The Role of Economic Decline & Malaise in the Rise of Extreme-Nationalist Populism

Diogo Ferrari, University of California Riverside
Rob Franzese, University of Michigan
Hayden Jackson, University of Michigan
ByungKoo Kim, University of Michigan
Wooseok Kim, University of Michigan
Patrick Wu, University of Michigan

Abstract

In recent years, the support for extreme-nationalist populist politicians and parties has grown in developed European as well as in developing Latin American nations. Two “competing” explanations in the literature have been offered to account for the rise of populist, anti-elite, extreme nationalist attitudes: economic malaise and cultural or status threat. We view these two explanations as not at all competing; rather, they are deeply connected and intertwined. In this paper, we argue that individual reactions to economic malaise are shaped by their sociocultural perceptions nurtured in heterogeneous personal and neighborhood experiences. Our theoretical prediction suggests that there will be heterogeneous groups within the samples that vary in their reaction to economic malaise. To gain empirical leverage on these heterogeneous and intertwined causal relations, we employ a novel method called hdpGLM. In our preliminary analyses on the replication of Mutz (2018), hdpGLM confirms the presence of multiple latent clusters in the data that differ in how economic malaise relates to the support for extremist parties.

Keywords: Economic malaise, Sociocultural perception, Causal mediation, hdpGLM
At the turn of the last century, 19th into 20th, as the previous Great Globalization was cresting its apex in trade, financial, and labor market integration, an anti-globalization, anti-establishment, anti-elite reaction grew in response (O’Rourke & Williamson 2001). The then developed world’s political economies began to restrict flows of people, capital, and goods, beginning with immigration. The previous Great Globalization generated a powerful political backlash, culminating by the end of the first half of the 20th Century with a tragic three decades marked by two World Wars and Great Depression between. Many have noticed disturbing parallels of this previous reaction to globalization and the present great globalisation (e.g., O’Rourke & Williamson 2001; Rodrick 2018). In recent years, the support for extreme-nationalist populist politicians and parties has grown in developed European as well as in developing Latin American nations (Golder 2016; Inglehart & Norris 2016).

One plausible explanation for all this anti-globalization, anti-immigrant, anti-minority, anti-establishment, anti-elite political backlash and increasing support of extreme-nationalist populist politicians focuses on regional economic decline and malaise (Colantone & Stanig 2018a, 2018b). As Franzese (2019) explains, one can understand these developments as following directly from basic international economics: globalization fosters the decline of comparatively disadvantaged areas and industries at the same time as it causes the expansion of comparatively advantaged areas and industries. The developed world, by definition, is relatively well endowed with human, physical, and financial capital, and relatively poorly endowed with moderately skilled and unskilled labor, and so comparatively advantaged in industries using the former relatively intensively and disadvantaged in industries with the
reverse relative intensity. As capital-intensive industries grow and labor-intensive ones shrink due to globalization, demand for capital increases greatly and demand for labor increases modestly, and supply of labor freed from the shrinking industries increases greatly, while the corresponding supply of capital increases only slightly. Thus, returns to lower-skilled labor, in the form of wages, stagnate or decline in real purchasing-power terms, while the returns to human, physical, and financial capital (high-skilled wages, rents, profits) increase. The human experience of all this is felt in the stagnation and malaise of factory towns in industrial areas, the increasing capitalization and concentration of farming, and the concomitant decline of rural livelihoods. As people experience sustained stagnation and decline of their standard of living, at the individual-level the reaction can include a rise in the support for populist appeals, perhaps including extreme-nationalistic tropes laying blame for the palpable economic, and accompanying social, malaise on “others” (call it: “otherizing”).

While this economic stagnation and decline is a core part of the catalyst for these feelings, the rise in support for extremist populism clearly goes well beyond a simple economics story. Rather, we argue economic stagnation and decline spurs and becomes entwined with a broader feeling of being left behind: a social, i.e., a socio-cultural and socio-economic experience, and not a purely economic one. People in these beset towns look around and see their whole way of life—their very identity—threatened, or at least looked down upon, and therefore come to feel, quite naturally, a very profound resentment. Cramer (2016) describes these attitudes in

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1 Automation, and technological advance more generally, have similar distributional implications, and those increasing capitalization trends are reinforced by, rather than competing with, globalization and its effects.
her study of rural Wisconsin. She finds that rural communities feel ignored by policymakers and disrespected by “city folks”. Personal and neighborhood economic conditions are a core component of Cramer’s story, but certainly not all, or even necessarily “the main” part, of the story; rather, neighborhood and personal economic decline are among the underlying conditions that render individuals (in our argument, crucially: some individuals, but not others) more open or susceptible to extremist appeals, because of and through this perceived personal and communal sociocultural or identity threat.

This article proceeds as follows. In the next section, we discuss two “competing” explanations in the literature for the rise of populist, anti-elite, extreme nationalist attitudes: economic malaise and cultural or status threat. We next elaborate our argument that and how these effects are not competing, but complementary—against a background of communal or neighborhood malaise and decline, and perhaps triggered by an exogenous shock, like a plant closing, and this affects some individuals’ perceptions of their socioeconomic and sociocultural status, perhaps their very identity being “under threat” or looked down-upon by outsider elites (winners in the background economic change). This feeling in some that their livelihoods and “way of life” are besieged or dying, renders some increasingly susceptible to extremist, “otherizing” appeals. Importantly, this dynamic operates in some clusters of people but not others, depending on latent traits and life experiences as well as observable ones like educational attainment, personal income, and demographics (race, most likely prominently). In the following section, we conduct two kinds of empirical explorations of these arguments. First, we conduct a replication and extension of Mutz (2018) to consider a causally mediated relation
from economic hardship to support for Trump through culture-threat perception, and then whether this path may be operating heterogeneously. Second, we conduct an initial study of engagement with extremist and hate groups on Twitter that correspond with the closing of auto plants in four towns in southeast Michigan and northeast Ohio. We conclude with the implications of our findings for our discipline and beyond.

**Existing explanations in the literature**

Currently, the literature divides explanations for the rise of populism, extremism, anti-elitism, and related sentiments into two camps—that these behaviors are best explained by economic hardship, malaise, and decline, or that we can best see these through a lens of cultural, status, or identity threat-perception or some sort of xenophobia or racism. There is an important disconnect, seemingly contradictory findings, in the empirical analyses to date that must be emphasized and rectified: Analyses at the individual level, especially in the United States, generally find strong role for sociocultural factors and little or none for economic ones; studies at regional or other aggregate levels, to the contrary, generally find very strong support for the economic malaise and decline pathway and unclear relations to regional social and demographic characteristics. We suggest that an understanding of the processes underlying the rise of extreme-nationalist populism would do well to reconcile these contradictory findings; we believe our arguments and analyses do.
Economic malaise

Many studies find a relationship between economic hardship and extremist support. Most of the studies finding strong support use subnational regions as units of analysis, finding positive relations of globalization-induced economic decline and anti-establishment populist support (Colantone & Stanig 2018a, 2018b; Hays et. al. 2019; Rodrik 2018, 2020). Similarly, Goldstein and Peters (2014) find that feelings of economic threat are important, but reject that these economic-threat perceptions link to objective individual-level economic circumstances, and find them instead rooted in a subjective view of the local or national economy as a whole. Broz, Frieden, and Weymouth (Broz et al. 2020) examine trends of populist backlash to globalization across the US and Europe and find populist support is strongest in communities with a history of economic and social decline. Although some regional-level studies do find differently—Greece’s far-right Golden Dawn party saw an increase in share of the vote in areas with high immigration and crime rates, long-standing right-wing tradition, and low tourism, while individual economic hardship could not explain this increase in vote share (Roumanias et al. 2020)—in general, studies at levels aggregated beyond the individual find very strong support for a connection to economic malaise & decline, especially globalization-induced economic decline. Other explanations find more complex relationships between economics extreme-nationalist populist support. Manza & Crowley (2017) find that high levels of income and education drive support for Trump in the 2016 primary election. Orgorzalek et al. (2019) find that nationally poor and locally affluent (above the local median income) whites support Trump.
Status threat

In contrast to studies at regional levels, individual-level analyses usually find stronger support for the bases of rising support for “otherizing populism” lying in some sort of cultural or identity threat perception. These latter explanations point instead to racial, ethnic, or xenophobic attitudes, fears, or biases, or social threat perceptions toward out-member groups as the basis for this populist-extremist backlash. Many studies at individual level, particularly of the 2016 U.S. presidential elections and U.K. Brexit referendum, pit these explanations against each other and conclude that voters’ support for the populist option is not rooted in economic hardship but rather in racial, ethno-religious, anti-immigrant animus (e.g., Collingwood et al. 2017; Cerrato et al. 2018), nationalist and anti-elite sentiment (Iakhnis et al. 2018), or perceptions of socioeconomic “status threat” (Mutz 2018). Some studies specifically find that while there are effects of import penetration, the extremist support goes in different directions, left or right, based on whether the Congressional district is a majority white or a majority-minority district (Autor et al. 2016), which is suggestive of the heterogeneous effect we emphasize.

More broadly viewed, however, the evidence on these proposed sociological bases for support for extremist otherizing is also mixed. Some studies find an “exposure effect”, i.e. those individuals who are exposed to diverse communities are less likely to vote far-right—see Steinmayr (2016), Vertier & Viskanic (2018), and Knowles & Tropp (2018). Intuitively, this is certainly plausible, particularly if ‘community’ is highly salient to an individual’s experience of the world. But other studies find a positive relationship between the proportion of
immigrants in the community and far-right voting—Bowyer (2008) and Halla et al. (2017). On balance, the evidence seems to lean in favor of the former: heterogeneous areas, like cities, seem to show less support for far right and populist parties than do homogenous areas like the rural heartland. We suspect there is something further to be explained here, connecting these seemingly opposite stories; our initial hypothesis is heterogeneous responses, with some individuals reacting negatively and others positively and/or not reacting to community sociocultural and demographic change. For instance, Freund & Sidhu (2017) seem to find these different results stem from heterogeneous cultural values: the reason more ethnically diverse areas vote further to the left than ethnically homogenous areas is because the voters have different interests and views, not because exposure to ethnic diversity has changed the views of white voters. Furthermore, politicians can weaponize these differences: Trump uses speeches to raise the moral status of white Americans as hard-working Americans afflicted by globalization, and to attack the morality and worthiness of Latino and Muslim immigrants and refugees (Lamont et al. 2017).

**Our argument**

We argue that these two explanations, socioeconomic and sociocultural, are not at all competing; rather, they are deeply connected and intertwined. One’s views and behaviors grow from all their economic and sociocultural experiences. Their personal and neighborhood economic experiences influence their sociocultural perceptions and self-identity, and vice versa. Moreover, different people will have different prior experiences and predispositions, and so are
likely to respond differently to the same economic and social shocks and conditions. Accordingly, to gain empirical leverage on these heterogeneous and intertwined causal relations from socioeconomic conditions and experiences to support for extreme nationalist “otherizing” populist ideas, candidates, and parties,\(^2\) we will need to use methodological techniques that are able to uncover and estimate causal mediation, causal complexity, and context-dependent effect-heterogeneity, and we will need rich, geolocated data available at least at neighborhood-regional granularity (and at other granularities).

By our arguments, personal and/or neighborhood-regional economic decline may trigger xenophobic, anti-elite, identity-threat reactions in some subgroups of the population, but not others. Furthermore, these groupings may be in part unobserved, or latent, because people’s sociopolitical predispositions are acquired over long socialization processes throughout life, childhood or young-adult experiences, family history, etc. (Fiorina 1996; Miller & Shanks 1996; Hess & Torney 1967; Sears 1975; Sears & Valentino 1997), implying that the economic decline and malaise of a person’s region or neighborhood will affect different people with similar observed characteristics\(^3\) in different ways due to these latent traits or life experiences. Call these latent groups that differ in their acquired predispositions latent dispositional types. Those predispositions make some people more susceptible or open to otherizing appeals

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\(^2\) Our focus on this causal path from socioeconomic conditions through sociocultural perceptions does not intend to suggest that it is the only or necessarily the primary path, or to neglect or downplay other paths such as those originating in sociocultural threat-perception. Rather, we focus on this path originating in socioeconomic conditions because we think it the more neglected heretofore in previous work, because socioeconomic conditions may plausibly be more exogenous than sociocultural perceptions, and because economic conditions may be more actionable than threat-perceptions and xenophobia.

\(^3\) Heterogeneity in responses as a function of observed characteristics, e.g. race and ethnicity, is also very likely, but these are modeled more simply in the usual ways: multiplicative-interaction and multilevel modeling (GLM).
blaming others, such as immigrants, for their and their community’s economic hardship. In this way, economic hardship affects perceptions about the socioeconomic environment and the threats posed by out-group members, and that effect on perceptions exhibits latent (as well as observed) heterogeneity in the population due to unobserved or unobservable factors (e.g., lifelong personal history and socialization).

Putting this all together: if support for nationalist-Otherizing populist extremism derives from perceived and objective xenophobic/sociocultural/identity and socioeconomic threats, then there are three sorts of extreme-nationalist populist supporters: those with xenophobic predispositions responding directly to their perceived sociocultural threats; those reacting directly to economic distress; and those perceiving cultural-xenophobic threat as a result of, or as part of single composite with, economic distress. Restated in terms of the extant arguments, perceptions of the sociocultural “threats” posed by other groups connect in our argument to support for extreme-nationalist populism in three possible ways: as a mediation effect in a group for whom economic hardship triggers or leaves fertile ground for threat perceptions about out-group members; as a direct effect deriving from one’s core xenophobic and similar predispositions independent of economic hardship triggering; and as an orthogonal factor (i.e., null effect). Likewise, economic stressors will lead directly to extreme anti-establishment support in some, to more-favorable dispositions toward extreme-nationalist “Otherizing” and

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4 That mediation effect argument was recently explored by Hays et al (2019), finding strong support. See also Colantone & Stanig (2019), Rodrik (2020), and Velasco (2020).
by that path to extreme-nationalist support in others, and neither in a third group. The diagram below illustrates our argument:

Importantly, we aim not to test whether the “true story” is economic instead of cultural; rather, we aim to estimate how much of a role economics may have in this rising extreme-nationalist xenophobia. In our view, these two explanations are better seen, not alternative and competing, but rather as complementary and part of a single causal nexus: a profound resentment that “I and we, and people like us” are being “left-behind” and “looked-down-upon”. We focus our examination on causal pathways that begin with objective economic conditions, as these are perhaps more actionable and more exogenous to the outcome than the perceptions of socio-economic-cultural status threats. We are further interested in exploring whether there is heterogeneity, observed and unobserved, in these relations, and understanding the content of such heterogeneity. However, we must also stress that the methodological tools we employ (Ferrari 2019, 2020) will evidence homogeneity if the data more strongly supports it (Ferrari 2019, 2020).

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5 In our argument diagram to the right, the “no-effect” relationships are left implicit, and the possible direct independent channel from xenophobic predispositions to extremist support is omitted to highlight novel aspects distinct to our view.
Preliminary results

In this section, we summarize the results from our two preliminary analyses: Replication and extension of Mutz (2018) and analysis of Twitter data from selected US regions of Michigan and Ohio. Our aim is to conduct classical (Baron & Kenny 1986; Hayes 2009), design-based (causal-inference) (Imai et al. 2010a & 2010b; Keele et al. 2010), and Bayesian semi-parametric (Miles et al. 2020) causal-mediation analyses to investigate if and how socioeconomic malaise and decline fosters support for extreme-nationalist populism via heightened perceptions of sociocultural threats posed by out-group members.6 Recognizing the possibility (likelihood in our view) of subgroup heterogeneity—both as functions of observed covariates like education and community sociodemographics and as latent classes or types perhaps reflecting long-term socialization—in these causal relations, we propose to conduct these causal mediations using a recently developed Bayesian latent-clustering

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6 Notwithstanding the challenges that confront observational-data analysis of causal mediation, experimental approaches seem to us obviously unavailable in proper context and extremely likely to be ineffective in survey or laboratory experimental context. Our mediator is some manner of sociocultural status-threat (SST); that seems obviously impossible (likely unethical) to manipulate in the actual political environment. Moreover, even leaving aside the severe external-validity concerns this implies for attempts to manipulate SST in laboratory or survey, it is unclear to us how much manipulation of an individual's perceived SST could possibly be generated in laboratory or survey and then, too, how validly those laboratory or survey manipulations would map onto actual treatments and mediators in our analysis: variations in actual SST or real-time appeals thereto by actual demagogues. Thus, we do not believe experimental-level credibility of exogeneity is possible, or that, even if it were, its results would have much external validity to the contexts of actual interest. Accordingly, we intend to pursue methods of causal-mediation analysis in observational data, that being both possible and potentially informative in the intended population of interest. Methods of observational causal-mediation analysis have extended beyond classical Baron & Kenny (1986) regression-based causal-mediation analysis as Gidron & Hall (2017) use, e.g.; to design (causal-inference) based methods due to Imai et al. (2010a & 2010b), as Colantone & Stanig (2018c) and Hays et al. (2019) use, all three of which find strong evidence of causal mediation along lines similar to our arguments; to most recently a semi-parametric Bayesian causal-inference method (Miles et al. 2020) that synergizes conveniently with Ferrari's (2020) hdpGLM, and which synergy we intend to pursue in this research.
(hierarchical Dirichlet-process) generalized-linear (multilevel) model: hdpGLM (Ferrari 2020). The model can be used to identify the heterogeneous effects of context-level features (e.g., neighborhood decline or sociodemographics) and/or individual characteristics (education, demographics, opinions) in latent subpopulations with different behavioral responses to (coefficients on) these covariates. In this preliminary analysis, the hdpGLM will be used to uncover clusters for next-stage exploratory analysis and to determine (via traditional interaction terms, e.g.) which observed covariates connect in which groups in what ways to extreme-nationalist-populist support.

First, we primarily consider the reanalysis of Table S4 (see Appendix A) of Mutz (2018) “Status Threat, Not Economic Hardship” study in a preliminary application of our heterogeneous causal-mediation approach. In the figure below, we first use hdpGLM to estimate the first stage of the (design-based, following Imai et al. 2010a & 2010b) causal-mediation analysis—Path A in the theory diagram above—revealing five latent clusters in terms of how economic conditions relate to sociocultural threat (Mutz’ SDO): right panel. That panel also shows the single average effect of local economics on SDO that a standard GLM estimate. Four of the five clusters have modest coefficient point-estimates with large intervals including zero, but the fifth and largest Cluster 1 (31.2% of the sample) manifests a very large and reasonably precisely estimated causal-path. The second-stage decomposition of the overall relationship (using GLM) of economic hardship to the respondent’s 2016

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7 The pure replication was successful, allowing for some inconsequential differences likely due to some missing control variables in the replication dataset.
thermometer score for Trump (with all the controls of Table S4 in Appendix A) is given in the left panel. The estimated average total effect is small, positive, indistinguishable from zero; average direct (unmediated) effect small, negative, indistinguishable from zero; but the average mediated effect is positive, quite sizable, and well distinguishable from zero. In other words, the mediated path from economic decline through status threat to support for Trump is appreciable, significant, and had been fully masked by controlling SDO.

We can also depict these mediated relationships in traditional causal-path graphs, both the single, on-average one estimated by the standard GLM (left panel and bottom of the right panel above) and for the largest cluster (second from bottom at right above, in red below):
Even using the more-modest average causal-mediation effect, we find a large 72% of the total effect is mediated thusly (not dissimilar from the findings of Hays et al. (2019) regarding a similar causal-path to support for extreme-right parties in Europe).

In the above, hdpGLM was applied in stage 1 (Path A from economic hardship to SDO) but not stage 2 (Path B from SDO to Trump support). Below we come closer to what a full hdpGLM causal-mediation analysis would look like by again deploying hdpGLM in the first stage, then using those identified clusters to estimate by cluster the direct Path C from economic hardship, and the second stage of the mediated path from SDO, to Trump support.
Again, for the type of voter in the largest cluster (31% of sample), the first stage of our mediated path is three times as large as the on-average mediated relation, and now we find the second stage, from sociocultural threat-perception to Trump support, is also about 20% larger than average in this group.

In our second pilot study, we focus on structural differences that appear in the Twitter data before and after a plant shutdown in selected localities. Our pilot results on Twitter data strongly suggest that neighborhood economic shocks, here: automotive plant closings, and in particular the Lordstown, OH General Motors plant closing repeatedly emphasized by candidate and then President Trump, triggered rising extremist expression in at least some contexts. In this preliminary analysis, the positive extremist-engagement response—i.e., the increase in extremist-engaging Tweet activity—is largest in a predominantly white, exurban/rural context hit by a major closing, Lordstown, OH, and/but slightly negative in a predominantly black, urban context also hit by a closing, Hamtramck, MI. For this pilot, we obtained a sample (Twitter randomizes) of 1,066 users who tweeted the 30 days on or before 11/19/2019 in a 5-mile radius around the Lordstown GM assembly plant. We then obtain the last 3,200 tweets of these 1,066 users, keeping all tweets from 01/01/2018 to 11/19/2019. We then record each user interaction (defined as retweeting, quoting, mentioning, linking, or hashtagging) an SPLC-identified hate group or a SafeHome.org or AllSides.com identified alt-right media group or person. This process was repeated for the GM transmission plant in Warren, MI, the GM assembly plant in Hamtramck, MI, and the Ford assembly plant in Flat Rock, MI, but only 3-mile radii were used for Hamtramck and Warren, due to their far higher
density (being within or bordering Detroit). These tweets were mined on 3/1/20 from the latter three locations, over the same date range (01/01/2018 to 11/19/2019).

Adding Flat Rock, Warren, and Hamtramck to Lordstown, and plotting with LOESS smoothed fit, with announcement and closing dates indicated, and comparing the pre-to post-close Tweet engagement with extremism as before, these four preliminary case-studies seem to us enormously suggestive. The graphs plot the daily counts of area Tweets including some interaction (mention, quote, retweet, link, hashtag) with an alt-right or hate group (now
augmented list). Note the same general shape of response in Lordstown also appears in Warren around its closing, but much less sizably. The Warren closing involved many fewer employees in a plant operating at greatly reduced capacity already. Interestingly, we see a similar, but smaller magnitude response in Flat Rock around the Lordstown closing dates, even though no plant closing was announced or implemented for Flat Rock. We believe this reflects the national attention to the Lordstown case (which candidate and then President Trump touted, promised, and then decried) and the likelihood that appreciable shares of Twitter-active auto-plant-workers and their communities swim in the same Twitter streams. Hamtramck, meanwhile, shows no reaction. This pattern suggests to us the following set of hypotheses:

A single plant closing has affects across many ‘connected’ plants – the pattern and strength of these connections being another important feature to explore, but it seems to us very plausible that some appreciable share of auto workers in different plants are attuned to similar streams, so we’d see a smaller echoing response in other plants to a major closing in any single plant. The magnitude of that response seems likely to depend on (1) the size of the closure ‘shock’, which depends on whether it is the plant in question or how closely connected to it, and on how many workers are involved, both absolutely and as share of locality employment or population, and (2) sociodemographic characteristics of the locality and the workers – most notably: the community’s urban-suburban-exurban-rural nature and the racial breakdown. These two considerations (so far) seem to us key to determining magnitude and even sign of extremist-engagement response. Notice that across these four plots, the reaction is of strongest increased alt-right and hate-group engagement in exurban/rural and
predominantly white (94%) ground zero Lordstown; then essentially the same smaller-magnitude increases in (1) Warren, also hit but by a far-less closure, which is just outside Detroit, majority-white but more diverse (70% white, 20% black) and seems to have been already more-highly extremist-engaged than the other localities, and (2) predominantly white (91.5% white, 5% black), more-distantly exurban Flat Rock; and lastly the far-more diverse and interior to Detroit, Hamtramck (53.5% white, 24.5% Asian, 14% black), announced but ultimately did not close, with effectively no response.

As a preliminary check that these figures are not simply reflecting an increase in Twitter activity generally, but rather in Alt-Right and Hate linked activity specifically, we can measure proportions of all Tweets that are extremist-engaging instead of counts. The graphs below show the daily share of all Tweets from a given locale that indicate some kind of interaction (mention, quote, retweet, link, or hashtag) with an alt-right or hate group. A very similar pattern emerges: we see a dramatic increase in extreme-right engagement in Lordstown, a dampened echo of that in also white exurban/rural Flat Rock, and now a null, meaning not-disproportionate, response in more-diverse, urban/suburban Warren, and even a slight down-tick proportionately (exactly .05 significant) in urban, very diverse Hamtramck. We find these preliminary results extremely encouraging indeed.
Future Plans

We plan to develop this research in 3 areas: further analysis on pilot results, data acquisition and method. First, we plan to conduct further analyses on the detected latent clusters. More precisely, we will study heterogeneous responses to socioeconomic and sociocultural threats both as a function of observed covariates like neighborhood sociodemographics and latent clusters to be explored for the post-estimation for hypothesis-generating patterns.
We also want to analyze in two ways what differentiates the respondents in the cluster who are so inclined to see sociocultural threat when experiencing economic duress: in traditional (confirmatory) manners of analyzing heterogeneous and conditional effects using interactions with observed covariates—like respondent education or neighborhood demographics, for plausible examples—and in ways facilitated by hdpGLM’s uncovering of latent “types”, wherein we can study patterns of the covariate distributions and parameter heterogeneity across the clusters, as well as the sizes and size-distributions of the clusters and their correlations across contexts (observed larger-area subsets of the data: by State in the US), in exploratory data-analysis to hypothesize substantive-theoretical descriptions of the “types” of voters the clusters identify. For the latter analyses, we will need to set aside test samples in which to evaluate the hypothesized type-characterizations derived from the exploratory analysis of the hdpGLM estimation-sample results.

Second, we aim to collect and analyze evidence far more broadly and systematically than piloted in the above. In this light, we plan to get an access to the Premium Twitter API, with which we could obtain all users who tweeted from an area going as far back as the API has data (years). The Premium Twitter API also provides more precise geolocation information and fuller Tweet content information for all users over this longer period. These content data would enable us to build a sentiment classifier that could differentiate between positive, neutral, or negative interactions with hate or alt-right groups.
In addition, we plan to use research designs such as matching, difference-in-difference and regression discontinuity for the estimation of causal effect of plant-closings. Our plan is to gather Twitter data for many localities struck by some economic shock like a plant closing (see Appendix B for list of some plant closings in the past several years) and for localities without such shocks; then we will gather socioeconomic and demographic, etc. to balance out our samples. We can also use these data to explore robustness of our conclusions (using placebo tests, for instance) about whether, how, to what extent, and in what contexts economic hardship triggers engagement with extremism, and we can use various text-analytic tools to derive and utilize more information about the nature and positive or negative sentiment of the engagement.

Finally, in current form, we employed hdpGLM as a first stage analysis to capture latent clusters and used the detected clusters to perform secondary analysis for causal mediation. In future research we plan to develop a new methodological framework in which Ferrari’s (2020) hdpGLM is systematically combined with Imai et al. (2010a & 2010b) or Miles et al. (2020) causal-mediation.

**Broader Implications**

This paper provides an important corrective and substantial depth to our understanding of the connections between economic distress, sociocultural threat perception, and extreme-nationalist xenophobia. In applied terms, this corrective will hopefully suggest
strategies for more effectively and constructively counteracting the more dangerous and destructive outcomes from perceptions and reality of economic and cultural threats.

Within the discipline, we hope to demonstrate the productive potential of empirical methods for uncovering heterogeneous context-conditionality and overlapping causal complexity. We also hope to show that the question should not be whether populism is on the rise due to economic threat or sociocultural threat, but rather how these two are connected.

Future studies need to explore what may be bases for and covariates of the uncovered heterogeneity in disposition toward extreme-nationalist populism, xenophobia, and racism from economic shocks and conditions. Future studies should also examine more countries and contexts, and more parties and candidates. In addition, while our study provides an overview of the mechanism by which support for far-right parties increases, future work could more thoroughly explore the connection between these attitudes and right-wing parties. Why have these extreme-nationalist attitudes tended toward right-wing parties and otherizing appeals, and not, or not as much, toward left-wing extremist and anti-system parties in these contexts? Under what conditions might they instead push leftward?
References


Appendix A: Mutz (2018) Table S4

Table S4. Cross-sectional analysis of predictors of Trump support, 2016

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Trump thermometer advantage</th>
<th>Trump vote preference</th>
<th>Trump/Clinton vote preference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>t Value</td>
<td>Coefficient</td>
</tr>
<tr>
<td>Party identification (Democratic)</td>
<td>-2.340</td>
<td>-25.010***</td>
<td>-1.107</td>
</tr>
<tr>
<td>Education (not college graduate)</td>
<td>0.173</td>
<td>1.140</td>
<td>0.140</td>
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<tr>
<td>Race (white)</td>
<td>1.203</td>
<td>6.990***</td>
<td>0.591</td>
</tr>
<tr>
<td>Gender (female)</td>
<td>-0.548</td>
<td>-4.030***</td>
<td>-0.069</td>
</tr>
<tr>
<td>Age</td>
<td>-0.196</td>
<td>-4.380***</td>
<td>0.019</td>
</tr>
<tr>
<td>Religiosity</td>
<td>0.025</td>
<td>1.130</td>
<td>0.033</td>
</tr>
<tr>
<td>Economic hardship/anxiety</td>
<td>0.017</td>
<td>0.960</td>
<td>0.048</td>
</tr>
<tr>
<td>Income</td>
<td>0.055</td>
<td>0.250</td>
<td>0.173</td>
</tr>
<tr>
<td>Looking for work</td>
<td>0.042</td>
<td>0.430</td>
<td>-0.023</td>
</tr>
<tr>
<td>Concern about future expenses</td>
<td>-0.001</td>
<td>-0.020</td>
<td>0.047</td>
</tr>
<tr>
<td>Perceptions of family finances (better)</td>
<td>-0.337</td>
<td>-4.180***</td>
<td>-0.154</td>
</tr>
<tr>
<td>Support better safety net</td>
<td>0.000</td>
<td>0.550</td>
<td>0.000</td>
</tr>
<tr>
<td>Immediate economic context</td>
<td>-3.107</td>
<td>-1.500</td>
<td>-2.832</td>
</tr>
<tr>
<td>Median income</td>
<td>0.686</td>
<td>0.630</td>
<td>-1.122</td>
</tr>
<tr>
<td>Unemployed, %</td>
<td>0.565</td>
<td>8.060***</td>
<td>0.345</td>
</tr>
<tr>
<td>Manufacturing, %</td>
<td>0.129</td>
<td>1.360</td>
<td>0.243</td>
</tr>
<tr>
<td>Perceived status threat</td>
<td>0.107</td>
<td>2.390*</td>
<td>0.077</td>
</tr>
<tr>
<td>Perceived discrimination against high-status groups &gt; low-status groups</td>
<td>0.098</td>
<td>1.580</td>
<td>0.124</td>
</tr>
<tr>
<td>American way of life threatened</td>
<td>0.252</td>
<td>2.960**</td>
<td>-0.106</td>
</tr>
<tr>
<td>SDO</td>
<td>0.231</td>
<td>1.990*</td>
<td>0.060</td>
</tr>
<tr>
<td>Domestic prejudice</td>
<td>-0.776</td>
<td>-9.510***</td>
<td>-0.815</td>
</tr>
<tr>
<td>Support for isolationism</td>
<td>-0.302</td>
<td>-4.400***</td>
<td>-0.182</td>
</tr>
<tr>
<td>China as opportunity</td>
<td>0.046</td>
<td>0.540</td>
<td>0.159</td>
</tr>
<tr>
<td>National superiority</td>
<td>0.824</td>
<td>-10.970***</td>
<td>-0.376</td>
</tr>
<tr>
<td>National economy (better)</td>
<td>-0.135</td>
<td>-1.380</td>
<td>0.203</td>
</tr>
<tr>
<td>Terrorist threat</td>
<td>22.859</td>
<td>23.490***</td>
<td>2.640</td>
</tr>
<tr>
<td>Constant</td>
<td>0.69</td>
<td>0.56</td>
<td>0.78</td>
</tr>
<tr>
<td>R²/pseudo-R²</td>
<td>2,600</td>
<td>2,845</td>
<td>2,175</td>
</tr>
</tbody>
</table>

Data were collected by Amerispeak/NORC, October 2016. All variables are described in detail in Cross-Sectional Survey. Trump thermometer rating is on a 20-point scale. Trump vote preference is dichotomous, indicating support for Trump (one) or anyone else (zero). Trump/Clinton vote is a dichotomous indicator of voting for Trump (one) or Clinton (zero), with third party voters eliminated. Trump thermometer advantage is analyzed using ordinary least squares regression. Trump vote preference and Trump/Clinton vote are analyzed using logit regression. *P < 0.05; **P < 0.01; ***P < 0.001.
Appendix B: Plant Closures

**Lordstown, OH:** General Motors Lordstown Complex  
Announcement: November 26, 2018  
Closure: March 6, 2019  
Jobs Lost: 1,700  
Notes: Now owned by Lordstown Motors, an electric car company.

**Warren, MI:** General Motors Transmission Operations Plant  
Announcement: November 26, 2018  
Closure: July 29, 2019  
Jobs Lost: 262  
Notes: About 60 workers from Warren Transmission have accepted transfers or have already transferred to other locations. About 25 workers will retire. Of the 60 workers transferring, more than 40 will go to Flint, Toledo, and the GM Tech Center in Warren. The balance of the other transfer offers are in-process.  

**Detroit, MI:** Chrysler Conner Avenue Assembly  
Announcement: July 12, 2017  
Closure: August 31, 2017  
Jobs Lost: 86  
Notes: All 86 jobs relocated

**Announced to Close, but Closure Plans Rescinded**

**Detroit / Hamtramck, MI:** GM Automobile Assembly Plant  
Announcement: November 26, 2018  
Closure: Not yet closed  
Notes: An interesting case where they said the plant would be "unallocated" in 2019 but ended up continuing production. In fact, the last Chevrolet Impala rolled off the line today. The plant will be redesigned to be an all-electric vehicle facility.

**Not Closed**

**Flint, MI:** General Motors Flint Truck Assembly
Fort Wayne, IN: General Motors Fort Wayne Assembly
Romulus, MI: General Motors Romulus Engines
Toledo, OH: General Motors Toledo Transmissions
Louisville, KY: Ford Kentucky Truck Plant
Dearborn, MI: Ford River Rouge Complex
Flat Rock, MI: Ford Flat Rock Assembly Plant
Claycomo, MO: Ford Kansas City Assembly Plant
Georgetown, KY: Toyota Motor Manufacturing Kentucky (TMMK)
Blue Springs, MS: Toyota Motor Manufacturing Mississippi (TMMM)