Political Extremism and Economic Activity

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Abstract

We study the effect of economic activity on the vote share of extremist political parties in Europe. Using a model that addresses the prevalent endogeneity problem, which is likely to have discouraged similar research, we find that small fluctuations in economic growth have significant inverse effects on the vote share of far-right parties. Our results explain the widespread success of such parties in entering European parliaments following the 2007-2008 crisis. They also suggest that, *ceteris paribus*, far-right parties on the margin of electoral thresholds run the risk of losing parliamentary representation in the face of a steadily recovering world economy.

Keywords: Political Extremism, Economic Growth

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1 Introduction

In the wake of the 2007-2008 economic crisis, a wave of electoral triumphs by political parties that belong to the ideological fringes swept across the European political landscape.[1] The timing and severity of this electoral shift reignited a long-standing interest in the role of economic activity in political radicalization (e.g., Reinhart and Rogoff, 2014; and Funke et al., 2016). For the most part, relevant research relies on discrete manifestations of crises as economic events that drive electoral outcomes. This approach engenders an important methodological advantage. Because the political environment of any one country is almost never the singular cause of a global crisis (Summers, 2000), the direction of causation is unambiguous. It runs from the emergence of a crisis to electoral results, and not the other way around. Of course, by concentrating on a small number of elections that follow the kind of extreme economic downturns associated with crises, this approach is not designed to shed light on the extent to which economic activity drives electoral results *on the margin*. Yet, casual empiricism and formal theory suggest that it does (Bruckner and Gruner, 2010). All fluctuations in economic growth, however small, are likely to have an impact (de Bromread et al., 2013; Leigh, 2009). Measuring this impact will provide answers to a host of important questions. For example, it will shed light on relatively mild economic downturns that, while not severe enough to qualify as crises, have the potential to enable extremist parties to break specific electoral thresholds and enter federal parliaments.

In this study, we set out to fill this gap in the literature by investigating the extent to which growth in per capita GDP impacts the electoral success of extremist parties at the regional level across Europe during 1990–2016. An important challenge that we face is that economic growth is endogenous to political outcomes.[2] This could be the result of unobserved variables that simultaneously drive economic fluctuations and voting behavior. For example, extensive immigration may contribute positively to economic growth and, independently, to the electability of far-right candidates that typically promote isolationist policies (Becker and Fetzer, 2016). Alternatively, endogeneity may result from reverse causation. For instance, electoral success by

[1] The electoral accomplishments of these parties are staggering. For example, the vote share of Greece's *Golden Dawn* increased from 0.1% in 1996 to 7% in 2012. The *True Finns* and the *United Kingdom Independence Party* increased their share of the vote in their respective, 2011 and 2015, parliamentary elections fourfold. Finally, the Spanish *Podemos*, that was established in 2014, received over 20% of the share of the vote in the national elections of 2015.

[2] Contributions that examine the impact of GDP on radicalization either ignore the issue of endogeneity (de Bromread et al., 2013; Leigh, 2009) or rely on survey, rather than observed electoral, data (Bruckner and Gruner, 2010).

far-left parties may lead to programs that decrease wage inequality which can, in turn, impact on economic growth (Madsen et al., 2018).

We overcome this problem by carefully constructing an appropriate instrumental variable. Our instrument interacts global prices of minerals with the existence of regional mining activity in such minerals that predates the electoral contests under consideration. This instrument, which draws from the work of Acemoglu et al. (2013), exploits two key sources of variation. First, the time variation in global prices of mined resources. Second, the cross-regional variation in mining activity. As we elaborate in a subsequent section, this variable is independent of electoral results, yet highly correlated with regional economic growth.

2 Empirical strategy

We estimate the impact of growth in GDP per capita on the vote share of extremist parties using the following log-linear specification:

$$VoteShare_{it} = \alpha_i + \tau_t + \beta ln(GDPpc_{it}) + \gamma ln(pop_{it}) + \epsilon_{it} \tag{1}$$

where i and t index region and time, respectively. $VoteShare$ measures the percentage of votes that different political groupings receive and it can take one of three forms: *TotalExtremist*, *FarLeft*, and *FarRight*. They represent the vote share of parties on both the far-left and the far-right, only those on the far-left, and only those on the far-right, respectively. α_i represents regional fixed effects and τ_t captures time fixed effects. $ln(GDPpc_{it})$, which is the explanatory variable of interest, is the natural log of GDP per capita in region i at year t. $ln(pop_{it})$ is the natural log of the total population in region i at year t. Finally, ϵ_{it} represents the error term.

To address the endogeneity of $GDPpc$, we use a two-stage least squares (2SLS) estimation approach with the following first-stage regression:

$$ln(GDPpc_{it}) = \alpha_i + \tau_t + \delta(M_i \times p_t) + \gamma' ln(pop_{it}) + u_{it} \tag{2}$$

The instrumental variable is interaction $M_i \times p_t$. M_i is a dummy variable that assumes the value of 1 if region i is home to at least one active mine whose existence predates the electoral contests under consideration. p_t is the natural log of the world price of the resource extracted in that mine. If there are multiple minerals extracted in any given region, p_t is the natural log of the simple average of the global prices of such minerals.

Our identifying assumption is that the mining activity dummy and the variation in global mined resource prices, are orthogonal to the error term in the second stage. The premise is twofold. First, the mining activity dummy, M_i, is time-invariant and only includes mines that became active prior to the beginning of our sample period. Hence, this variable is not affected by openings or closings that might be correlated with electoral outcomes. Second, Europe is a relatively small supplier of mined resources to the world and is therefore unlikely to influence the world prices of such resources. At the same time, $M_i \times p_t$ is a good proxy of the value of mining activity in individual regions that is a component of regional GDP. Hence, the interaction is correlated with GDP growth and an appropriate instrument for this variable.

3 Data

We require data on electoral contests; GDP; population; and mining activity, at the regional level across Europe and over time. We also require data on the global prices of mined resources during a comparable time period. For regional subdivisions of European countries we rely on the Nomenclature of Territorial Units for Statistics (NUTS). NUTS is a geocode standard for referencing the subdivisions of countries for statistical purposes. We use the 'regional' level (NUTS-2) classification which offers the most extensive data for both elections and mining activity.

GDP and population data were collected from Eurostat (2016). Data on regional mining activity were obtained from the United States Geological Survey (USGS, 2016) that conveniently reports European data using the NUTS framework. Global mineral prices were sourced from the World Bank (2016a, 2016b) and USGS (2016). Finally, electoral results of parliamentary elections were collected from the European Union's (2016) European Election Database. Following the definitions of the previous section, they were coded in the form of *TotalExtremist*, *FarLeft*, and *FarRight*. Classification of political parties in different categories follows Funke et al. (2016).

Our final data cover 218 regions across 16 European countries and 90 elections during 1990-2016. Table 1 provides descriptive statistics.

Table 1 around here

4 Findings

The results of estimating the regression equations of the previous section are reported in Table 2. 2SLS, OLS, reduced form, and first stage estimates appear in panels A, B, C, and D, respectively. We discuss them in reverse order.

Overcoming endogeneity is central in any effort to link growth to electoral outcomes. In this light, it is reassuring that our instrument has a first stage coefficient that is significant at the 1% level and an F-statistics of 11.75 that satisfies Staiger and Stock's (1997) critical value of 10 (panel D). The reduced form estimates of panel C suggest that this instrument does most of the heavy lifting in relation to the vote share of far-right than far-left parties. Naturally, this is reflected in the large (small) difference across panel B's OLS and panel A's 2SLS coefficients of GDP per capita when the dependent variable is the vote share of far-right (far-left) parties.

Consider now the 2SLS coefficients of panel A. A 1% decrease in regional GDP per capita increases the regional vote share of extremist parties by 0.53%, an effect that is statistically significant at the 1% level. For the most part, this reflects the effect on the vote share of far-right parties which corresponds to 0.48% and which is significant at the 5% level. By contrast, the corresponding effect on the far-left is only 0.047% and statistically insignificant.

Table 2 around here

The 2007–2008 crisis led to a reduction of European GDP per capita in the order of 2-5% (e.g., Funke et al., 2016). Other things equal, this implies a rise in the vote share of far-right parties in the neighborhood of 1-2.5%. Given that electoral thresholds in European parliaments are typically around 3%, our results can partly explain recent electoral successes by the far-right movement. Currently, a number of far-right parties represented in European parliaments stand on a vote share that is only marginally above the electoral threshold. Examples include Belgium's Flemish Interest at 3.7%, Ukraine's Svoboda at 4.7%, Italy's Lega Nord at 4.08%, etc. If Europe's 2017 GDP per capita growth of 2-3% continues, our results suggest that it will translate into an annual vote share loss by far-right parties in the order of 1-1.5%. Other things equal, these figures predict that at least some far-right parties are likely to be forced out of Europe's parliaments in forthcoming elections.

5 Conclusion

Small fluctuations in economic activity have a big inverse effect on the vote share of far-right parties. This result explains the ascendancy of such parties in the wake of the 2007-2008 crisis. Subject to unique national and regional characteristics (from which our estimations abstract using fixed-effects), it also suggests that far-right parties on the margin of electoral thresholds run the risk of losing parliamentary representation in the face of a steadily recovering world economy.

References

Acemoglu, D., A. Finkelstein, M.J. Notowidigdo, 2013. Income, and Health Spending: Evidence from Oil Price Shocks. *Review of Economics and Statistics* 95, 1079–1095.

Becker, S., T. Fetzer, 2016. Does Migration Cause Extreme Voting?, CAGE Working Paper 306.

Bruckner, M., H.P. Gruner, 2010. Economic Growth and the Rise of Political Extremism: Theory and Evidence, C.E.P.R. Discussion Papers.

de Bromhead, A., B. Eichengreen, K.H. O'Rourke, 2013. Political Extremism in the 1920s and 1930s: Do German Lessons Generalize? *Journal of Economic History* 73, 371–406.

European Union, 2016. European Election Database: http://www.nsd.uib.no.

Eurostat, 2016. GDP at the Regional Level: http://ec.europa.eu/eurostat/statistics-explained.

Funke, M., M. Schularick, C. Trebesch, 2016. Going to extremes: Politics after Financial Crises, 1870–2014. *European Economic Review* 88, 227–260.

Leigh, A., 2009. Does the World Economy Swing National Elections? *Oxford Bulletin of Economics and Statistics* 71, 163–181.

Madsen, J. B., Md. R. Islam, H. Doucouliagos, 2018. Inequality, Financial Development and Economic Growth in the OECD, 1870–2011. *European Economic Review* 101, 605–624.

Reinhart, C.M., K.S. Rogoff, 2014. Recovery from Financial Crises: Evidence from 100 Episodes. *American Economic Review* 104, 50–55.

Staiger, D., J. H. Stock, 1997. Instrumental Variables Regression with Weak Instruments. *Econometrica* 65, 557–586

Summers, L.H., 2000. International Financial Crises: Causes, Prevention, and Cures. *American Economic Review* 90, 1–16.

World Bank, 2006a. Global Economic Monitor (GEM) Commodities: http://databank.worldbank.org.

World Bank, 2006b. World Development Indicators - Contribution of Natural Resources to Gross Domestic Product: http://wdi.worldbank.org/table/3.14.

Tables

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.
$TotalExtremist$	10.301	10.034	0.000	47.530
$FarRight$	5.158	7.985	0.000	47.000
$FarLeft$	5.144	5.832	0.000	34.007
$ln(GDPpc)$	9.775	0.629	7.881	11.225
$ln(pop)$	7.024	0.921	3.207	9.361
$ln(p)$	1.013	6.012	0.000	77.395

Table 2: Local Economic Activity and Vote Share of Extremist Parties

	(1)	(2)	(3)
	$TotalExtremist$	$FarLeft$	$FarRight$
	Panel A. 2SLS Estimates		
$ln(GDPpc)$	-0.531***	-0.047	-0.484**
	(0.189)	(0.110)	(0.220)
	Panel B. OLS Estimates		
$ln(GDPpc)$	-0.034*	-0.027**	-0.006
	(0.019)	(0.012)	(0.014)
R^2	0.305	0.315	0.268
	Panel C. Reduced form Estimates		
$(M \times p)$	-0.191***	-0.017	-0.174***
	(0.042)	(0.047)	(0.035)
R^2	0.308	0.312	0.277
	Panel D. First stage Estimates [Dependent variable: ln(GDPpc)]		
$(M \times p)$		0.004***	
		(0.001)	
First-stage Kleibergen-Paap F-statistic		11.75	

Notes: There are 1,011 observations. An observation corresponds to a single NUTS-2 region and year. All specifications include $ln(pop)$, NUTS-2-region-fixed effects, and year fixed effects. However, their coefficients are suppressed in the interest of parsimony. In panels C and D, the point estimates and standard errors are multiplied by 1,000 for presentation purposes. Huber-White standard errors appear in parentheses. ***, **, and * signify statistical significance at the 1%, 5%, and 10% levels, respectively.