Globalization, robotization and electoral outcomes: Evidence from spatial regressions for Italy*

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Abstract

Criticism of economic globalization and technological progress has gained support in Italy in the last two decades. However, due to the differentiated exposure of local labor markets to this process, electoral outcomes have varied considerably across the country. By observing the local impact of three global economic phenomena (flows of migrants, foreign competition in international trade, and diffusion of robots) alongside with the patterns of local electoral outcomes potentially associated with discontent, this work analyses the economic forces driving the evolution of general elections in 2001, 2008 and 2013 in Italy. The analysis reveals that all these global factors had an impact on political outcomes associated with discontent, albeit in different ways and changing over time. All three factors are associated with increases in votes for far-right parties in the period 2001-2008, but only robotization continues to have such an impact in the following period, while immigration is associated with an increase in votes for the Five-Star Movement at the expense of far-right parties. The results and extensions exploiting recent advances in political geography, political economy and spatial econometrics make it possible to draw some general and methodological conclusions. Global drivers interact with elements pertaining to the political supply that empirical researchers should not be oblivious about. Political spillovers across neighbouring areas add to the direct impact of locally-mediated economic factors. Finally, the adoption of shift-share instrumental variables to identify the impact of robotization may lack robustness.
Keywords: local electoral outcomes, local labor markets, immigration, import competition, robotization.
JEL Classification Codes: D72, F14, F60, O33.

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1 Introduction

Criticism of contemporary economic and social trends, particularly those associated with economic globalization and technological progress, has grown in intensity and gained support in Italy as well as in several other countries (Frieden, 2018; Kriesi, 2014). Mapping electoral trends across the Atlantic, Rodrik (2018) finds that the rise of populism in Europe is a recent swift phenomenon (moving from below 5 percent in the late 1980s to more than 20 percent by 2011-2015) and is associated with right-wing positions: economic anxiety and discontent have been channelled through nationalistic narratives emphasizing identity cleavages against foreigners and technological progress. Indeed, the 2018 general elections in Italy certified the emergence of parties framing "the people" in a territorial sense (Heinisch et al., 2018), whereby locals and natives are portrayed as threatened by foreign migrants, foreign firms and technological innovations introduced by internationalized companies and multinationals as means to obtain extra profits.

However, as argued by Agnew and Shin (2017), this process started much earlier in Italy, probably right after the demise of the main traditional parties in the early 1990s, and its evolution is worth investigating. Initially, according to their account, the wave of discontent manifested itself at general elections either in lower turnout rates or in growing shares of votes accruing to far-right parties (as also shown by Barone et al., 2016; Caselli et al., 2020), whereas it was more recently conducive to a shift towards populist movements (Ruzza and Fella, 2011), in particular the *sui generis* Five-Star Movement (5SM, hereafter). But are these widely-held conjectures true? Is the empirical evidence consistent with such political account of Italian politics? And does the analysis of the recent elections in Italy allow to draw more general conclusions and suggestions informing a lively strand of the political economy literature focusing on global economic trends and voting patterns?

Short of data on individual voting preferences and actions, the distribution of the electoral outcomes across Italian areas can be explored to test these conjectures and, more generally, to improve our understanding of the geographic evolution of Italian politics over the period 2001-2013. The literature has shown that the regional variation in local socio-economic features can be used to identify the impact of global economic drivers on the voting patterns within countries.[1] People, even within the same country, differ across areas in their interests and identities, that in turn evolve over time as the result of the interaction between historical legacies and the contingent socio-economic and institutional context: as convincingly argued by Shin and Agnew (2007, p. 300), "[p]olitical change is seldom uniform across a democracy". Furthermore, places are highly differentiated in terms of their exposure to three main global phenomena shaping the local economy: the higher flows of migrants coming from countries of the Global South, the fiercer trade competition from new international players, and the diffusion of skill-biased and labor-substituting technological change. As the transitional costs of adjusting to the shocks associated with globalization and technological progress are significant at the local, sec-

[1] This approach has been adopted to address various political phenomena, such as the success of specific parties (Malgouyres, 2017b; Halla et al., 2017), the strengthening of nationalist and autarchic forces in Western European countries (Colantone and Stanig, 2018b), the polarization of voters in the US (Autor et al., 2016), and the success of the Leave option in referendum on Brexit in the UK (Colantone and Stanig, 2018a; McCann, 2018).

toral and individual level (Holm et al., 2017), dynamic areas offering opportunities and good jobs coexist with areas of discontent and 'places that don't matter' (Rodríguez-Pose, 2018), where populist, nationalist and highly conservative narratives gain traction. The empirical approach focusing on the distribution of local voting patters fits Italy very well, due to the presence of a political environment characterized by changing political parties with non-overlapping manifestos and considerable regional differentiation in terms of economic structure and electoral results. Hence, by observing the local evolution of the above-mentioned global phenomena alongside with the local patterns of electoral outcomes, this work analyses from a spatial perspective the locally-mediated effect of the global economic drivers on the Italian general elections in 2001, 2008 and 2013.

Surprisingly, the most influential studies in the political economy literature focusing on the impact of globalization and technological progress on political phenomena did neglect an important dimension of the "geography of discontent", namely the fact that people in nearby areas influence each other in ways that can lead to geographical clusters of voting choices. Indeed, limited attention has been paid to the existence of economic and political spillovers across proximate areas: as argued by Cutts et al. (2014), voters are aware of the political sentiment in the neighbouring areas and tend to be influenced in their voting decisions even when they are not directly exposed to the factors operating in such adjacent areas. To address this potential issue affecting the estimations, and in particular those based on small-scale geographical units of analysis such as municipalities, this work adopts two solutions. To tackle economic spillovers related to the labor markets, we choose sub-regional areas that aggregate municipalities in terms of commuting flows: as the literature posits that global economic drivers are linked to voting patterns through labor market-related channels, we look at local labour market areas (LLMAs, hereafter) so as to ensure that economic spillovers across regions are, by construction, limited. Using LLMAs does help to control for the spatial dependence associated with economic spillovers, but it does not address political spillovers across adjacent areas following routes that are not related to labour markets. To account for this possibility, we consider an extension of the baseline empirical approach that allows for spatial dependence: it represents an element of novelty with respect to the approach usually adopted in the recent political economy literature.

Anticipating our main findings, the analysis reveals a change over time in the way immigration, Chinese import competition and skill-biased and labor-substituting technological change (in the form of robotization) impact on voters' turnout and on the shares of votes accruing to far-right parties, both typically associated with popular discontent (Inglehart and Norris, 2016). As found in various related studies focusing on other countries, the higher the change in the local exposure to Chinese import competition, the larger the increase in the share of votes accruing to far-right parties (and the larger the fall in voters' turnout) during the period 2001-2008. During the period 2008-2013, instead, neither the far-right parties, nor the 5SM gained systematically larger shares where the exposure to China imports had increased relatively more, and local turnout rates did not decline more patently either. This can be explained by the decreasing intensity of Chinese competition in the second period (as discussed by Bugamelli et al., 2018), as well as by the differentiated impact that China's growth in the world markets exerted on the different Italian industries in the more recent period. Indeed, some industries reacted as complementary, possibly because integrated in growing global value chains, while others suffered of competition in local and third markets.[2] In the areas where immigration had grown relatively more, turnout rates and votes for far-right parties respectively decreased and increased, as expected, during the period 2001-2008; in the period 2008-2013, instead, it was the 5SM that gained more in the areas most exposed to immigration flows. To interpret this result, it is necessary to consider the exogenous changes occurred in the political supply across the far-right parties in this period, namely, the scandals hitting the largest far-right party (i.e., the Northern League) - that negatively affected its credibility and its perceived trustworthiness - as well as the merge between one far-right party and a more moderate one. Besides their significance for scholars interested in Italian politics, these findings are thus of general interest in that they draw the attention on a kind of risk underestimated in previous works, namely the presence of exogenous shocks in the political supply that do not regard the parties' political platforms. Finally, the empirical findings indicate an impact on electoral results of the variations in the local exposure to robotization: in both periods, stronger local increases in robotization appear as associated with a higher share of votes to far-right parties and, in 2008-2013, a lower turnout. These findings are in line with previous results obtained at the European level by studies adopting larger geographical units of analysis mapping the continent (Anelli et al., 2018; Im et al., 2019).

Furthermore, by employing state-of-the-art methodologies developed to analyse the sources and the validity of the identification based on shift-share instrumental variables (IV) (Adão et al., 2018; Borusyak et al., 2018; Goldsmith-Pinkham et al., 2020), we provide evidence on the plausibility of the identification strategy for assessing the impact of Chinese import competition on the local electoral outcomes. The analysis supports the validity of the shift-share IV approach in both periods and it makes it possible to appreciate that, in the second time span, the impact of the China shock is differentiated across industries as certain sectors benefited from the expansion of Chinese exports to other advanced countries, while others suffered from the direct competition. The analysis also shows that, in fact, it is more difficult to identify the role of robotization and to validate the identification strategy based on shift-share IV, mainly because of the limited number of industry-related shocks available when using a two-digit sectoral classification of industrial robots. This calls for great care in interpreting the results obtained in empirical analyses using shift-share IV instruments for robots: this methodological conclusion is a further contribution to the literature as, to the best of our knowledge, no previous work has discussed the identification problems for the impact of robotization on voting patterns (as well as on labor markets dynamics) when the shift-share IV design is employed.

With regards to the possible existence of political spillovers across LLMAs, the analysis shows that accounting for spatial dependence does not modify radically the main results, probably because of the use of LLMAs within which labor market shocks are absorbed. Yet, the study provides evidence that "pure" political spillovers from neighbouring LLMAs do exist, in line with the intuitive idea that voter's perceptions and people's interactions are not confined within LLMAs. In more general terms, this finding informs economists interested in exploring the economic drivers of local political outcomes: first, they should use care in comparing the results from analyses that use diversified geograph-

[2] In line with this, Caselli and Schiavo (2020) show that French firms responded in a differentiated way to the China shock and some managed to preserve their mark-ups by challenging Chinese competition and increasing their integration in the global economy.

ical units of analysis; second, they could borrow some political geographers' tools to draw further insights on spatial dependence.

As mentioned, many contributions in the recent political economy literature have focused on the economic determinants of the electoral results in advanced economies. Most of them, however, have looked at the localized impact of one global economic driver at a time. An exception is Caselli et al. (2020), who consider both trade and immigration in Italy from the 1990s to the 2000s.[3] As to what concerns immigration by itself, its impact on the FPÖ in Austria and on the right-wing coalition and voters' turnout in Italy was recently assessed, respectively, by Halla et al. (2017) and Barone et al. (2016), whereas Otto and Steinhardt (2014) analysed its influence on the districts within Hamburg, and Edo et al. (2019) assessed the impact of immigration on voting for far-left and far-right candidates in French presidential elections from 1988 to 2017. All studies concur on the positive relationship between immigration and votes for far right parties. The impact of fiercer Chinese competition has been the object of various empirical studies in the last few years. Autor et al. (2016) find evidence of its contribution to the growing political polarization in the US, while Malgouyres (2017b) and Dippel et al. (2017) show its positive relationship with, respectively, the gains recorded by the Front National in France and by far-right parties in Germany. Enlarging the territory of interest as well as the size of the geographical units of analysis, Colantone and Stanig (2018b) estimate a positive impact of Chinese competition on the electoral results of nationalist and radical-right parties across NUTS-2 regions in Western Europe. The impact of industrial robots on political outcomes in Western Europe has been the object of limited research for the time being. Anelli et al. (2018) look at large NUTS-2 regions in Western European countries and reveal a tilt towards nationalist parties and radical-right parties, probably also because the economic nationalist platforms tend to emphasize the protection of workers among their political goals and the radical-right parties appeal to nostalgia to address societal pessimism (Steenvoorden and Harteveld, 2018). Focusing on US commuting zones, Frey et al. (2018) show that the support for President Donald Trump is higher in the local labour markets more exposed to the adoption of robots. Using individual political preferences in eleven Western European countries, Im et al. (2019) also conclude that automation threats tend to increase support for radical-right parties.[4]

While confirming several results found for other countries, our work contributes to this rich literature along several lines: first, it considers all three global economic forces simultaneously and it focuses on the local results in Italian general elections at a level of disaggregation that fits with labor market-related channels linking global economic drivers, labor distress, discontent and voting. Second, this work provides evidence of the alternate fortunes of far-right and populist movements in the 2000s and the early 2010s:

[3] Guiso et al. (2017) also look at both immigration and Chinese competition, but they focus on individual surveys rather than on electoral results.

[4] Several scholars address the impact of these global drivers on sectoral dynamics and/or local labour markets, but do not look at their political implications. For instance, following the lead by Acemoglu and Restrepo (2020), Acemoglu et al. (2020), Chiacchio et al. (2018) and Dauth et al. (2017) estimate the impact of digitalization and robotization on EU, France and Germany's labor markets (see Adams, 2018, and Terzidis et al., 2019, for recent reviews of this strand of the literature), whereas Autor et al. (2013) and Malgouyres (2017a) estimate the impact of Chinese competition on the US and France's labor markets, respectively.

although specific to the Italian case, this result can be related to a widespread shift of far-right parties towards populist stances and vice versa, as well as to the existence of exogeneous changes in political supply that are often neglected by the empirical literature, particularly in cross-country studies. Third, this work takes seriously the issue of spatial dependence: it employs geographical units of analysis limiting issues with economic spillovers and adopts also a spatial autoregressive specification to account for possible political spillovers. Fourth, by opening the black box of the shift-share IV design, this works casts some light on the validity and the interpretation of a widely used research method in this strand of the literature. Finally, this analysis informs (and is informed by) the work of scholars in other disciplines. With respect to previous analyses carried out by political scientists and sociologists on the voting patterns in Italy, this work sheds light on three global economic drivers and provides a spatial representation of the electoral results in terms of these locally-mediated global forces. With respect to previous contributions in the political geography of Italian politics (see, for instance, Shin and Agnew, 2011, Agnew and Shin, 2017 and Abbondanza and Bailo, 2018) this work employs more advanced techniques of empirical analysis with a view to addressing omitted-variable bias and reverse causality problems in the estimations.

The remainder of the paper is organized as follows. Section 2 briefly introduces the three locally-mediated global economic drivers of interest and their possible impact on political outcomes in Italy. Section 3 presents the data and describes the empirical strategy, while Section 4 illustrates and discusses the results and the research design. Section 5 concludes.

2 Global Economic Drivers and Political Outcomes in Italy

Italy represents an interesting political environment for its dynamic evolution over time and for the geographical diversification of the electoral results across regions.[5] The remarkable heterogeneity of social and economic conditions and of electoral outcomes across different areas in Italy makes it suitable to investigate empirically how the local electorate has moved in response to the evolution of three important global economic phenomena often considered as causes of discontent: inflows of migrants, competition from developing countries (in particular, China) and robotization. While truly global, the impact of these phenomena has been locally mediated and, in particular, it has been determined by the persistent differences across areas in the underlying structure of the economy.

The first locally-mediated global driver that we consider refers to international migration flows. Albeit to a different extent in different places, migration flows have led to a progressive expansion in the number of foreign-born citizens residing in Italian cities, raising identity issues (Ambrosini, 2013), feeding perceived insecurity (Abbondanza and Bailo, 2018), affecting residential markets (Accetturo et al., 2014), and causing concerns for local labor markets (Barone et al., 2016), in particular among the least-skilled workers.

The second locally-mediated economic driver to consider is the rapid increase in the degree of international competition following the admission of China to the WTO in 2001

[5] On the crisis of traditional political parties in the early 1990s, see Morlino (1996); Newell and Bull (1997); Passarelli and Tuorto (2012), among others. Shin and Agnew (2002; 2007) discuss the transition towards a new electoral map of Italy and the complex patterns of party replacement.

and the subsequent expansion of Chinese exports in all advanced countries. This expansion occurred in particular at the expense of regions specialized in traditional (unskilled labor-intensive) manufacturing activities, such as textile, leather, paper, steel, and metals. As shown by Amighini et al. (2011), Federico (2014), Bugamelli et al. (2015) and Bugamelli et al. (2018), several traditional industries, and thus regions, in Italy have suffered from the competition stemming from the expansion of Chinese companies. Notably, while import competition increased over time for the entire country, its effects have been geographically differentiated.[6]

The third global economic driver refers to the widespread adoption of robots in a number of manufacturing and service activities. According to Chiacchio et al. (2018), industrial robot density started growing fast in Italy from the mid-90s and reached 3 robots per thousand workers in 2015 (against less than 2 robots per thousand workers in France and Spain). Again, while robotization was widespread, it concentrated in those industries and regions where economic prospects were sufficiently positive to justify investment in high-tech capital goods. While automation can potentially increase workers' productivity and have a positive effect on employment in the long run, it tends to displace workers from performing specific tasks and, thus, to exert pressure on local labor markets in the short run (Acemoglu and Restrepo, 2020; Acemoglu et al., 2020; Chiacchio et al., 2018; Goos et al., 2014; Graetz and Michaels, 2018).

All these global economic phenomena are likely to impact on local electoral results through multiple channels. All, however, have the potential to impinge on local labor markets by forcing adjustment processes that, especially in the short term, tend to hurt certain workers, firms and regions (Hoekman and Nelson, 2018). In sum, cheap foreign-born labor force, competition from China, and more intensive use of robots may, *ceteris paribus*, reduce local labor demand and depress wages, thereby worsening living standards and reducing perceived economic security. The associated discontent, in turn, will likely influence individuals' voting behaviour. The empirical analysis concerning the impact of these global drivers on local voting patterns has to rely on geographical units where labor market-related effects can be captured with limited spillovers from adjacent areas. Accordingly, this work focuses on so-called labor market areas (LLMAs), i.e., geographical units within which most people tend to live and commute to work.

To improve the identification of this channel, the empirical strategy embraces the use of instrumental variables as well as of various local socio-economic controls and fixed-effects. In a dedicated section, this work exploits the recent advances in the analysis of the shift-share IV design with a view to interpreting the mechanisms underpinning the estimated impact of China competition and robotization on electoral outcomes.[7]

[6] For example, the area surrounding the city of Fabriano, traditionally specialized in the production of paper and paper products as well as domestic appliances, was one of the local labor markets facing the largest increase in competition from China. Another example is Montegranaro and its surrounding local labor market specialized in the manufacturing of footwear.

[7] The authors would like to thank an anonymous reviewer for the suggestion.

3 Data and Empirical Approach

3.1 Data

Our investigation starts off from a dataset constructed combining data from multiple sources that cover information on the economic structure, the demographic composition and the electoral outcomes of Italian municipalities (about 8,000) in 2001, 2008 and 2013. As the focus of the analysis is the impact of global economic drivers on electoral outcomes through local labor markets, we aggregate the municipal data at that level, adopting as geographical units of analysis the local Labor Market Areas (LLMAs) developed by the Italian Institute of Statistics (Istat). In 2001, there were 684 sub-regional, economically integrated, units identified on the basis of daily workers' commuting patterns, rather than administrative boundaries.

Electoral results were provided by the Italian Ministry of the Interior. To identify far-right parties we resort to the University of North Carolina's Chapel Hill Expert Survey 2014 (CHES), a dataset collecting experts' opinions on the stance that individual parties take over several political issues.[8] According to the CHES and the chosen cut-off scores, the Northern League has been classified as a far-right party. Indeed, the Northern League has gradually shifted from being a regionalist protest party in the 1990s to a movement similar to European extreme-right parties (Ignazi, 2005), but still with a strong regionalist profile in line, according to Massetti (2009), with what occurred to other regionalist parties in Europe. Similar conclusions about the classification of the Northern League are reached also by Passarelli and Tuorto (2012), Fella and Ruzza (2013) and Passarelli (2013).

Data on the local economic structure come from the 2001 wave of the Census of Industry and Services (CIS) carried out by Istat. The CIS presents information on the industry mix of employment for all municipalities and at the three-digit level of the NACE industry classification. Data on socio-demographic factors used as controls for municipalities and NUTS-2 regions also come from Istat databases. The number of immigrants and resident population come from the Istat Population Census and Istat Demo database. The data on Chinese imports, disaggregated at the six-digit product level of the WCO Harmonized System (HS), have been drawn from the United Nations International Trade Statistics Database (Comtrade) and matched with three-digit NACE sectors on the basis of Eurostat RAMON correspondence tables so as to relate trade flows and local industrial production.[9] Data on robots were purchased from the International Federation of Robotics (IFR), which defines an industrial robot as "an automatically controlled, reprogrammable, multi-purpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications". The

[8]More specifically, we look at the position of each party in terms of left-right score (provided in an interval between 0 and 10) and identify as far-right every party with a score greater than or equal to 7. We also check the robustness of our definition of far-right parties by using different cut-off scores. It turns out that all parties currently defined as far right have a score above 7.5 and the large majority of them above 8. On the other hand, there are a few parties that have values just below 7 (yet all above 6.5). Such parties are Forza Italia, The People of Freedom and some of their allies. When we include all these parties among the far-right parties, the results do not change qualitatively, as can be seen in Appendix E. We thank an anonymous reviewer for suggesting this robustness check.

[9]A more detailed description of a similar dataset, with data up to 2008, is provided in Caselli et al. (2020).

IFR dataset contains the stocks of industrial robots purchased in Italy and other countries by sector and by year. As the IFR data are based on the ISIC Rev 4 classification, in order to match them with data for the local industrial production from the CIS, we employ a correspondence table between ISIC Rev 4 and NACE Rev 1 classifications at the two-digit level of aggregation.

Next, we describe how our global economic drivers are constructed. The first variable refers to changes in the local presence of immigrants and is captured by changes in the number of immigrants per resident in LLMA i at period t, times 100. Hence,

$$\Delta IMM^{shr}_{i,t} = \Delta Immigrants_{i,t}/Residents_{i,2001} \times 100, \tag{1}$$

where $\Delta Immigrants_{i,t} = Immigrants_{i,t} - Immigrants_{i,t0}$. As we study changes between 2001 and 2008 and between 2008 and 2013, $t0$ is 2001 when $t = 2008$ and 2008 when $t = 2013$.

The intensity of the local exposure to import competition from China is measured by interacting data on local sectoral employment with country-level data on imported goods following the shift-share methodology adopted by Autor et al. (2013). This makes it possible to exploit the large heterogeneity in the regional industry mix to allocate aggregate national trade data at the local level. In practice, we attribute higher values of Chinese imports per worker to the LLMAs specialized in those sectors in which Italian imports from China are larger. Changes over time in Chinese imports per worker are then calculated as

$$\Delta IPW^{chn}_{i,t} = \ln\left(\sum_s \eta_{is}\frac{IMP^{chn}_{s,t}}{L_s}\right) - \ln\left(\sum_s \eta_{is}\frac{IMP^{chn}_{s,t0}}{L_s}\right), \tag{2}$$

where $IMP^{chn}_{s,t}$ indicates the value (expressed in thousands of constant 2010 US dollars) of imports from China of goods belonging to three-digit NACE sector s at time t. As before, $t0$ is 2001 when $t = 2008$ and 2008 when $t = 2013$. L_s is the total employment of sector s in 2001, and $\eta_{is} = L_{is}/L_i$ stands for the fixed weight of sector s in local labor market i in 2001, at the beginning of the period analyzed. Values for the employment structure are calculated for the year 2001 so as to ensure that local specialization is not due to contemporaneous trade exposure.

The local intensity of robotization is calculated in a similar way, as the data on robots are available only at the national level (Acemoglu and Restrepo, 2018; 2020). Accordingly, changes in the number of robots per worker at the LLMA level are given by the formula:

$$\Delta RPW_{i,t} = \sum_q \eta_{iq}\ln\left(\frac{RBT_{q,t} * 1000}{L_q}\right) - \sum_q \eta_{iq}\ln\left(\frac{RBT_{q,t0} * 1000}{L_q}\right), \tag{3}$$

where $RBT_{q,t}$ indicates the number of robots belonging to the two-digit NACE sector q that were installed in Italy at time t, normalized by the (thousands of) workers employed in q in 2001. When t is 2008 $t0 = 2001$, and when t is 2013 then $t0 = 2008$. Again, the values for the employment structure (η_{iq}) are calculated for the year 2001. It is worth noticing that the geographical distribution of Chinese imports can be calculated exploiting a finer disaggregation (three digits) than that of robotization (two digits). This is likely to produce smaller variation in $\Delta RPW_{i,t}$ across neighboring LLMAs than

Table 1: Descriptive statistics - LLMA level

Panel A: 2001-2008	Mean	St. dev.	25th pct	Median	75th pct
Δ Share of votes for far right x 100	-5.729	8.518	-11.836	-8.108	-0.709
Δ Voters' turnout x 100	1.621	6.716	-2.852	-0.484	4.412
Δ Immigration share x 100	2.739	1.935	0.951	2.337	4.275
Δ China imports pw, log	1.377	0.294	1.239	1.399	1.521
Δ Robots pw, log	0.455	0.147	0.364	0.443	0.527
Panel B: 2008-2013	Mean	St. dev.	25th pct	Median	75th pct
Δ Share of votes for far right x 100	-2.225	6.370	-6.407	-0.263	1.407
Δ Share of votes for 5SM x 100	24.442	6.619	20.430	24.516	28.548
Δ Voters' turnout x 100	-6.674	3.668	-8.620	-5.750	-4.247
Δ Immigration share x 100	1.404	0.869	0.757	1.271	1.904
Δ China imports pw, log	-0.228	0.161	-0.292	-0.221	-0.149
Δ Robots pw, log	1.502	0.263	1.356	1.544	1.678

Notes: The table reports means, standard deviations, 25th percentile, median and 75th percentile of each variable. The number of observations is 684. The analytical units are 2001 LLMAs. Chinese imports per worker (pw) is expressed in thousands of constant 2010 US dollars. Robots per worker is expressed in number of robots.

in $\Delta IPW_{i,t}^{chn}$: this will be proved important in the assessment of the shift-share IV design strategy that we shall conduct in Section 4.3.

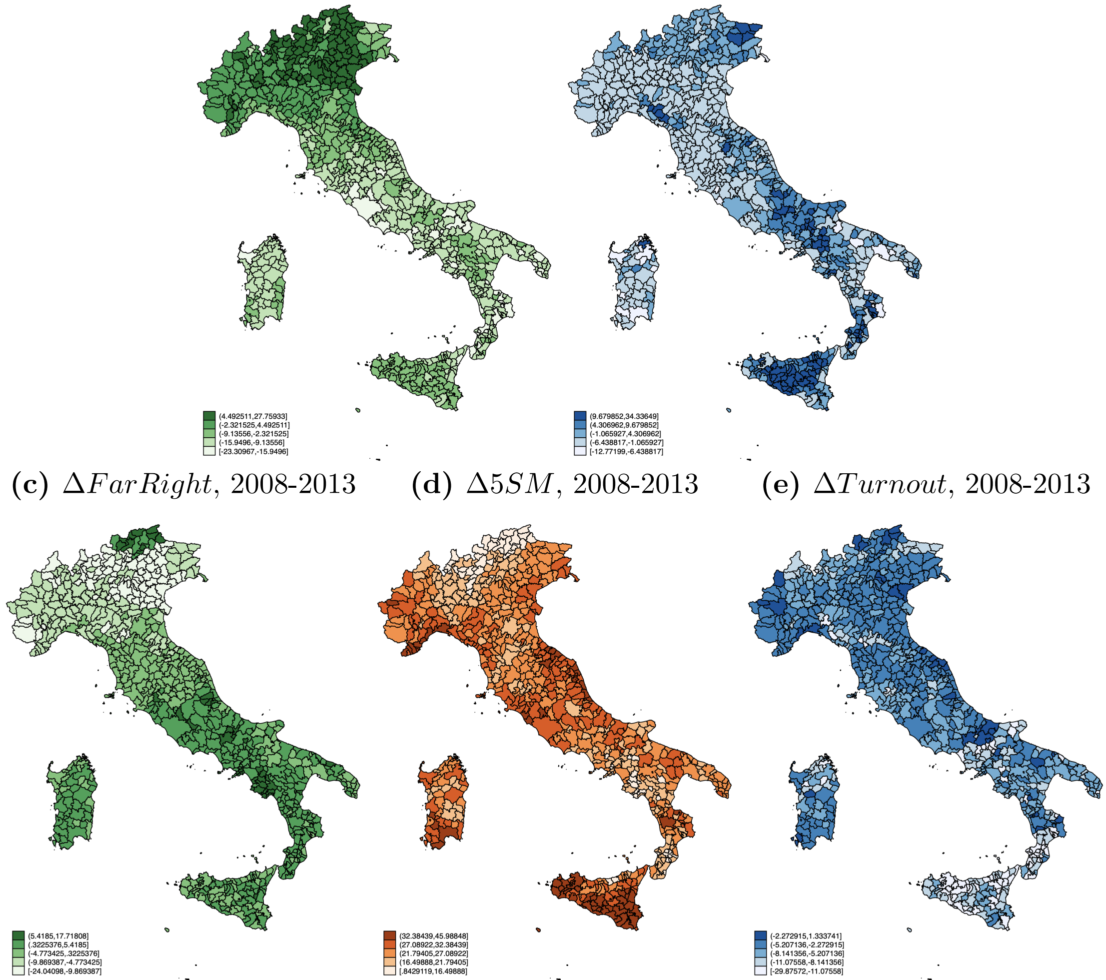
In all regressions below, we standardize our three main global drivers, i.e., we divide the values by their standard deviations. This standardization is applied in order to be able to compare the coefficients and, thus, the size of the different effects.

As explained, our investigation focuses on changes in local electoral outcomes between 2001 and 2008 and between 2008 and 2013.[10] Table 1 presents means, standard deviations and quartiles of the variables of interest in both sub-periods, calculated using the LLMAs as units of analysis. This table hides significant heterogeneity in our variables of interest across geographic units, although no outliers can be detected as shown by the unconditional scatter plots in Appendix B.

It is possible that the ideas and preferences of people living in nearby areas influence each other's voting choices. One can think of various channels through which the electoral intentions in nearby LLMAs can influence those in the LLMA of interest. Residents in a LLMA may work in one nearby region even though the overall commuting patterns are not sufficiently large to determine the merge of the two LLMAs. Residents in two neighbouring LLMAs may be exposed to the same local media that cover news regarding both areas, thereby facilitating the circulation of ideas and perceptions. Individuals may entertain personal relationships with relatives and friends who leave in neighbouring LLMAs, and listen to their political opinions and voting intentions. Moreover, as shown by Johnston et al. (2004), electors in one area may be conditioned by the electoral campaign in nearby regions. Recently, Vermeulen et al. (2020) ascertained empirically that

[10]We do no consider the elections in 2006 because the time span between 2006 and 2008 is not sufficiently long to capture structural changes in the economy. Following the long-term approach developed by Autor et al. (2013), we focus on long-lasting economic changes able to exercise an important impact on voting behaviour.

Figure 1: Changes in voting for far-right parties, 5SM and voters' turnout



(a) $\Delta FarRight$, 2001-2008 **(b)** $\Delta Turnout$, 2001-2008

(c) $\Delta FarRight$, 2008-2013 **(d)** $\Delta 5SM$, 2008-2013 **(e)** $\Delta Turnout$, 2008-2013

Source: Own calculations based on data from the Italian Ministry of the Interior.

groups of closely related persons concentrated in neighbouring areas affect each other's voting preferences and Maza et al. (2019) found evidence about the political spillovers in pro-independence vote in the 2017 regional election in Catalonia.

To start, we show a graphical representation of the geographical distribution of the changes in the shares of votes going to far-right parties and the 5SM, as well as in voters' turnout, over the two periods analyzed in Italy. A cursory look at the maps in Figure 1 reveals that electoral outcomes are spatially clustered and spatial autocorrelation between adjacent LLMAs may be present. Indeed, we can observe that during the period 2001-2008, votes for far-right parties increased more in north-eastern regions, particularly in Veneto, while turnout decreased more in north-western regions as well as in some central and southern regions. These patterns suggest that political discontent over traditional parties manifested itself in different ways depending on the area. Voting patterns, moreover, changed substantially during the period 2008-2013. The northern regions, except for Alto Adige, observed the largest decreases in votes for far-right parties. The 5SM generally gained large shares of votes, particularly in Sicily, Marche and Liguria. Finally,

Table 2: Moran's I tests for spatial dependence

	2001-2008		2008-2013		
	$\Delta FarRight$	$\Delta Turnout$	$\Delta FarRight$	$\Delta 5SM$	$\Delta Turnout$
Spatial weight matrix M	1265.43***	522.92***	1260.57***	855.55***	446.06***

Notes: The table reports the chi-squared values of Moran's I tests for spatial dependence. The number of observations is 684. The spatial weight matrix M is equal to one for contiguous local labor markets and zero otherwise. *** indicates rejection of the null hypothesis of i.i.d. error terms at the 1% level.

voters' turnout decreased in all regions, particularly in the South.[11]

To explore more formally the possibility of spatial autocorrelation in the above electoral outcomes, Table 2 shows Moran's I tests to assess the degree of spatial dependence between adjacent LLMAs. The data reject the null hypotheses that the electoral outcomes in a given LLMA are spatially independent from those in contiguous areas. This result is in line with that in Agnew and Shin (2017), who use a less fine level of geographical disaggregation.

Building on this *prima facia* evidence, the issue of spatial dependence will be addressed more formally in an extension of the baseline model presented in Section 4.2, where the baseline empirical specification will be augmented to include the spatially-lagged dependent variable to capture pure political spillovers from neighbouring LLMAs.

3.2 Empirical Specifications

The empirical analysis is based on a mixed first-difference model, that is a model in which the dependent variable and the main variables of interest are in first differences, while the additional controls are in levels and measured at the beginning of each time period. This specification addresses the unobserved time-invariant heterogeneity at the LLMA level while the set of controls in levels helps to eliminate possible confounds and to reduce the risk that the variables of interest may pick up part of other regional trends Autor et al. (2013).

The two periods covered in the analysis are, as said, 2001-2008 and 2008-2013. The empirical specification for the mixed first-difference models can be described by the following formula:

$$\Delta y_{i,t} = \alpha_1 \Delta IMM^{shr}_{i,t} + \alpha_2 \Delta IPW^{chn}_{i,t} + \alpha_3 \Delta RPW_{i,t} + \boldsymbol{x}'_{i,t0}\boldsymbol{\gamma} + \boldsymbol{r}'_{i,t0}\boldsymbol{\psi} + \epsilon_{i,t}, \tag{4}$$

where $\Delta y_{it} = y_{it} - y_{i,t0}$ denotes the change in the share of votes for a certain party or group of parties (i.e., far-right parties or the 5SM) or the change in voters' turnout in LLMA i between t and $t0$ (with $t0$ equal to 2001 when $t = 2008$ and equal to 2008 when

[11]In Appendix A, we show the geographical distribution of our global economic factors. Figure A1 shows that, during the period 2001-2008, all three variables, i.e., immigration share, Chinese imports per worker and robots per worker, increased relatively more in richer northern and central regions. On the other hand, during the crisis period from 2008 to 2013, immigration still increased, particularly in north-western and some central regions, while Chinese imports per worker and robots per worker experienced more idiosyncratic changes, even though they generally decreased, especially in northern regions. We should notice that spatial autocorrelation of these variables is not taken into account in our models below as, by definition, labor market shocks should be absorbed within local labor market areas.

$t = 2013$). The vector $\boldsymbol{x}_{i,t0}$ is a vector of controls at the LLMA level measured at the beginning of the period and $\boldsymbol{r}_{i,t0}$ is a vector of controls at the regional level measured at the beginning of the period. The LLMA-level controls include the number of residents (in logs), the share of residents over 65 in the adult population, the share of residents with primary or lower secondary education and the share of residents with tertiary education. The regional-level controls include the share of informal labor, the share of expenditure on cultural activities, tickets in cultural activities per capita, volunteering, attractiveness of universities, internet diffusion and hospital migration rate (to other regions).[12] Although the impact of the control variables may be of interest per se, we include these terms only to avoid possible omitted variables and we do not discuss their effects in detail.[13]

Despite the inclusion of many controls, the estimation might still suffer from endogeneity problems. In particular, difficulties may arise when both the dependent variable and the regressors are correlated with unobserved shocks. For instance, voters' turnout and immigration inflows could both shrink in areas where social capital worsens, and this effect might bias the estimation of the coefficient. Similarly, Ariu et al. (2016) show that governance quality promotes positive net inflows of high-skilled migrants, and this may have implications for the structure and the performance of the local economy, as well as for the approach of the electorate towards migrants and pro-/anti-migrant parties. Our controls may also miss to capture certain confounding factors associated with the relationship between policies and authorities at the local and national levels (Dalle Nogare and Kauder, 2017), affecting both the local economy and the support to parties in national elections. Moreover, it is possible that spatial political polarization is in part driven by selective migration patterns: partisanship may be a driver of movers' chosen destinations (Bishop, 2009; Gimpel and Hui, 2015; Rohla et al., 2018). In addition, local amenities may foster in-migration of like-minded people (Scala et al., 2015): this is another potential source of endogeneity that needs to be controlled for. Similarly, the adoption of robots and people's access to social media, affecting perceptions and voting behaviour, may be co-determined by unobserved factors such as the speed and the diffusion of high-speed internet connections (Schaub and Morisi, 2018). Another endogeneity problem to mention refers to the fact that robot adoption is pro-cyclical and economic cycles are associated with support for different parties. Hence, to address these and other endogeneity concerns, we adopt an IV approach, in line with what done in the most recent political economy literature.

As suggested by Autor et al. (2013), the potential endogeneity of imports per worker can be tackled by using a shift-share approach and information on the imports from China recorded in eight high-income countries outside the European Union (EU). This helps to identify the exogenous and 'supply-driven' component of the surge in Chinese

[12] Perceptions play a key role in determining political preferences and voting decisions (Guiso et al., 2017) and they are shaped by individual experiences, but also by the way in which the media report relevant news on salient topics. Socio-economic facts revealed by the press contribute to influencing perceptions (Garz, 2018). Accordingly, several measures of the state of the local economy are to be included as controls in the estimations with a view to capturing those socio-economic features that may affect people directly as well as those that may influence their perceptions through the media.

[13] Our approach differs from that adopted by Essletzbichler et al. (2018), who focus on the role played by local structural and cyclical conditions in the rise of right-wing populist vote in the US, Austria and the UK, and not on their underlying global causes.

imports in Italy. Thus, we instrument ΔIPW_{it}^{chn} with a new variable defined as

$$\Delta\widetilde{IPW}_{i,t}^{chn} = \sum_s \eta_{is} \ln\left(\frac{\widetilde{IMP}_{s,t}^{chn}}{L_s}\right) - \sum_s \eta_{is} \ln\left(\frac{\widetilde{IMP}_{s,t0}^{chn}}{L_s}\right), \tag{5}$$

where $\widetilde{IMP}_{s,t}^{chn}$ represents the average of sectoral imports from China of eight non-EU countries at time t expressed in thousands of constant 2010 US dollars.

A similar approach can be adopted to build the shift-share instrumental variable for $\Delta RPW_{i,t}$ so as to capture the impact of exogenous factors influencing robot adoption, rather than local demand-driven forces affecting both robotization and voting (Anelli et al., 2018; Frey et al., 2018). Thus, we build the following instrumental variable:

$$\Delta\widetilde{RPW}_{i,t} = \sum_q \eta_{iq} \ln\left(\frac{\widetilde{RBT}_{q,t} * 1000}{L_q}\right) - \sum_q \eta_{iq} \ln\left(\frac{\widetilde{RBT}_{q,t0} * 1000}{L_q}\right), \tag{6}$$

where $\widetilde{RBT}_{q,t}$ indicates the number of robots belonging to the two-digit NACE sector q that were installed in other advanced economies at time t.

As immigration might also be endogenous, we follow Otto and Steinhardt (2014) and instrument $\Delta IMM_{i,t}^{shr}$ with the share of immigrants at the beginning of each period, $IMM_{i,t0}^{shr}$.[14]

Both the instrumental variables for ΔIPW_{it}^{chn} and $\Delta RPW_{i,t}$ follow a shift-share IV design, where local industry shares are interacted with exogenous measures of shocks for trade with China and robot adoption. This approach is widely used in the literature that studies labour market developments and voting patterns on the basis of the differentiated regional exposure to common shocks. Recent technical advances make it possible to investigate the validity of such design and to refine the interpretation of the findings associated with it (Adão et al., 2018; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2018). By employing such state-of-the-art techniques, in Section 4.3 we shall discuss the plausibility of the identification strategy and exploit the Rotemberg decomposition of the shift-share IV to interpret the results.

Before that, to address the geographical correlation in the electoral outcomes of interest found in Section 3.1, we analyze the effects of our global drivers on electoral outcomes using a spatial regression model accounting for "pure" political spillovers. Following the literature, and in particular Agnew and Shin (2017), we adopt a spatial autoregressive model that contains a spatially-lagged dependent variable constructed with a binary spatial weight matrix M, taking value one for contiguous local labor markets and zero otherwise. As the empirical analysis focuses on LLMAs as units of analysis, we believe that the inclusion of spatial lags of the independent variables would not be appropriate as, by definition, labor market shocks should not spill over nearby areas and should rather be absorbed within each local labor market. On the other hand, for the reasons discussed in the introduction and in Section 3.1, people in nearby areas may influence each other's voting choices in other ways: these "pure" political influence across regions is captured

[14] We do not use a shift-and-share instrument, such as that employed by Barone et al. (2016), because its behaviour in the first stage of our IV regressions is not entirely satisfactory.

by the spatial lag of the dependent variable. The empirical specification of this extension, therefore, is given by the following formula:

$$\Delta y_{i,t} = \beta_1 \Delta IMM_{i,t}^{shr} + \beta_2 \Delta IPW_{i,t}^{chn} + \beta_3 \Delta RPW_{i,t} + \beta_4 M_i \cdot \Delta y_t + \boldsymbol{x}'_{i,t0}\boldsymbol{\gamma} + \boldsymbol{r}'_{i,t0}\boldsymbol{\psi} + \epsilon_{i,t}, \quad (7)$$

where $M_i \cdot \Delta y_t$ is the spatially lagged dependent variable, which is constructed as the weighted average of the electoral outcomes in the neighboring LLMAs. The results from this extension of the baseline model will be presented and discussed in Section 4.2.

4 Empirical Results

4.1 IV Results

We first estimate the baseline specification in equation (4) by means of a two-stage least squares (2SLS) estimator with robust standard errors. Table 3 shows the estimates of the mixed first-difference 2SLS specifications with instrumental variables for the three global economic drivers, ignoring spatial dependence. In all regressions (one per political outcome of interest and per period), the relatively high values for the Kleibergen-Paap F statistics imply that the instruments used are informative for our endogenous variables. This is also confirmed by the first-stage results reported in Appendix D. Moreover, it is worth noting that the IV results tend to be larger and more significant than the results based on the OLS estimator (reported in Appendix C). Specifically, in the OLS regressions, import competition from China is never significant, nor is immigration in the period 2008-2013. This is in line with all the previous literature (Autor et al., 2016; Caselli et al., 2020), and it hints at the fact that unobservable characteristics can dampen in absolute terms the effects analyzed.

Columns (1) and (2) of Table 3 report the estimates for the period 2001-2008. The estimated coefficients reveal that the LLMAs where immigration increased more during the period 2001-2008 were characterized by a larger reduction in voters' turnout and a higher increase in the share of votes accruing to far-right parties. Relatively larger increases in Chinese imports were also positively associated with larger gains by far-right parties, whereas no highly significant effect is found for changes in voters' turnout. Finally, in those LLMAs where the increase in robots was larger, the share of votes to far-right parties increased relatively more, whereas voters' turnout was not significantly affected.

The first two results are in line with the predicament that positive changes in the exposure to globalization are associated with political discontent, which tends to manifest itself in lower participation and a more extremist voting pattern, as occurred in rich northern regions. These findings are in line with the outcomes of previous studies in other countries (Barone et al., 2016; Colantone and Stanig, 2018b; Halla et al., 2017; Malgouyres, 2017b; Otto and Steinhardt, 2014), thereby reinforcing the idea that immigration and China's competition exerted a similar political influence in several Western countries in this period of time. It is worth noticing that the exposure to the China's shock is assessed in the recent contributions through a similar shift-share IV design that combines the sectoral composition of the local economic structure and differentiated surge of Chinese industries: the concurring evidence found in different countries suggests that in this period the emergence of China did have an impact on Western labour markets

Table 3: Effects of globalization and robotization on electoral outcomes, FD-IV

	2001-2008		2008-2013		
	$\Delta FarRight$	$\Delta Turnout$	$\Delta FarRight$	$\Delta 5SM$	$\Delta Turnout$
	(1)	(2)	(3)	(4)	(5)
Δ Immigration share	1.755***	-1.262***	-2.136***	2.002***	0.017
	(0.654)	(0.478)	(0.656)	(0.624)	(0.278)
Δ China imports	2.528***	1.049*	-0.031	0.079	-0.119
	(0.748)	(0.579)	(0.379)	(0.428)	(0.182)
Δ Robots	1.816**	0.001	1.580***	-0.480*	-0.403***
	(0.816)	(0.560)	(0.277)	(0.280)	(0.135)
LLMA controls	yes	yes	yes	yes	yes
Regional controls	yes	yes	yes	yes	yes
2SLS	yes	yes	yes	yes	yes
Observations	684	684	684	684	684
F statistic	54.25	25.58	54.70	18.67	29.30
Kleibergen-Paap F	18.28	18.28	23.88	23.88	23.88

Notes: Columns (1) and (2) refer to changes between 2001 and 2008, while columns (3), (4) and (5) refer to changes between 2008 and 2013. The dependent variable is the percentage point change in the votes for far-right parties, columns (1) and (3), the votes for the Five-Star Movement (5SM), column (4), and voters' turnout, columns (2) and (5). The variable immigration share is multiplied by 100, while Chinese imports per worker (pw) and robots per worker are in natural logarithms and all three explanatory variables are standardized (i.e., divided by their standard deviations). The LLMA controls include number of residents, share of residents above 65 in the adult population, share of residents with primary or lower secondary education and share of residents with tertiary education. The regional controls include hospital migration, informal labor, share of expenditure on cultural activities, tickets in cultural activities per capita, volunteering, attractiveness of universities and internet diffusion. The 2SLS specifications instrument for the change in the immigrants using the value at the beginning of the period, for the change in Chinese imports in Italy using the change in other developed countries' imports from China and for the change in robots using the change in the number of robots used in other developed countries. Robust standard errors are shown in parentheses. *, ** and *** indicate coefficients significantly different from zero at the 10%, 5% and 1% level respectively.

and voting patterns, mediated by the industry-related exposure of the local areas. We shall come back on this in Section 4.3.

The findings for robotization follow a similar line of reasoning. The increase in robots per worker turns out to be positively associated with a rise in the support to far-right parties, albeit only at the 5% significance level. Although no similar study exists for Italy and Europe yet, these results resonate well with Frey et al. (2018), who find that the support for President Trump was higher in those local labour markets that were more exposed to the adoption of robots, and with Anelli et al. (2018) who find evidence on a positive relationship between individual exposure to robot and conservative political preferences. Based on recent research on the impact of robotization on labour markets (see for instance Acemoglu and Restrepo, 2020; Acemoglu et al., 2020; Chiacchio et al., 2018; Dauth et al., 2017), the mechanism at work is likely dependent on the (actual and perceived) displacement of workers due to automation. The increase in robots per worker in this period is not negatively associated with voters' turnout: at least in the years before the 2008 crisis, voters' perception of increasing investment in industrial robots might be mixed, therefore not necessarily leading to electoral behaviors associated with resentment and dissatisfaction.

The standardization of the variables makes it possible to compare the estimated coefficients as they can all be interpreted in the same way. For example, an increase by one standard deviation in the exposure to Chinese competition has led to an increase by 2.5 percentage points in the votes for far-right parties in the 2001-2008 period. While all drivers seems to favor far-right parties to a similar extent, the exposure to Chinese competition has probably had a larger impact. Conversely, only immigration is associated with a reduction in voters' turnout. To the extent that lower turnout can be considered (as it is in the political economy literature) as a clear sign of discontent, the estimated results may indicate that in the pre-crisis period (2001-2008) immigration was the driver associated with discontent, in turn leading to more extreme anti-immigrant positions, whereas the exposure to Chinese competition and robotization was not affecting participation but re-orienting the electorate towards more conservative positions, as also suggested by Colantone and Stanig (2018b) and Anelli et al. (2018).

Columns (3), (4) and (5) in Table 3 report the estimates for, respectively, the change in the share of votes for far-right parties and for the newly-born 5SM, and in voters' turnout over the second period, 2008-2013. The estimates change considerably compared to the previous period analysed. This is likely due to three main reasons: the differentiated evolution of the three drivers, the rising importance of other shocks (such as the sovereign debt crisis and of the response to it by the incumbent government), and serious modifications in the political supply side, in particular, the exogeneous shock (i.e., the scandals) hitting the Northern League.

The empirical results show that increases in immigration shares become negatively associated with changes in votes to far-right parties, but positively associated with changes in votes for the 5SM. On the other hand, changes in immigration are not significantly associated with changes in voters' turnout. These findings indicate that in the LLMAs subject to higher immigration during the 2008-2013 period, i.e., mainly rich northern and central regions, a larger share of votes shifted from far-right parties to the 5SM. As the 5SM has never had an anti-immigration platform, this may appear bizarre. However, it is only seemingly puzzling. During the period 2001-2013, we observe substantive changes in terms of political supply among Italian right-wing parties. Most notably, National Alliance (*Alleanza Nazionale*), which was the largest far-right party in the coalition led by Mr Berlusconi in 2001, merged with *Forza Italia* right before the 2008 national elections to form a new politically moderate party called The People of Freedom (*Popolo delle Libertà*). The role of the largest far-right party in the coalition led by Mr Berlusconi was taken up by the Northern League, which saw a doubling of votes during the period 2001-2008.[15] Yet, in the following period, the Northern League faced a series of scandals that led to a substantial reduction in its support. Moreover, the far-right party Brothers of Italy was founded just a few months before the 2013 elections. Accordingly, there were no

[15] According to Passarelli and Tuorto (2012), the success of the Northern League in the 2008 elections can be explained by the ability of the party to gains votes from the dominant moderate forces, both within the right-wing and the left-wing coalitions. The authors argue that this was mainly due to a uniquely strong stance against immigration and globalization, in line with the findings by Beirich and Woods (2000), and our results support this claim. A more nuanced view is proposed by Huysseune (2010), who claims that the Northern League faced a tension between its resistance against globalization and its historically privileged connections with a territory characterized by export-oriented companies: the Northern League proposed an asymmetric model of globalization based on unequal rights and obligations, emphasizing, in particular, the drawback of foreign immigrant workers.

strong and consolidated far-right parties in Italy in 2013. This implies that the negative estimates for the coefficient for immigration may indicate that former far-right voters and electors holding anti-immigration preferences did exercise their right to vote (as turnout was not affected), but decided to switch to other political parties, in particular the 5SM, for the lack of alternatives on the far-right side and the belief that the 5SM could be more effective in addressing immigration.[16] Notably, such relevant changes in the supply of political platform should not be considered as endogeneous: first, the scandals hitting the Northern League are exogenous; second, far-right parties standing for election in 2013 were already moving towards the centre of the political arena, despite the rising concerns of voters for immigration.

This reading of the results is also in line with those observers and politicians claiming that the 5SM attracted part of the electorate who would have otherwise abstained from voting (Agnew and Shin, 2017). The 5SM leader himself, Mr. Beppe Grillo, has repeatedly claimed that the movement reduced abstention on election days and eroded votes previously accruing to extremist parties.[17] Moreover, these conclusions are in line with other works, for instance Rodrik (2018) finds a gradual shift of far-right voters towards populist parties and a shift of the latter towards more conservative platforms. The results in 2013 set the stage for the more radical changes observed in the following period: the setback that the far-right parties faced in 2013 was the trigger of the so-called sovranist and conservative twist adopted by the Northern League before the 2018 elections.

It is worth noticing that these findings make it possible to draw more general considerations informing researchers interested in other countries and time periods and it illustrates well the importance of accounting for exogeneous changes in political supply for the interpretation of the results. These issues are often neglected, in particular in those cross-country studies where several parties are considered jointly in *ad hoc* coalitions. To a certain extent, this implies that the findings from the empirical studies regarding the economic determinants of specific political outcomes should be generalized with great caution, accompanied by political information, and compared across different political environments with care. In line with the conclusions of Bovens and Wille (2008), this finding informs the empirical analysis in other countries where and when new important parties enter the scene (e.g., En Marche in France, Podemos in Spain) and established parties are hit by national scandals (i.e., the 2013 Bavaria nepotism scandal in Germany, the Gürtel case in Spain, the Publifin and Samusocial scandals in Belgium, and the like), occurrences that, as shown by Laroze (2019), often go together.

With regard to the coefficients related to Chinese imports during the period 2008-

[16]This interpretation is confirmed by individual-level data on political preferences taken from the surveys run by the Italian National Election Studies (ITANES). According to such data, 46.8% of respondents in 2008 answered that the centre-right coalition was the most capable of addressing the issue of immigration. In 2013, the percentage of voters that answered in the same way decreased to 35.8%, while at the same time 17.9% of respondents believed that the 5SM was the most capable of dealing with immigration.

[17]In an interview to the Time in 2013 (Faris, 2013), Mr. Beppe Grillo was asked whether the forces that pushed the 5SM up could also push up darker forces. To this he replied, "I channel all this rage into this movement of people, who then go and govern. They should be thanking us one by one. If we fail, [Italy] is headed for violence in the streets. But if we crumble, then they come. Everything started in Italy. Fascism was born here. The banks were born here. We invented debt. The mafia, us too. Everything started here. If violence doesn't start here, it's because of the movement. If we fail, we're headed for violence in the street. Half the population can't take it anymore."

2013, we can observe no significant effects. This may seem puzzling if one considers that this variable was that exerting the largest impact in the previous period. In fact, as one can see in Figures B1 and B2, the percentage changes in the local exposure to competition from China are in general smaller in the second period that in the first one and, in most cases, the changes are negative, as can be also seen in Table 1. This suggests a modification in global Chinese export patterns, probably associated with the graduation of the Chinese economy and the impact of the global financial crisis.

The effects of robotization also partly change over this period, as robotization is associated with a positive change in the votes for the far-right parties and a negative change in the votes for the 5SM. One could be tempted to carry over the interpretation of the estimates in 2001-2008 to 2008-2013 to account for the positive estimates for the far-right parties, but it would be hard to justify the negative impact on the 5SM. In fact, the estimates and the visual representation of the areas where robots grow relatively more suggest that robotization increases in the more dynamic LLMAs and that here is where the 5SM gained relatively less support. The 5SM obtained better results in less dynamic regions, such as Sicily, Marche and Liguria, and worse results in more dynamic areas, such as Lombardy, Veneto, and Trentino-Alto Adige. This interpretation of the results suggests that the robotization variable might be a more general proxy for local industrial sophistication rather than a true measure of the extent to which industrial robots affect local workers.[18] According to the literature, the adoption of shift-share instrumental variables and the inclusion of several controls in level in the estimation should minimize confounding effects: this is the very reason of the wide success of this two-stage mixed differences model in the literature studying the impact of global shocks on labour markets, electoral results and political preferences. Yet, the interpretation provided above for the results on robotization suggests that these may not be enough. To explore the issue further, we shall adopt more sophisticated statistical tools in Section 4.2 and discuss the validity and interpretation of the shift-share IV design. Anticipating our conclusions, we find that the results for China competition are solid and the interpretation proposed is in line with the theoretical mechanism inspiring the analysis; on the contrary, the results for the impact of robotization are subject to greater uncertainty. In particular, the distribution of local industry shares for robots across LLMAs may not be strictly exogenous and the number of categories in which robots are classified is too narrow to ensure the consistency of the estimates on the basis of the exogeneity of the robot shocks.

4.2 Spatial Regressions

Most of the previous studies in this strand of the political economy literature have neglected the possible existence of "pure" political spillovers across LLMAs, that is the effects associated with the impact of electoral intentions in nearby LLMAs on voters in the LLMA of interest through channels different from those controlled for in the estimations. As discussed in the previous sections, this is not a mere theoretical possibility as Moran's I tests in Table 2 suggest that spatial dependence is an issue that needs to be

[18] As a matter of fact, the shift-share approach to build the variable and the instrument takes as given the sectoral composition of the economy at the beginning of the period. To the extent that the adoption of industrial robots is correlated with certain features of the local economy, this widespread solution to instrument the variable does not entirely solve the endogeneity problems.

considered. In this Section, therefore, we estimate the augmented version of the baseline equation, that is equation (7) including the spatially-lagged dependent variable and instrumental variables, with the use of the generalized spatial two-stage least-squares (GS2SLS) estimator.[19] This modelling choice was previously used by Agnew and Shin (2017) and Buonanno et al. (2016) in Italian elections, Vermeulen et al. (2020) for voting behaviour in Amsterdam, Maza et al. (2019) for pro-independence vote in Catalonia and Branton et al. (2019) for the Peace Treaty referendum in Colombia.

The results for the spatially autoregressive specification are shown in Table 4. First of all, the coefficients for the spatial lag in all regressions (but that for 5SM in 2008-2013) are positive, lower than one and significantly different from zero at least at the 1% confidence level. Notably, spatial dependence is stronger for the estimation of the increase in votes for the far-right parties than for the 5SM.

With regard to the main variables of interest, it suffices to say that most of the previous findings carry along in these spatial specifications, with only a few changes in statistical significance. In particular, the impact of robotization loses significance for all political outcomes in 2001-2008 and only for 5SM in 2008-2013, while the impact of immigration loses some significance in the regressions for far-right parties.

With regard to the direct and indirect effects of our main variables of interest, it is interesting to notice that, as the coefficients for the spatial lag are always positive and lower than one, the two effects have always the same sign. The direct effects show the same levels of significance as the estimated coefficients (and similar sizes too). The same observation is true for the total effects. On the other hand, the indirect effects tend to be slightly less significant.

While, all in all, this confirms the results from the first part of the analysis without the spatially autoregressive terms, the inclusion of spatial dependence suggests that there might be a spatial component of the political results that is hard to capture with local controls and with the explanatory variables of interest.[20]

These findings indicate that what happens within a LLMA is not only determined by the decisions of local voters as people residing in neighbouring areas do influence each other by exchanging views and ideas. This is an important finding, even though the reduced form does not allow to distinguish more clearly the exact mechanisms behind the "pure" political spillovers and the analysis relies on the tenet that spillovers occur only across bordering LLMAs, irrespective of actual distance.

4.3 Shift-Share IV estimator

Instrumental variables based on a shift-share design combine exogenous shocks to global drivers and the composition of the local economic structure in terms of pre-determined

[19]The GS2SLS estimator is a generalized method-of-moments estimator. Among its instruments, it includes not only those used in the IV regressions above, but also a linear combination of those instruments with the spatial weighting matrices applied to the dependent variable.

[20]The inclusion of regional controls in the specifications and the focus on labor market areas, which by definition represent the units of analysis within which labor market shocks can be absorbed, may contribute to limit the importance of this phenomenon. Possibly, spatial dependence becomes more and more relevant when the specifications are simpler, with several missing variables and different geographical units of analysis.

Table 4: Effects of globalization and robotization on electoral results, SAR-IV

	2001-2008		2008-2013		
	$\Delta FarRight$	$\Delta Turnout$	$\Delta FarRight$	$\Delta 5SM$	$\Delta Turnout$
	(1)	(2)	(3)	(4)	(5)
Δ Immigration share	0.672*	-0.716*	-0.272	1.357***	-0.203
	(0.402)	(0.409)	(0.307)	(0.523)	(0.270)
Δ China imports	1.511***	0.184	0.097	-0.140	-0.120
	(0.422)	(0.437)	(0.240)	(0.420)	(0.214)
Δ Robots	0.564	0.015	0.580***	-0.434	-0.425***
	(0.450)	(0.454)	(0.169)	(0.285)	(0.144)
$M \cdot \Delta\, Y$	0.552***	0.671***	0.861***	0.026	0.187***
	(0.056)	(0.083)	(0.050)	(0.035)	(0.052)
Direct impact, average					
Δ Immigration share	0.699*	-0.763*	-0.309	1.357***	-0.204
	(0.417)	(0.432)	(0.347)	(0.523)	(0.272)
Δ China imports	1.571***	0.196	0.110	-0.140	-0.120
	(0.439)	(0.465)	(0.273)	(0.420)	(0.215)
Δ Robots	0.586	0.016	0.659***	-0.434	-0.426***
	(0.468)	(0.483)	(0.188)	(0.285)	(0.145)
Indirect impact, average					
Δ Immigration share	0.478*	-0.753*	-0.592	0.026	-0.032
	(0.278)	(0.425)	(0.648)	(0.038)	(0.046)
Δ China imports	1.067***	0.193	0.211	-0.003	-0.019
	(0.356)	(0.449)	(0.522)	(0.009)	(0.034)
Δ Robots	0.398	0.016	1.261***	-0.008	-0.067**
	(0.330)	(0.476)	(0.396)	(0.012)	(0.031)
Total impact, average					
Δ Immigration share	1.174*	-1.516*	-0.902	1.383***	-0.236
	(0.687)	(0.833)	(0.991)	(0.537)	(0.316)
Δ China imports	2.639***	0.389	0.321	-0.143	-0.139
	(0.765)	(0.913)	(0.794)	(0.429)	(0.248)
Δ Robots	0.984	0.032	1.920***	-0.443	-0.494***
	(0.794)	(0.959)	(0.553)	(0.290)	(0.169)
LLMA controls	yes	yes	yes	yes	yes
Regional controls	yes	yes	yes	yes	yes
GS2SLS	yes	yes	yes	yes	yes
Observations	684	684	684	684	684
Wald chi-squared	1422.08	540.76	1860.93	336.17	438.70

Notes: Columns (1) and (2) refer to changes between 2001 and 2008, while columns (3), (4) and (5) refer to changes between 2008 and 2013. The dependent variable is the percentage point change in the votes for far-right parties, columns (1) and (3), the votes for the Five-Star Movement (5SM), column (4), and voters' turnout, columns (2) and (5). The variable immigration share is multiplied by 100, while Chinese imports per worker (pw) and robots per worker are in natural logarithms and all three explanatory variables are standardised (i.e., divided by their standard deviations). The spatial weight matrix M is equal to one for contiguous local labor markets and zero otherwise. $\Delta\, Y$ refers to the percentage point change in the dependent variable of interest in each column. The GS2SLS specifications instrument for the change in the immigrants using the value at the beginning of the period, for the change in Chinese imports in Italy using the change in other developed countries' imports from China and for the change in robots using the change in the number of robots used in other developed countries. Standard errors are shown in parentheses. *, ** and *** indicate coefficients significantly different from zero at the 10%, 5% and 1% level respectively.

employment shares, thereby capturing the exposure to shocks of the various geographical units of analysis.

This approach raises legitimate questions about the validity and interpretation of the results. Are the tenets upon which the identification works valid? Do the shocks matter for the electoral outcomes? Do voters' decisions map any differences across LLMAs that are correlated with variations in the local economic structure but not with the shocks of interest? To address these questions and to shed light on the mechanisms driving the results, we use state-of-the-art methodologies developed to analyse the identification approach based on a shift-share IV (Adão et al., 2018; Borusyak et al., 2018; Goldsmith-Pinkham et al., 2020).[21]

To start, we recall that the adoption of a shift-share IV to identify the causal impact of globalization and robotization on electoral results must rely on a well-defined identification strategy. A shift-share IV instrument is the inner product of initial local industry shares and industry shocks. As shown by Goldsmith-Pinkham et al. (2020), a shift-share IV estimator is a two-stage least squares estimator numerically equivalent to a generalized method of moments estimator using local industry shares as instruments and a specific weight matrix constructed upon the industry shocks. Hence, a shift-share IV estimator can be seen as a weighted combination of just-identified estimations, each using the local exposure to a single industry as a separate instrument.[22]

This account of the shift-share IV estimator has a number of consequences on the assessment of its validity and informs identification. For the validity of the shift-share IV estimator, a sufficient condition is the validity of the local shares as instruments, in particular those with the largest weights in the combined estimation. The initial shares have to be relevant and exogenous to the changes in the electoral outcomes, conditional on the controls introduced into the estimation. As pointed out by Goldsmith-Pinkham et al. (2020), the identification based on local industry shares as exogenous instruments is consistent with a research design pooling the differentiated local exposure to shocks in various industries. Moreover, in this setting, we observe a large sample of locations and a fixed number of industries: the consistency of the shift-share estimator thus requires the exogeneity of the shares as the number of locations goes to infinity.

An extension of this set up based on industry shares, as studied by Borusyak et al. (2018), assumes the consistency of the SSE under increasingly larger samples of industries: this assumption would make the exogeneity of independent trade shocks in many industries a sufficient condition for identification, even when local industry shares are not strictly exogenous. The validity of the SSE under this assumption would thus hold only if the global shocks were numerous and independent (i.e., as-good-as-random). These assumptions can hardly hold in the case of trade and robotization in our set up. While the disaggregation of the industries is sufficiently detailed in our setting to have many shocks, the assumption that these are independent is not straightforward as the state-driven process of economic development observed in China does not match well the idea

[21] We are indebted to an anonymous reviewer for suggesting to explore this analytical venue and to use the results for improving the interpretation of the main findings.

[22] We refer to Goldsmith-Pinkham et al. (2020) for the details of the decomposition of the shift-share IV estimator (SSE) in terms of just-identified estimations using local industry shares and the so-called Rotemberg weights (interpreted as the sensitivity-to-misspecification elasticities associated with each instrument). Using their notation, $\hat{\beta_{SSE}} = \sum_k \hat{\alpha_k} \hat{\beta_k}$ where $\hat{\beta_k} = (Z_k^{'} X^{\perp})^{-1} (Z_k^{'} Y^{\perp})]$, the Rotemberg weights for industry k is $\hat{\alpha_k} = \frac{g_k (Z_k^{'} X^{\perp})}{\sum_k g_k (Z_k^{'} X^{\perp})}$, g_k is the exogenous trade shock to industry k, Z_k is the matrix of local shares for industry k, and $X^{\perp}$ is the vector of the endogenous variables conditioning for the additional controls.

of as-good-as-random trade shocks. In the case of robots, as we can consider only 20 groups of industries, it is implausible to base the consistency of the SSE on few and non-independent shocks. Accordingly, in what follows we shall investigate the shift-share IV estimator using the framework developed by Goldsmith-Pinkham et al. (2020) and will focus on local industry shares.[23]

To assess whether the shift-share IV approach makes economic sense, it is useful to start by identifying what industries have the largest weights ($\hat{\alpha_k}$) in the Rotemberg decomposition of the SSE. As their misspecification would heavily affect the bias of the SSE, it is important to verify whether the largest-weight industries are in line with the theoretical mechanism inspiring the analysis, and whether the corresponding instruments are valid. In the case of import competition from China, for instance, one would be very surprised if the sectors connected with food and beverages have the largest Rotemberg weights given that the competition exerted by China on Italy was certainly stronger in manufacturing industries such as iron and steel.

4.3.1 Trade shocks

In the case of imports from China (see Panel C in Tables F1 and F5), the five largest-weight industries for the first period 2001-2008 are: Basic iron, steel and ferro-alloy; Motor vehicles; Tanning and dressing of leather; Structural metal products; Other first processing of iron and steel. In the second period 2008-2013, the largest-weight industries are: Basic iron, steel and ferro-alloys; Tanning and dressing of leather; Mining of chemical and fertilizer minerals; Mining of non-ferrous metal ores; Optical instruments and photographic equipment. *Per se*, these findings are in line with the theoretical mechanism underpinning the specification. The distribution of the Rotemberg weights is skewed in both periods: the sum of the weights of these industries accounts for 44% (0.544/1.225) of the positive weights in the estimator for the period 2001-2008 and for 54% (0.665/1.229) for the period 2008-2013 (see Panel A). The fact that the relevance of these industries makes sense is reassuring. The share of industries with positive weights, moreover, is large and also this bodes well for the validity of the identification.[24]

As said, the consistency of the shift-share IV estimator depends on the exogeneity of the local industry shares. At the theoretical level, one cannot exclude that the geographical distribution of the local industry shares is correlated with other local factors affecting the observed changes in voting patterns. The correlations between the local shares of each of the five largest-weight industries and the values of the variables that we use as controls in the estimations, however, suggest that the local shares for these five industries are not systematically associated with many observed variables (Tables F2 and F6).[25]

[23] Adão et al. (2018) suggest a sophisticated approach to make standard errors robust to the possible correlation across locations. This approach relies on the same assumptions underpinning Borusyak et al. (2018), that is a large number of locations and a large number of as-good-as-random industries. Due to the above-mentioned considerations on the plausibility of this latter, we do not explore this approach further.

[24] Moreover, the correlation between the Rotemberg weights and the first stage F-tests obtained from the just-identified estimations using the local exposure to one industry at a time as instrument is around 0.4 in both periods (Panel B): the largest-weight industry shares are therefore relevant instruments.

[25] Notably, as we control for all these local factors in the estimations, the conditional exogeneity of the instruments (i.e., what matters for consistency) would be ensured even if we had found several significant

Furthermore, it is interesting to look at the correlation of the Rotemberg weights (α_k) with trade shocks (g_k) and with the variation in the industry shares across LLMAs ($Var(z_k)$). When the correlation of the weights with the trade shocks is high (low), the latter explain much (little) of the variation in the shift-share instrument: focusing exclusively on the sectors with the largest trade shocks would then be advisable (not advisable). When the correlation with the variation in the industry share across locations is high (low), it is only (not only) the industries with the largest variation across locations that matter for the identification of the shift-share IV parameter. In our sample, the correlation of the Rotemberg weights with the trade shocks is higher (but not very high) in the period 2001-2008 when the size of imports from China to other developed countries explains about a quarter of the variance in the Rotemberg weights. In both periods, instead, it is not the most unevenly distributed industries that drive the identification of the shift-share estimator, in line with what found by Goldsmith-Pinkham et al. (2020) for the US data used by Autor et al. (2013). These results imply that it is a large set of trade shocks that matter, and in a way that depends on factors different from their mere size. Imagine, for instance, that the Italian production in any sector moves together with the Chinese exports in some LLMAs while it competes with the Chinese exports in other LLMAs: such spatial heterogeneity would generate different point estimates for the (just-identified) coefficient associated with that sector and would affect the Rotemberg weights as well.

These results suggest to look at all the relevant industry shares to draw further insights on the shift-share IV estimates. We recall that the estimated parameter for China imports is positive and significant for the far-right parties in 2001-2008, whereas it is not significantly different from zero in 2008-2013. Indeed, these findings can be understood by looking at the distribution of the just-identified coefficients obtained by regressing the voting patterns on the local shares of each industry at a time. These parameters are plotted in Figures F1 and F3. Only few parameter estimates associated with positive Rotemberg weights (circles) are far from the shift-share coefficient and there are no estimates with large negative Rotemberg weights (large squares). Yet, the dispersion of the estimated coefficients is large and the values vary both above and below zero. In the first period, the positive coefficients for the far-right parties and turnout rates seem mainly driven by some of the five largest-weight industries, as well as by a multitude of other industries with small positive weights. In the period 2008-2013, no statistically significant coefficient for the shift-share parameter for the far-right votes is found for two possible reasons: some of the largest-weight industry shares are associated with coefficients that are negative and close to zero (see Panel C of Table F6) and the small positive weight industry shares are associated with parameters distributed evenly above and below zero. A similar interpretation holds also for the insignificance of the estimated coefficient for voters' turnout. Instead, the estimated coefficient for the 5SM in the second period is not significantly different from zero mainly because of the wide dispersion of the estimated coefficients for industries both with large and with small positive weights.

All in all, we can conclude that the insignificant impact of China import competition on voting patterns in 2008-2013 seems to be explained by the fairly different evolution

correlates. The interpretation of these auxiliary estimations is in fact more speculative: the larger is the number of observed local factors significantly correlated with the local industry shares, the more likely it is that other unobserved factors may be present as well (Goldsmith-Pinkham et al., 2020).

of China's global exports in the two periods and by the diversified correlation of voting patterns with different industry shocks. The local shares of Italian employees in sectors where China increased its global exports more do not exercise a homogeneous effect across sectors and locations, in line with the idea that, after an initial common shock, the participation of China in the global economy did not represent only a problem for the Italian economy. As the European Union recently acknowledged in its official documents, China is indeed a destination market, a competitor and a partner.

4.3.2 Robotization shocks

We run the same kind of analysis for the adoption of robots. In a nutshell, even though the estimated shift-share IV coefficient is significantly different from zero in most estimations, the support for the shift-share IV research design is more controversial in this case.

As can be seen in Panel C of Table F3, the five largest-weight industries for the first period 2001-2008 are: Construction, Textiles, Food and beverages, Other non manufacturing, and Pharmaceutical and cosmetics. As we do not have a strong prior regarding the activities in which robotization exerted greater pressures on workers, this information does not help to assess the plausibility of the exposure design. Yet, there are other signs that the overall identification strategy is not very strong for this period. First, the sum of the Rotemberg weights for the five largest-weight industries is higher than 100%, implying that most of the remaining industries have non-negligible negative Rotemberg weights. Second, the correlation of the Rotemberg weights with the first stage F-tests obtained from just-identified estimations (using, as instrument, the local exposure to a single industry at a time) is slightly negative (Panel B). The correlation of the Rotemberg weights with the variation in the industry shares across LLMAs is high, whereas the correlation with the shocks is low. This implies that it is those industries with the largest variation in employment shares across locations that matter most for the identification. This raises some doubts on whether the shift-share strategy for robots truly picks up the impact of robotization or whether it may subsume other shocks that hit the industries most unevenly distributed across LLMAs and that correlate also with changes in the electoral outcomes. Indeed, the correlations between the local shares of each of the five largest-weight industries and the variables we use as controls in the estimations, reported in Table F4, casts some doubts on the conditional exogeneity of the industry shares.

The distribution of the just-estimated coefficients obtained by using as instrument each industry at a time for the period 2001-2008 is plotted in Figure F2. As can be seen, most of the estimated coefficients for the industries with large positive weights vary within a large range going from -4 to 4 in the regressions for the votes to the far-right parties and turnout rates. This finding alongside with the presence of several industries receiving large negative weights and a clear outlier in the regressions for the far-right parties concur to suggest that the strategy is not entirely solid.

The situation in 2008-2013 is slightly different. The five largest-weight industries are: Other non-manufacturing industries, Textiles, Wood, Metal (non automotive), and Chemical products (see Panel C of F7). The overall identification strategy seems to work better than in the previous period. The industries with negative weights are few and their weights (in absolute value) are small, both individually and collectively. The dispersion of the just-identified coefficients is smaller for the far-right parties, the 5SM (but for one outlier) and the turnout rates, as can be appreciated in Figure F4. The estimated parameters for the industries with the largest weights (Panel C) are in line with the shift-share IV parameters. Finally, the correlation between the Rotemberg weights and the first stage F-tests obtained from the just-identified estimations is positive and close to 1 (Panel B). All these results, however, are strongly affected by the overwhelming role played by the sector "Other non-manufacturing industries": this should not come as a surprise as robots have been heavily adopted in labour-intensive services, such as logistics.

The results related to the local correlates of the local industry shares are also not satisfactory (Tables F4 and F8). The correlations between the local shares of each of the five largest-weight industries and the controls are significant for a large number of factors. The exogeneity of these industry shares could be legitimately questioned. As these local variables are controlled for in the estimation, they are not a concern *per se* but they suggest that there might be also other local factors, associated with the geographical distribution of certain industries and having an impact on voting patterns, that are omitted. One example to consider for the second time span is the local impact of the economic crisis: logistics is characterized by an uneven distribution of the employees across LLMAs and has been severely hit by the recession induced by the debt crisis, which has also raised discontent among voters. Given that in the estimations we do not use controls able to capture the local exposure to the debt crisis, one cannot exclude that this is the case. This is most likely a problem for robots than for Chinese competition for the higher level of aggregation used for the industries in the shift-share allocation of robots.

5 Closing Remarks

This work adopts a spatial perspective to analyze the role of global forces driving major changes in the Italian national elections in 2001, 2008 and 2013. In particular, the paper studies the locally-mediated effect of three global economic drivers (i.e., the higher flows of migrants coming from countries of the Global South, the fiercer foreign competition in international trade especially from China, and the diffusion of skill-biased and labor-substituting technological change in the form of robotization) on the local electoral outcomes associated with discontent in Italy, i.e., larger shares of votes for far-right parties and the Five-Star Movement, and lower voters' turnout.

The main findings of the analysis are that all these global factors had significant but heterogeneous impacts on electoral outcomes. In particular, the effects of the three shocks do not appear to be time-invariant. Between 2001 and 2008, the variation in the local exposure to immigration seems to favor the far-right parties and general discontent via lower voters' turnout, while in the following period from 2008 to 2013 it seems to favor the 5SM to the detriment of far-right parties. In a similar fashion, Chinese competition seems to have a positive effect on the votes for far-right parties only in the first period and not in the second one. On the contrary, robotization is more likely to have had a positive impact on the votes far-right parties in the second period. These findings, seemingly at odds with previous studies finding an unabated positive impact of these forces on far-right parties, have two complementary explanations. On the political demand side, for example, Chinese competition seems to change in nature over time: industry trade shocks are smaller in the second period and not all industries in every location are equally affected by the evolution of Chinese exports in the world markets. On the political supply side, one can observe significant changes that have to do with scandals and party mergers (and not with endogenous political platforms). The very emergence of the 5SM seems to be a big change in the political supply in Italy that has helped voters to express their dissatisfaction without voting for far-right parties or abstaining. Moreover, the analysis provides some evidence for the existence of "pure" political spillovers, stemming probably from the circulation of ideas across neighbouring LLMAs. These spillovers add to the direct effects of the three global drivers on the local economy and thus reinforce them. Yet, the main conclusions seem not to change substantially when a spatially autoregressive model is employed, probably because of the focus on local labor market areas and the inclusion of many local controls in the estimations.

In retrospective, our findings help to account for the subsequent shift towards more populist positions that characterised various far-right movements in Italy after the poor performances in the 2013 elections. To a certain extent, these results show the premises for the so-called 'Yellow-Green' coalition between the League and the 5SM, formed after the 2018 elections. Yet, our findings are of more general interest and provide several methodological insights.

Although the hypothesis that trade competition, immigration and robotization tend to raise social concerns that, in turn, increase support for far-right parties seems to be well supported by the literature, our results suggest that such generalization should be made with caution. Not only the salience of various concerns may vary across time and places, but there might be exogenous changes in the political supply that affect the perception of which parties and coalitions are most capable of addressing the social concerns mentioned above. In a nutshell, we stress that the the link between economic phenomena and electoral outcomes is conditional on the evolution of the political supply, which needs to be adequately illustrated and discussed, in a way similar to what quantitative political scientists typically do.

The spatial dependence analysis reveals that "pure" political spillovers may be present and that failing to consider them is risky. This is particularly true for those empirical studies that adopt smaller geographical units, where both economic and political spillovers may be at work. Care is also recommended while comparing the results from investigations using diversified geographical units of analysis. The tools developed by political geographers and spatial economists could be used to draw further insights on this.

This last issue points to the fact that, by combining various methodological advances coming from the political geography, party politics and the political economy literature, this paper tries to bridge the divide that exists between various disciplines sharing similar interests but adopting different tools of analysis. Notwithstanding various innovative traits, this could imply that the analysis has some limitations and addressing them could represent a venue of future research. The discussion on the shift-share IV estimators for robotization, for instance, reveals problems that no other study has so far addressed, in particular associated with the small number of industries in the IFR classification of robots. The high significance of the estimated parameters associated with robotization may in fact hide some problems: although no direct test is available, the strict exogeneity of the local industry shares of robots may be jeopardized by local unobserved factors that affect also the voting patterns. Furthermore, although the presence of "pure" political spillovers is well grounded in the literature and it is theoretically sensible to distinguish "pure" political spillovers from the cross-border effects of economic drivers (and that we account for by considering LLMAs), the analysis does not make it possible to dip deeper in this direction; one could explore possible mediating factors, such as physical and cultural distance or economic interdependence. To the more, there is a seemingly unsolvable tension between the two extensions that we consider: the shift-share IV estimators assume the absence of serious spatial dependence. Further econometric work is thus needed to explore the properties of shift-share IV estimators when spatial dependence is non-negligible.

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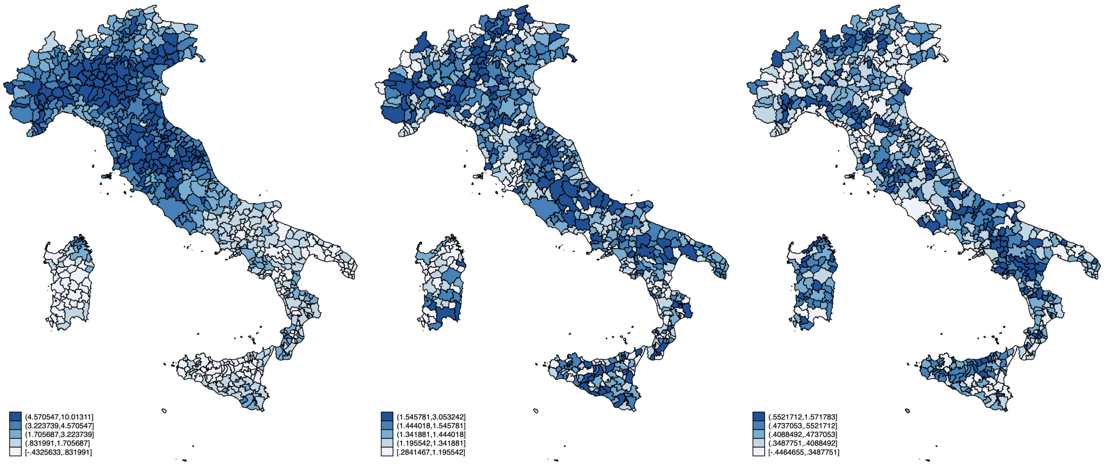
Appendix

A Geographical distribution of changes in global economic factors

Figure A1: Changes in immigration, Chinese imports and robotization

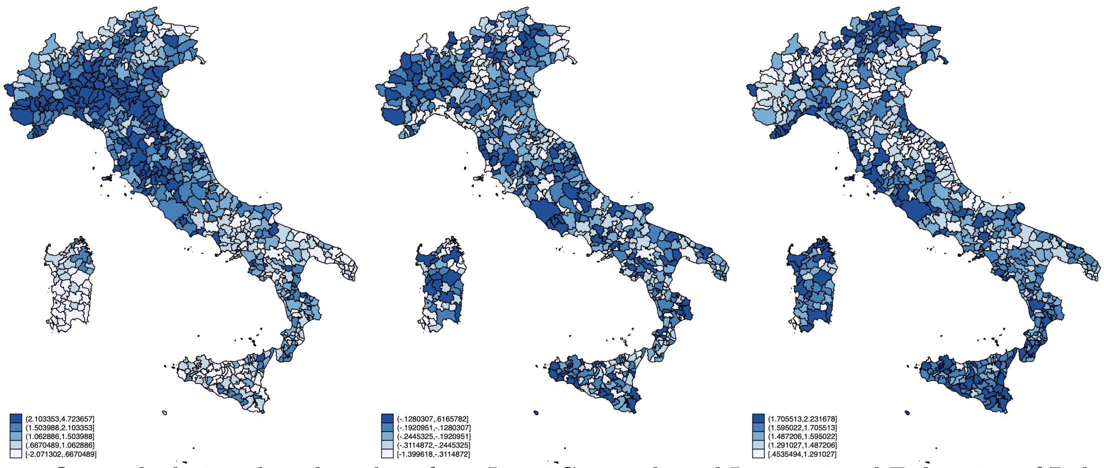
2001-2008

(a) Δ Immigration share **(b)** Δ China imports pw, log **(c)** Δ Robots pw, log



2008-2013

(d) Δ Immigration share **(e)** Δ China imports pw, log **(f)** Δ Robots pw. log



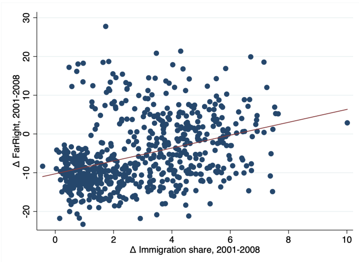
Source: Own calculations based on data from Istat, Comtrade and International Federation of Robotics.

B Scatter plots of changes in voting outcomes and global economic factors

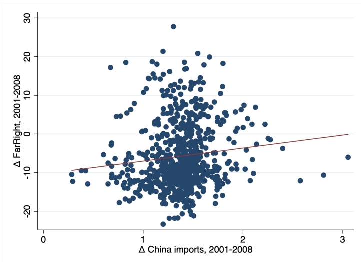
Figure B1: Changes in voting outcomes vs immigration, Chinese imports and robotization

$\Delta FarRight$, **2001-2008**

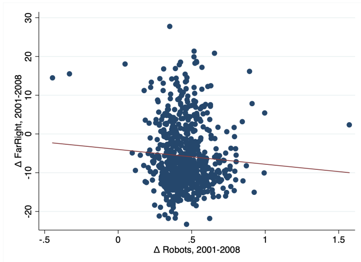
(a) Δ Immigration share



(b) Δ China imports

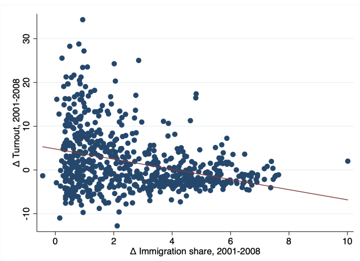


(c) Δ Robots

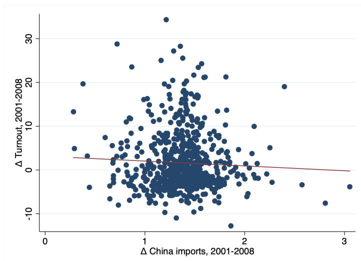


$\Delta Turnout$, **2001-2008**

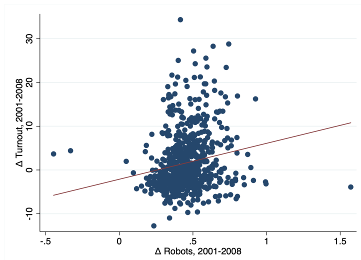
(d) Δ Immigration share



(e) Δ China imports



(f) Δ Robots

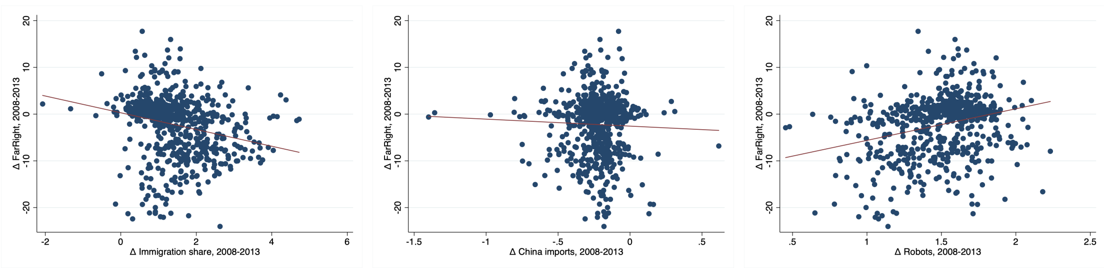


Source: Own calculations based on data from Italian Ministry of the Interior, Istat, Comtrade and International Federation of Robotics.

Figure B2: Changes in voting outcomes vs immigration, Chinese imports and robotization

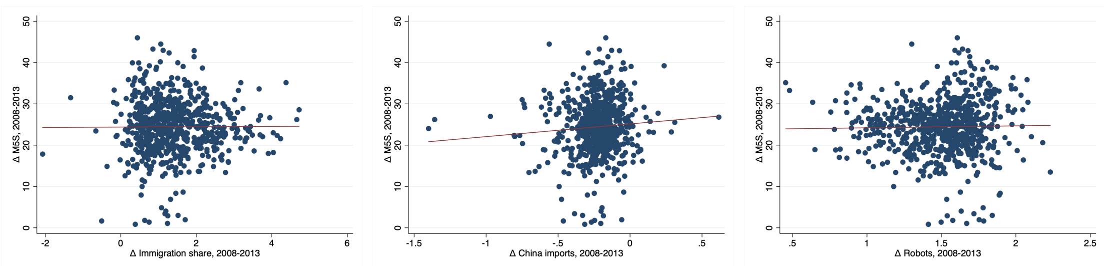
$\Delta FarRight$, 2008-2013

(a) Δ Immigration share **(b)** Δ China imports **(c)** Δ Robots



$\Delta 5SM$, 2008-2013

(d) Δ Immigration share **(e)** Δ China imports **(f)** Δ Robots



$\Delta Turnout$, 2008-2013

(g) Δ Immigration share **(h)** Δ China imports **(i)** Δ Robots

Source: Own calculations based on data from Italian Ministry of the Interior, Istat, Comtrade and International Federation of Robotics.

C OLS results

Table C1: Effects of globalization and robotization on electoral outcomes, FD

	2001-2008		2008-2013		
	$\Delta FarRight$	$\Delta Turnout$	$\Delta FarRight$	$\Delta 5SM$	$\Delta Turnout$
	(1)	(2)	(3)	(4)	(5)
Δ Immigration share	0.848**	-1.278***	-0.229	0.098	-0.073
	(0.379)	(0.331)	(0.193)	(0.258)	(0.122)
Δ China imports	0.062	0.150	-0.177	0.321	-0.106
	(0.214)	(0.247)	(0.160)	(0.201)	(0.099)
Δ Robots	-0.252	0.180	1.163***	-0.297	-0.394***
	(0.331)	(0.249)	(0.211)	(0.248)	(0.129)
LLMA controls	yes	yes	yes	yes	yes
Regional controls	yes	yes	yes	yes	yes
Observations	684	684	684	684	684
R-squared	0.586	0.341	0.546	0.335	0.363
F statistic	78.11	26.20	69.12	19.61	28.35

Notes: Columns (1) and (2) refer to changes between 2001 and 2008, while columns (3), (4) and (5) refer to changes between 2008 and 2013. The dependent variable is the percentage point change in the votes for far-right parties, columns (1) and (3), the votes for the Five-Star Movement (5SM), column (4), and voters' turnout, columns (2) and (5). The variable immigration share is multiplied by 100, while Chinese imports per worker (pw) and robots per worker are in natural logarithms and all three explanatory variables are standardised (i.e., divided by their standard deviations). The LLMA controls include number of residents, share of residents above 65 in the adult population, share of residents with primary or lower secondary education and share of residents with tertiary education. The regional controls include hospital migration, informal labor, share of expenditure on cultural activities, tickets in cultural activities per capita, volunteering, attractiveness of universities and internet diffusion. Robust standard errors are shown in parentheses. *, ** and *** indicate coefficients significantly different from zero at the 10%, 5% and 1% level respectively.

D First-stage results

Table D1: First-stage results of globalization and robotization

Panel A: 2001-2008	Δ Immigration share	Δ China imports	Δ Robots
	(1)	(2)	(3)
Lagged immigration share	0.628***	-0.062	-0.068
	(0.041)	(0.053)	(0.059)
Δ China imports (other countries)	0.026	0.466***	-0.174***
	(0.029)	(0.059)	(0.040)
Δ Robots (other countries)	-0.045*	0.041	0.368***
	(0.023)	(0.040)	(0.051)
LLMA controls	yes	yes	yes
Regional controls	yes	yes	yes
Observations	684	684	684
Kleibergen-Paap F	18.277	18.277	18.277
Panel B: 2008-2013	Δ Immigration share	Δ China imports	Δ Robots
	(1)	(2)	(3)
Lagged immigration share	0.579***	-0.114**	-0.036
	(0.066)	(0.056)	(0.023)
Δ China imports (other countries)	0.005	0.550***	-0.040*
	(0.038)	(0.087)	(0.020)
Δ Robots (other countries)	0.165***	0.154***	0.949***
	(0.048)	(0.052)	(0.022)
LLMA controls	yes	yes	yes
Regional controls	yes	yes	yes
Observations	684	684	684
Kleibergen-Paap F	23.880	23.880	23.880

Notes: Panel A refers to changes between 2001 and 2008, while Panel B refers to changes between 2008 and 2013. The dependent variable is the change in immigration share in column (1), the change in Chinese imports per worker in column (2) and the change in robots per worker in column (3). All three dependent variables are standardised (i.e., divided by their standard deviations). The LLMA controls include number of residents, share of residents above 65 in the adult population, share of residents with primary or lower secondary education and share of residents with tertiary education. The regional controls include hospital migration, informal labor, share of expenditure on cultural activities, tickets in cultural activities per capita, volunteering, attractiveness of universities and internet diffusion. Robust standard errors are shown in parentheses. *, ** and *** indicate coefficients significantly different from zero at the 10%, 5% and 1% level respectively.

E Robustness checks

Table E1: Effects of globalization and robotization on elections, FD-IV, $FarRight2$

	2001-2008 $\Delta FarRight2$ (1)	2008-2013 $\Delta FarRight2$ (2)
Δ Immigration share	0.683**	-2.421***
	(0.344)	(0.715)
Δ China imports	0.718*	0.150
	(0.378)	(0.440)
Δ Robots	1.300***	0.698**
	(0.438)	(0.308)
LLMA controls	yes	yes
Regional controls	yes	yes
2SLS	yes	yes
Observations	684	684
F statistic	12.03	24.57
Kleibergen-Paap F	18.28	23.88

Notes: Column (1) refers to changes between 2001 and 2008, while column (2) refers to changes between 2008 and 2013. The dependent variable is the percentage point change in the votes for far-right parties defined as all those with a left-right score of the CHES above 6.5 ($FarRight2$). The variable immigration share is multiplied by 100, while Chinese imports per worker (pw) and robots per worker are in natural logarithms and all three explanatory variables are standardised (i.e., divided by their standard deviations). The LLMA controls include number of residents, share of residents above 65 in the adult population, share of residents with primary or lower secondary education and share of residents with tertiary education. The regional controls include hospital migration, informal labor, share of expenditure on cultural activities, tickets in cultural activities per capita, volunteering, attractiveness of universities and internet diffusion. The 2SLS specifications instrument for the change in the immigrants using the value at the beginning of the period, for the change in Chinese imports in Italy using the change in other developed countries' imports from China and for the change in robots using the change in the number of robots used in other developed countries. Robust standard errors are shown in parentheses. *, ** and *** indicate coefficients significantly different from zero at the 10%, 5% and 1% level respectively.

F Shift-Share Instruments

F.1 China imports, 2001-2008

Table F1: Rotemberg weights, China imports, 2001-2008

Panel A: Negative and positive weights

	Sum	Mean	Share
Negative	-0.225	-0.003	0.155
Positive	1.225	0.009	0.845

Panel B: Correlations

	$\hat{\alpha}_k$	g_k	F_k	Var(z_k)	$\hat{\beta}_k^{FR}$	$\hat{\beta}_k^{TO}$
$\hat{\alpha}_k$	1					
g_k	0.417	1				
$\hat{F}_k$	0.393	0.081	1			
Var(z_k)	0.102	0.027	0.118	1		
$\hat{\beta}_k^{FR}$	0.015	-0.212	0.022	-0.028	1	
$\hat{\beta}_k^{TO}$	0.017	-0.207	0.025	-0.042	–	1

Panel C: Top 5 Rotemberg weight industries

	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k^{FR}$	$\hat{\beta}_k^{TO}$
Basic iron, steel and ferro-alloy	0.252	2.649	-0.275	-0.438
Motor vehicles	0.136	3.404	-1.250	2.143
Tanning and dressing of leather	0.061	-0.745	0.005	-0.551
Structural metal products	0.060	1.907	1.307	2.211
Other first processing of iron and steel	0.035	1.768	0.558	0.031

Notes: This table reports statistics about the Rotemberg weights. In all cases, we report statistics about the aggregated weights, where we aggregate a given industry across years. Panel A reports the share and sum of negative Rotemberg weights. Panel B reports correlations between the weights ($\hat{\alpha}_k$), the national component of growth (g_k), the first-stage F-statistic of the industry share ($\hat{F}_k$), the variation in the industry shares across locations (Var(z_k)), and the just-identified coefficients in the regressions for far-right parties ($\hat{\beta}_k^{FR}$) and turnout ($\hat{\beta}_k^{TO}$). Panel C reports the top five industries according to the Rotemberg weights.

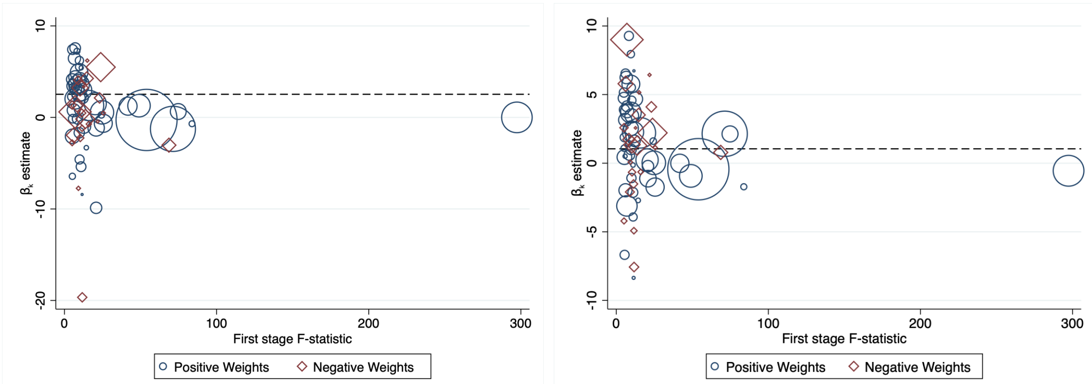
Table F2: Relationship between industry shares and characteristics, China imports, 2001-2008

	Basic iron, steel and ferro-alloy	Motor vehicles	Tanning and dressing of leather	Structural metal products	Other first processing of iron and steel
Δ Immigration share (pred.)	-0.015	-0.125	0.299	0.060	0.032
	(0.113)	(0.090)	(0.227)	(0.067)	(0.030)
Δ Robots (pred.)	0.104	-0.015	-0.576*	-0.018	0.047
	(0.090)	(0.069)	(0.328)	(0.076)	(0.034)
Share of residents above 65	0.620	2.608	-0.314	3.474***	0.351
	(1.185)	(1.873)	(1.097)	(0.981)	(0.502)
Residents (ln)	0.144**	0.283***	0.033	0.229***	0.033***
	(0.056)	(0.094)	(0.053)	(0.038)	(0.012)
Share of res. w max lower sec. ed.	-0.232	-1.427	0.858	-3.216**	-0.686
	(0.794)	(2.685)	(2.569)	(1.334)	(0.517)
Share of res. w tertiary ed.	-2.411	-12.769*	-21.913*	-18.771***	-2.422**
	(2.405)	(6.821)	(12.173)	(3.156)	(1.048)
Internet diffusion	-0.001	0.024	0.040	0.027**	0.004
	(0.013)	(0.028)	(0.031)	(0.013)	(0.005)
Tickets for cultural activities pc	-0.006*	0.007	-0.010	0.002	-0.004***
	(0.003)	(0.014)	(0.008)	(0.004)	(0.001)
Hospital migration rate	-0.003	0.041*	0.019	0.004	-0.003
	(0.014)	(0.023)	(0.052)	(0.015)	(0.007)
Volunteering	0.006	-0.028	0.010	-0.022*	0.002
	(0.008)	(0.029)	(0.016)	(0.011)	(0.005)
Expenditure on cultural activities	0.055	-0.072	-0.061	0.057	-0.021
	(0.071)	(0.095)	(0.056)	(0.059)	(0.022)
Attractiveness of universities	0.001	-0.000	-0.000	-0.001	0.000
	(0.001)	(0.003)	(0.004)	(0.001)	(0.000)
Share of informal labor	-0.019	-0.016	0.037	0.009	-0.018***
	(0.014)	(0.031)	(0.034)	(0.020)	(0.006)
Observations	684	684	684	684	684
R-squared	0.027	0.037	0.046	0.111	0.068

Notes: Each column reports a separate regression. The dependent variable is the industry share (times 100) in each local labor market. The variables Δ Immigration share and Δ Robots are measured in changes as the predicted values following a first-stage regression based on the IV instruments used in the main regressions. All other explanatory variables are measured at the beginning of the period. Robust standard errors are shown in parentheses. *, ** and *** indicate coefficients significantly different from zero at the 10%, 5% and 1% level respectively.

Figure F1: Heterogeneity of coefficient estimates, China imports, 2001-2008

(a) Far Right **(b)** Turnout



Notes: These figures plot the relationship between each instruments' $\hat{\beta}_k$, first stage F-statistics and the Rotemberg weights. Each point is a separate instrument's estimates (industry share). The figures plot the estimated $\hat{\beta}_k$ for each instrument on the y-axis and the estimated first-stage F-statistic on the x-axis. The size of the points are scaled by the magnitude of the Rotemberg weights, with the circles denoting positive Rotemberg weights and the diamonds denoting negative weights. The horizontal dashed line is plotted at the value of the overall $\hat{\beta}$ reported in the main IV regressions. The figure excludes instruments with first-stage F-statistics below 5.

F.2 Robots, 2001-2008

Table F3: Rotemberg weights, Robots, 2001-2008

Panel A: Negative and positive weights						
	Sum	Mean	Share			
Negative	-0.322	-0.027	0.196			
Positive	1.322	0.110	0.804			
Panel B: Correlations						
	$\hat{\alpha}_k$	g_k	F_k	$\text{Var}(z_k)$	$\hat{\beta}_k^{FR}$	$\hat{\beta}_k^{TO}$
α_k	1					
g_k	0.135	1				
F_k	-0.196	0.156	1			
$\text{Var}(z_k)$	0.526	-0.289	-0.041	1		
$\hat{\beta}_k^{FR}$	0.095	-0.126	0.075	0.115	1	
$\hat{\beta}_k^{TO}$	0.076	-0.119	0.075	0.136	–	1
Panel C: Top 5 Rotemberg weight industries						
	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k^{FR}$	$\hat{\beta}_k^{TO}$		
Construction	0.396	1.659	0.702	1.304		
Textiles	0.320	-1.922	3.310	-1.904		
Food and beverages	0.204	1.606	0.009	-2.213		
Other non-manufacturing	0.176	-0.804	2.173	4.094		
Pharmaceuticals, cosmetics	0.112	5.284	1.738	0.142		

Notes: This table reports statistics about the Rotemberg weights. In all cases, we report statistics about the aggregated weights, where we aggregate a given industry across years. Panel A reports the share and sum of negative Rotemberg weights. Panel B reports correlations between the weights ($\hat{\alpha}_k$), the national component of growth (g_k), the first-stage F-statistic of the industry share ($\hat{F}_k$), the variation in the industry shares across locations ($\text{Var}(z_k)$), and the just-identified coefficients in the regressions for far-right parties ($\hat{\beta}_k^{FR}$) and turnout ($\hat{\beta}_k^{TO}$). Panel C reports the top five industries according to the Rotemberg weights.

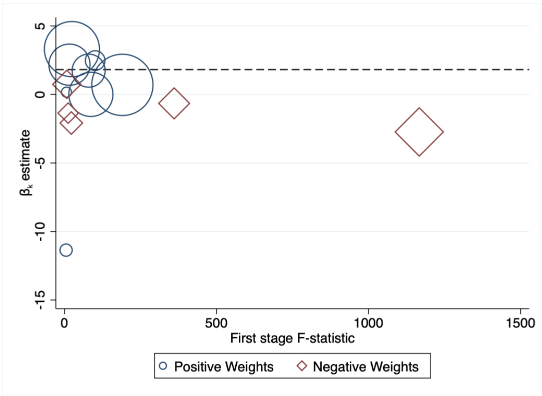
Table F4: Relationship between industry shares and characteristics, Robots, 2001-2008

	Construction	Textiles	Food and beverages	Other non-manuf.	Pharmac., cosmetics
Δ Immigration share (pred.)	-1.738***	4.528***	0.085	-4.080***	-0.104
	(0.247)	(0.943)	(0.207)	(0.887)	(0.079)
Δ China imports (pred.)	-1.271***	-0.151	-0.062	-14.251***	0.122**
	(0.310)	(0.944)	(0.263)	(1.251)	(0.052)
Share of residents above 65	16.390***	-28.546**	8.101**	12.869	0.926
	(4.845)	(12.994)	(3.337)	(11.025)	(0.926)
Residents (ln)	-0.607***	0.189	-0.005	1.592***	0.064**
	(0.168)	(0.549)	(0.126)	(0.465)	(0.029)
Share of res. w max lower sec. ed.	0.811	41.497***	-1.636	-28.607*	-1.855
	(6.589)	(15.092)	(3.653)	(14.778)	(2.149)
Share of res. w tertiary ed.	-35.421**	-24.629	-26.478***	216.194***	-2.184
	(14.770)	(37.275)	(9.492)	(35.792)	(5.301)
Internet diffusion	0.169***	-0.045	-0.105*	-0.544***	0.030***
	(0.060)	(0.119)	(0.057)	(0.127)	(0.010)
Tickets for cultural activities pc	-0.000	-0.201***	-0.009	0.196***	0.000
	(0.020)	(0.030)	(0.012)	(0.040)	(0.006)
Hospital migration rate	0.266***	0.227	0.057	0.443***	-0.011
	(0.069)	(0.154)	(0.049)	(0.161)	(0.007)
Volunteering	-0.114**	-0.287***	-0.041	0.362***	-0.023
	(0.048)	(0.093)	(0.031)	(0.090)	(0.014)
Expenditure on cultural activities	-0.184	0.223	0.824***	-0.949	-0.029
	(0.230)	(0.517)	(0.196)	(0.591)	(0.034)
Attractiveness of universities	-0.006	0.019**	0.010***	0.026**	-0.000
	(0.006)	(0.009)	(0.003)	(0.012)	(0.001)
Share of informal labor	-0.377***	-0.725***	-0.034	-0.185	-0.021
	(0.085)	(0.182)	(0.068)	(0.198)	(0.024)
Observations	684	684	684	684	684
R-squared	0.407	0.231	0.089	0.616	0.092

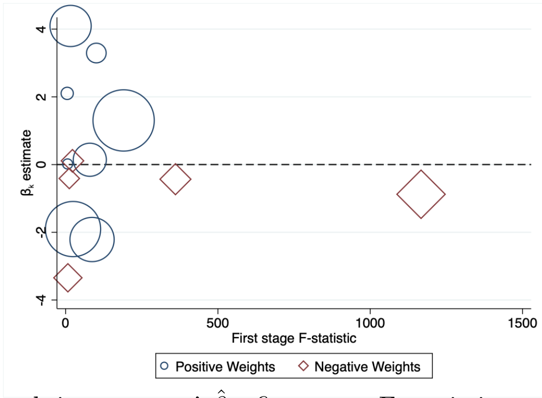
Notes: Each column reports a separate regression. The dependent variable is the industry share (times 100) in each local labor market. The variables Δ Immigration share and Δ China imports are measured in changes as the predicted values following a first-stage regression based on the IV instruments used in the main regressions. All other explanatory variables are measured at the beginning of the period. Robust standard errors are shown in parentheses. *, ** and *** indicate coefficients significantly different from zero at the 10%, 5% and 1% level respectively.

Figure F2: Heterogeneity of coefficient estimates, Robots, 2001-2008

(a) Far Right



(b) Turnout



Notes: These figures plot the relationship between each instruments' $\hat{\beta}_k$, first stage F-statistics and the Rotemberg weights. Each point is a separate instrument's estimates (industry share). The figures plot the estimated $\hat{\beta}_k$ for each instrument on the y-axis and the estimated first-stage F-statistic on the x-axis. The size of the points are scaled by the magnitude of the Rotemberg weights, with the circles denoting positive Rotemberg weights and the diamonds denoting negative weights. The horizontal dashed line is plotted at the value of the overall $\hat{\beta}$ reported in the main IV regressions. The figure excludes instruments with first-stage F-statistics below 5.

F.3 China imports, 2008-2013

Table F5: Rotemberg weights, China imports, 2008-2013

Panel A: Negative and positive weights

	Sum	Mean	Share
Negative	-0.229	-0.003	0.157
Positive	1.229	0.009	0.843

Panel B: Correlations

	α_k	g_k	F_k	Var(z_k)	$\hat{\beta}_k^{FR}$	$\hat{\beta}_k^{5SM}$	$\hat{\beta}_k^{TO}$
α_k	1						
g_k	-0.144	1					
F_k	0.429	-0.190	1				
Var(z_k)	0.069	0.024	0.056	1			
$\hat{\beta}_k^{FR}$	0.005	-0.037	0.015	0.016	1		
$\hat{\beta}_k^{5SM}$	0.011	-0.044	0.021	0.018	–	1	
$\hat{\beta}_k^{TO}$	0.020	-0.035	0.034	0.053	–	–	1

Panel C: Top 5 Rotemberg weight industries

	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k^{FR}$	$\hat{\beta}_k^{5SM}$	$\hat{\beta}_k^{TO}$
Basic iron, steel and ferro-alloys	0.365	-0.889	-0.082	0.236	-0.155
Tanning and dressing of leather	0.088	-0.563	-0.961	1.339	-0.897
Mining of chemical and fertilizer minerals	0.080	-0.769	-0.170	-0.060	-0.442
Mining of non-ferrous metal ores	0.074	-1.447	-0.062	-1.179	-0.954
Optical instruments and photographic eq.	0.059	0.208	-3.753	2.203	-1.401

Notes: This table reports statistics about the Rotemberg weights. In all cases, we report statistics about the aggregated weights, where we aggregate a given industry across years. Panel A reports the share and sum of negative Rotemberg weights. Panel B reports correlations between the weights ($\hat{\alpha}_k$), the national component of growth (g_k), the first-stage F-statistic of the industry share ($\hat{F}_k$), the variation in the industry shares across locations (Var(z_k)), and the just-identified coefficients in the regressions for far-right parties ($\hat{\beta}_k^{FR}$), Five-Star Movement ($\hat{\beta}_k^{5SM}$) and turnout ($\hat{\beta}_k^{TO}$). Panel C reports the top five industries according to the Rotemberg weights.

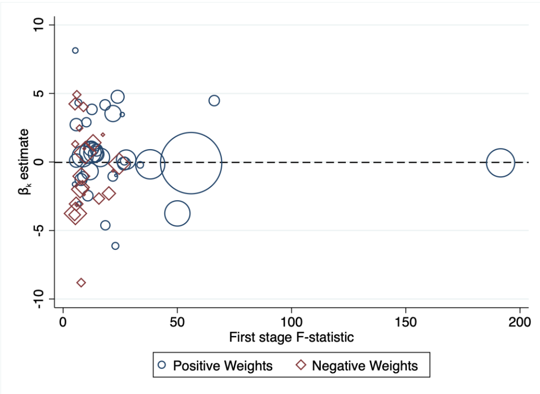
Table F6: Relationship between industry shares and characteristics, China imports, 2008-2013

	Basic iron, steel & ferro-alloy	Tanning & dressing of leather	Mining of chemical & fertilizer min.	Mining of non-ferrous metal ores	Optical instr. & photo eq.
Δ Immigration share (pred.)	-0.075	0.280	0.029	-0.019	-0.607*
	(0.095)	(0.181)	(0.049)	(0.012)	(0.310)
Δ Robots (pred.)	0.068	-0.421*	0.020	-0.006	-0.384*
	(0.054)	(0.221)	(0.024)	(0.009)	(0.226)
Share of residents above 65	0.984	-2.726	-0.250	0.012	9.444*
	(1.019)	(2.345)	(0.795)	(0.395)	(4.868)
Residents (ln)	0.148**	-0.016	-0.017	-0.006	-0.129
	(0.061)	(0.068)	(0.028)	(0.015)	(0.110)
Share of res. w max lower sec. ed.	0.654	-4.604	2.375*	1.379*	-14.237*
	(1.364)	(3.994)	(1.387)	(0.772)	(7.725)
Share of res. w tertiary ed.	-4.121**	-9.097	3.105	2.641	-13.948*
	(1.798)	(6.614)	(2.458)	(1.805)	(7.527)
Internet diffusion	-0.014	0.008	0.009	0.014*	-0.030*
	(0.014)	(0.019)	(0.012)	(0.008)	(0.017)
Tickets for cultural activities pc	0.001	-0.008	-0.002	-0.003*	0.011
	(0.003)	(0.008)	(0.002)	(0.002)	(0.007)
Hospital migration rate	0.018	-0.049	-0.009	-0.014*	-0.124
	(0.018)	(0.040)	(0.012)	(0.009)	(0.080)
Volunteering	-0.006	0.003	0.008	0.011**	0.031*
	(0.005)	(0.016)	(0.007)	(0.005)	(0.017)
Expenditure on cultural activities	0.187**	-0.236	-0.035	-0.049*	0.240
	(0.092)	(0.158)	(0.045)	(0.028)	(0.148)
Attractiveness of universities	-0.000	0.000	0.000	0.000*	-0.006*
	(0.001)	(0.002)	(0.000)	(0.000)	(0.003)
Share of informal labor	-0.025	0.025	0.007	0.015	0.074
	(0.017)	(0.028)	(0.015)	(0.009)	(0.049)
Observations	684	684	684	684	684
R-squared	0.033	0.053	0.029	0.057	0.081

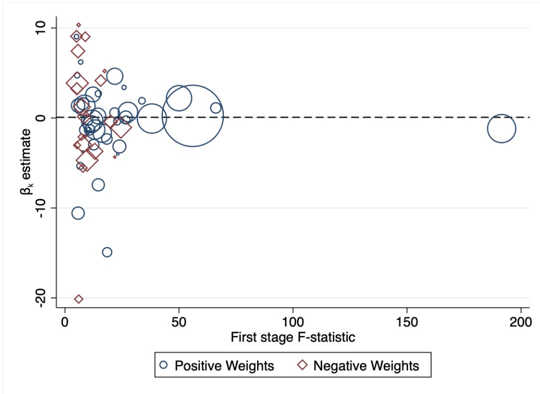
Notes: Each column reports a separate regression. The dependent variable is the industry share (times 100) in each local labor market. The variables Δ Immigration share and Δ Robots are measured in changes as the predicted values following a first-stage regression based on the IV instruments used in the main regressions. All other explanatory variables are measured at the beginning of the period. Robust standard errors are shown in parentheses. *, ** and *** indicate coefficients significantly different from zero at the 10%, 5% and 1% level respectively.

Figure F3: Heterogeneity of coefficient estimates, China imports, 2008-2013

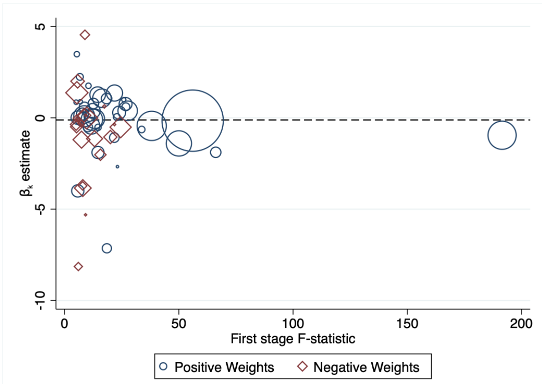
(a) Far Right



(b) Five-Star Movement



(c) Turnout



Notes: These figures plot the relationship between each instruments' $\hat{\beta}_k$, first stage F-statistics and the Rotemberg weights. Each point is a separate instrument's estimates (industry share). The figures plot the estimated $\hat{\beta}_k$ for each instrument on the y-axis and the estimated first-stage F-statistic on the x-axis. The size of the points are scaled by the magnitude of the Rotemberg weights, with the circles denoting positive Rotemberg weights and the diamonds denoting negative weights. The horizontal dashed line is plotted at the value of the overall $\hat{\beta}$ reported in the main IV regressions. The figure excludes instruments with first-stage F-statistics below 5.

F.4 Robots, 2008-2013

Table F7: Rotemberg weights, Robots, 2008-2013

Panel A: Negative and positive weights							
	Sum	Mean	Share				
Negative	-0.047	-0.004	0.043				
Positive	1.047	0.081	0.957				
Panel B: Correlations							
	α_k	g_k	F_k	$\text{Var}(z_k)$	$\hat{\beta}_k^{FR}$	$\hat{\beta}_k^{5SM}$	$\hat{\beta}_k^{TO}$
α_k	1						
g_k	0.324	1					
F_k	0.989	0.364	1				
$\text{Var}(z_k)$	0.825	0.135	0.774	1			
$\hat{\beta}_k^{FR}$	-0.026	0.038	-0.029	-0.003	1		
$\hat{\beta}_k^{5SM}$	-0.023	0.015	-0.023	-0.173	–	1	
$\hat{\beta}_k^{TO}$	-0.025	0.012	-0.026	-0.200	–	–	1
Panel C: Top 5 Rotemberg weight industries							
	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k^{FR}$	$\hat{\beta}_k^{5SM}$	$\hat{\beta}_k^{TO}$		
All other non-manufacturing branches	0.714	2.645	1.592	-0.417	-0.402		
Textiles	0.175	-1.126	1.024	-0.700	-0.794		
Wood and furniture	0.051	-1.479	1.068	-1.370	-1.029		
Metal products (non-automotive)	0.050	-1.451	3.154	1.217	0.496		
Other chemical products	0.014	4.195	-0.499	0.993	0.828		

Notes: This table reports statistics about the Rotemberg weights. In all cases, we report statistics about the aggregated weights, where we aggregate a given industry across years. Panel A reports the share and sum of negative Rotemberg weights. Panel B reports correlations between the weights ($\hat{\alpha}_k$), the national component of growth (g_k), the first-stage F-statistic of the industry share ($\hat{F}_k$), the variation in the industry shares across locations ($\text{Var}(z_k)$), and the just-identified coefficients in the regressions for far-right parties ($\hat{\beta}_k^{FR}$), Five-Star Movement ($\hat{\beta}_k^{5SM}$) and turnout ($\hat{\beta}_k^{TO}$). Panel C reports the top five industries according to the Rotemberg weights.

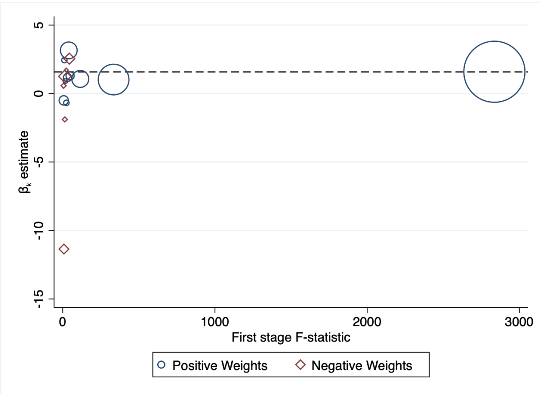
Table F8: Relationship between industry shares and characteristics, Robots, 2008-2013

	Other non-manuf.	Textiles	Wood & furniture	Metal products	Other chem. prods.
Δ Immigration share (pred.)	4.063***	-0.969	-0.522	-0.396	0.158
	(1.252)	(0.773)	(0.474)	(0.414)	(0.120)
Δ China imports (pred.)	-2.128**	-0.785	0.350*	0.171	0.145
	(1.021)	(1.168)	(0.206)	(0.240)	(0.175)
Share of residents above 65	32.855**	-66.144***	-20.634***	-1.499	2.339
	(14.175)	(14.179)	(5.191)	(4.606)	(1.553)
Residents (ln)	-1.703***	0.058	-0.573***	0.622***	0.301***
	(0.507)	(0.407)	(0.212)	(0.138)	(0.072)
Share of res. w max lower sec. ed.	-95.123***	90.550***	9.296	-3.463	-1.154
	(18.728)	(16.915)	(6.173)	(5.449)	(1.555)
Share of res. w tertiary ed.	80.826**	96.454***	18.959	-49.678***	-8.475*
	(40.814)	(33.243)	(16.102)	(12.085)	(4.489)
Internet diffusion	0.041	-0.322***	-0.107***	0.040	0.011
	(0.120)	(0.103)	(0.040)	(0.044)	(0.018)
Tickets for cultural activities pc	0.001	0.019	0.035**	-0.013	-0.004
	(0.050)	(0.036)	(0.016)	(0.015)	(0.005)
Hospital migration rate	-1.512***	1.075***	0.130*	0.119*	-0.019
	(0.207)	(0.175)	(0.076)	(0.064)	(0.021)
Volunteering	0.662***	-0.550***	0.127***	-0.084*	-0.008
	(0.123)	(0.089)	(0.049)	(0.051)	(0.014)
Expenditure on cultural activities	-6.111***	3.666***	0.695***	1.148***	-0.101
	(0.704)	(0.592)	(0.195)	(0.268)	(0.130)
Attractiveness of universities	0.007	0.003	0.001	-0.003	-0.003
	(0.013)	(0.009)	(0.005)	(0.004)	(0.003)
Share of informal labor	1.867***	-1.537***	-0.151**	-0.289***	-0.011
	(0.157)	(0.172)	(0.062)	(0.061)	(0.021)
Observations	684	684	684	684	684
R-squared	0.424	0.254	0.132	0.245	0.055

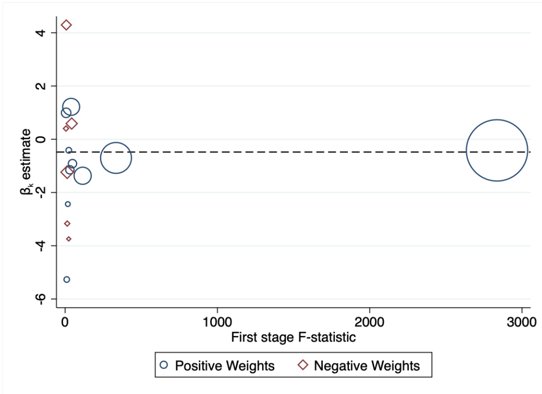
Notes: Each column reports a separate regression. The dependent variable is the industry share (times 100) in each local labor market. The variables Δ Immigration share and Δ China imports are measured in changes as the predicted values following a first-stage regression based on the IV instruments used in the main regressions. All other explanatory variables are measured at the beginning of the period. Robust standard errors are shown in parentheses. *, ** and *** indicate coefficients significantly different from zero at the 10%, 5% and 1% level respectively.

Figure F4: Heterogeneity of coefficient estimates, Robots, 2008-2013

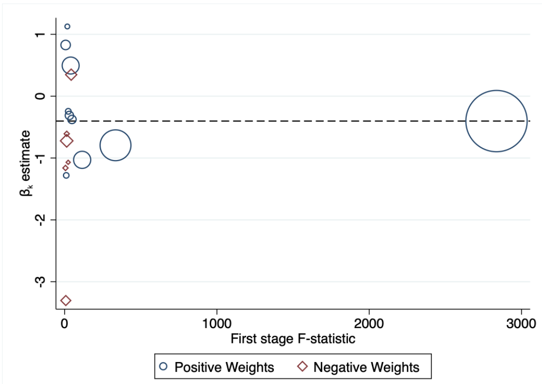
(a) Far Right



(b) Five-Star Movement



(c) Turnout



Notes: These figures plot the relationship between each instruments' $\hat{\beta}_k$, first stage F-statistics and the Rotemberg weights. Each point is a separate instrument's estimates (industry share). The figures plot the estimated $\hat{\beta}_k$ for each instrument on the y-axis and the estimated first-stage F-statistic on the x-axis. The size of the points are scaled by the magnitude of the Rotemberg weights, with the circles denoting positive Rotemberg weights and the diamonds denoting negative weights. The horizontal dashed line is plotted at the value of the overall $\hat{\beta}$ reported in the main IV regressions. The figure excludes instruments with first-stage F-statistics below 5.