, ** < 0.05, *** < 0.01. Heteroskedasticity robust standard errors are reported in round brackets, while industry structure clustered standard errors from [Adao, Kolesár, and Morales \(2019\)](#) are reported in square brackets.

Appendix 4: Trade & Robots - Employment Effects (Natives Only)

	1995-2017		2002-2017	
	Manuf. (1)	Non-Manuf. (2)	Manuf. (3)	Non-Manuf. (4)
Panel A: Net-Import Exposure				
Δ Net-Imports	-3.026 (2.624) [1.052]***	-0.528 (0.995) [0.498]	-3.534 (1.873)* [0.779]***	-0.758 (1.143) [0.69]
First-Stage F-Statistic:	15.36	15.36	29.99	29.99
Panel B: Import- & Export-Exposure separately				
Δ Imports	-3.096 (3.367) [1.115]***	-1.225 (1.628) [0.626]*	-3.55 (2.526) [1.397]**	-1.391 (1.709) [0.974]
First-Stage F-Statistic:	18.85	18.85	12.16	12.16
Δ Exports	2.973 (2.18) [0.942]***	-0.002 (0.911) [0.441]	3.515 (1.503)** [0.797]***	-0.027 (1.064) [0.51]
First-Stage F-Statistic:	20.05	20.05	9.78	9.78
Panel C: Robot-Exposure				
Δ Robots			-3.244 (1.548)** [1.116]***	-0.919 (1.273) [0.734]
First-Stage F-Statistic:			27.94	27.94
Full Controls	x	x	x	x
Commuting Zones	100	100	100	100
Periods	4	4	3	3
Observations	400	400	300	300

Notes: * < 0.10, ** < 0.05, *** < 0.01. Heteroskedasticity robust standard errors are reported in round brackets, while industry structure clustered standard errors from [Adao, Kolesár, and Morales \(2019\)](#) are reported in square brackets.

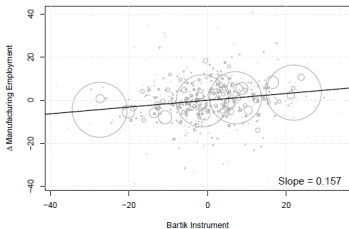
Appendix 5: Import- and export-exposure separately

	Dependent Variable: % Δ Far-right vote share		
	1995-2017	2002-2017	
	(1)	(2)	(3)
Δ Imports	11.41 (5.371)** [3.192]***	12.046 (5.56)** [2.922]***	10.28 (5.88)* [2.97]***
Δ Exports	-7.472 (3.407)** [1.609]***	-7.239 (3.487)** [1.468]***	-3.755 (3.91) [1.337]***
First-Stage F-Statistic: Δ Imports	18.85	13.96	12.16
First-Stage F-Statistic: Δ Exports	20.05	13.86	9.78
Period Fixed Effects	x	x	x
Commuting Zone Fixed Effects	x	x	x
Industry Structure	x	x	x
Regional Characteristics	x	x	x
Demographic Characteristics	x	x	x
Tech. Shock: Δ ICT	x	x	x
Migrant shares (by skill)	x	x	x
Δ Migrant shares	x	x	x
Tech. Shock: Δ Robots			x
Commuting Zones	100	100	100
Periods	4	3	3
Observations	400	300	300

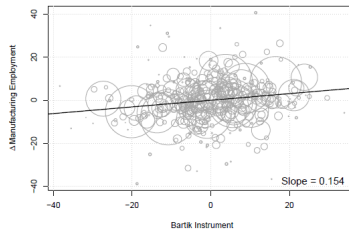
Notes: * < 0.10, ** < 0.05, *** < 0.01. Heteroskedasticity robust standard errors are reported in round brackets, while industry structure clustered standard errors from [Adao, Kolesár, and Morales \(2019\)](#) are reported in square brackets.

Appendix 6: Outliers & Influential Observations

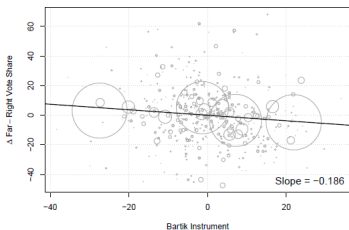
(a) First-Stage



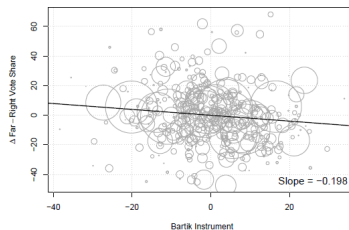
(b) First-Stage
(exclude Vienna commuting zone)



(c) Reduced Form



(d) Reduced Form
(exclude Vienna commuting zone)



Appendix 7: Further robustness checks

	Internal Migration Responses					
	Baseline (1)	Fixed Exposure Shares (2)	Changes in Turnout (3)	Δ Population Size (4)	Dem. Composition in t=2 (5)	Both (6)
Panel A: Changes in Manufacturing Employment						
%Δ Manufacturing Employment:	-1.181 (0.418)*** [0.23]***	-1.891 (0.684)*** [0.233]***	-1.413 (0.553)** [0.385]***	-1.111 (0.41)*** [0.222]***	-1.123 (0.502)** [0.246]***	-1.114 (0.517)** [0.258]***
First Stage F:	51.3	15.77	51.3	47.18	26.72	23.75
Panel B: Changes in Trade Exposure						
Δ Net-Imports (1995-2017; excl. Robot controls):	9.175 (3.431)*** [2.106]***	9.633 (3.715)** [2.272]***	9.225 (3.697)** [2.167]***	9.508 (3.389)*** [2.087]***	10.487 (3.571)*** [1.766]***	10.676 (3.576)*** [1.828]***
First Stage F:	15.36	15.13	15.36	15.46	16.11	16.68
Δ Net-Imports (2002-2017; incl. Robot controls):	7.366 (3.597)** [1.235]***	6.89 (3.876)* [1.083]***	9.18 (4.038)** [1.237]***	6.92 (3.557)* [1.272]***	7.158 (3.75)* [1.696]***	6.834 (3.636)* [1.751]***
First Stage F:	29.99	26.39	29.99	29.51	28.53	29.88
Panel C: Changes in Robot Exposure						
Δ Robots:	6.421 (3.09)** [2.033]***	6.876 (2.779)** [1.892]***	5.734 (3.093)* [1.975]***	6.349 (3.066)** [1.991]***	8.035 (3.187)** [2.027]***	8.118 (3.229)** [2.051]***
First Stage F:	27.94	26.03	27.94	29.52	25.42	25.36

Notes: * < 0.10, ** < 0.05, *** < 0.01. Heteroskedasticity robust standard errors are reported in round brackets, while industry structure clustered standard errors from [Adao, Kolesár, and Morales \(2019\)](#) are reported in square brackets. Units of observation are 100 clustered commuting zones. All specifications include a full set of controls corresponding to the controls used in the respective estimations in [Tables 1, 4, and 5](#). All estimations are weighted by the start-of-period native voting-age population.

Appendix 8: Alternative definition of regional units

	(1)	(2)	(3)	(4)	(5)	(6)
						Baseline
LLM Definition:	Districts	h = 0.98	h = 0.9825	h = 0.985	h = 0.9875	h = 0.99
Units:	94	238	197	158	124	100
Commuters within LLM:	65.62 %	70.07 %	71.57 %	72.75 %	74.18 %	75.31 %
<hr/>						
A Manufacturing Employment:	-0.72 (0.173)*** [0.147]***	-1.126 (0.291)*** [0.071]***	-1.074 (0.285)*** [0.182]***	-1.184 (0.359)*** [0.225]***	-1.151 (0.378)*** [0.213]***	-1.181 (0.418)*** [0.23]***
First-Stage F:	0	63	73.97	56.81	54.96	51.3
Moran's I:	0.478	0.055	0.028	0.122	0.11	-0.027
(p-Value)	(0)***	(0)***	(0.088)*	(0)***	(0)***	(0.317)
<hr/>						
A Net-Imports (1995-2017)	6.15 (2.567)** [1.467]***	6.308 (3.173)** [0.776]***	7.035 (3.644)* [1.026]***	6.845 (3.869)* [1.273]***	6.395 (3.79)* [1.663]***	9.175 (3.431)*** [2.106]***
First-Stage F:	44.97	15.05	14.62	13.22	12.88	15.36
Moran's I:	0.432	0.085	0.06	0.156	0.138	0.066
(p-Value)	(0)***	(0)***	(0)***	(0)***	(0)***	(0.005)***
<hr/>						
A Net-Imports (2002-2017)	5.865 (2.553)** [1.741]***	5.351 (2.734)* [0.527]***	6.566 (3.077)** [0.784]***	6.385 (3.3)* [0.932]***	6.803 (3.604)* [1.473]***	7.366 (3.597)** [1.235]***
First-Stage F:	8.55	1.98	2.15	0.05	10.35	2.92
Moran's I:	0.317	0.118	0.117	0.076	0.155	0.073
(p-Value)	(0)***	(0)***	(0)***	(0)***	(0)***	(0.006)***
<hr/>						
A Robots	9.341 (3.055)*** [3.331]***	4.067 (2.024)** [0.82]***	4.839 (2.16)** [1.039]***	4.881 (2.457)** [1.278]***	4.694 (2.401)* [1.323]***	6.332 (3.103)** [2.038]***
First-Stage F:	39.79	27.1	29.21	30.02	29.12	27.44
Moran's I:	0.27	0.049	0.057	0.015	0.079	0.06
(p-Value)	(0)***	(0.004)***	(0.003)***	(0.439)	(0.001)***	(0.025)**
<hr/>						
Full Controls	x	x	x	x	x	x

Notes: * < 0.10, ** < 0.05, *** < 0.01. Heteroskedasticity robust standard errors are reported in round brackets, while industry structure clustered standard errors from [Adao, Kolesár, and Morales \(2019\)](#) are reported in square brackets.