U.S. Innovation Inequality and Trumpism: The Political Economy of Technology Deserts in a Knowledge Economy

Victor Menaldo
University of Washington
vmenaldo@uw.edu

Nicolas Wittstock
University of Washington
nwitts@uw.edu

ABSTRACT: While on the 2016 presidential campaign trail, Candidate Trump embraced economic populism centered on trade protectionism, restrictions on international capital and technology flows, and subsidies for American raw material providers and domestic manufacturers. Once in office, President Trump pursued policies either orthogonal to or actively detrimental to the economic interests of highly innovative industries. We find that more innovative U.S. counties roundly rejected this economic paradigm: voters in innovation clusters of all sizes and across the country repudiated Trumpism in both 2016 and 2020. This manuscript argues that Trump's tariffs and attacks on global supply chains, restrictions on visas for skilled foreign workers, and his overall hostility towards high-tech sectors threatened the innovative firms that motor these places' economies. Our findings are robust to both different measures of Trumpism and innovation, state fixed effects, a host of control variables, including localized "China Trade Shocks" and localized increases in automation, adjustments for spatial correlation, and instrumenting innovation with exogenous geographical factors that explain the origin and endurance of American innovation clusters. Among other endowments, a temperate climate sustained the abundant biomass needed to feed and fuel innovation since the early 1800s. We also document strong path dependence in innovation clusters since 1930 and explain why innovation clusters reinforced their economic edge over less innovative places historically. Places with increased patenting activity between presidential elections saw a further rejection in Trumpism: reductions in both Trump's campaign donations and electoral support versus 2016. This manuscript thus suggests that populism may be more than resentment towards elites and experts and go beyond nationalism and trade protectionism: it may threaten innovation in ways that elicit a strong reaction from places economically invested in technological progress.

1. Introduction: Trumpism as Neo-Luddism

> Some in liberal-leaning Silicon Valley…derided Trump in 2016 as a Luddite unfit for public office in an age when questions about self-driving cars and cancer cures no longer seem the distant stuff of science fiction. To the policy wonks of Washington, Trump's greatest sin wasn't just his abrogation of technology — many of his voters shared his digital reluctance anyway. Rather, it was Trump's absent science or technology agenda and his missing complement of aides advising him on the issues (Romm 2017).

During the presidential campaign trail in 2016, Candidate Trump espoused a new brand of populist economic nationalism. He campaigned against Chinese and Mexican imports (see, for example, Diamond 2016). Trump decried American trade deficits and international supply chains (Trump 2016b). He championed restrictions on international capital and technological flows and teased big subsidies for both U.S. raw material producers and domestic suppliers in heavy manufacturing if he got elected. Trump advocated industrial policies to revive mature or declining sectors such as steel, fossil fuel powered vehicles, coal, and oil.

Correspondingly, he said little about basic science, research and development (R&D), and education. If anything, Trump expressed hostility towards technologically dynamic sectors, especially so-called Big Tech firms. In short, Trump spoke the language of semitrucks, not semiconductors.

Fast forward to July 2021, when the U.S. Senate passed the Innovation and Competition Act during President Biden's first year in office. It pledged investments of more than $110 billion in the American semiconductor industry, the National Science Foundation (NSF), the Department of Energy (DOE), regional technology hubs, and the 5G wireless network.[1] It vowed to help the

[1] In February 2022, the U.S. House of Representatives passed a companion bill, the America COMPETES Act, to, among other things, subsidize American semiconductor chip manufacturing, increase spending on scientific research and R&D, and promote international trade. In July 2022, the component of the bill subsidizing U.S. semiconductors was put into a separate bill.

U.S. improve the development and commercialization of AI, quantum computing, biotechnology, and advanced energy. President Biden signed it into law as the CHIPS and Science Act in August 2022.[2]

During his 2020 presidential campaign, Candidate Biden had spoken, quite often, about the need to revive American leadership in public R&D and promote technological development.[3] In particular, he promised substantial increases in green energy R&D, which were eventually enshrined in the Inflation Reduction Act in 2022.[4] Biden also promised funding for other "breakthrough technologies" such as AI and quantum computing, and made the case for the reshoring of semiconductor manufacturing, as well as increased support for startups, incubators, and innovation hubs. And he spoke about enhancing broadband infrastructure and making increased public investments in the 5G network.[5] While on the hustings in 2020, Biden pledged well over $300 billion dollars for these initiatives.[6]

Had he secured reelection in 2020, it seems unlikely that a second term Trump presidency would have championed similar policies focused on science, technology, and innovations.[7] His

[2] This law provides roughly $280 billion in new funding for domestic research and the manufacturing of semiconductors in the US.
[3] This paragraph draws extensively on Atkinson et al. (2020).
[4] The law includes $370 billion in spending on energy and climate change, expands clean energy tax credits for wind, solar, nuclear, clean hydrogen, clean fuels, and carbon capture, and makes it easier to claim a tax credit for clean vehicles.
[5] These promises were delivered in the form of the $1 trillion infrastructure bill, which Biden signed into law in November 2021. It includes provisions to broaden access to broadband, provide electric vehicle charging stations, and enhance cybersecurity.
[6] Once elected president, Biden further signaled his commitment to R&D by including record spending on science and technology in each of his budgets, including for both basic and applied research. He also proposed funding for the new Directorate for Technology, Innovation, and Partnerships within the NSF, which focuses on the commercialization of new technologies, and for ARPA-H, which is dedicated to health research.
[7] Three exceptions were his support for increasing R&D in Artificial Intelligence (AI) and quantum computing, as well as U.S. semiconductor manufacturing, and providing greater internet and wireless coverage in rural areas (see Atkinson et al. 2020).

brand of trade protectionism, threats to global supply chains, and antipathy towards immigration, including that of skilled foreign workers who are usually employed by innovative American firms to help them compete globally, seemed to presage a slower pace of technological development in dynamic sectors, especially regarding the internet of things and AI (Deng, Delios, and Peng 2020). Trump's record on education, basic scientific research, R&D, and green energy were roundly lambasted by the high-tech community (Lapowsky 2018; O'Mara 2022).

Unsurprisingly, therefore, a long parade of high-tech firms' leaders congratulated Joe Biden in effusive terms after he won the 2020 presidential election, with many praising his campaign promises around education, immigration, and digital infrastructure. For example, Aaron Levie, the CEO of Box, a software company located in Silicon Valley, California, tweeted that the results were "great for American competitiveness" and that "[w]hile there's nothing magical Biden can do, that's the point"…"[b]usinesses need market stability, global trade relations that don't change on a whim, talent from everywhere, long-range planning and a lack of constant distractions" (cited in Palmer 2020).

Michigan, Pennsylvania, and Wisconsin, previous Democratic Party strongholds known as Blue Wall states, helped launch Trump into power (McQuarrie 2017; Clark 2017).[8] Did Trump's economic populism win him votes in places with less innovation and cost him votes in places with more of it? To our knowledge, researchers have not systematically explored the relationship between innovation and Trumpism and, specifically, the spatial distribution of technology creation and commercialization and how it maps onto electoral support for Trump.

[8] They made him competitive in 2020 (Williams 2020).

To be sure, some researchers attribute his appeal in the Rust Belt and similar places to nostalgia for a bygone economy based on heavy industry (Cohn 2016a).[9] Autor, Dorn, and Hanson (2016) show that increased import-competition from China significantly decreased wages and employment in the rustbelt and Midwest. Autor et al. (2020) find that Chinese imports induced a big rightward political shift that predated Trump's 2016 election and helps explain his surprising win that year.[10] Further, several scholars have found evidence that employment in routine jobs and industries at risk of automation reduced wages and employment in similar ways as that associated with Chinese import competition (Autor, Dorn, and Hanson, 2015). Frey, Berger, and Chen (2018) find evidence for a seemingly causal relationship between American locations' susceptibility to automation and support for Trumpism in 2016.[11]

While these findings have significantly contributed to our knowledge of the economic catalysts of populism and support for Trump and Trumpism, no scholars have yet analyzed to what extent the geography of U.S. technology creation and commercialization explains the unique appeal of Trump's economic message. Researchers have not hitherto documented the

---

[9] Numerous researchers and pundits also suggest that President Biden has sometimes echoed Trump's protectionism to directly appeal to blue collar workers hurt by international trade in the Rust Belt, and thus to secure the support of critical swing voters in Pennsylvania, Michigan, and Wisconsin (Barret 2020; Hull 2020).

[10] To measure the exogenous variation in the so-called China Trade shock, these authors isolate the initial shares of employment in a given location and industry multiplied by the growth of Chinese imports in eight developed countries. Later in the manuscript, we evaluate the relationship between localized Chinese import penetration and support for Trump in 2016 using a similar strategy to ensure our results, based on the idea that innovation deserts embraced Trump while innovation clusters rejected him, are robust to the trade exposure explanation for his political appeal vis-a-vis previous Republican presidential nominees.

[11] To measure the exogenous variation in automation at the commuting zone level, these authors both isolate the historical path dependence of industrial specialization captured by sectoral employment shares in 1980 and exploit robot penetration in ten European countries. Later in the manuscript, we evaluate the relationship between localized automation and support for Trump in 2016 using a similar strategy to ensure our results are robust to the automation explanation for his political appeal vis-a-vis previous Republican presidential nominees.

spatial dynamics of innovation in the U.S., let alone assessed the relationship between technology creation and commercialization and political support for Trump across both the 2016 and 2020 presidential elections.

This manuscript is the first, to our knowledge, to document the extreme inequality in U.S. localities' contributions to the creation and commercialization of technology and thus the first to show that the U.S. is divided into innovation deserts dotted with oases. We then use this fact to also document a new explanation for Trump's unique political appeal in some geographies historically associated with heavy, labor-intensive manufacturing, loss of blue-collar jobs to China, and automation that is not the typical one centered on the decline of industry, trade competition with China, or the rise of factory robots.

This manuscript shows that, across the U.S., voters who live in innovation clusters (large and small, both in "blue" and "red" states) repudiated Trump in both 2016 and 2020.[12] Indeed, we find very strong evidence for a causal relationship between the geographical distribution of technology creation and commercialization and Trump's electoral results in each presidential election.[13] We argue this phenomenon was driven by Trump's economic agenda that either threatened the innovative firms that voters in these areas worked for and/or imperiled their locations' economic engines. Conversely, voters in relatively less innovative places were more likely to support Trump during both presidential elections.

Once we understand that the geographic distribution of innovation in the U.S., like elsewhere, is not arbitrary, this electoral pattern makes more sense. The geography of innovation

---

[12] Economic clustering in general is very strong in the U.S. Take manufacturing: 446 out of 459 sub industries in this category are spatially concentrated (Kerr and Nanda 2013: 2).

[13] We use several strategies to identify a causal relationship, including exploiting instrumental variables based on demography, climate, and geography that capture the exogenous variation in innovation operationalized as localities' patenting patterns, which we measure at different historical intervals.

and technology commercialization is explained by the spatial mechanics through which new ideas are produced and disseminated. Innovation and commercialization of technology hinges on the geographically bounded transfer of information and knowhow rooted in face-to-face interactions and knowledge networks with physical footprints (Breschi and Lissoni 2003). After all, knowledge cannot always be codified, as developing and mastering technology often depends on the hands-on demonstration of specific techniques (Menaldo 2021). Putting inventions into practice relies on learning by doing (Bessen 2015). In the U.S. there are strong agglomeration effects in terms of R&D, industrial production that develops and uses high tech machinery and tools, and human capital. This helps to explain the spatial concentration of U.S. innovation, and thus technology creation and commercialization (Moretti 2012).

Innovation clusters are locations where R&D, patenting, and the commercialization of ideas and inventions take place. These are zip codes where firms boast high levels of intangible capital embodied in things such as trade secrets, patents, and knowhow that employ creative and nimble workers. These are not necessarily places where American manufacturing has fled to China, or that house highly automated factories. Indeed, the spatial concentration of U.S. innovation, and thus technology creation and commercialization, is an entirely different phenomenon, which we will empirically demonstrate further below.

For now, take North Carolina’s Research Triangle as an example. This high-technology cluster encompasses several universities, including North Carolina, North Carolina State, and Duke. It also houses firms working in Information Technology (IT) and biotech. Leading companies in the area, some of them conducting R&D there, include Apple, Google, and Toyota. While many of the region’s residents are highly educated and work in high-tech industries (e.g.,

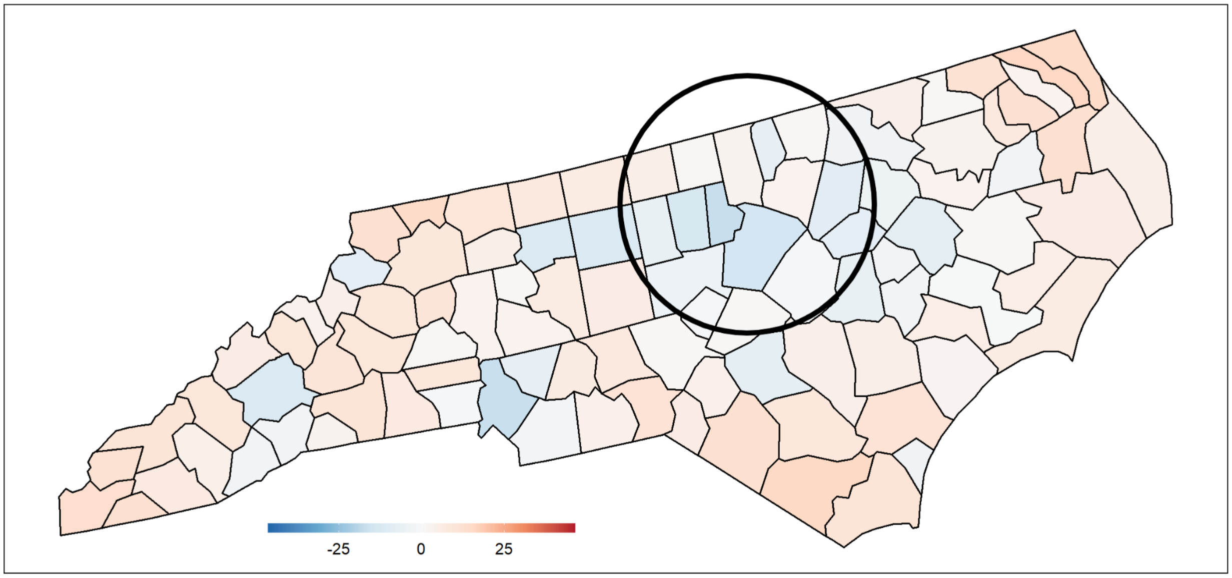

Figure 1.1 Electoral Support for Trumpism in 2016 in North Carolina

Note: Following Autor et al. (2020), we calculate "Trumpism" by subtracting the two-party Republican vote share in 2000 from the two-party Republican vote share in 2016. Sources: David Leip's U.S. Elections Atlas, as used by Autor et al. (2020).

as computer engineers), most provide goods and services derived from the presence of these colleges and firms.

Figure 1.1 is a map that adduces the electoral returns in North Carolina from the 2016 presidential election. The counties in the north-central part of the state that comprise the so-called Research Triangle (contained within the black circle) voted decidedly against Trump in 2016 and did so again in 2020.[14] Outside of there, he had stronger support in the Tarheel state.

It turns out that the same relationship obtains beyond North Carolina. As this manuscript will show in great detail, U.S. counties that were more innovative at the turn of the 21st Century

[14] The "North Carolina Research Triangle" is not a fixed category. Including the broadest set of research triangle counties, the difference between the two-party vote percentage earned by Trump in 2016 versus Bush in 2000 is as follows: Durham (-16.9), Chatham (-4.7), Franklin (+2.7), Granville (+2.5), Johnston (-0.8), Lee (-1.4), Person (+1.7), Vance (-6.5), Wake (-14.3), Harnett (+0.5), Moore (+1.2), Orange (-13.1), and Wilson (-7.3). The average (unweighted) difference across these counties in Republican presidential vote shares is -4.3 percentage points.

strongly rejected Trumpism.[15] They did so both in 2016 and 2020. And this relationship does not only pertain to the ballot box, but also reveals itself in terms of financial contributions made to Trump's presidential campaigns.

1.1 Neo-Luddism and Trumpism: Correlation Does not Equal Causation

Even if we can show that innovative places beyond North Carolina rejected Trumpism, this relationship may suffer from endogeneity: *Perhaps more politically populist places are less innovative*? Or, perhaps an omitted factor *jointly determines both relatively low patenting per capita and high support for Trumpism*?[16] For example, highly dense cities may be both relatively more innovative and relatively more anti-Trump. Or places with more educated voters may produce more patents per capita and may have also rebuked Trump for reasons having little to do with innovation.

Therefore, this manuscript takes pains to isolate the exogenous, spatial variation in innovation. We instrument counties' patents per capita with predetermined geographic and demographic factors that made the emergence and endurance of innovation clusters more likely. Specifically, we develop several instrumental variables for local innovation circa 2000 inspired by Haber, Elis, and Horrillo (2022). Places with temperate climates–those with relatively low to moderate temperatures and moderate to high precipitation levels–were more likely to develop the quantity of biomass (and therefore food and energy) needed to drive innovative manufacturing facilities since the early 1800s. Likewise, places with denser populations in 1900, irrespective of

[15] In this manuscript, we primarily measure innovation as patents per capita and do so for several different periods, both historical and contemporary. We primarily measure Trumpism as Trump's 2016 presidential vote percentage versus Bush's percentage in 2000, but also compare Trump's presidential vote share to Bush's in 2004 and McCain's in 2008 and Romney's in 2012.
[16] See Acemoglu (2009) for the institutional, legal, political, and policy determinants of innovation. Even at the local level, there may be wide variation in some of these factors within the U.S.; for example, in tax policy and the provision of public goods and infrastructure.

their climates, were also likely to develop the innovation clusters associated with the Second Industrial Revolution, centered on electrification and the internal combustion engine, and the Third Industrial Revolution, centered on the microprocessor.[17]

To defend our causal identification strategy, we argue and show that geography and demography not only helped determine the spatial distribution of American innovation clusters since the 1800s, but these patterns endured over time. Throughout U.S. history, innovation clusters have consistently hosted patent-intensive industries at the cutting edge of process and product innovation. Individual inventors and firms have conducted innovative manufacturing, if not pure R&D, in locations such as Bell Labs in Murray Hill, New Jersey. They still rely on advanced manufacturing and are R&D intensive, albeit sometimes with smaller workforces than in the past, due to both automation and outsourcing (Bessen 2015). They continue to be characterized by highly skilled laborers who hop between firms located in the same region.[18]

Our empirical evidence supports the claim that the exogenous factors that drove the location of innovation yesterday also explain it today. We show that innovation clusters in 1930, measured as a county's patents per capita, are highly correlated with innovation clusters in 2000.

---

[17] The Second Industrial Revolution began after the Civil War, exemplified by the opening of the Pearl Street Electric Station by Thomas Edison in 1882, ushering in the era of widespread electrification. The Third Industrial Revolution began circa 1973, when the microprocessor (the programmable computer within a computer chip) was invented by Intel and, soon after, commercialized in the form of multiple electronic digital devices and services, including the personal computer, the internet, and, eventually, smartphones and the digital platform economy. We elucidate these claims ahead.

[18] Often, high-tech firms strategically relocate to these places so they can poach skilled workers from firms that are already there. In turn, this drives up wages, enticing even more skilled workers to migrate to innovative areas. Plus, a critical mass of tech startups encourages laborers to take jobs at new firms that may fail, knowing they can always lateral to another local firm (Casper 2007). This virtuous circle reinforces spatial clustering (see Gross and Sampat 2022 and Figure 4.2 in this manuscript). For the original take on agglomeration effects in general, see Marshall (1920). Porter (1998) and Moretti (2012) offer a more recent, general take on innovation clusters.

Patents per capita in 1930 are also highly correlated with patents per capita for several years in between, including patents per capita observed in 1950 and in 1990.

Consider a city such as Lowell, in Middlesex County, Massachusetts. During the early 1800s, it was a world-renowned hub for textile manufacturing. By the mid to late 19th Century, it had transitioned to hosting cutting edge firms that made machines and machine tools, as well as pharmaceuticals. During World War I, another economic reinvention saw Lowell produce munitions and other war materials. After World War II, the computer revolution came to the city, in the form of Wang Laboratories. Middlesex county is now part of New England's much-vaunted innovation cluster known as Route 128. Accordingly, since 1930, if not before, Middlesex County's patents per capita have been in the top 10 percent of the distribution.[19]

Our manuscript's finding that more innovation equals less Trumpism is resilient. It is not driven by a location's demographics, overall educational level, economic prosperity, degree of urbanization, manufacturing footprint, unemployment rate, living standards, and unemployment rate. It holds once we control for localized exposure to increased Chinese imports.[20] It is also robust to state fixed effects, as well as corrections for spatial correlation.

We also take several additional steps to ensure that our instrumental variables are valid: that the exclusion restriction is satisfied and that our geographic and demographic measures indeed capture the exogenous variation in localities' innovation both yesterday and today. First, we conduct diagnostics that increase our confidence that the instruments are orthogonal to the error term. These include a "Plausibly Exogenous Instrument Test" (see Conley, Hansen, and

---

[19] The county's patents per capita in 1930 were .5 (this and all figures that follow are per one thousand people), versus a national average of .2 (the 90th percentile is .4). Its patents per capita in 1990 were .7, versus a national average of .1 (the 90th percentile is .2). Its patents per capita in 2000 were 1.1, versus a national average of .1 (the 90th percentile is .3).

[20] As well as instrumenting those shocks with so-called shift-share exogenous variables, as Autor et al. (2020) do.

Rosen 2012) and the “Imperfect Instrument” test developed by Nevo and Rosen (2012). Both strongly suggest that the exclusion restriction is satisfied.[21] In addition to these statistical tests, we look for violations of the exclusion restriction directly: We control for several alternative pathways through which our instruments might influence Trump’s electoral appeal in both 2016 and 2020.

Past climate, geography, and demography may have affected current political, economic, and social conditions in localities beyond the level of innovation to impact contemporary electoral outcomes.

First, there is the possibility of sorting. These factor endowments may have separately shaped a place’s demographic and ideological makeup: more progressive people might flock to denser places and have voted against Trump. Similarly, over both colonial and U.S. history, many people of faith migrated to new places–the western frontier, for example–to either convert others, escape persecution, or develop communities of faith centered on the availability of cheap arable land, water, or other geographic and climactic features. More religiously homogeneous or generally more observant parts of the country may have been more likely to view Trump favorably for reasons unrelated to innovation. Similarly, climate, geography, and demography in the past may have influenced where universities were located and survived, and those institutions

[21] When we impose the restriction that the coefficients on the instruments are zero using the Plausibly Exogenous Instrument Test, the bounds covering the coefficient on our measure of innovation tightly overlap with those obtained when we use the regular IV-2SLS approach. Furthermore, an Imperfect Instrument Test that assumes that our measure of innovation is endogenous, and our instruments are correlated with the error term estimates bounds around the innovation measure point estimate that closely approach those returned by both the IV-2SLS approach and the Plausibly Exogenous Instrument Test. Taken together, these diagnostics strongly vindicate the original IV-2SLS estimates and suggest the exclusion restriction is satisfied.

of higher education may explain political attitudes today, with more liberal minded individuals who are drawn to colleges voting against Trump.

Alternatively, these factor endowments might influence today's climate or susceptibility to meteorological events. For example, places that are hotter, or more humid, or that experience more climate extremes, may be home to voters who care more about climate change. In turn, this may translate into less support for Trump independent of a location's level of innovation.

Finally, it might be the case that past climate, geography, and demography drive the presence of capital intensive and technologically advanced manufacturing. In particular, those places may make more intensive use of industrial robots. In turn, higher localized levels of automation may explain support for Trump separate from whether technology is created and commercialized in those places.

In a series of robustness tests, we demonstrate that our IV-2SLS results are upheld even after taking these alternative channels potentially linking our instruments to Trumpism into account. To address the possibility that our instruments affect electoral support for Trump through the various sorting mechanisms outlined above, we control for current population density, the number of evangelical adherents, the presence of universities, and enrollment in higher education. To capture the possibility that our instruments work through contemporary attitudes about climate change to explain variation in support for Trump, we control for climate change attitudes, including whether individuals believe climate change is affecting their specific locations. To neutralize the risk our instruments are working through automation today we control for changes in a location's exposure to industrial robots; when doing so, we also instrument the use of industrial robots in U.S. locations with information on robot penetration in European countries. Our results are unaffected by taking these alternative channels into account.

Our main results are also unaffected by other robustness tests. They hold when using different measures of innovation: either as patents per capita in 2015, patents per capita in 2008, patents per capita in 1990, patents per capita in 1930, or the change in the stock of patents between 2016 and 2020. They are robust to whether we relegate attention to counties outside of three prominent innovation clusters: Silicon Valley, Route 128 in New England, and the North Carolina Research Triangle. Finally, they hold across both the 2016 and 2020 elections and are robust to evaluating whether changes in patenting during Trump's presidency mapped onto less support for Trump in 2020, both in terms of his campaign contributions and electoral backing.

1.2 Why Innovative Places Rejected Trumps' Economic Agenda

While we robustly document the county-level nexus between innovation and anti-Trumpism in the 2016 and 2020 presidential elections, this manuscript also explores *why this happened*. We argue that Candidate Trump promised to enact policies that would likely hurt the economic interests of voters in places that benefited from digital technologies, green energy, and technological progress in more mature industries, including advanced manufacturing sectors.[22]

His proposals went beyond mere trade protectionism, which itself threatened to harm these places, and included restrictions on international capital and technology flows, restrictions on visas for skilled foreign workers, and breaking up "Big Tech" firms. They heralded a return to a "Fordist" economy centered on import-substituting heavy industry. We also show that, once in

[22] For its time, the U.S. economy was very innovative in the 19th and 20th Centuries (Bessen 2015; Goldin and Katz 2008; Lamoreaux and Sokoloff 2009). Yet, if the U.S. were to somehow return to an economy centered on heavy manufacturing that was more inward looking, based on older vintages of technology, it would hurt places that have embraced the IT revolution and honed business models based on cloud computing, digital platforms, light manufacturing around 3-D printing, and greater automation. Moreover, we show that there is strong path dependence in terms of the geography of innovation in the U.S.: places that are innovation clusters today, as measured by patenting per capita, were also so yesterday (see also Gross and Sampat 2020).

office, President Trump followed through on these policies and adopted other ones that harmed innovation, including reductions in basic science, R&D, and the supply of skilled labor.

Conversely, voters in places that are less innovative, but not necessarily more rural, were receptive to Trump's allusions to an earlier industrial era in 2016. They had less to lose from them and perhaps much to gain. This was also the case in 2020: they voted for Trumpism with both their wallets, in terms of contributions to his presidential campaign, and their votes.

1.3 Implications and Contributions

Our findings suggest that voters' support for populism may go beyond antipathy against established parties, institutions, cosmopolitanism, and expertise. It may also contain a strong element of "Luddism": voters in less innovative areas pine for a local economy anchored to older industries, which doubles down on older business models and technologies, if not a national economy that mirrors their local conditions. This means eschewing the state's support for basic research and the commercialization of new ideas and inventions, which often calls on trading freely with the rest of the world and global supply chains.

The implication is profound. As we argue theoretically and show empirically, economic populism of the Trumpist variety is not just about trade protectionism or increased automation but, more generally, it is Neo-Luddism. Populist politicians' intentions to raise tariffs on imports and reverse globalization are only one part of a larger package of ideas that may harm the invention, commercialization, and diffusion of new products and processes. Or at least it may be perceived that way by voters who benefit from innovation.

Populist campaign promises may thus continue to activate a backlash beyond the 2016 and 2020 presidential elections in places such as innovation clusters where voters' well-being depends on technological progress. But, considering the electoral importance of Rust Belt states and similar places that have been left behind by the digital revolution, passing up on elements of this political package may be perilous for politicians of any stripe.

Indeed, President Biden followed in Trump's protectionist footsteps by focusing on reshoring American manufacturing and making supply chains more resilient and less centered on China (see White House 2021). Consider his passage of restrictions on exports of high-end semiconductors to China; the Inflation Protection Act, which includes several content requirements, prescribing the purchase of U.S. produced batteries for electric vehicles and the domestic sourcing of minerals for these batteries; and generous subsidies for U.S. chip manufacturing contained in the CHIPS Act. And Biden has so far retained many Trump era tariffs on Chinese imports, which total more than $350 billion, justifying them on national security grounds (see Blinken 2021; Swanson 2021).[23]

The evolution of the Republican Party from pro-business and largely pro-innovation to one that is, for lack of a better term, Trumpian, also attests to the new populist reality.[24] While they depart from Democrats in including censorship against conservative voices by digital platforms and support for progressive cultural issues within their grievances against digital platforms, Republican Senators Josh Hawley, Marco Rubio, J.D. Vance, and Steven Daines are some of the most notable politicians who favor "reining in" Big Tech, along with Representative James Comer and Jim Jordan. These GOP lawmakers have increasingly advocated on behalf of blue-collar workers and unions and rail against free trade. Texas Governor Greg Abbott, along with the Republican run state house, has barred the state from doing business with various asset managers and banks on the grounds that they shun fossil fuels and thus hurt workers employed in

---

[23] President Biden has also spoken in favor of bolstering internet privacy protections, especially for children, strengthening antitrust enforcement around digital platforms' potential monopolization practices, and reforming Section 230 of the Communications Decency Act.
[24] On all these points see Mullins (2023).

those industries. Changes in Republican campaign funding exemplify the populist ascendance, as most GOP donations are now in the form of small money contributions instead of corporate money from Political Action Committees.

Our theoretical and empirical contributions suggest that spatial inequality in the production and commercialization of new technology partially explains this broader populist phenomenon. Trump was simply the canary in the coalmine. Unless the bipolar geographic distribution of innovation is somehow mitigated, more politicians on both sides of the aisle may ape his rhetoric and policies, potentially hurting innovation writ large. Ironically, this may foster a bipartisan consensus around skepticism of Big Tech and the still nascent AI Revolution.

1.4 Manuscript's Organization

The rest of this manuscript is organized as follows. Chapter 2 contextualizes the idea that Trumpism is Neo-Luddism by situating the manuscript in the emerging literature on the political economy of populism. Chapter 3 defines and measures Trumpism in 2016 and explores its geography across U.S. locations. Chapter 4 introduces the manuscript's theoretical framework. Chapter 5 explores the theory's mechanisms, applying them to the 2016 presidential election. Chapter 6 tests outlines the theory's chief empirical implications and sets the stage for testing them. Chapter 7 evaluates the causal relationship between innovation and Trumpism at the local level in 2016. Chapter 8 measures and discusses Trumpism in 2020, explores its geography across U.S. locations, and evaluates the causal relationship between innovation and Trumpism at the local level in 2020. Chapter 9 concludes by summarizing the manuscript's key contributions and outlines directions for future research.

2. Contextualizing Trumpism as Neo-Luddism

We are not the first researchers to explore a connection between local economic conditions and political support for former president Trump or populism in general. Most of the work in this area focuses on the impact of globalization. Specifically, it explores both differences in trade exposure within the U.S. and across other developed countries.[25] This chapter contextualizes Trumpism as Neo-Luddism by placing this idea in the extant literature.

Several scholars posit that local vulnerability to imports help *explain* the Trump phenomenon. Autor et al. (2020) show that the change in the county-level two-party vote share for Republican presidential candidates between 2000 and 2016 is substantially driven by the exposure of local labor markets to Chinese imports during the early 2000s, even after instrumenting this variable with a weighted average of Chinese exports to eight high-income countries.[26] As we ourselves do in this manuscript, they compare the 2016 GOP vote share with the 2000 vote share because in 2000 voters were largely unaffected by the so-called China Trade Shock, which really began in earnest in 2001, when China joined the WTO (Autor et al. 2013).[27]

---

[25] Of course, researchers do not argue that antipathy against trade or, by extension, the desire for protectionism, is the primary reason for Trump's election in 2016 (see, for example, Broz et al. 2021). Many scholars acknowledge that it often ranks near the bottom of voters' concerns (e.g. Rho and Tomz 2017). And virtually all scholars agree that the type of populism embodied by Trump encompasses a range of positions that includes not only protectionism, but other salient issues too, including opposition to immigration, ethnocentrism, status anxiety, and racism (Mutz 2018). However, it is not clear that Trump's anti-immigrant rhetoric and similar chauvinistic appeals helped him win in 2016 (see Hill, Hopkins, and Huber 2019).
[26] Calibrated by a location's initial industry composition.
[27] Che et al. (2016) qualify this finding. They show that voters in areas more exposed to trade liberalization with China at first shifted their support towards Democrats, but this reaction wanes after 2010.

Why would more trade ignite support for populism in the U.S.?[28] Researchers argue that, despite remaining the world's industrial powerhouse in both absolute and value-added terms, in the face of rising imports from China and elsewhere the U.S. witnessed a major reallocation from manufacturing to service jobs during the 2000s (Dinlersoz and Wolf 2018).[29] This created clear economic losers.

The numbers are staggering. Acemoglu et al. (2016) estimate that increased import-competition associated with China's accession to the WTO led to the loss of between 2.0 to 2.4 million jobs in U.S. manufacturing sectors by 2011. Autor, Dorn, and Hanson (2013) note these effects are geographically concentrated in the Rust Belt. Autor, Dorn, and Hanson (2016) add that labor market adjustments to trade shocks have been exceptionally slow in the last decade. Autor et al. (2014) show that American workers who once worked in manufacturing activities exposed to various import waves make less money, are more likely to request public disability, have higher rates of labor market turnover, and are less likely to continue to work in industrial sectors (see also Russ et al. 2021). Freund and Sidhu (2017) find that, between 2006 and 2014, American firms across industries were subject to increased competition from Chinese firms,

[28] The relationship between greater import penetration and support for rightwing populism seems to extend beyond the U.S. Focusing on Germany, Dippel et al. (2022) find that rising imports from developing countries between 1987 and 2009 increase electoral support for nationalist parties, especially for the rightwing, populist party Alternative for Germany, and especially among low-skilled manufacturing workers (see Bromhead, Eichengreen, and O'Rourke 2013 for a historical take vis-a-vis Germany). Analogously, Colantone and Stanig (2018a) show that exposure to Chinese imports increased the Brexit vote share in the U.K. In a separate manuscript, the authors show that increased import competition in 15 Western European countries raises the regional vote share of nationalist and isolationist parties (Colantone and Stanig 2018b).

[29] U.S. manufacturing industries are larger and more valuable than ever, but often require fewer workers due to labor-replacing technologies that have driven productivity gains (see Bessen 2015). Indeed, while offshoring has certainly contributed to some job losses in these sectors (see the works cited above), Acemoglu et al. (2016) argue these have been primarily engendered by rapid technological change. Whether workers in those sectors—or even politicians—are aware of these "contextualizing" facts is an altogether different story.

leading them to lose market share or even go bankrupt. Public finance and the provision of public goods and social insurance also suffered (Feler and Senses 2017).

Researchers then connect these adverse economic dynamics with support for rightwing populism. Broz et al. (2021) show that support for Trump was higher in counties with larger declines in manufacturing employment. Autor et al. (2020) find that adverse economic impacts related to Chinese imports induced a big rightward political shift in general in places with majority-white populations that predated Trump's election.[30] Baccini and Weymouth (2021) document that white voters in locations adversely affected by imports, and who suffered job losses in manufacturing sectors, were responsive to Republican candidates who promised to mitigate their economic hardship. Ritchie and You (2021) show that redistributive policies targeted to voters exposed to import competition reduced support for Trump and his protectionism during the 2016 presidential race.

Further, several scholars argue that automation has also contributed to the rise of Trumpism. There is strong evidence that, like the effects of Chinese import competition, U.S. workers in routine jobs and industries at risk of automation have suffered declines in wages and job losses (Dorn and Hanson 2013; Autor, Dorn, and Hanson 2015; Goos, Manning, and Salomons 2014). Unsurprisingly, exposure to robots increases voters' favorability towards redistribution (Thewissen and Rueda 2019). Frey, Berger, and Chen (2018) find that locations' degree of automation, which they instrument with automation exposure in European countries, helps explain Trump's vote share in the 2016 elections. Petrova et al. (2022) ratify these findings using a similar approach and also discover that low-skilled workers who have experienced the

[30] See Choi et al. (2021) for similar evidence of this phenomenon after passage of the North American Free Trade Agreement (NAFTA).

largest deterioration in their expected lifetime earnings due to automation were the most likely to vote for Trump in 2016.[31]

2.2 Addressing Gaps in the Literature

In this manuscript, we go beyond the view that the protectionist and redistributive economic policies advanced by populists react to voters' resentment about trade and automation, thus earning them electoral support. While there is a lot to learn about why Trump won in 2016– and was competitive in 2020–from the literature we reviewed above, it is incomplete. There are several reasons why.

First, Trump did not only tout protectionism when he promised during the 2016 presidential elections that he would "make America great again." Rather, import tariffs and industrial policy geared towards subsidizing American manufacturing and related industries, such as fossil fuel production, were part of a larger package of ideas based on economic nostalgia and industrial renewal. The overall message was that the federal government would help revitalize a bygone economy based on natural resources and heavy industry and centered on products manufactured in the U.S., rather than look forward, towards newly dynamic sectors. In other words, by ignoring or actively opposing dynamic sectors of the American economy, candidate Trump's message was broadly anti-innovation, or at the very least ignored more dynamic industries. It was also about restoring America's prowess in heavy industries.

[31] As in the case of trade, the relationship between greater automation and support for rightwing populism seems to extend beyond the U.S. Anelli, Colantone, and Stanig (2019) focus on regions within several European countries between 1993 and 2016 and find that places with industries more exposed to robots experience increased support for far-right nationalist parties. Im et al. (2019) uncover similar findings, also within Europe, using survey data; moreover, they discover that the relationship between the risk of automation and support for extreme right-wing parties is stronger for individuals who report relatively low levels of income security.

Second, several researchers have argued that while increased exposure to trade emanating from developing countries such as China is new, the transition away from labor intensive manufacturing has occurred since before the Cold War: American manufacturing employment has experienced a steady, secular decline since the 1940s (see Bessen 2015: 122). Indeed, this phenomenon far predates the most recent automation boom, which really began its ascendance in the early 2010s (see Guriev and Papaioannou 2022: 775).

Third, a high-tech knowledge economy is not a new occurrence. Goldin and Katz (2008) aver that skill-biased technological change is an enduring feature of the U.S. economy and goes back to at least 1890, if not earlier. They argue that, although unprecedented in magnitude in some ways, the patterns we observe today around inequality and the college wage premium are recurring phenomena that ebb and flow over time. These depend more on *the supply of skilled workers tied to changing access to educational opportunities*, not the demand for these workers, which has remained relatively constant throughout American history.[32]

Fourth, the U.S. productivity slowdown that is partially responsible for stagnant wages, at least for workers below the distribution's median, began in 1972. This preceded China's entry into the WTO, and thus any China related trade shocks, by almost two decades. It also preceded the latest automation boom by decades and, if anything, increased use of robots may herald increased labor productivity and wages for some unskilled workers (Leduc and Liu 2023). Indeed, a pause in this productivity slowdown, albeit one of short duration—lasting from 1996 to

[32] Goldin and Katz (2008) argue that the late 19th and early 20th Centuries witnessed an economy centered on chemicals, electricity, automobiles, aircraft, and new communications technologies that was just as high-tech and knowledge intensive as now. What both eras share in common is that, like today, technology won the race against wage earners because only some of the latter acquired the skills highly rewarded by labor markets.

2004—coincided with increased economic interconnection between the U.S. and China (Gordon 2016) and was also partially a result of increased automation.

Finally, while exposure to Chinese trade–and before that trade with Mexico (after passage of the North American Free Trade Agreement, NAFTA, in 1994)–had big impacts on American manufacturing, industrial employment, and wages (see literature cited above), the U.S. had experienced negative distributional impacts associated with imports from developing nations before these episodes. This includes increased trade liberalization with Japan, beginning in the 1960s (Batistich and Bond 2019), and with the "Asian Tigers" (South Korea, Singapore, Taiwan, and Hong Kong), starting in the 1970s.

However, it is not clear that these earlier examples of import exposure informed voting patterns among the communities that were adversely affected. There is certainly no evidence they increased support for the economic populism of the sort championed by Candidate Trump. A key difference, perhaps, is the paucity of opportunistic political candidates openly yearning to resurrect jobs lost to trade and automation and "Make America Great Again."[33]

Nonetheless, as we outlined above, several studies have found a convincing link between either trade or automation and reductions in pay and job losses for unskilled workers who engage in routine tasks. Some have also identified a connection between exposure to trade shocks or robots and support for Trump in 2016 and have argued that the mechanism linking these variables are reductions in income and job losses. However, scholars have yet to scrutinize the

[33] To be sure, Ronald Reagan famously used this same slogan during his first presidential campaign in 1980. However, unlike Trump, Reagan's economic platform was generally open to international trade, with some exceptions, such as when he imposed tariffs on Japanese motorcycles, and pro-innovation, at least in terms of being more future oriented and optimistic (O'Mara 2019). Clearer examples of populist presidential candidates who fell short in their quixotic campaigns to increase protectionism include Ross Perot's third place finish as an independent in the 1992 election and Pat Buchanan's failed attempt to secure the Republican presidential nomination shortly before November of that year.

fact that innovation and the creation and commercialization of technology, which is an altogether different phenomenon from outsourcing or robotization, are heavily geographically concentrated.

Recent economic dynamism, growth, and job creation in the U.S. has been concentrated in urban clusters that feature high-tech firms. Ninety percent of employment growth in the most innovative U.S. sectors–composed of 13 of the “highest-tech”, highest R&D” advanced industries–between 2005 and 2017 was concentrated in just five cities: Boston, San Francisco, San Diego, Seattle, and San Jose (Atkinson, Muro, and Whiton 2019). Highly educated workers have flocked to these cities and greater metro regions to work in internationally oriented companies producing high value-added goods and services (Iversen and Soskice 2018). These firms operate in industries centered on the design, testing, and marketing of computer hardware and software, as well as operating digital platforms, or they provide consulting, financial and legal services, insurance, and entertainment (Boix 2019).

But not all digital economy firms and jobs are located in this handful of places, as internet platforms, cloud computing providers, data centers, and software makers have fanned out across the U.S. and established a presence in the country’s interior. Moreover, innovation in so-called hardtech continues apace, as does employment, in industrial activities involving transportation equipment, aerospace, chemicals, electronic machinery, medical equipment, and telecommunications. Manufacturing in these sectors takes place largely outside of the most famous U.S. innovation clusters such as Silicon Valley. Indeed, several places outside of coastal regions boast specialized, highly productive plants and distribution centers and highly skilled workforces.

Many of these locations were once home to America’s most innovative industries; some are new to advanced manufacturing. Both rely on process and product innovation around robotics and AI, green energy, electric vehicles, batteries, semiconductors, machinery and equipment, and biosciences. First, consider Ohio and its major metro areas. Cities such as Akron and Cleveland once produced radios, tires, and machinery, and are now known for vehicles and robots. And, after Intel finishes its planned, $20 billion semiconductor plant, Columbus might soon be known for microchips. Another example is Milwaukee, still known for machinery, tools, and instruments. Still other enduring industrial hubs that remain innovative include cities in Pennsylvania, Michigan, Indiana, Illinois, upstate New York, Minnesota, Birmingham, Alabama, St. Louis, Missouri, and Memphis, Tennessee. Nascent innovation clusters include Boise, Idaho, Provo, Utah, Des Moines, Iowa, several Sunbelt cities, Jackson Hole, Wyoming, Bozeman Montana, Austin, Texas, Greenville, South Carolina, and Fort Myers, Florida.

Does a more systematic assessment corroborate the view that innovation clusters are relatively geographically prevalent? To find out, we henceforth operationalize innovation as patents granted by the USPTO to inventors. Patents are temporary property rights to ideas (granted for a 20 year term that can sometimes be extended) and represent a valid, widely used proxy for innovation.[34] Patents granted to inventors in a given location strongly correlate spatially with other measures of innovation, such as R&D spending (Acs, Anselin, and Varga

[34] A U.S. patent application must describe a useful, novel, and non-obvious invention in great detail and, in doing so, outline a series of explicit claims that comprise the invention. Visual diagrams must explicate the claims and the patent must cite the prior art it builds upon. A professional examiner must then screen, evaluate, and approve the application and decide whether the patent should be granted or rejected. Utility patents last for 20 years and are granted for processes, products, machines, combinations of materials, and improvements upon previous patents. This includes software patents, which can be obtained in the U.S. without affiliated hardware. Patents are also granted for plants and modifications of plants. Patents are widely disclosed in the U.S. (easily findable through a USPTO search engine) and strongly enforced, with broad protection under the "Doctrine of Equivalents" overseen by a specialized court–the U.S. Court of Appeals for the Federal Circuit; IP holders who sue for infringement may gain injunctive relief and, if they win, earn treble damages.

2002), and identify technologies developed by both individuals and firms.[35] Thus, several researchers have used patents to operationalize innovation at the U.S. county level (Acemoglu, Moscana, and Robinson 2016; Corradini 2020; Xu, Watts, and Reed 2019; Gross and Sampat 2020; Hean and Partridge 2021).

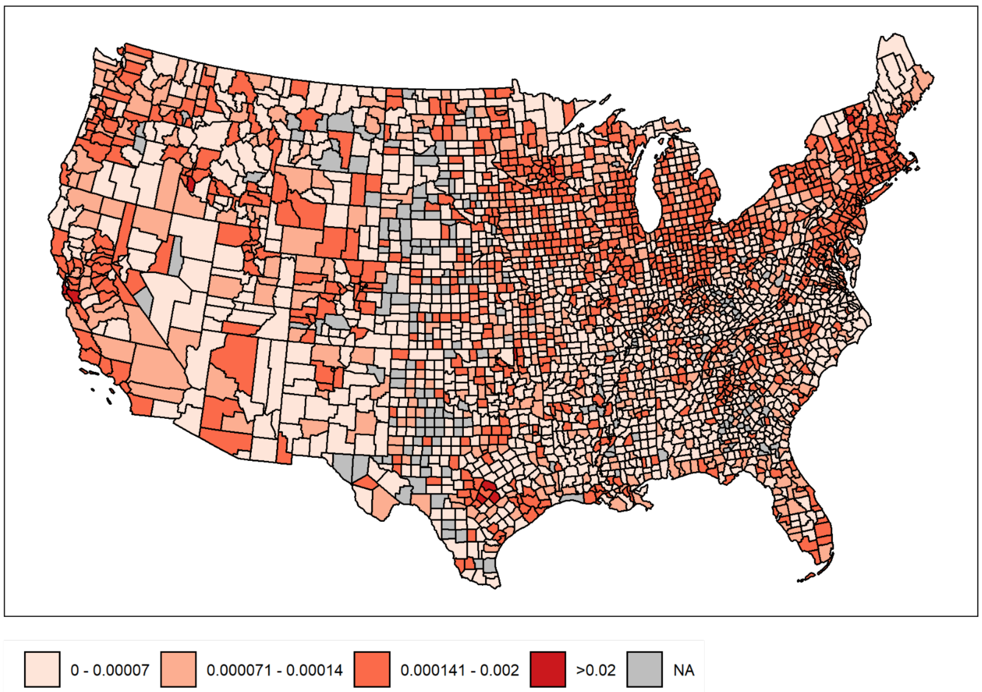

Figure 2.1 County-level Patents Per Capita Granted to Inventors, 2000.

Notes: Number of utility patents awarded in 2000 assigned to the county they originate from as determined by the residence of the first-named inventor (as appearing in the granted patent document issues by the United States Patent and Trademark Office (USPTO). We exclude patents granted in Alaska and Hawaii to match the coverage on the Trumpism variable in Figure 3.1 (Chapter 3). We divide granted patents by the county population estimates from the U.S. Census for 2000. NAs refer to counties for which the USPTO does not report patent data between 2000-2015.
Source: USPTO Patent Technology Monitoring Team (2022); U.S. Census (2000).

---

[35] Patents are not perfect measures of innovation, however. First, not all innovations are patented. Some are held as trade secrets or are common pool resources (open source). Second, not all patented inventions are commercialized or, even if commercialized, equally innovative. Indeed, only some patents introduce disruptive innovations that introduce a whole new product line or make a big impact on an extant product's quality adjusted price; or, similarly, only some patents constitute important process inventions. Most patents represent merely incremental inventions.

Figure 2.1 exhibits the spatial variation in patents awarded to U.S. counties in 2000 (in per capita terms).[36] Coastal regions tend to have relatively high levels of patents per capita.[37] This is especially the case for California and Washington State in the West and for New England and the tristate area in the East (York, New Jersey, and Connecticut). However, innovative clusters seem to be sprinkled throughout the U.S. They are also readily apparent in Florida, Colorado, New Mexico, the Southwest, Texas, and the midwestern states, especially the Great Lakes region. Figure 2.1 suggests that the creation and commercialization of new technologies is distributed quite unequally, however, as some areas are innovation deserts and evince very low levels of patents per capita or no patents whatsoever.[38]

This manuscript provides an economic explanation for the variation in Trump's appeal that is unrelated to exposure to Chinese imports and its associated job losses and downward mobility, on the one hand, and automation that threatens routine jobs and the income associated with those jobs, on the other. How does the pattern of technological inequality represented by Figure 2.1 relate to what are the most predominant economic explanations for Trumpism? While we explore this question systematically in Chapter 7 when conducting more formal statistical analyses of the separate relationship between all three economic factors–innovation, the Chinese

[36] We follow Autor et al. (2020) and primarily use observations from the year 2000 for our independent variables to avoid post-treatment bias, including patents per capita and our controls, across both the descriptive analyses conducted here and statistical analyses pursued in Chapter 7 and Chapter 8; however, we also show ahead that our results are robust to using other years.
[37] Focusing on the counties for which we have observations on Trumpism (see Figure 3.1 in Chapter 3), the mean number of patents per 1,000 residents is. 14; the standard deviation is .26.
[38] We note that there are 189 counties missing Per Capita Patents observations compared to the data coverage for Trumpism (6% of observations), which we map in Chapter 3, in Figure 3.2. Texas accounts for a relatively large number: we lack data on this variable for 40 Texan counties. We note, however, that the results hold if we omit Texas from the analyses or if we interpolate the missing values in different ways, including coding them as 0s. Moreover, the mean and median for Trumpism is essentially the same across both the uncensored sample and the sample for which we are not missing patent observations.

trade shock, and automation exposure–and electoral support for Trump, below we offer a preliminary exploration of this issue.

Figure 2.2, a scatterplot of county-level patenting in 2000 and counties' changes in exposure to Chinese imports between 2000-2008, conveys the idea that the U.S. locations that innovate the most are not necessarily those that have experienced less exposure to Chinese trade. A scatterplot of the relationship between these variables instead resembles a cloud. While a simple bivariate regression that corresponds to the observations in the scatterplot graphed in Figure 2.2 yields a coefficient of 15.594, the t-statistic associated with it is 0.34 (p-value = 0.74), and the r-squared is 0. A county's innovation intensity–its production and commercialization of technology–appears to be unrelated to its Chinese import exposure.

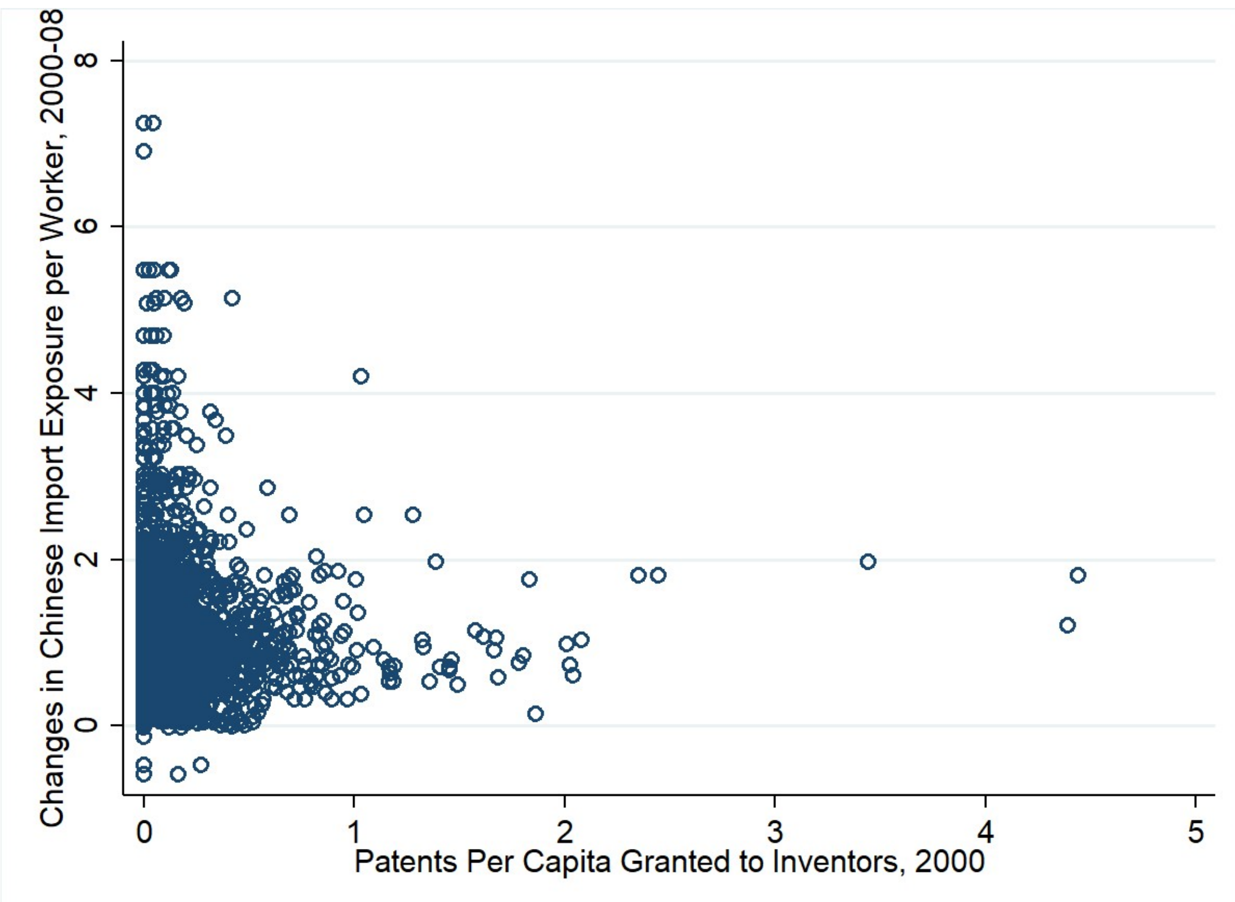

Figure 2.2 Innovation and Chinese Import Exposure in U.S. Counties

Notes: Number of utility patents awarded in 2000 assigned to the county they originate from as determined by the residence of the first-named inventor (as appearing in the granted patent document issues by the United States Patent and Trademark Office (USPTO). We divide granted patents by the county population estimates from the U.S. Census. The per capita values are expressed per 1,000 residents. The county level changes in Chinese import exposure per worker between 2000 and 2008 capture the change in ad valorem U.S. imports from China within a given locality (according to industries' local share of national employment) in real dollars divided by the number of workers in each location.
Sources: USPTO Patent Technology Monitoring Team (2022); U.S. Census (2000); Autor et al. (2020).

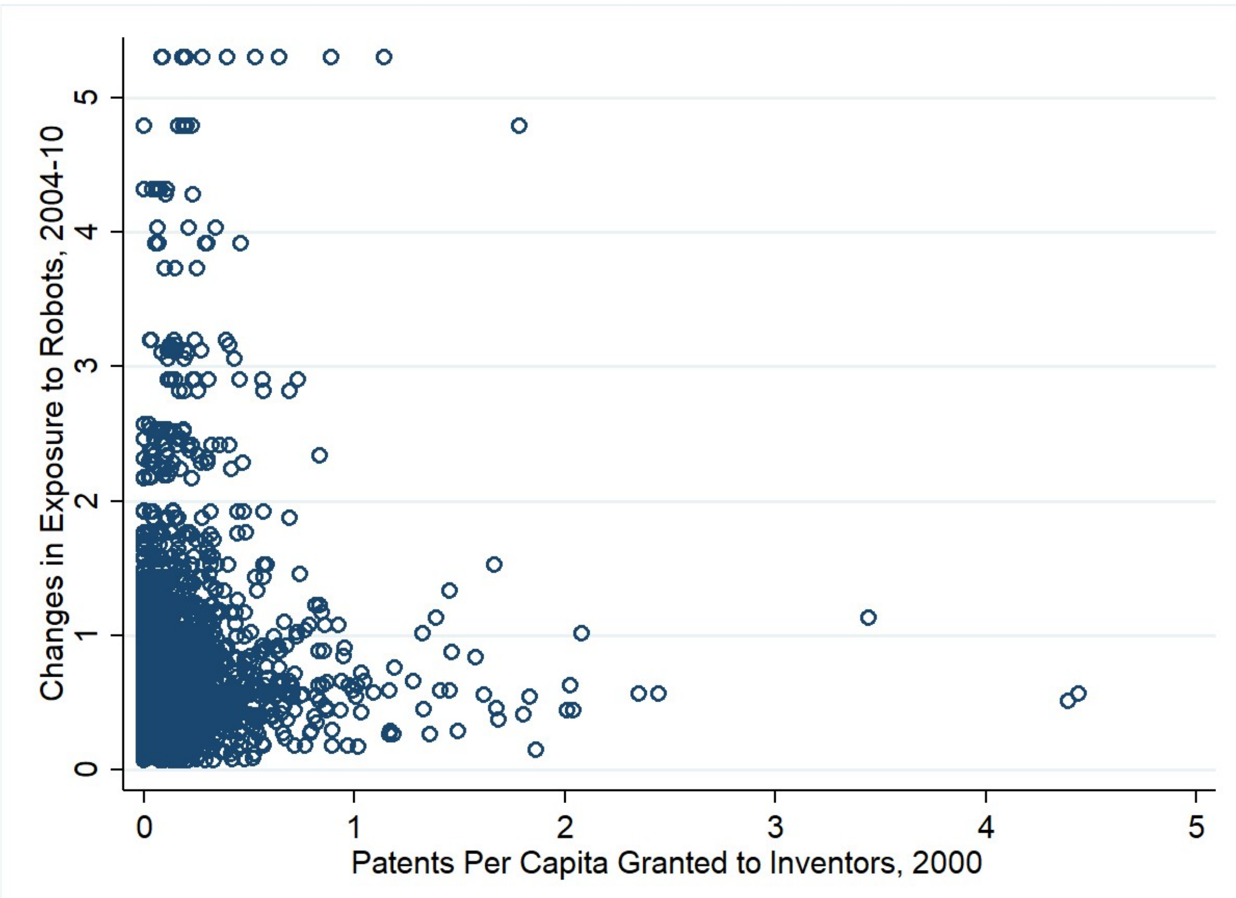

Figure 2.3. Innovation and Exposure to Robots in U.S. Counties

Notes: Number of utility patents awarded in 2000 assigned to the county they originate from as determined by the residence of the first-named inventor (as appearing in the granted patent document issues by the United States Patent and Trademark Office (USPTO). We divide granted patents by the county population estimates from the U.S. Census. The per capita values are expressed per 1,000 residents. The county level increase in exposure to automation between 2004 and 2010 captures the average change in the local industry-level penetration of industrial robots between 2004-2010, based on the share of national employment according to 1990 Community

Business Pattern industry data. For this graph and later analyses, we crosswalk the values originally calculated at the commuting zone to the county level.
Sources: USPTO Patent Technology Monitoring Team (2022); U.S. Census (2000); Acemoglu and Restrepo (2020).

Figure 2.3 shows a scatterplot of the relationship between patents per capita at the county level in 2000 and the change in the exposure to robots between 2004 and 2010. The graph conveys the idea that U.S. locations that innovate are not necessarily those that have had greater exposure to industrial robots or automation, as the relationship appears relatively weak. A simple bivariate regression that corresponds to the observations in the scatterplot graphed in Figure 2.3 reveals that a 1 standard deviation change in patents per capita is associated with merely a .068 standard deviation change in the exposure to industrial robots. While the t-statistic associated with the coefficient is 2.79 (p-value = 0.005), the r-squared is only 0.005. In short, a place's innovation output, namely its production and commercialization of technology, is only weakly related to its exposure to automation.

We have now set the stage to understand how spatial patterns of innovation map onto electoral support for Trump separate from any effect made by either exposure to trade with China or automation risk. In the next chapter, we explore the geography of Trumpism in 2016 as a first step in understanding how it differs from more traditional conservatism and how it relates to innovation. To do so, we first define Trumpism and explain our measurement strategy. This allows us to return to map and examine its spatial distribution in 2020 in Chapter 8.

3. Geography of Trumpism in 2016

This chapter outlines how we define and measure the manuscript's chief outcome of interest, the unique "Trumpist" element of the 2016 Republican vote share; we also map this variable across U.S. counties and discuss some salient geographic patterns. In Chapter 8, we do the same for Trumpism in the 2020 presidential contest, as well as document county level changes in support for Trump between the 2016 and 2020 presidential elections.

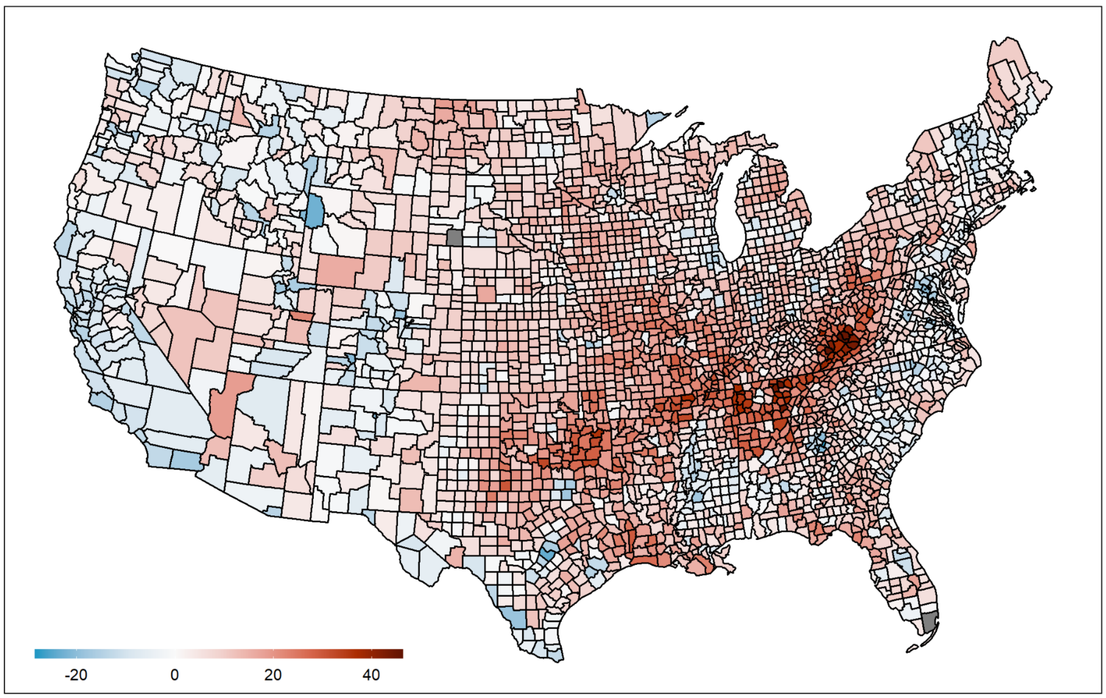

Figure 3.1. Electoral Support for Trumpism in 2016 across the Continental U.S.

Note: Following Autor et al. (2020), we calculate "Trumpism" by subtracting the two-party Republican vote share in 2000 from the two-party Republican vote share in 2016. Like they do, we exclude Alaska and Hawaii because of missing data.
Sources: David Leip's Atlas for US Elections, as used by Autor et al. (2020).

3.1 Defining and Measuring Trumpism.

We seek to strip out support for conservatism per se from Trump's electoral support. We therefore follow Autor et al. (2020): the change in percentage of the two-party vote obtained by

Trump versus Bush in 2000 may capture the singular appeal of Donald Trump's 2016 populist message.

Counties that are firmly conservative, irrespective of who the party nominates to run in a presidential election, should not display significant changes in the two-party vote share earned by the Republican Party presidential nominee between elections. There are Republicans who always vote Republican, no matter who is at the top of the ticket, whether it be Bush, McCain, Romney, or Trump. Indeed, they may not necessarily be big fans of the former president. However, swings away from Al Gore, towards Trump (or Gary Johnson, for that matter), point to potentially independent and liberal voters who are attracted to Trump's message. Conversely, swings away from Bush, towards Hilary Clinton (or Jill Stein, for that matter), point to potentially independent and conservative voters who are disaffected with Trump.

Of course, voters who switched their vote from Republican to Democrat between 2000 and 2016, and vice-versa, are not the whole story. There is also the possibility that voters who sat out previous presidential elections–and in this case, the 2000 edition–turned out in 2016. If they voted for Trump, this may mean greater Trumpism if their votes were not offset by voters who sat out the 2016 election. Similarly, there were voters who were not old enough to vote in 2000 who may have reached voting age by 2016; and, similarly, if they voted for Trump, this may have also increased Trumpism if their votes were not offset by voters who died before casting ballots in 2016.

In short, swings in Trump's favor vis-a-vis Bush are at least partially demonstrative of the local salience of his economic promises; swings against him, conversely, partially indicate local dissatisfaction with his populist agenda.[39]

3.2 Mapping Trumpism Across U.S. Counties in 2016

Figure 3.1 displays the unweighted county level change in the two-party vote share received by the Republican presidential candidate between the 2000 and 2016 elections. Locations differed substantially in their reaction to Trump. For the 3,107 counties with data, the variable's mean value is a 7.88 swing (change in percentage of the two-party vote obtained by Trump versus Bush in 2000).[40] There is considerable heterogeneity within states in support for Trumpism. Some examples that stand out are Texas, Washington, Arizona, Florida, Colorado, Wyoming, and North Carolina.

A closer look at the data confirms the notion that Trumpism is meaningfully different from traditional support for the Republican party.[41] Counties in red states that voted Republican in aggregate in 2016, including Texas, Florida, Arizona, and Utah, swung firmly against Trump relative to Bush. Conversely, Trump registered strong electoral gains in the Appalachian and Midwest regions, especially the so-called Rust Belt.[42]

---

[39] Of course, these swings could also reflect a judgment about Trump's individual attributes, or be about something other than his economic message, such as his views on issues where he differed from Bush but was not necessarily more populist.

[40] The standard deviation is 10.2; the minimum value is -28.3; and the maximum value is 46.2. A histogram of the distribution of Trumpism, juxtaposed with a normal distribution (not shown), reveals that the data resembles a bell curve. This is attested to by the fact that the mean and median are essentially identical: 7.9 and 8.2, respectively. If we weigh this variable by the county's total votes in 2000, which we do in the regressions that follow, per Autor et al. (2020), the mean change between 2000 and 2016 is -0.74 and the standard deviation is 9.95.

[41] In Chapter 7, when evaluating the relationship between how innovative a county is and support for Trumpism, we show that our results are robust to comparing Trump's votes to both McCain in 2008 and Romney in 2012.

[42] Michigan, Wisconsin, Iowa, Pennsylvania, and Ohio are key states that Trump "flipped" in 2016: that is, that Romney lost in 2012.

Why do we expect the local level of innovation to be connected to the local appeal of Candidate Trump in 2016? As a first step in offering an answer, in the next chapter we outline a theoretical framework that connects the literature on trade and technology to make sense of the political economy of innovation, globalization, and protectionism.

4. Theoretical Framework

In this chapter, we discuss why developed countries' innovative firms and their workers support globalization, which we define broadly, and why workers outside of innovation clusters may not always immediately benefit from the economic policies favored by innovation clusters. Several politically important economic actors in developed countries are hurt when populist ideas retard globalization. These include not only protectionism, but policies that promise to disrupt the global supply chains and international technology transfer relied upon by U.S. firms operating in high-tech sectors such as software, hardware, machinery, vehicles, biotechnology, aerospace, telecommunications, diagnostics, chemicals, and green energy.[43] Before exploring these ideas, it behooves us to summarize the well-understood aggregate benefits of globalization, especially *for developed countries*.

4.1 Globalization and Efficiency

By allowing nations to position themselves at the optimal location on their production possibilities frontier, international trade engenders static efficiency: specialization along the lines of comparative advantage reduces the costs of producing the goods and services exchanged between trading partners, therefore lowering their prices. When scarce raw materials, inputs, goods, services, and capital can flow across international borders with fewer impediments, they can be allocated to their more efficient use. What that means is that international market prices—exchange ratios between goods—improve economic coordination, ensuring that scarce resources

[43] Although trade protectionism itself threatens these supply chains, in that almost 30% of world trade takes place within firms that import both inputs and goods manufactured by their multinationals' foreign subsidiaries (see Mariotti forthcoming).

are directed to where their opportunity costs are lowest (in other words, according to comparative advantage) and they are most valued.[44]

International trade also engenders dynamic efficiency. By helping countries acquire new ideas, technology, and business processes from abroad, trade between countries also shifts out demand and supply curves for goods and services—sometimes pushing out nations' entire production possibility frontiers in the process—and promotes increased productivity and reductions in quality adjusted prices.[45] Coupled with international capital flows, this sometimes helps technology to flow from the developing world to the developed world (Menaldo 2021; Menaldo and Wittstock 2021).[46]

Finally, international trade fosters global supply chains. In part, this is due to the institutional scaffolding that supports vertical disintegration, including stronger IP protections. This is a separate channel that further increases specialization, reduces costs, and exposes nations to new processes and products.

---

[44] Therefore, the benefits of inbound Foreign Direct Investment (FDI) for developed countries are similar to those conferred by their ability to import raw materials, inputs, and products from abroad. They can consume more foreign made products and services and, along with portfolio investments, this allows them to run trade deficits, while also reducing interest rates on their sovereign debt. In turn, borrowing costs for private borrowers and inflation are both reduced (see Menaldo and Wittstock 2021).

[45] Consider just one example: smartphones. Past buying behavior and surveys of U.S. consumers reveal that they are willing to pay thousands upon thousands of dollars for a smartphone but typically only pay a fraction of that price. We know that consumers bought 1G phones for $10,500 in 2017 dollars. Taking that as a lower bound estimate on their willingness to pay for 2022 smartphones, consumer surplus for this product runs into the trillions of dollars: A globally disintegrated supply chain that relies on China's skilled and unskilled labor to produce supercomputers that fit in consumers' pockets and can be purchased for as low as $30 dollars. See Galetovic and Haber (2017) on all these points.

[46] The U.S., for example, is a big recipient of FDI from China, India, and even Mexico. Indeed, billions of Mexican pesos flow yearly into businesses located in the U.S. that make food and beverages, auto components, plastics, and provide services. While this creates American jobs and helps reduce consumer prices, it also introduces the U.S. to Mexican technology and knowhow. Consider the flow of technology from Japan to the U.S. after World War II, including both product (e.g., electronics and cars) and process (e.g., robots) innovations.

In this vein, a crucial element of the Tokyo Round of the General Agreement on Tariffs and Trade (GATT) talks (1973–1979) were efforts by developed countries to spread standardized, stronger IP rules to the developing world (Sell 2003). In 1994, the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS), codified this goal during the GATT's Uruguay Round (Drahos and Braithwaite 2002). The U.S. then strengthened global IP protection during subsequent rounds of multilateral trade negotiations and through bilateral and multilateral trade deals such as NAFTA and the Transpacific Partnership (TPP).

4.2 How Developed Country High-tech Firms Benefit from Globalization

Consider firms in developed countries that specialize in higher value-added endeavors in vertically disintegrated global supply chains. International trade may allow them to reach economies of scale, reduce costs, and become more innovative. Also, freer trade creates new export markets for the goods and services offered by developed countries' firms.

For example, take an American semiconductor company like Qualcomm, which focuses exclusively on designing high performance computer chips that firms in Taiwan fabricate. Qualcomm then reimports the final, finished microprocessors. Relatively free international trade allows this innovative company to dedicate itself entirely to what it does cheapest (with fewest opportunity costs): designing chips. In turn, its costs are relatively lower, its profits are relatively higher, its R&D budgets are relatively bigger, and its products continually improve and become cheaper (in quality adjusted prices). And, because Taiwanese foundries manufacture these chips, they pay wages to workers who may, in turn, consume not only the smartphones that use them, but other developed world goods and services too.[47]

[47] The same goes for China, which also fabricates and tests American designed chips. It is the biggest consumer of semiconductors designed and produced by American companies.

This not only benefits Qualcomm, but also Apple and Motorola, not to mention Google (Android) and app developers, if not American digital platforms such as Facebook. Indeed, the benefits go beyond the smartphone ecosystem. Apple outsources the manufacture of their electronic devices to China. Because of this and its growing economy, China is a top export market for non-digital U.S. companies such as Boeing, General Motors, Coca Cola, and Nike.

Domestic suppliers in developed countries may also emerge and/or expand to help satisfy increased global demand for these nations' exports. For example, when U.S. semiconductors are purchased by consumers abroad in the form of finished goods such as iPhones, jobs for American software engineers, app developers, and even hardware manufacturers, including the makers of complementary products such as headsets (many are manufactured in Colorado), blossom. Ditto for jet engine manufacturers, such as General Electric, which produce these in Ohio to power Boeing 787s made in Washington State that are purchased by Chinese airlines.[48]

Certain labor market participants may also benefit. The demand for *skilled* workers in U.S. manufacturing should continue to rise; for example, those involved in robotics. The same should be true for complementary service sector jobs, especially for workers who master computers (Bessen 2015: 118). Indeed, real wages for skilled workers in both manufacturing and outside of it have continued to steadily increase (Goldin and Katz 2008).[49]

---

[48] Increased jobs in developed country export sectors and higher pay for their workers also generates "derived demand" for domestically produced goods and services. For example, Boeing workers spend the money they earn making airplanes on purchasing homes and American made appliances and services, such as haircuts and restaurant meals.

[49] However, one of the biggest problems faced by several American industries is a shortage of skilled workers, especially as craftspeople and laborers in precision manufacturing retire. This has sometimes induced low skilled laborers to "upskill" and seek these higher paying jobs. Employers face some barriers filling these jobs, however, including inadequate vocational training (many of these jobs require a high school degree and technical skills), a mismatch between where these jobs are located and where unemployed workers live, chronic drug use problems (e.g., the opiate epidemic), and rampant absenteeism (see Bessen 2015).

4.3 Workers Outside of Innovation Clusters may not Always Benefit

There are potential losers from increased trade between developed countries and developing countries. In the short run, in a capital-rich but labor-scarce economy, such as the U.S., labor should do relatively worse off as a result of freer trade. Assuming that capital is relatively mobile and abundant, classical distributional trade theory holds that free trade benefits capital holders (Stolper and Samuelson 1941). Rents earned by labor will be dissipated as the overall supply of labor increases, in that a previously scarce factor now competes with a more abundant pool of labor located abroad and producing manufactured goods imported by developed countries. Meanwhile, returns to capital should increase because capital is scarce abroad. Therefore, the income gap between these factors should widen.[50]

But a class-based framework is incomplete. Rogowski (1987) predicts that the relative scarcity of labor or capital in aggregate does not tell the whole story. If either labor or capital are tied to specific sectors and largely immobile between industries, then labor and capital will unite within their industry to oppose changes to trade policy that either foreclose foreign markets, if they benefit from exports, or increase international trade, if they benefit from tariffs on

[50] While this may be true in static terms, it is not necessarily so dynamically. That is because the demand curve for labor may repeatedly shift outward over time, leading to an upward sloping demand curve for labor over the long run. As a society gets richer, and as innovation intensifies, there will be increased demand for goods and services (hence, demand curves will keep shifting out) and, in turn, increased demand for the domestic labor who make these goods and services domestically will follow. In other words, employers will have an increased willingness to pay laborers—especially because innovation will make them more productive. While the scholars who model these dynamic effects focus on skilled (educated) labor to explain why the returns to college degrees have increased, even though the pool of college educated workers has also steadily increased (Goldin and Katz 2008; Acemoglu 2009), conceivably the same process may apply to unskilled labor too (see Bessen 2015). However, a word of caution is in order here: Autor, Dorn, and Hanson (2021) find that local labor markets that were more exposed to import competition from China experienced big declines in employment population ratios and personal income per capita two decades after the 2001 trade shock, which holds even after factoring in the benefits of cheaper consumer goods.

competing imports (see Viner 2016). Analyzing congressional voting records, Hiscox (2002) ratifies this idea, finding that when factor mobility is low, industry distinctions are more politically salient to preferences over trade. Scheve and Slaughter (1999) use surveys to show that individuals' trade preferences are partly determined by their concerns over asset values, which are tied to the performance of local industries.

In line with this literature, the effects of increased trade with China and other developing countries on unskilled workers in developed countries are heterogeneous: it has engendered job losses in some sectors, such as toys, furniture, and textiles; yet, it has created employment and raised wages in others, such as agriculture, machinery, and vehicle parts. The latter is true for both exporting industries (consider blue collar workers helping to manufacture jet engines for airplanes shipped to China or working as janitors at companies that design the apps downloaded by smartphone users in Saudi Arabia) and domestic ones that service newly created demand induced by increased exports (e.g., cooks, waiters, barbers). Plus, as trade liberalization reduces prices across the board, all workers, skilled and unskilled, and those working for exporters and non-tradable sectors, have more income to spend on leisure activities and goods and services.[51]

4.4 Developed Countries' Innovative Firms and their Workers Support Globalization

---

[51] This is reflected in the mixed evidence for the hypothesis that globalization explains increased asset and income inequality in developed economies (e.g., O'Rourke 2002; Celik and Basdas 2010; Bergh and Nilsson 2010). One reason for this is that there are a lot of time-varying confounders that have evolved in parallel to trade and capital liberalization, and that could instead account for the increased inequality between capital and labor observed in the developed world since the 1970s. These alternative explanations include increased immigration flows and automation. While Bergh and Nilsson (2010) suggest that stronger trade liberalization increases income inequality in some developed countries, the most powerful explanation for inequality in the U.S. is skilled biased technological change: citizens with more education are able to exploit innovations associated with IT investment and other technologies complemented by white collar labor (Goldin and Katz 2008; Acemoglu 2009). See the previous footnote about U.S. locations that fared relatively poorly after trade with China intensified, even after considering the benefits of cheaper imported goods (Autor, Dorn, and Hanson 2021).

Innovative firms tend to support free trade, the liberalization of financial flows, and international institutions that include the WTO (Osgood 2018; Iversen and Soskice 2018).[52] So do their workers (Baccini et al. 2022). This is especially the case when these firms, and by extension their employees, compete by providing goods and services located on higher rungs in the quality ladder (Kim 2017). There are good reasons for this.

First, high-tech firms in developed countries specialize in the design and sometimes production of processes, products, and services that are both R&D- and human capital-intensive. Specifically, they focus on high value-added endeavors such as design, marketing, and high-end component manufacturing. These firms benefit from reducing costs or introducing new products that consumers are willing to pay more for. Moreover, firms with differentiable products, which face fewer substitutes, are less vulnerable to competing imports.

Second, these innovative firms enjoy a global reach. They often export their goods and services. They may also deploy high levels of FDI to foreign locations. Moreover, imports and inbound FDI may help introduce new technologies to these firms in the form of machinery, intermediary goods, and finished products. This is even the case when the exporting country is relatively technologically unsophisticated (Menaldo 2021; Menaldo and Wittstock 2021).

Third, these innovative firms' profits rest on complicated, vertically disintegrated global supply chains. This calls on them to import and export all manner of raw materials, intermediate inputs, and finished goods and services. It also means they need to rely on relatively free international capital flows and the international enforcement of their IP. For example, rules-based globalization based on reduced tariffs, capital liberalization, and the international

[52] Voters in developed countries who respond to populist appeals, whether protectionist or not, may be less knowledgeable about globalization's positive economic effects than those who do not because they lack economic and financial literacy (see Magistro 2022).

protection of IP fostered the creation and commercialization of electronic devices produced in global supply chains, nurturing an app-based economy centered on digital platforms, big data, and Artificial Intelligence (Menaldo and Wittstock 2021).

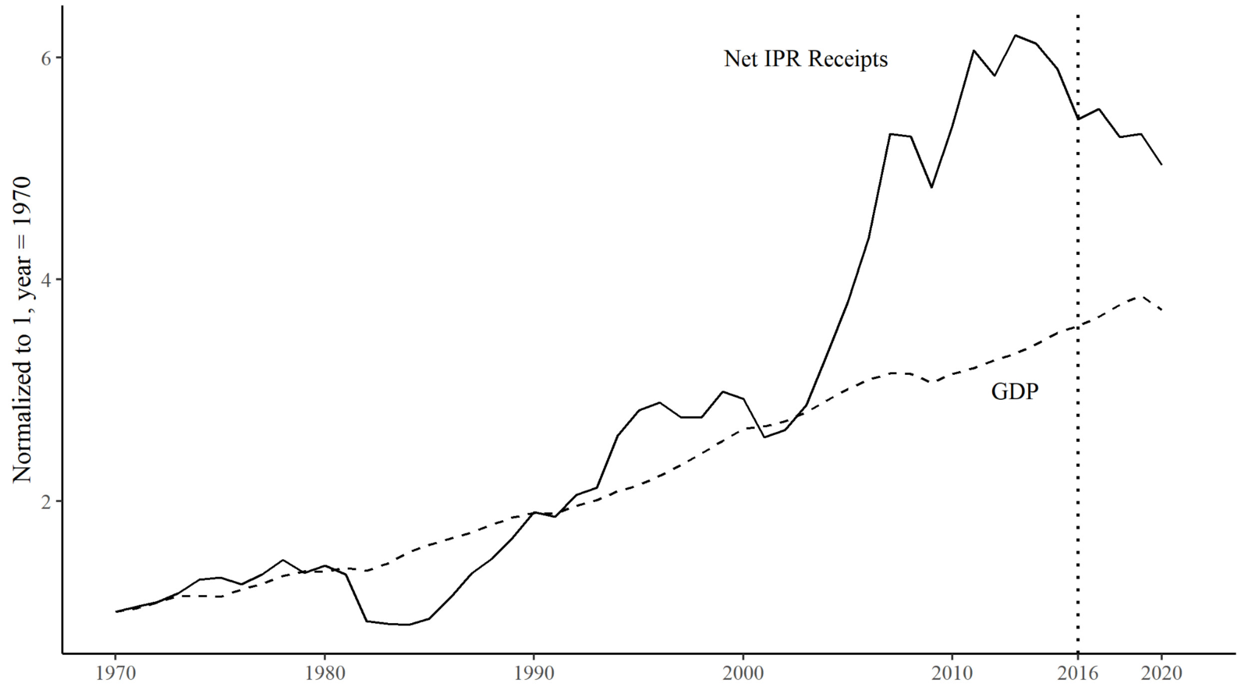

Figure 4.1 U.S. Net Receipts of IP Payments Compared to U.S. GDP since 1970.

Notes: Net IP receipts are obtained by subtracting incoming receipts from outgoing payments measured in 2010 dollars. GDP is expressed in 2010 dollars. Both are normalized to 1970, which equals 1. The vertical line, 2016, marks the election of Donald Trump to the U.S. presidency. Source: IMF Balance of Payments Statistics Yearbook and data files.

The U.S.'s ability to secure international cooperation over enhanced IP enforcement in venues such as the WTO has been particularly important for globalizing U.S. innovation. It has allowed American firms to generate profits from their intangible capital, including branding, R&D, and the commercialization of novel technologies (Schwartz 2019). The biggest beneficiaries include Apple, Microsoft, Oracle, Intel, IBM, Cisco Systems, Pfizer, Johnson & Johnson, and Procter & Gamble (Forbes 2022). Figure 4.1, which graphs American IP exports over several decades, shows their increasing predominance, especially since the start of the 21st

Century. Indeed, the U.S. has by far become the largest exporter of ideas and high value-added services (Menaldo and Wittstock 2021).

Workers who have benefited from this development include both skilled and unskilled laborers who live and work in innovation clusters. This is especially true for places that host firms that export their high value-added goods and services abroad.

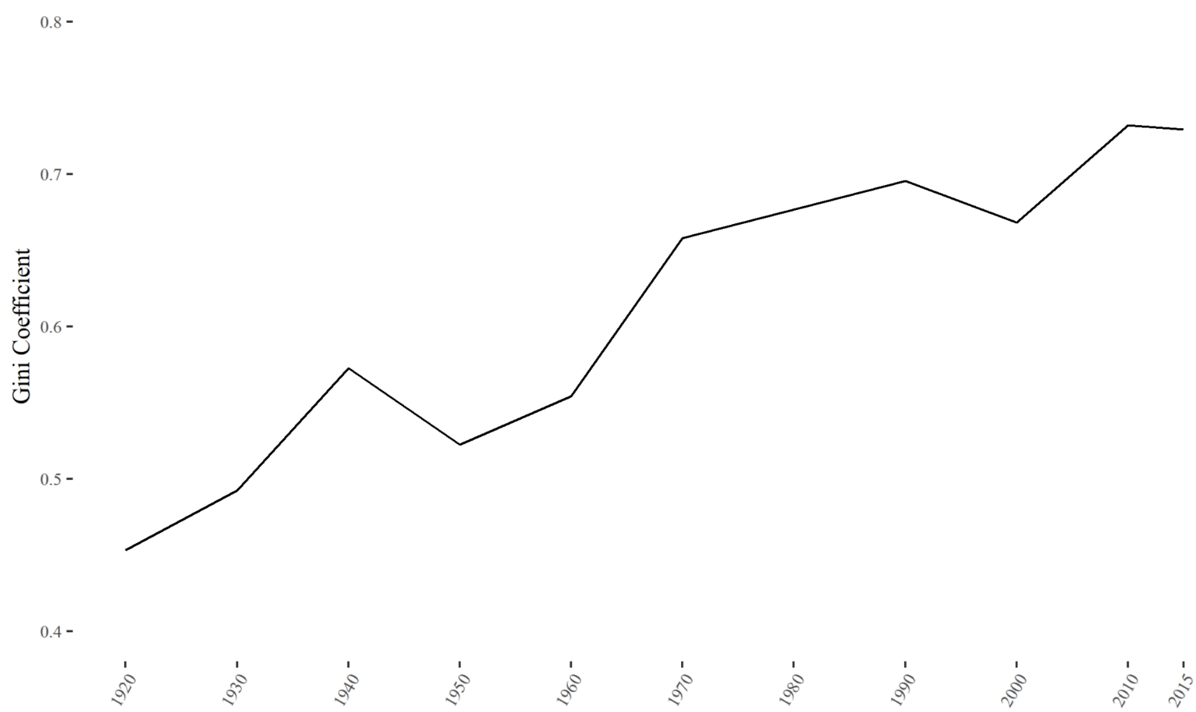

Figure 4.2 Gini Coefficients of Patents Per Capita at the County Level, 1920 to 2015

Notes: We calculate Patents per Capita at the county level relying on patent grant data from Histpat and then divide them by county-level population estimates from the U.S. census for the years graphed: 1920, 1930, 1940, 1950, 1960, 1970, 1990, 2000, 2010, and 2015. We then calculate Gini Coefficients for each of these years.
Sources: Histpat (Petralia, Ballard, and Rigby 2016); U.S. Census; authors' calculations.

Yet not all places have benefited equally from this development: the U.S. has witnessed widening inequality in terms of the location of innovation. Figure 4.2 graphs the Gini Coefficient for Patents Per Capita from 1920 to 2015, with 0 representing a distribution marked by total uniformity and 1 representing one county monopolizing all patents per capita.[53] The geographical clustering of innovation has intensified over time: places that were relatively more innovative in the past have increased their innovation edge over places that were less so (see also Gross and Sampat 2020). Laborers outside of innovation clusters have not necessarily benefited from globalization and, in fact, may have been hurt by it over a relatively long span of time. That is, they may not have adjusted by finding new, well-paying jobs in the service sector, upskilling for new manufacturing jobs, or moved to more innovative locations in search of work.

Considering this phenomenon, and following the theoretical framework we outlined above, in the next chapter we discuss why and how innovation inequality may help explain differing reactions to Trumpism during the 2016 presidential election and beyond. In Chapter 8, we return to drawing on this framework when we report reactions to Trump's presidency and his 2020 reelection campaign.

---

[53] When we described Figure 2.1 in Chapter 2 (see page 26) we explained why Patents per Capita is an excellent proxy for the spatial distribution of American innovation.

5. Why Less Innovation Equals Support for Trumpism

This chapter explores the theoretical framework's mechanisms. Specifically, it outlines how during the 2016 presidential election, Candidate Trump's sometimes-vague populist rhetoric concealed tangible policy proposals. They heralded winners and losers. We explore what Trump said about economic policy and promised to deliver if elected, contrasting this with Candidate Clinton's proposals. We explain why voters in innovation clusters had strong economic incentives to reject Trump's contempt of high-tech industries and instead embraced Clinton's innovation friendly policies. In Chapter 8, we document how, once elected, President Trump followed through with his innovation skepticism, contrasting his administration's policies with what Candidate Biden proposed during the 2020 elections.

5.1 What Trump Said and Promised to Deliver

In the runup to the 2016 presidential election, Trump espoused muscular economic nationalism informed by the grievances voiced by residents of regions that were "left behind" by globalization and missed out on the prosperity associated with innovation clusters. Candidate Trump presented himself as an outsider who would "drain the swamp", reverse globalism ("build a wall" and "bring jobs back"), and faithfully represent the interests of America's "forgotten men and women." (Williams 2019; Conley 2018).

Only after much research, Candidate Trump explicitly targeted anxious working-class voters in less innovative, relatively unprosperous areas in 2016—promising to return lost industries to past glory.[54] Many of these potential voters worked in, or were laid off from,

[54] Contrary to conventional wisdom, these appeals were not based on Trump's preternatural political instincts. Nor were they impulsive. Trump and his advisors began planning his campaign strategy and policy platform as early as 2011, determining what voters to target and how (Conley 2018; Sherman 2016). While the 2009 Tea Party Movement portended a potential base composed of working-class white Americans anxious about economic and social change,

declining manufacturing sectors such as automobiles, mining, and steel (Conley 2018). He targeted anti-globalization appeals to the Rust Belt in particular (see Davidson 2016; Pacewicz 2016).

Candidate Trump proposed several policies designed to appeal to voters living and working in places with declining industries, including those centered on natural resource extraction and manufacturing. Like conventional Republicans, Trump promised low-touch regulation and tax-cuts. Unlike establishment conservatives, he also promised to curtail immigration, bring back blue-collar jobs via industrial policy, slap tariffs on imports, and renegotiate trade deals or bilateral trade relationships—especially with China.

Candidate Trump targeted places that specialized in mining, promising to reinvigorate the American fossil fuel energy sector. Specifically, if elected president, he vowed to approve the Keystone XL pipeline project, dramatically scale back the Environmental Protection Agency, "save the coal industry", achieve energy independence, and cancel the Paris Climate Agreement (Hejny, 2018).

Candidate Trump also floated several protectionist measures that he claimed would revitalize American manufacturing and create blue collar jobs. At an aluminum factory outside of Pittsburgh on June 28th, 2016, he declared "economic independence", arguing that globalization

who lived primarily in the Midwest, it was only after intensive research that Trump targeted these voters with a precise message (Conley 2018; Tesler 2016; Cohn 2016b). Even before Trump declared his candidacy for president on June 16, 2015, Trump's election team picked a policy program, talking points, and slogans that mirrored preexisting sentiments expressed by potential voters in areas they deemed critical to his electoral coalition, including, but not restricted to, Tea Party strongholds. They crafted their messaging around detailed and data-driven research (Conley 2018). They spent at least $100,000 a week on polling, and paid $5 million dollars to Cambridge Analytica, a data analytics firm, to create psychographic profiles of potential Trump voters (Green and Issenberg 2016; Grassegger and Krogerus 2017; Hope 2016).

had undermined the livelihoods of American middle-class workers, and that tariffs would restore American manufacturing (Trump 2016b).

Trade protectionism was the keystone of Trump's economic platform; during his 2016 presidential campaign, Trump repeatedly singled out China and its putative exploitation of the U.S. and its workers. Candidate Trump spoke directly to blue-collar workers who were potentially hurt by China's entry into the WTO in 2001 (The Economist, 2017). He infamously declared that: "We can't continue to allow China to rape our country, and that's what they're doing…" (referring to China's large export surplus with the U.S. during the 2016 presidential race).[55] In his campaign manifesto, Trump therefore pledged to "cut a better deal with China that helps American businesses and workers compete."[56] The premise was that China's cheap labor steals jobs away from American workers, allowing it to flood the U.S. market with cheap goods.[57]

These grievances against globalization went beyond China. Candidate Trump also promised to withdraw the U.S. from NAFTA and walk away from the TPP.[58] In a USA Today op-ed in March 2016, Trump warned that the TPP was a direct threat to the U.S. auto industry (Trump 2016a). He also threatened to slap tariffs on European imports–criticizing Germany's large trade surplus and specifically stigmatizing the preponderance of German-made cars on American streets (Jacoby 2020; Taylor and Rinke 2017).

Conversely, Trump's economic agenda may have repelled voters tied to high-tech sectors. This includes both white- and blue-collar workers employed in semiconductor and computer hardware manufacturing, e-commerce, and software and internet services, as well as in other

---

[55] Diamond (2016).
[56] See, for example, BBC (2016).
[57] These grievances also included China's supposed currency manipulation and its subsidies of state-owned enterprises (Menaldo and Wittstock 2021).
[58] The TPP is a free trade pact agreed to by Australia, Brunei, Canada, Chile, Japan, Malaysia, Mexico, New Zealand, Peru, Singapore, and Vietnam.

innovative areas beyond the digital economy, such as higher education. As outlined above, these industries rely on international trade, both to establish and coordinate complex global supply chains and access foreign markets that consume their exports. They also benefit from federal investments in basic science, R&D, and education. And they depend on skilled labor, which means they have a stake in a liberal immigration policy for high-skilled foreign workers.

Trump promised tariffs on specific imports and road-tested mercantilist policies during the 2016 campaign that would ostensibly benefit American workers but were certain to hurt innovative firms and their employees in the process. First, foricng U.S. firms to hire American citizens over foreign-born workers or reshore production to the U.S (Trump 2016b).[59] Second, promoting content requirements such as compelling infrastructure projects to utilize U.S. made steel (ibid.). Third, promising to bring antitrust lawsuits against high-tech companies.

Consider Trump's complaints against several big tech firms' market power. He accused Amazon of being a retail monopoly, even though, at the time, prices on its goods and services were falling like a stone as its costs kept declining, and it continued to plow its profits into R&D, allowing it to innovate across industries such as e-commerce, cloud computing, entertainment, and retail.

Candidate Trump threatened to curtail immigration, both illegal and legal. He promised to tighten immigration laws, remove all undocumented immigrants, cancel visas to foreign countries that did not take undocumented immigrants back, triple Immigration and Customs Enforcement personnel, amend the J-1 Visa Jobs Program, increase visa fees, limit legal immigration, cancel funding for sanctuary cities, build a wall on the southern border, and ban Muslim immigrants (Trump 2016c).

[59] For example, Candidate Trump hectored Apple to make iPhones in the U.S. (Lapowsky 2016).

Many of these policies were slated to harm high-tech firms and their workers and communities. On his campaign website, Trump declared he would end the "abuse" of the H1B Visa Program, which is heavily used by tech companies to recruit foreign talent (see Lee 2016). His antipathy towards the Common Core educational standards program also threatened high-tech firms, who have long argued for educational reforms that can help increase the ranks of so-called STEM (Science, Technology, Engineering, and Math) workers (see Carey 2016).

5.2 Clinton's Pro-innovation Positions

Conversely, Hillary Clinton's 2016 Presidential Campaign spoke directly to the economic and social preferences of workers in innovative areas. She promised to increase investments in infrastructure, including telecommunications, and create a clean energy economy with well-paying jobs (Democratic Party 2016). This is a vision shared by many American venture capitalists (VCs) and startups, which see this as the next great high-tech frontier.

Funders and voters closely linked Candidate Clinton to her husband's technological and economic policy accomplishments (see O'Mara 2020). President Bill Clinton's administration presided over the commercialization of the Internet, big investments in science, technology, and education, and a variety of tech-friendly policies across variegated areas. His tangible policy victories included the Internet Tax Freedom Act, the Digital Millennium Copyright Act, comprehensive telecommunications reforms, including Section 230 of the Communications Decency Act, and various investments that increased access to digital technologies.

Indeed, Candidate Clinton's 2016 policy platform outlined an explicit innovation agenda that harkened back to the 1990s. It included increased federal support for science, research, especially in medicine, education, and technology; it also promised to bolster and improve cities and metro areas and strengthen legal immigration (Democratic Party 2016). Clinton also promised to eliminate tuition for in-state students at public colleges whose families earn less than $125,000 a year. These are the types of students who usually end up working in high-tech firms (see Goldin and Katz 2008).

In June 2016, Candidate Clinton published a policy proposal specifically targeted at bolstering technology and innovation (Clinton 2016). She reiterated her ambition to invest in education and Federal R&D. Clinton promised to issue green cards for international students that obtain graduate degrees in science and engineering. She also planned to invest heavily in digital infrastructure, with a specific view towards 5G and the IOT. Clinton vowed to expand high speed internet coverage, both at home and abroad. Crucially, Clinton intended to improve the international enforcement of IP and facilitate U.S. IP exports (Clinton 2016). Candidate Clinton occasionally used Twitter to get her message out: "We should deploy 5G internet to make sure we have the fastest online connections possible."[60]

5.3 Trump's Anti High-tech and Anti-Trumpism

We hasten to emphasize that besides floating policy proposals that threatened to harm high-tech firms and other innovative industries, and unlike Candidate Clinton, Candidate Trump never explicitly discussed technology or innovation during his campaign.[61] Revealingly, he did not vow to create U.S. jobs in semiconductor manufacturing. In fact, Trump lacked an explicit technology and innovation strategy altogether. Indeed, in the rare instances he did publicly speak about high-tech companies, Trump articulated disdain or personally attacked their leaders.

Evidence from Candidate Trump's social media feeds bear this out. Between Trump's announcement he was running for president on June 16th 2015, and the Presidential Election on

[60] https://twitter.com/hillaryclinton/status/748265729116475392

[61] The one notable exception is that Candidate Trump vowed to end the alleged abuse of American IP by Chinese firms. However, many of his accusations were specious and his proposals to improve the situation were mercantilist (see Menaldo and Wittstock 2021).

November 12th 2016, Trump sent out 7,779 tweets (including retweets).[62] Whenever Trump mentioned terms such as "industry" or "manufacturing", he never referred to high-tech sectors. In fact, in one of the few tech-related tweets Trump sent during this timeframe, and the only one that mentioned "Apple" by name, called on the company to decrypt an iPhone associated with a suspected terrorist couple from San Bernardino, California who had orchestrated a mass shooting against their coworkers.[63] Conversely, Trump's tweets about manufacturing were always about industries such as automobiles and steel, or adjacent sectors such as coal and energy.

Candidate Trump's skeptical, if not openly hostile, stance towards high-tech industries was unprecedented. There has generally been broad bipartisan support in Washington, D.C. for technology and innovation, especially after the end of World War II. If anything, Republicans had staunchly supported high-tech sectors since the Reagan Administration, which granted industries such as semiconductors, hardware, software, and telecommunications generous concessions during the 1980s. This included reductions in capital gains taxes and subsidies for venture capital and R&D spending, favorable immigration policies, government procurement of high-tech products, especially related to defense spending, and improved IP enforcement (O'Mara 2019).[64]

Tellingly, several notable high-tech luminaries, many of them conservative, firmly opposed Candidate Trump.[65] Yet, in March 2016, the CEOs of high-tech companies including

---

[62] To arrive at this conclusion, we searched through Trump's 7,779 tweets using a list of technology-industry related keywords. See the Trump Twitter Archive: https://www.thetrumparchive.com/

[63] The tweet can be found here: https://www.thetrumparchive.com/?searchbox=%22iphone%22

[64] In contrast to Candidate Trump, the Republican Party's campaign platform, published on July 18th 2016, did make some efforts to parrot the GOP's typical commitments to U.S. innovation: repeating Trump's concerns over China's IP infringement, it framed these as a national security issue. The platform also made some promises to create a business-friendly environment for innovative companies and gave lip service to tax policy, education, and infrastructure (Republican National Convention 2016).

[65] While PayPal cofounder and famed venture capitalist Peter Thiel is a notable exception, he would not have been much of an outlier before 2016. While certainly more cosmopolitan and

Apple, Tesla, Napster, and Google met with Senate Majority Leader Mitch McConnell and House Speaker Paul Ryan to try to prevent Trump from becoming the GOP's Presidential Nominee (Grim, Baumann, and Fuller 2016). Former Hewlett Packard CEO Meg Whitman, a Republican, openly declared she would not vote for Donald Trump, pledged to raise money for Hillary Clinton, and urged other Republicans to follow suit. Likewise, venture capitalist and former Netscape co-founder Marc Andreesen, who had supported Republican Mitt Romney in 2012, declared on Twitter in early May 2016 that he was voting for Hillary Clinton in 2016 (Ferenstein 2016).[66] In July 2016, 145 leaders from the U.S. high tech sector (including Qualcomm, Instacart, Facebook, Apple, and various venture capitalists) signed an open letter that explicitly declared the danger of a Trump presidency to innovation and economic growth.[67]

Tech workers seemed to generally share their bosses' antipathy towards Trump. In June of 2016, Crowdpac reported that only 52 "tech-workers" had contributed to Candidate Trump's presidential campaign, compared with 2,087 contributions for Candidate Clinton.[68] In July 2016, data from the Federal Election Commission corroborated this picture: among high-tech companies, Google employees donated the most to Candidate Clinton, followed by workers employed by IBM, Microsoft, Amazon, and Apple; few workers at high-tech firms donated to Candidate Trump. Meanwhile, individuals employed in finance, manufacturing, and agriculture were among the top donors to his 2016 campaign (see Perlstein 2016).

---

liberal leaning than the rest of the country in general, not all voters living in Silicon Valley, Seattle, New England's Route, and North Carolina's Research Triangle have historically been lockstep supporters of the Democratic Party; nor have the leaders of the tech firms headquartered there (see O'Mara 2019).

[66] Andreesen's original tweet has since been deleted.

[67] The letter stressed the importance of maintaining liberal immigration policies, and the government's key role in investing in infrastructure, education, and scientific research (see "Trump Would be a Disaster for Innovation" in Stanton 2016).

[68] "Tech-workers" is a capacious category that includes Gig-workers such as Uber drivers.

Combined with our theoretical framework, this chapter's interrogation of Trump's economic policies generates clear predictions about the 2016 U.S. presidential election. The next chapter is dedicated to outlining those, as well as spelling out other hypotheses about the history of American technological progress and innovation clusters. This will allow us to set the stage to systematically test our main empirical implications in Chapter 7 using a county level dataset. In Chapter 8, we again test these empirical implications using not only 2020 presidential election data, but also financial contributions made to both of Trump's presidential campaigns.

6. Setting the Stage to Test the Theoretical Framework's Implications in 2016

This chapter outlines our theoretical framework's empirical implications. We spell out our key hypotheses; take a first look at the evidence; hash out a strategy for exploiting exogenous variation in innovation clusters as a way of causally identifying the relationship between innovation and Trumpism; and report significant path dependence in U.S. innovation clusters since the early 1800s. In Chapter 7, we evaluate the empirical implications for the 2016 presidential election. In Chapter 8, we do so for the 2020 presidential election.

6.1 The Major Empirical Implications

In 2016, voters in U.S. innovation clusters, however small, should have reacted negatively to Candidate Trump's calls for protectionism and his associated threats to technology transfer, global supply chains, R&D, skilled foreign workers, and the creation and commercialization of innovative products and services. His promises to disrupt the international liberal architecture, including free trade agreements and international institutions such as the WTO, threatened the innovative firms these voters worked for and the communities hosting them. Second, innovation clusters that are highly productive and only loosely connected to the global economy may have also rejected Trump's general bid to "make America great again"—or, in other words, take the U.S. economy back to a past populated by vertically integrated and fossil fuel intensive firms operating in heavy industries.

The converse should also be true. Firms that are less innovative should have responded positively to Candidate Trump. They may favor protectionism outright or be less averse to other anti-globalization policies that threaten to hurt R&D and the commercialization and diffusion of technology. These may include restrictions on the immigration of skilled workers and less government support for basic science and higher education. The same should hold true for their workers and the residents of places that host them.

In the 2020 presidential elections, the same patterns should have held true. Moreover, support for Trump in America's more innovative U.S. counties should have experienced further erosion between the 2016 and 2018 contests, albeit this electoral softening should be relatively muted. The reason is because voters in both innovative and less innovative places should have already priced in President Trump's Neo-Luddism by the 2020 elections since he had amply revealed his economic policy platform during the 2016 presidential campaign. Notwithstanding that fact, because Trump followed through and implemented several innovation retarding ideas during his presidency, including some he had not yet previewed in 2016—something we will document in Chapter 8—Trump should have experienced a greater reduction in campaign contributions in 2020 versus 2016 in more innovative U.S. counties.

6.2 A First Look at the Evidence

What is the spatial relationship between innovation and Trumpism? As a first step, we can compare the map of innovation at the U.S. county level represented by Figure 2.1 in Chapter 2 with electoral support for Trump in 2016 (versus Bush) in Figure 3.1 in Chapter 3. Visually, it is obvious that innovative places' support for Trumpism was relatively low in 2016. As a second step, consider a bivariate Ordinary Least Squares (OLS) regression with counties as the unit of analysis. It reveals that increasing Per Capita Patents by 1 percent maps onto a decrease in Trumpism of 1.19 percentage points (p-value < .001). In Chapter 7, Table 7.1, Column 1 reports that finding.[69] In the next chapter, we investigate whether the spatial relationship between these

[69] We follow Autor et al. (2020) and cluster the standard errors by commuting zone and also weigh the observations by counties' total votes in the 2000 presidential election. We also log Per Capita Patents after adding $1x10^{-9}$ (to address 0 values). This result and those from the ensuing

variables indeed runs from the relative degree of innovation to the relative electoral support for Trump. Before doing that, however, we must do some more legwork.

6.3 Exogenous Variation in Innovation Clusters

To establish whether there is a causal relationship between innovation and Trumpism, we exploit exogenous geographical features that made innovation more likely in the U.S. during the 19th and early 20th Centuries. Following Haber, Elis, and Horrillo (2022), places with temperate climates–those with relatively low or moderate temperatures and relatively moderate to high precipitation levels–were more likely to develop the quantity of biomass (and therefore food and energy) needed to sustain innovative manufacturing facilities in the 1800s. In the early 20th Century, places with greater population densities, no matter their climates, attracted inventors and capitalists who commercialized new technologies, ushering in new innovation clusters.

Throughout American history, efforts by firms and entrepreneurs to reduce transportation and communication costs have motivated them to strategically locate manufacturing and innovation activities such as R&D; access to relatively cheap energy has also mattered (Keer and Nanda 2013: 2). Figure 6.1 maps the spatial distribution of biomass (the presence of animals and plants, which proxy for crops and timber and energy: stored radiation from the sun) in the U.S. in 2012.[70] Contemporary biomass patterns, which proxy for historical ones, should track the location of American innovators circa 1800.

At the turn of the 19th Century, American industrialists and innovators sought access to abundant food and fuel. For example, Haber, Elis, and Horrillo (2022: 37) recount how during this time the New York hinterland, laden with biomass from hardwood forests and then cereal crops,

regressions are robust to instead applying a hyperbolic sine transformation to our per capita patent variables without adding anything to the values beforehand.

[70] This variable's mean is 105,356,000 tons; its median is 69,140,000 tons.

attracted an agglomeration of sawmills, gristmills, manuscript mills, and manufacturers of various types. In this and other U.S. locations like it, farmers settled and cleared forests to grow storable grains and legumes, a very salient concern for inventors and industrialists at the time: it was too expensive, if not impossible, to import food from long distances (Haber, Elis, and Horrillo 2022). In turn, this fostered accumulation, specialization, trade, finance, and manufacturing (ibid.: 37).

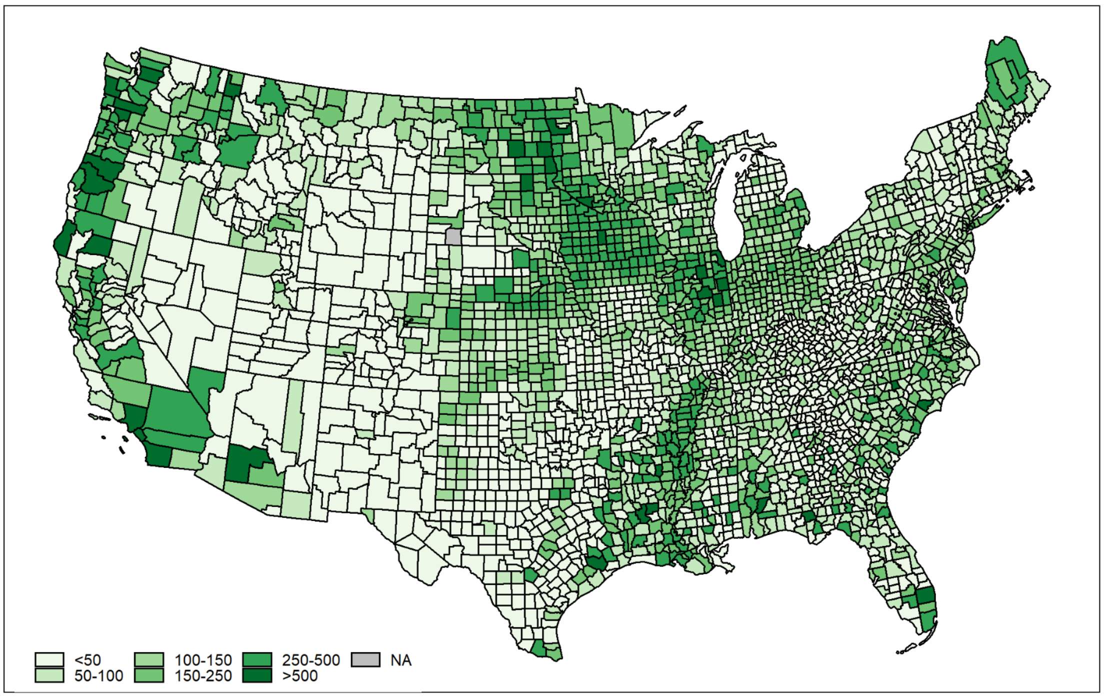

Figure 6.1 Total Biomass Resources in 2012

Notes: Solid biomass resources are measured in thousands of tons per year, including crop residues (which is the 5-year average between 2003 and 2007), forest, and primary mill residues (measured in 2007), and secondary mill residues (measured in 2009), and urban wood waste (measured in 2010). This proxies for historical biomass as reliable data for biomass is not readily available before 2012.
Source: Roberts (2014).

Biomass also proxies for access to readily available energy sources, most obviously from burning wood but also refined crop oils. Up until the mid-19th Century, biomass constituted the single largest source of total annual U.S. energy consumption (U.S. Energy Information Administration 2022). It remained an important fuel source into the first half of the 20th Century.

The U.S.'s early industrialization was centered on textiles, arms manufacturing, machine tools, and railroads. Several technologies were brought over from England or were developed in the U.S. in parallel to English and sometimes French innovations (Haber, Elis, and Horrillo 2022: 37).[71] This was the era of "the great inventor", marked by firms eschewing inhouse R&D and instead purchasing innovations from serial inventors in vibrant, albeit geographically segmented technology markets, sometimes via patent agents (Lamoreaux and Sokoloff 2007).[72] These inventors collocated in places with abundant biomass, so that "[t]he invention of jigs and milling machines for cutting metal to precise tolerances, such that parts made from them would fit into any assembly of the same type, came out of workshops in Connecticut, Rhode Island, New York and Pennsylvania in the 1810s" (Haber, Elis, and Horrillo 2022: 38).

Textile manufacturing, in particular, was an early form of high-tech industry centered on self-acting mules (mechanized cotton spinning) and power looms (weaving).[73] It occurred primarily in New England and the Mid-Atlantic states. Distinct innovation clusters proliferated because industrialists needed to co-locate in places with a critical mass of skilled workers who could master the technical knowledge and knowhow associated with these new technologies;

[71] The authors tell how the U.S. Patent Act of 1793 improved upon the British patent system by simplifying patent filing and IP enforcement and reducing patenting costs by 95% (see pg. 6).
[72] The federal government did not only help stimulate innovation by providing strong IP rights; it supplied a robust postal network, granted land to railroads and homesteaders, established land grant universities and subsidized agricultural and mining research, allowed liberal bank chartering that made credit widely available, spent readily on infrastructure, and conducted geological surveys that were made public. Local governments spent generously on education.
[73] Textile manufacturing also benefited from the invention of the cotton gin. And, similar to England, the U.S. witnessed the widespread application of new technologies beyond textiles, including coke smelting, iron puddling and rolling, and steam engines applied to mining, manufacturing, and transportation.

textile mills expended great efforts attracting literate and trainable workers, most of them women, to help run their new equipment efficiently (Bessen 2015).

What climactic conditions favor greater biomass? Soil humidity, soil and air temperature, photoperiod, solar radiation, and precipitation all impact the availability of water and soil nutrients. In turn, both are critical for fostering healthy forests and the crops that may potentially displace them (Haber, Elis, and Horrillo 2022). In the U.S., abundant biomass is thus more prevalent in temperate climates with relatively high soil quality, moderate precipitation, and relatively low temperatures, as the latter reduces evaporation and plant transpiration and winter frost helps kill parasites and pests that cause plant diseases and improves topsoil and thus soil fertility (see Khalifa 2022: 26-27). This translates into more abundant food. Plus, the cereal crops that can be grown in temperate places can be more effectively stored (Haber, Elis, and Horrillo 2022).

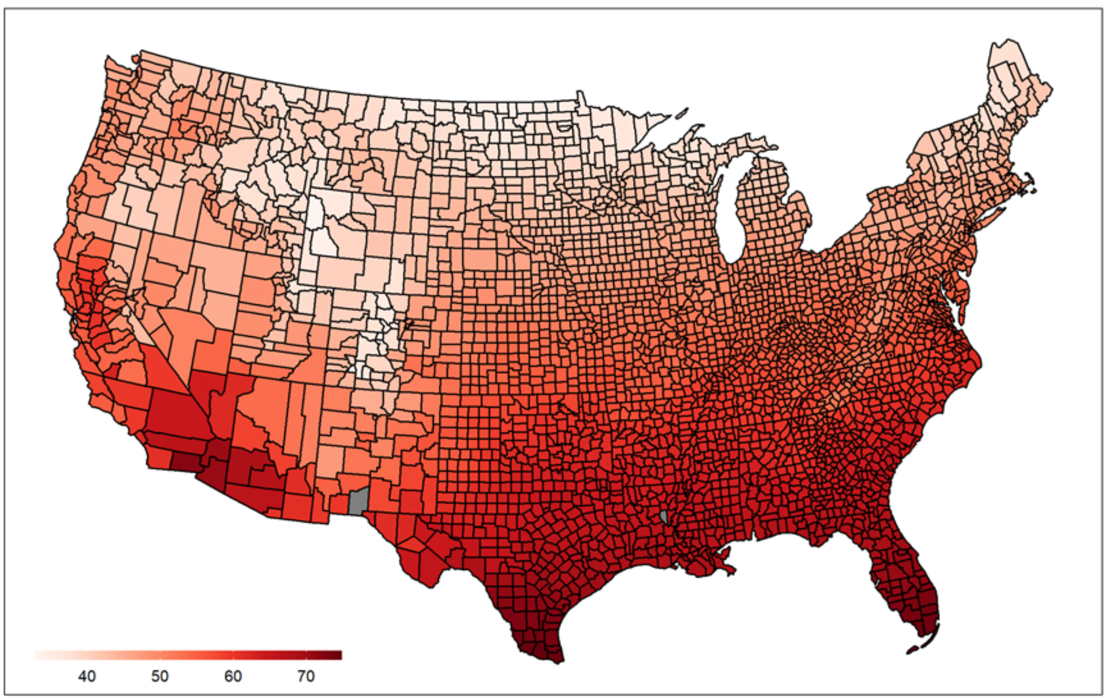

Figure 6.2: Annual Mean Temperature in 1900

Notes: Measured in Fahrenheit. The continental U.S. is separated into 344 separate climate divisions. For each, monthly temperature values are computed from daily observations collected from weather stations. These values are weighted by area to compute local values (Karl and Koss 1984).
Source: U.S. Climate Divisional Database (CDD) and published by the National Oceanic and Atmospheric Administration's National Centers for Environmental Information (NOAA-NCEI).

Figures 6.2 and 6.3 reveal the historic distribution of temperature and precipitation in the U.S., respectively. Both were measured in 1900 for 2,660 counties. Temperature is the average degrees per year, with the mean and median values both equal to 53.7 Fahrenheit. Precipitation is total inches of rainfall per year, with a mean of 35.8 and a median of 37.1. These maps adduce a strong relationship between temperate climates (low to moderate temperature and moderate to high rainfall) and abundant biomass (see Figure 6.1).

6.4 History of American Innovation Clusters and Path Dependence

To bolster confidence in our causal identification strategy, we now explore the spatial persistence of American innovation inequality over time. The presence of abundant biomass in some U.S. locations with temperate climates fostered early innovation clusters during the early 19th Century. These were likely to endure and strengthen during the ensuing centuries. Consequently, the exogenous factors that explain innovation in the distant past should also map onto innovation in later periods.

As Figure 4.2 in Chapter 4 reveals, U.S. spatial innovation inequality increased over time. Places with high quantities of food and fuel attracted innovators and industrialists. These advantages were reinforced as they attracted rising levels of capital-intensive machinery, R&D activity, and talented high-skilled workers. Geographically blessed locations were therefore more likely to continue to churn out process and product innovations over succeeding industrialization waves. And high transportation costs and transaction costs compounded by long distances limited technology transfer between temperate and non-temperate climates (Haber, Elis, and Horrillo 2022; Khalifa 2022: 28).

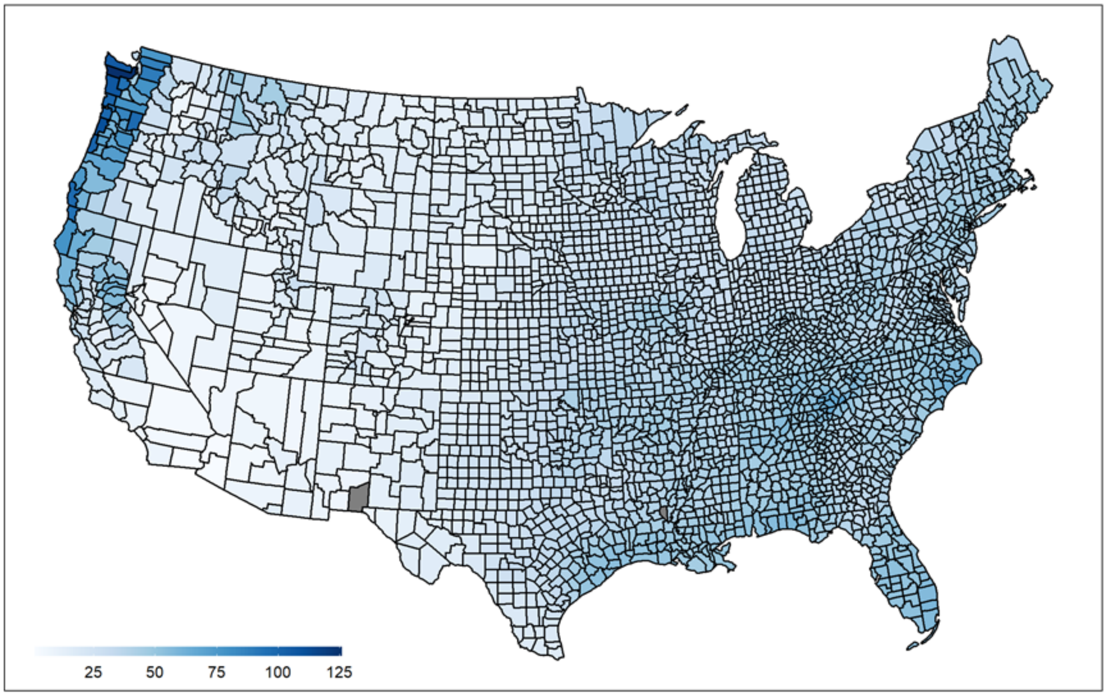

Figure 6.3: Annual Precipitation in 1900

Notes: Measured in annual inches of rain. The continental U.S. is separated into 344 separate climate divisions. For each, monthly precipitation values are computed from daily observations collected from weather stations. These values are weighted by area to compute local values (Karl and Koss 1984).
Source: CDD and published by NOAA-NCEI.

After the Civil War, the U.S. experienced the so-called Second Industrial Revolution– before any other country, and with greater intensity than its followers. This industrialization wave was centered on General Purpose Technologies (GPTs) such as electricity and the internal combustion engine. During this era, there was a concomitant proliferation of innovative batch and continuous-process manufacturing. Vertically integrated, multidivisional firms that took direct control of suppliers and distribution channels and produced at large scale emerged and reached a national, if not global, market (Lamoreaux and Sokoloff 2007). Mass produced U.S.

exports that relied on sophisticated, capital-intensive technology exploded and, by around 1890, the U.S. surpassed the U.K. in terms of technological prowess, industrial intensity, and overall prosperity (see Nelson and Wright 1992).

After the turn of the 20th Century, American innovation, industrialization, and productivity intensified further. Between 1909 and 1929, the U.S. experienced a six-fold increase in the use of electricity to power manufacturing and residential power use and a similar increase in the amount of horsepower to workers.[74] An explosion in capital intensive process innovations around rubber, glass, petrochemicals, standardized machinery, and electrical equipment followed. New product inventions during this period included mass produced automobiles and airplanes, radio, motion pictures, telephones, household appliances, and canned food, along with synthetic materials, dyes, and fabrics.

The Second Industrial Revolution relied on highly skilled labor. Most manufacturing jobs began to require a high school education and college educated workers earned a significant wage premium, many of them employed as managers, engineers, and chemists in factories engaged in mass scale Fordist production (Goldin and Katz 2008). The number of scientists and research engineers working in industrial labs also exploded. In turn, Total Factor Productivity grew at an unprecedented 1.29% a year between 1899 and 1941, giving American producers an edge over those from other countries.[75] By 1929, the American share of global motor vehicle exports exceeded 70% (Nelson and Wright 1992: 1945).

---

[74] This was made possible by the full electrification of factories with moving assembly lines and individuated (unit driven) workspaces outfitted with machines plugged into electric sockets (David 1993). In turn, after abandoning centralized line shafts and their cumbersome pulleys and belts, factories transformed their layouts and workflows. This made manufacturing more flexible and efficient and reduced capital outlays.

[75] See Bakker, Crafts, and Woltjer (2017). While Gordon (2016) argues that gangbusters productivity growth over this period and beyond was the result of the widespread diffusion of

Figure 6.4 identifies the spatial distribution of patents per capita granted in 1930, near the end of this peculiarly innovative era.[76] Technological progress during the Second Industrial Revolution was geographically concentrated. A few metro areas in New York, Massachusetts, Ohio, Michigan, Illinois, Texas, California, and Washington State stood out. In these places, new companies were formed as capital became available after investors developed methods to better screen ideas with commercial potential; entrepreneurship opportunities mushroomed as employees spun off new ventures (Lamoreaux and Sokoloff 2007). R&D programs were housed in corporate labs including Eastman Kodak, B.F. Goodrich, General Electric, Dow, DuPont, Wesginthouse, RCA, US Steel, Unocal, and Goodyear.

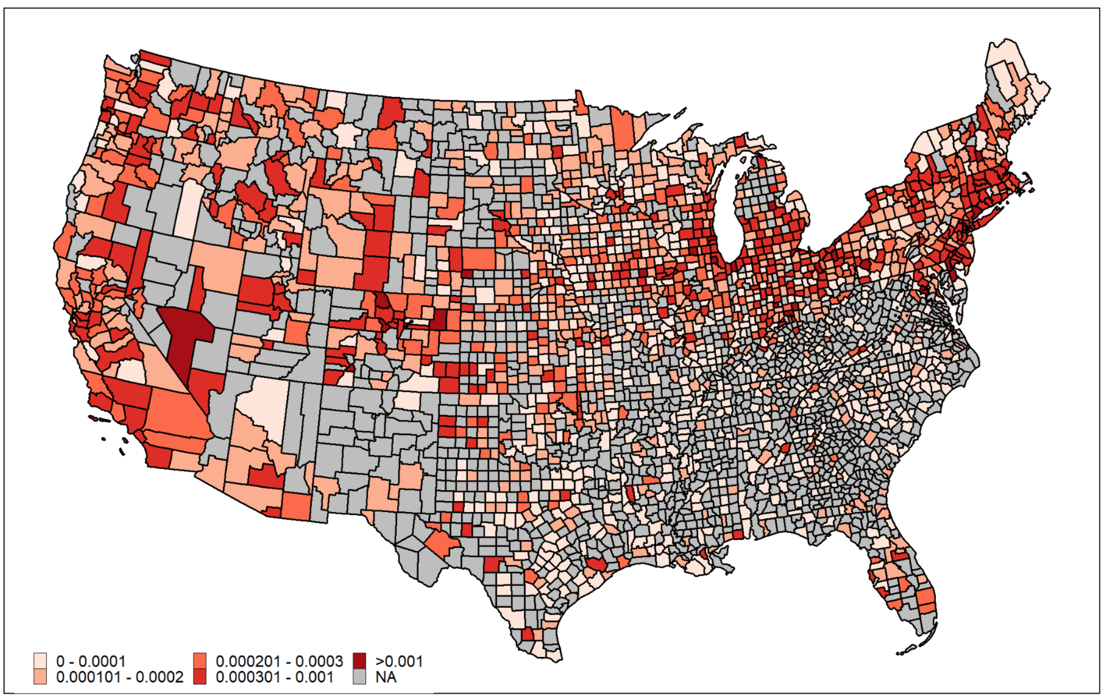

Figure 6.4 Patent Grants per capita filed by inventors in each county in 1930

GPTs such as electricity, Bakker, Crafts, and Woltjer (2017) disagree: they identify more of a mushroom pattern and claim that several innovations across economic sectors were responsible.

[76] Note that this is a flow variable, like Figure 2.1: it is patent granted per capita in 1930, not the total stock of patents per capita granted by 1930.

Notes: We use HistPat, which spatially identifies patents granted by the USPTO from 1790 to 1975. HistPat allocates patents to each county using digitized records of original, publicly available patent documents that list the residence of the first inventor. We then divide these figures by county-level population estimates obtained from the U.S. Census.
Sources: Petralia, Ballard, and Rigby (2016); U.S. Census (1930).

The similarity between the spatial patterns depicted by this map and Figure 2.1 in Chapter 2, which showcases patents per capita in 2000, is striking. Places that were innovation clusters in 1930 tend to be innovation clusters at the turn of the 21st Century. An OLS regression corroborates this visual correlation: an increase in counties' granted patents by 1 percent in 1930 maps onto an increase of .65 percent in counties' per capita granted patents in 2000 (p-value < .001).[77]

Moreover, there is spatial persistence in innovation across different time intervals between 1930 and 2000 too. An increase in counties' per capita patent grants by 1 percent in 1930 maps onto an increase of .63 percent in counties' per capita patent grants in 1950 (robust p-value < .001). Similarly, an increase in counties' per capita patent grants by 1 percent in 1930 maps onto an increase of .76 percent in counties' per capita granted patents in 1990 (robust p-value < .001).[78] Many of the places that pioneered the Second Industrial Revolution seamlessly welcomed the computer era and the space race.

The Third Industrial Revolution witnessed innovation in several hardware and software based high-tech industries, with semiconductors leading the way. It began as a sequel to the Second Industrial Revolution in terms of vertically integrated companies that conducted intensive R&D in research parks. Notable contributions to innovation were developed at

---

77 To calculate this regression, we log each variable and cluster the standard errors by commuting zone. There are 1,688 observations.
78 To calculate these regressions, we log each variable and cluster the standard errors by commuting zone. There are 1,286 observations and 1,699 observations, respectively.

AT&T's Bell Labs, Xerox PARC, various IBM research labs, and Hewlett Packard's Laboratories.

Eventually, a vertically disintegrated and global supply chain evolved.[79] First was the advent of the personal computer stack (the separation of microprocessors from hardware from software embodied by the Wintel system: Intel, personal computers around the IBM standard, and Microsoft, including outside developers, respectively). Second was the horizontalization of semiconductors themselves, with most chip design occurring in the U.S. and most production offshored to East Asia. Third was the development of the smartphone stack (the separation of chip designers, chipmakers, handset manufacturers, the Android operating system, and outside developers). Horizontalization was accompanied by the advent of "outsourced R&D" conducted by startups purchased by established firms to acquire their technology and a more multinational approach to R&D based on cross national alliances between firms.

Besides vertical integration in its early stages, the Third Industrial Revolution was like the second in several ways. It called for a highly skilled workforce specialized in capital intensive process innovations (see Goldin and Katz 2008: 121). Central processing units based on programmable microprocessors were widely adopted throughout the U.S. economy, bolstering overall productivity (Gordon 2017). For example, Walmart forged several innovations in supply chain management and warehousing, including the widespread use of barcodes, computer networks, and data storage, which trickled out to other firms in its industry, such as Target. These innovations allowed retailers to forecast sales with great accuracy, slash their

[79] This industrial revolution was powered by Moore's Law, the exponential improvement in microchip performance roughly every two years per dollar spent. It was the result of rising R&D investments and continuous experimentation by semiconductor firms to cram more transistors onto an integrated circuit's surface area, thereby shrinking electronic devices, improving their processing speed, and inducing constant price reductions (see Galetovic 2021).

inventories—and thus cut down on waste and reduce costs—adopt uniform standards for labeling products, and create interoperable production and sales information that could be automatically shared in a standardized manner up and down their global supply chains and between their retail outlets (see Bonacich and Hardie 2006: 108).

The Third Industrial Revolution matured across innovation clusters in California, Washington, State, New Mexico, Texas, New England, Illinois, Virginia, Ohio, upstate New York, and other parts of the country that boast research universities and highly educated workers (see Greenstein 2010: 512). And it was characterized by innovative funding processes, e.g., venture capital, and spinoffs that fostered continuous entrepreneurship in these clusters (Lamoreaux and Sokoloff 2007). Most importantly, for our purposes, the industries that were forged during the Second Industrial Revolution continued to exist and innovate deep into the third one. By extension, enduring innovation clusters around steel, petrochemicals, automobiles, aircraft, chemicals, and synthetics remained economically relevant, even if they were overshadowed by places such as Silicon Valley and Route 128 (see Kerr and Nanda 2013).

The Third Industrial Revolution was subsidized, if not choreographed, by the U.S. Federal Government. Starting in World War II, the military oversaw the development of computers that could crack encrypted messages and sought to develop the hydrogen bomb. During the Cold War, Washington, D.C. awarded billions of dollars in grants to universities and labs for basic scientific research that culminated in the development of radar, lasers, semiconductors, GPS, and hardware. Military-led procurement efforts around precision guided weapons subsidized semiconductor firms' efforts to obtain scale; as did spending by NASA on the so-called Space Race. Moreover, the federal government and military helped to develop the internet by, among other things, encouraging standards that facilitated interoperability.

Importantly, this pattern of government stewardship around R&D strengthened preexisting innovation clusters. While Gross and Sampat (2020) tell this story primarily for the post World War II era, we have confirmed it across the 20th Century. This includes Figure 4.2 in Chapter 4, where we looked at increases in technological inequality across U.S. locations over time. It also includes a comparison of Figures 2.1 and 6.4, and the results of the OLS regressions reported above that adduce strong path dependence in innovation clusters over the 20th Century.

We now have all the pieces in place to evaluate the causal relationship between the degree of innovation at the U.S. county level and electoral support for Trumpism. That is precisely what we do in the next chapter for the 2016 presidential election. In Chapter 8, we repeat that exercise for the 2020 presidential election, while also looking at financial support for both of his presidential campaigns.

7. The Causal Relationship Between Innovation and Trumpism, 2016

This chapter systematically evaluates the relationship between innovation and Trumpism at the U.S. county level during the 2016 presidential elections; a similar analysis of the 2020 elections follows in Chapter 8. To investigate whether it indeed runs from more local innovation to less local electoral support for Trump, we explore a series of IV-2SLS regressions. That allows us to isolate the causal effect made by spatially concentrated innovation. Following the previous chapter, we instrument Patents Per Capita with Precipitation and Temperature and their interaction (all measured in 1900) and log(Population Density), measured in 1900. The latter helps us isolate reasons other than a temperate climate for innovation clustering during America's industrialization, such as larger labor and consumer markets (Khalifa 2022: 29).

7.1 Econometric Strategy

To assess the causal spatial relationship between innovation and electoral support for Trump, we first revisit Table 7.1, Column 1, which reports the bivariate, OLS relationship between log(Patents Per Capita, in 2000) and Trumpism. We remind readers that we first introduced this regression in the previous chapter. Increasing Per Capita Patents by 1 percent maps onto a decrease in Trumpism of 1.19 percentage points (p-value < .001).[80] How can we ascertain whether this correlation is a causal one?

[80] There are 189 counties missing Per Capita Patents observations compared to the data coverage for Trumpism (6% of observations). Texas accounts for a relatively large number: we lack data on this variable for 40 Texan counties. We note, however, that the results hold if we omit Texas from the analyses or if we interpolate the missing values in different ways, including coding them as 0s. If we treat these missing observations as 0s and rerun the regression represented by Table 7.1, Column 1, we obtain essentially the same coefficient on innovation, albeit with an even stronger t-statistic (4.93 for 3,104 observations versus 4.79 for 2,918 observations). Moreover, the mean and median for Trumpism is essentially the same across both the uncensored sample and the sample for which we are not missing patent observations.

We can proceed in several steps. As a first step, we can do so by estimating IV-2SLS models that are conducted in two stages. As a second step, we can conduct diagnostics that increase our confidence that the instruments are orthogonal to the error term. As a third step, we can rule out violations of the exclusion restriction by controlling for several alternative pathways through which our instruments might influence Trump's electoral appeal in both 2016 and 2020.

We begin by describing the structure of our IV-2SLS models and introduce and explain both our IV diagnostics and direct tests of whether the exclusion restriction is satisfied further ahead, within the context of our discussion of our statistical results. The first stage estimates the determinants of log(Per Capita Patents) using excluded instruments. The second stage estimates the determinants of Trumpism. We follow Autor et al. (2020) and both cluster the standard errors by commuting zone (addressing spatial correlation between counties in encompassing metro areas) and weigh the observations by counties' total votes in the 2000 presidential election.[81] For the second stage regression, the most important thing to note is whether the predicted values of Per Capita Patents calculated from the first stage regression explain the variation in Trumpism.

The first stage regression of our unrestricted IV- 2SLS model is:

$$y_i = \alpha_j + \beta \boldsymbol{X}_i + \xi(\phi_i + \lambda_i + \phi_i \times \lambda_i) + \pi(\psi_i) + u_i \tag{1}$$

Here, y_i is the estimated value of log(Patents per Capita) for county i; α_j identifies invariant state fixed effects potentially correlated with $\boldsymbol{X}$, a vector of k explanatory variables in 2000 associated

[81] The results are robust to an IV-2SLS approach that clusters the standard errors by state, as well as an OLS approach that applies the spatial correction pioneered by Conley (1999). Using that approach, we experimented with different thresholds where the error term of each county was assumed to be correlated with those of all other counties located within a radius of different distances: 50 km, 100 km, 200 km, and 500 km. This meant constructing a binary variance covariance matrix with county-pairs coded as a "1" for the two counties located within the distance threshold and "0" otherwise. We also tried specifications with a distance linear decay function by applying weights in the matrix that linearly decrease as distance increases: near counties received values close to one and counties close to the distance cutoff received zeroes.

with β estimated parameters; ξ are estimates associated with ϕ_i, county Temperature in 1900, λ_i, county Precipitation in 1900, and their interaction; π are estimates of ψ_i, county Population Density in 1900 (in logs); and u_i is an error term.

The second-stage of the unrestricted model is:

$$y_i = \alpha_j + \beta \boldsymbol{X}_i + u_i \qquad (2)$$

Here, y_i is the estimated value of Trumpism for county i; α_j addresses invariant state fixed effects potentially correlated with $\boldsymbol{X}$, a vector of k explanatory variables that includes the predicted values of Patents Per Capita produced by equation (1); β are estimated parameters; and u_i is an error term.

7.2 Stepwise Regression Approach

Before estimating the unrestricted IV-2SLS model in Table 7.1, Column 8, we discuss several simpler models. We proceed in a stepwise fashion.

In Column 2a, we report the first stage regression results of our first IV-2SLS regression: we introduce a simple version of equation (1) that excludes control variables and state fixed effects. That is, we instrument log(Patents Per Capita) with Temperature, Precipitation and Population Density, all measured in 1900. In Column 2b, we report the second stage results. The only variable in that equation (equation 2) is the estimate (predicted values) of log(Per Capita Patents) generated by the first stage regression (equation 1).

Column 2a corroborates our expectations for the first stage regression.[82]

[82] In terms of the strength of our instruments, we note that for the first stage regression, the Partial R-squared is .05 and the F-statistic is 8.74, just shy of the threshold (10.0) for "reliable" instruments put forth by Stock, Wright, and Yogo (2002). However, Column 9 reports regression results for our unrestricted model from a limited information maximum likelihood estimator (LIML) in which our main findings are materially unchanged (compared to Column 8, an IV-2SLS regression for the same model). The LIML is a linear combination of OLS and IV-2SLS estimates, with the weights (approximately) eliminating any bias introduced by an IV-2SLS regression with weak instruments (see Hahn and Hausman 2003). Moreover, the F-statistic for

First, there is a positive relationship between a temperate climate and innovation: The interaction between Temperature and Precipitation is negative (p-value = .002); the effect of increased rainfall on Patents Per Capita in 2000 is positive only at relatively low to moderate temperatures. Increasing precipitation by 1 inch at an average temperature of 33.7 degrees in 1900 increases patents per person in 2000 by almost 5% (statistically significant at the 95 percent level); once average temperature crosses 55 degrees, however, the relationship between more rainfall and innovation turns negative (statistically significant at the 95% level). For example, at the highest average temperature, 74.8 degrees, a 1-inch increase in precipitation decreases patents per capita by 7% (statistically significant at the 95% level).[83]

Second, greater population density in the past maps onto greater innovation. Increasing population density by 1% in 1900 leads to a 32% increase in patents per capita in 2000 (p-value < .001).

Column 2b corroborates our expectations for the second stage regression. Innovation leads to less Trumpism: increasing log(Patents Per Capita) by 1% decreases Trump's share of the 2016 two-party presidential vote by 2.22 percentage points vis-a-vis Bush's vote share in 2000 (p-value = .001). The r-squared of that bivariate regression is .06.

---

that first stage regression is 9.7. We also note that the results are materially similar if we instead run an IV-2SLS for the unrestricted model that treats log(Patents Per Capita) as exogenous–does not include any instruments for it in the first stage regression.

[83] Consider three tropical states that fit that bill: Florida, Louisiana, and Alabama. Florida's annual rainfall in 1900 was 63 inches and its average temperature was 70 degrees; Louisiana's annual rainfall in 1900 was 65.5 inches and its average temperature was 67 degrees; Alabama's annual rainfall in 1900 was 67.5 inches and average temperature iwas 63.6 degrees. All of these readings are well above the mean and median values for both Precipitation and Temperature. Compared to the average for U.S. states in 2000, which was 0.14 per thousand people, Florida's patents per capita that year were 0.12, Louisiana's 0.07, and Alabama's 0.07.

Table 7.1 The Determinants of Trumpism and Justifying the Instrumental Variables

PANEL A

	(1)	(2a)	(2b)	(3)	(4)
Dependent Variable	*TRUMPISM*	*log(Patents P.C.)*	*TRUMPISM*	*log(Biomass)*	*TRUMPISM*
Estimation Strategy	OLS	IV (Stage 1)	IV (Stage 2)	OLS	IV (Stage 2)
log(Patents Per Capita, 2000)	**-1.193*** **		**-2.219*** **		**-2.315 *** **
	[0.081]		**[0.647]**		**[0.646]**
Temperature		0.071**		0.106***	
		[0.029]		[0.027]	
Precipitation		0.132***		0.119***	
		[0.465]		[0.437]	
Temperature X Precipitation		-0.003***		-0.003***	
		[0.002]		[0.001]	
Population Density 1900		0.319***		0.138***	
		[0.067]		[0.040]	
China Trade Shock					2.072***
					[0.882]
Shift Share Instrument	NO	NO	NO	NO	NO
State Fixed Effects	NO	NO	NO	NO	NO
Autor et al. 2020 Controls	NO	NO	NO	NO	NO
Additional Controls	NO	NO	NO	NO	NO
Observations	2,918	2,660	2,660	2,812	2,660

PANEL B

	(5)	(6)	(7)	(8)	(9)
Dependent Variable	*TRUMPISM*	*TRUMPISM*	*TRUMPISM*	*TRUMPISM*	*TRUMPISM*
Estimation Strategy	IV (Stage 2)	IV (Stage 2)	IV (Stage 2)	IV (Stage 2)	LIML (Stage 2)
log(Patents Per Capita, 2000)	**-2.384*** **	**-6.097*** **	**-2.177*** **	**-2.566*** **	**-4.798*** **
	[0.667]	**[1.145]**	**[0 .675]**	**[0 .641]**	**[1.759]**
China Trade Shock	3.485***	3.001***	1.634	1.316	1.407
	[1.185]	[1.168]	[1.267]	[1.305]	[2.060]
Shift Share Instrument	YES	YES	YES	YES	YES
State Fixed Effects	NO	YES	YES	YES	YES
Autor et al. 2020 Controls	NO	NO	YES	YES	YES
Additional Controls	NO	NO	NO	YES	YES
Observations	2,660	2,660	2,660	2,653	2,653

Notes: Significant at the .01 level (***); significant at the .05 level (**); significant at the .10 level (*). Following Autor et al. (2020), we calculate "Trumpism" by subtracting the two-party Republican vote share in 2000 from the two-party Republican vote share in 2016. Like they do, we exclude Alaska and Hawaii because of missing data. We estimate, but do not report, several first stage regression results for most of the 2SLS models, including both the IV and LIML estimators. We cluster the standard errors across all models by commuting zone and weigh the observations by counties' total votes in the 2000 presidential election. See text for what variables are included in both the "Autor et al. 2020 Controls" and "Additional Controls."

We now review the results of an OLS model that suggests that the mechanism behind our causal identification strategy is sound. The dependent variable in Column 3 is log(Biomass), measured in 2012.[84] The independent variables are Temperature, Precipitation, their interaction, and Population Density, all measured in 1900. First, there is a positive relationship between a temperate climate and biomass. As in the first stage regression of the IV-2SLS model reported in Column 2a, where the dependent variable is log(Patents Per Capita) measured in 2000, the interaction between Temperature and Precipitation is negative (p-value = .002); the effect of increased rainfall on log(Biomass) is positive only at relatively low to moderate temperatures. Second, greater population density in the past maps onto greater biomass today. Increasing population density by 1% in 1900 leads to a 14% increase in biomass in 2012 (p-value = .001).

Might it be the case that our exclusion restrictions are not satisfied, however? In the remainder of this section, we experiment with a variety of diagnostics and alternative specifications to ascertain if this is the case. That includes diagnostics that can help us establish whether the instrumental variables are indeed exogenous (uncorrelated with the error term) and work exclusively through local levels of innovation. It also includes introducing a host of control variables and state fixed effects. Some of these controls are potential confounders that may be correlated with patents per capita and some of them are potential alternative pathways connecting our demographic, geographic, and climactic instruments to electoral support for Trump in 2016.

[84] The results reported in Column 4 hold if we instead measure biomass as log(Biomass/Surface Area).

As a first step, we turn to a Plausibly Exogenous Instrument Test (see Conley, Hansen, and Rosen 2012). This test is performed on a reduced form equation that includes both our measure of innovation and our instruments for innovation simultaneously; formally speaking, the equation is represented by $y_i = \beta X_i + \xi(\phi_i + \lambda_i + \phi_i \times \lambda_i) + \pi(\psi_i) + u_i$ (3)

Here, y_i is the value of Trumpism for county i; X_i is log(Patents Per Capita) for country i; ξ are estimates associated with ϕ_i, county Temperature in 1900, λ_i, county Precipitation in 1900, and their interaction; π are estimates of ψ_i, county Population Density in 1900 (in logs); and u_i is an error term. We assume that X_i are potentially endogenous and ϕ_i, λ_i , $\phi_i \times \lambda_i$, and ψ_i are instruments uncorrelated with u_i.

We therefore test that assumption using the Plausibly Exogenous Instrument Test. To understand its logic, consider that when the X_i's in equation (3) are endogenous, β and ξ and π are not jointly identified, so prior information about ξ and π are used to estimate β. The IV-2SLS exclusion restriction is that ξ and π are equal to zero in this equation since X_i is included. When we impose the restriction that the coefficients on the instruments are zero using the Plausibly Exogenous Instrument Test with 95% confidence intervals and robust standard errors clustered by commuting zone, the bounds covering the coefficient on log(Patents Per Capita) tightly overlap with those obtained when we use the regular IV-2SLS approach. While the coefficient returned for this variable in Column 2b is -2.219, with -3.488 and -.950 confidence intervals (95%), the interval estimates for β using the Plausibly Exogenous Instrument Test are -2.744 and -1.694. This strongly suggests that the exclusion restriction is satisfied.

To ensure that this inference is not driven by the idiosyncrasies of the Plausibly Exogenous Instrument Test, we now turn to the Imperfect Instrument Test developed by Nevo and Rosen (2012). We now assume that X_i are potentially endogenous and ϕ_i, λ_i , $\phi_i \times \lambda_i$, and ψ_i

are instruments that are correlated with u_i. We further assume that the correlation between ϕ_i, λ_i, $\phi_i \times \lambda_i$, and ψ_i and u_i has the same sign as the correlation between X_i and u_i and that the instrumental variables are less correlated with the error term than is log(Patents Per Capita). Under these assumptions, the Imperfect Instrument Test calculates both lower and upper estimate bounds for β.[85] If we estimate those bounds using the Imperfect Instrument Test with bootstrapped standard errors, we obtain bounds for the log(Per Capita Patent) coefficient between -2.648 and -.676, with confidence intervals between -5.705 and -.558. If we compare this with the coefficient returned for this variable in Column 2b, which is -2.219, with -3.488 and -.950 confidence intervals (95%), this strongly vindicates the original IV-2SLS estimates.

What if we were to conservatively discount the IV-2SLS diagnostics we just reported for the simple, bivariate IV-2SLS regression and consider whether omitted variables may confound the negative relationship between innovation and Trumpism represented by Column 2b? We now turn to a series of less restrictive IV-2SLS specifications to address this possibility. These are reported in the rest of Table 8.1., where we report the second stage results of various models.

First, we consider that Autor et al. (2020) argue that increased (local) import competition from China after 2000 explains greater support for Trump during the 2016 elections. It may be the case that more innovation in 2000 unduly proxies for a smaller Chinese trade shock. To find out if this is true, in Column 4 we control for the county level change in Chinese import exposure

[85] Nevo and Rosen (2012) argue that to obtain two-sided bounds on the endogenous regressor's coefficient they need to make two straightforward assumptions. First, stronger restrictions on the correlation of the observables than the conventional IV-2SLS approach, as well as a weaker assumption about the unobservables than that approach (a non-zero correlation between the instruments and the error term). Second, the correlation between the instrumental variables and the error term must be assumed less than the correlation between the endogenous variable and the error term, which is itself implied by an IV-2SLS approach over an OLS approach. This then allows them to set boundaries for the degree of correlation between the instrumental variables and the error term between 0 and the actual correlation of the endogenous regressor and the error term.

per worker between 2000 and 2008. This is how Autor et al. (2020) measure the so-called Chinese Trade Shock; they argue this captures the extent to which local labor markets were faced with competition from Chinese imports during this period.[86] Compared to the bivariate specification in Column 2b (the second stage regression of our initial IV-2SL model), our substantive and statistical results strengthen somewhat. The localized China Trade Shock variable is, as in Autor et al. (2020), positive and statistically significant. Its point estimate (2.072; p-value = 0.02) suggests that an interquartile range change (of 0.567) in this variable increases Trumpism by 1.18 percentage points.[87]

What happens if, as Autor et al. (2020) do, we instrument localized China Trade Shock with a so-called shift-share instrument in the first stage regression? The latter is constructed by the authors as the initial shares of employment in a given location and industry multiplied by the growth of Chinese imports in eight developed countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) during the same time window.[88] According to Autor et al. (2020), this approach captures the exogenous variation in Chinese import exposure per worker (isolates the portion of U.S. county growth in Chinese imports driven by increased competitiveness: excludes the share driven by idiosyncratic increases in import demand).

[86] Specifically, the authors estimate the change in ad valorem U.S. imports from China within a given locality in real dollars and then divide this value by the number of workers in each location. They use trade data from the UN Comtrade dataset, obtaining the dollar value of net imports across different industries. They aggregate industry imports to the commuting zone level, and ultimately the county, according to industries' local share of national employment. They then divide by the total workers in a location, which they estimate by aggregating up industry wide data on employment to commuting zones and then counties.

[87] To obtain this result we performed the following calculation: 2.072 x 0.567.

[88] Autor et al. (2020) document that all eight comparison countries experienced import growth from China in 343 of 397 four-digit SIC manufacturing industries and that import patterns across these countries' industries are highly correlated with the patterns in U.S. industries. Autor et al. (2020) use bilateral trade data from the UN Comtrade Database to calculate U.S. import values, which they convert to real dollars, and crosswalk this information to four-digit SIC industries. As with their China Shock variable, they measure employment by industry at the commuting zone.

Column 5 reveals that this experiment produces materially similar results. Patents Per Capita's predictive value is now stronger, in both substantive and statistical terms. As expected, the China Trade Shock variable also strengthens once we isolate its exogenous variation: the coefficient increases by 67 percent. Therefore, in the regressions that follow, we continue to control for Chinese import exposure per worker instrumented with its shift-share in the ensuing first stage regressions (see equation 1). For now, we surmise that, while there may be a strong, positive relationship between exposure to increased Chinese imports after 2000 and Trumpism in 2016, there is also a strong, negative relationship between innovation and Trumpism.

Of course, our results may still be affected by omitted variable bias if our exclusion restrictions are not satisfied: our instruments are not fully orthogonal to the error term in equation (1). For that reason, in Column 6 we introduce state fixed effects. These capture the state-invariant, unobserved heterogeneity that is correlated with both Patents Per Capita in 2000 and Trumpism. While our results are much stronger, experiencing a three-fold rise in magnitude (increasing patents per capita by 1 percent engenders a 6.1 percentage point decrease in the Republican two-party vote share in 2016 versus 2000; p-value < .001), localized China Trade Shock remains positive and statistically significant (p-value = .01).

We now go further. Following Autor et al. (2020), in Column 7 we add a host of county-level controls (see Table 5 of that paper for the authors' full explanation and sources). First, industry and occupation controls: employment in the manufacturing sector; the share of occupations that involve routinized work (and can be potentially automated); the share of occupations that can be outsourced overseas. Second, census division dummies. Third, demographic controls that measure the share of the population across different age groups, races, gender, education levels, and immigration status (all these are measured in 2000). Finally, election controls that measure the Republican two-party vote share in the 1992 and 1996 presidential elections. While the substantive effect of Patents Per Capita is weakened, it is still statistically significant at the highest possible level; meanwhile, localized China Trade Shock is no longer statistically significant at conventional levels.[89]

Column 8 is our unrestricted model. It introduces yet more county-level variables beyond those included in Autor et al. (2020). We add log(Real Median Income Per Capita) in 1999 from the 2000 census. We also add the Unemployment Rate in 2000 from the USDA Economic Research Service. Finally, we also control for how rural a location is using Waldorf and Kim's (2015) Rurality Index. This specification is quite taxing, as more rural, less educated, and whiter voters have been increasingly left behind, both technologically and economically (Rodden, 2019). They may also be more likely to support Trumpism. Introducing these controls strengthens the substantive and statistical significance of our results, however, and does not materially change the impact made by localized China trade shocks.

Column 9 addresses the possibility that the instruments for log(Patents Per Capita) contained across the first stage regressions in the IV-2SLS specifications (equation 1) are weak. It reports the regression results from an LIML estimator, a linear combination of OLS and IV-2SLS estimates, with the weights (approximately) eliminating any bias introduced by an IV-2SLS regression run with weak instruments (see Hahn and Hausman 2003); the model is otherwise identical in terms of the variables included in Column 8. Compared to Column 8, Patents Per Capita is considerably stronger in both a substantive and statistical sense.

[89] These results hold after introducing interaction terms between the localized China Trade Shock variable and variables theorized by some researchers to condition its impact on support for Trumpism. First, the percent of the population that is white. Second, the percent of the population that is college educated. Third, whether the county is in the so-called Rust Belt. Third, a triple interaction term between China Trade Shock, Percent White, and Percent College Educated.

7.3 Robustness to Potential Violations of the Exclusion Restriction

This section and its accompanying regression table, Table 7.2, now evaluate potential violations of the exclusion restriction directly. We control for several alternative pathways through which our instruments might influence Trump's electoral appeal in both 2016 and 2020.

There are several potential channels through which a location's past climate, geography, and demography may have affected politics today beyond their impact on contemporary levels of innovation. First, these factor endowments may have influenced the demographic, attitudinal, and ideological makeup of different areas through sorting. More progressive people might live in denser places (Bishop 2009; Rodden, 2019) and have voted against Trump. Similarly, climate, geography, and demography in the past may have influenced where universities are located, and those institutions of higher education may have shaped political attitudes, with more liberal minded individuals drawn to colleges voting against Trump. Alternatively, these factor endowments might influence today's climate or susceptibility to meteorological events; voters who reside in hotter or more humid places, which may also experience more climate extremes, may care more about climate change, which may also translate into less support for Trump. Finally, it might be the case that past climate, geography, and demography drive the presence of capital intensive and technologically advanced manufacturing that makes greater use of industrial robots; in turn, higher levels of automation may explain support for Trump.

To remind readers, one of our instrumental variables (see equation 2) is Population Density in 1900. Therefore, Column 1 (in Table 7.2) is an IV-2SLS regression that is identical to Column 8, Table 7.1, except that it includes population density measured in 2000, which is from

Table 7.2 The Determinants of Trumpism and Direct Tests of the Exclusion Restriction

PANEL A

	(1)	(2)	(3)	(4)	(5)
Estimation Strategy	IV(State 2)	IV (Stage 2)	IV (Stage 2)	IV(Stage 2)	IV (Stage 2)
log(Patents Per Capita, 2000)	**-2.74*** **	**-2.442*** **	**-2.614*** **	**-2.625*** **	**-2.0*** **
	[0.858]	**[0.630]**	**[0.612]**	**[0.631]**	**[0.663]**
Population Density in 2000	YES	NO	NO	NO	NO
Evangelical Adherents P.C.	NO	YES	NO	NO	NO
College Density	NO	NO	YES	NO	NO
Higher Education Enrollment	NO	NO	NO	YES	NO
Climate Change Happening	NO	NO	NO	NO	YES
Climate Change Experience	NO	NO	NO	NO	NO
Robot Exposure	NO	NO	NO	NO	NO
Automation Risk	NO	NO	NO	NO	NO
Shift Share Instrument Trade	YES	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES	YES
Autor et al. 2020 Controls	YES	YES	YES	YES	YES
Additional Controls	YES	YES	YES	YES	YES
Shift Share Instrument Robots	NO	NO	NO	NO	NO
Observations	2,653	2,653	2,653	2,653	2,653

PANEL B

	(6)	(7)	(8)	(9)	(10)
Estimation Strategy	IV (Stage 2)	IV (Stage 2)	IV (Stage 2)	IV (Stage 2)	IV (Stage 2)
log(Patents Per Capita, 2000)	**-1.577*** **	**-2.675*** **	**-2.791*** **	**-2.47*** **	**-2.221*** **
	[0.614]	**[0.648]**	**[0.661]**	**[0.622]**	**[0.881]**
Population Density in 2000	NO	NO	NO	NO	YES
Evangelical Adherents P.C.	NO	NO	NO	NO	YES
College Density	NO	NO	NO	NO	YES
Higher Education Enrollment	NO	NO	NO	NO	YES
Climate Change Happening	NO	NO	NO	NO	YES
Climate Change Experience	YES	NO	NO	NO	YES
Robot Exposure	NO	YES	YES	NO	YES
Automation Risk	NO	NO	NO	YES	YES
Shift Share Instrument Trade	YES	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES	YES
Autor et al. 2020 Controls	YES	YES	YES	YES	YES
Additional Controls	YES	YES	YES	YES	YES
Shift Share Instrument Robots	NO	NO	YES	NO	YES
Observations	2,653	2,653	2,653	2,621	2,653

Notes: Significant at the .01 level (***); significant at the .05 level (**); significant at the .10 level (*). Following Autor et al. (2020), we calculate "Trumpism" by subtracting the two-party Republican vote share in 2000 from the two-party Republican vote share in 2016. Like they do, we exclude Alaska and Hawaii because of missing data. We estimate, but do not report, several first stage regression results for the IV-2SLS models. We cluster the standard errors across all models by commuting zone and weigh the observations by counties' total votes in the 2000 presidential election. See text for what variables are included in both the "Autor et al. 2020 Controls" and "Additional Controls."

the U.S. Census 2000. The logic is that whatever past conditions influenced population density in the past might reasonably also predict population density today. Thus, our instrument might work through population density today, which might be correlated with electoral outcomes for reasons unrelated to innovation. More progressive people may both flock to urban areas or the denizens of dense cities may become more liberal over time. Column 1 reveals that when controlling for population density in 2000, however, the coefficient on log(Patents Per Capita) is stronger, it is now -2.74 (p-value = 0.001) compared to -2.566 in Model 8 (Table 7.1).

Column 2 is an IV-2SLS regression that is identical to Column 8, Table 7.1, except that it includes the number of evangelical adherents per capita in 2000 (from Grammich et al. 2012). The logic is that past geographic, climactic, and demographic factors may have influenced the religious beliefs and therefore ideology of individuals living in different areas of the country today. Over both colonial and U.S. history, many people of faith migrated to new places–the western frontier, for example–to either convert others, escape persecution, or develop communities of faith centered on the availability of cheap arable land, water, or other geographic and climactic features. Different areas within the U.S. also vary substantially in their diversity of different religious denominations (see Warf and Winsberg 2007).

Our instrument might thus work through the presence of evangelicals today, which might be correlated with electoral outcomes for reasons unrelated to innovation. More conservative people may seek out these communities, or the incumbent evangelicals living there already may be less liberal leaning to start with. Moreover, increased homogeneity generally may translate into more support for Trump and our measure of evangelical adherents may also capture counties' relative religious and ideological homogeneity. Column 2 reveals that when controlling for evangelical adherents per capita, however, the coefficient on log(Patents Per Capita) remains basically unchanged, it is now -2.442 (p-value < 0.001) compared to -2.566 in Model 8 (Table 7.1).

Column 3 is an IV-2SLS regression that is identical to Column 8, Table 7.1, except that it includes College Density, the number of higher education institutions per square mile of a county's surface area (from IPEDS 2021). The logic is that because past geographic, climactic, and demographic conditions influenced the location of early mining activity, agriculture, and industrialization, they may have also determined where institutions of higher education were founded and survived (see Goldin and Katz 2008). In turn, institutions of higher education may explain political attitudes today: more liberal minded individuals who are drawn to colleges or who work in colleges or choose to live in college towns voting against Trump. Column 3 reveals that when controlling for College Density, however, the coefficient on log(Patents Per Capita) remains materially unchanged, it is now -2.614 (p-value < 0.001) compared to -2.566 in Model 8 (Table 7.1).

Column 4 is an IV-2SLS regression that is identical to Column 8, Table 7.1, except that it includes Higher Education Enrollment, the number of people enrolled in higher education in 2000, which includes both college and postgraduate students (from the U.S. Census 2000). While the logic of including this variable in the model is essentially the same as in Column 3, it could be the case that College Density have not fully captured the extent to which past geographic, climactic, and demographic factors may have influenced the sheer magnitude of the influence made by college and postgraduate students in a community. One big state college in a locality may fail to impact our measure of College Density, but its sizable student body may nonetheless represent an outsized proportion of county residents. Column 4 reveals that when controlling for Higher Education Enrollment, however, the coefficient on log(Patents Per Capita) remains materially unchanged, it is now -2.625 (p-value < 0.001) compared to -2.566 in Model 8 (Table 7.1).

Column 5 is an IV-2SLS regression that is identical to Column 8, Table 7.1, except that it includes Climate Change Happening, the estimated number of people in a county strongly agreeing with the notion that Climate Change is happening in 2021 (from Howe et al. 2015). The logic is that past climate, geography, and demography plausibly influences today's climate or susceptibility to meteorological events. Places that are hotter, or more humid, or that experience more climate extremes, may increase voters' concerns over climate change. For example, residents of coastal regions may be more aware of the destructive impact of storms like 2012's Superstorm Sandy or worsening beach erosion. In turn, climate change may be more politically salient and may translate into less support for Trump. In other words, to address the possibility that our instruments work through contemporary attitudes about climate change to explain variation in support for Trump, we control for climate change attitudes. Column 5 reveals that when controlling for Climate Change Happening, however, the coefficient on log(Patents Per Capita) only somewhat weakens, it is now -2.0 (p-value = 0.03) compared to -2.566 in Model 8 (Table 7.1).

Column 6 is an IV-2SLS regression that is identical to Table 7.1 Column 8, except that it includes Climate Change Experience, the estimated number of people in a county who strongly agree that they have personally experienced the effects of climate change (from Howe et al., 2015). While the logic of including this variable in the model is essentially the same as in Column 5, it could be the case that Climate Change Happening does not fully capture the extent to which past geographic, climactic, and demographic factors may have influenced the political salience of climate change for residents living in specific U.S. locations more susceptible to the negative consequences of climate change. Column 6 reveals that when controlling for Climate Change Experience, the coefficient on log(Patents Per Capita) weakens, it is now -1.576 (p-value = 0.01) compared to -2.566 in Model 8 (Table 7.1).[90]

Column 7 is an IV-2SLS regression that is identical to Column 8, Table 7.1, except that it includes Robot Exposure, the average change in the local industry-level penetration of industrial robots between 2004-2010. This variable is based on the share of national employment according to 1990 Community Business Pattern industry data (and is from Acemoglu and Restrepo 2020). The logic is that past geographic, climactic, and demographic conditions influenced the degree of automation in recent time periods by predisposing some places to greater degrees of capital-intensive industrialization and, in particular, technologically advanced manufacturing; in turn, higher levels of automation may explain support for Trump (Frey, Berger, and Chen 2018). Column 7 reveals that when controlling for Robot Exposure, however, the coefficient on log(Patents Per Capita) strengthens, it is now -2.675 (p-value < 0.001) compared to -2.566 in Model 8 (Table 7.1).

What happens if, as Frey, Berger, and Chen (2018) do, we instrument Robot Exposure with a so-called shift-share instrument in the first stage regression? These authors use data on the

[90] The results of this experiment are robust to including any of the other variables on climate change opinions from Howe et al. (2015) dataset instead of Climate Change Happening or Climate Change Experience. Namely, log(Patents Per Capita) remains substantively and statistically significant in the second stage of the IV-2SLS model no matter what survey question we add to the regression.

change in penetration of industrial robots in 10 European countries based on industries' share of national employment according to 1980 Community Business Pattern industry data (and is from Acemoglu and Restrepo 2020) during the same time window as Robot Exposure. According to the authors and Acemoglu and Restrepo (2020), this approach captures the exogenous variation in automation per worker (isolates the portion of U.S. county growth in automation driven by increased technological innovation generally and excludes the share driven by idiosyncratic increases in the demand for robots). [91]

Column 8 is an IV-2SLS regression that is identical to Column 8, Table 7.1, except that it includes Robot Exposure instrumented by the variable described above, Robust Exposure European Analogs (we match the Robot Exposure window and measure this between 2004 and 2010). Column 8 reveals that this way of accounting for the potential endogeneity of automation strengthens the main results: the coefficient on log(Patents Per Capita) is now -2.790 (p-value < 0.001) compared to -2.566 in Model 8 (Table 7.1).

Might it be that we have mismeasured the risk of automation and thus discounted the possibility that our own instrumental variables, which we argue capture the exogenous variation in local innovation, potentially work instead through increased automation in both goods and services to affect electoral support for Trump in 2016? The exposure to industrial robots may not

[91] Acemoglu and Restrepo (2020) use estimates on the average penetration of industrial robots across industries in Denmark, Finland, France, Italy, and Sweden, which were ahead of the U.S. in the use of industrial robots. This allows them to obtain an estimate of the global technology advances available to U.S. producers prior to widespread U.S. adoption, and thus not influenced by idiosyncratic U.S. factors. They use Community Business Patterns data for 1980 (which was prior to the introduction of industrial robots) to obtain data on employment patterns across U.S. commuting zones, allowing them to estimate the change in exposure to industrial robots based on analogous European industries. We crosswalk these values calculated at the commuting zone to the county level.

fully capture the extent to which voters might have been or fear of being exposed to automation and thus throw their support behind Trump in 2016 (Frey, Berger, and Chen, 2018).

Column 9 is an IV-2SLS regression that is identical to Column 8, Table 7.1, except that it includes Automation Risk, an estimate of the percentage of jobs at the county level that could be automated in 2015. This measure is based on 2015 data on county-level industry employment, drawing from the American Community Survey, together with estimates of the percentage of automatable jobs within different industries from Muro et al (2019).[92] Column 9 reveals that when controlling for Automation Risk, however, the coefficient on log(Patents Per Capita) is -2.47 (p-value < 0.001) compared to -2.566 in Model 8 (Table 7.1).

Column 10 is an unrestricted IV-2SLS model that simultaneously includes all of the potential alternative channels by which our demographic, geographic and climactic instruments may influence electoral support for Trump in 2016 that we outlined above. We return to using Robot Exposure instrumented with Robot Exposure European Analogs. Like Column 8, Table 7.1, this specification also includes state fixed effects and the numerous additional variables included in that specification: the Autor et al. (2020) China Shock variable instrumented with the initial shares of employment in a given location and industry multiplied by the growth of Chinese imports in eight developed countries during the same time window, their suite of controls, and the additional control variables we introduced, including log(Real Median Income Per Capita), the Unemployment Rate, and the Rurality Index.

---

[92] The American Community Survey provides estimates for the county-level employment across NAICS industry categories in 2015, which we multiply by the percentage of jobs at risk of automation according to Muro et al (2019). This allows us to create an average of the number of jobs at risk in a given county based on their employment across different industries. To create Automation Risk, we calculate the average percentage of jobs at risk across all industries at the county level.

Column 10 reveals that despite unrestricting the model to include all of these additional variables, the coefficient on log(Patents Per Capita) is -2.221 (p-value = 0.01) compared to -2.566 in Model 8 (Table 7.1). These results are almost identical to our baseline, bivariate instrument specification results in column 2.b, table 7.1 (-2.219; p-value = 0.001).

7.3 Robustness to Innovation Measure and Trumpism Measure

Are our results robust to how we measure innovation? Table 7.3, Columns 1 to 3, includes several robustness tests to find out using the IV-2SLS framework and specification reported in Table 7.1, Column 8: that is, including the same instrumental variables in the first stage regression, the shift-share instrument for China Trade Shock, state fixed effects, and the same control variables. In Column 1, rather than measure the level of patents per capita in 2000, we use patents per capita in 2008.[93] Increasing patents per capita by 1 percentage point during this window leads to a decrease in Trumpism of 2.6 percentage points (p-value < .001). In Column 2, we measure innovation as log(Patents Per Capita in 1990); increasing patents per capita by 1% that year leads to a decrease of 2.3 percentage points (p-value < .001) in the two-party vote share for Trump in 2016 versus Bush in 2000. In Column 3, we instead use log(Patents Per Capita in 1930); increasing patents per capita by 1% that leads to a decrease of 5.5 percentage points (p-value = .002) in Trumpism.

Are our results robust to the way we measure Trumpism? To find out, Table 7.3, Columns 4 to 6, includes a number of robustness tests using the IV-2SLS framework and unrestricted specification reported in Table 7.1, Column 8. We now return to using log(Patents Per Capita in 2000) to measure innovation. In Column 4, rather than measure Trumpism as the two-party vote share for Trump in 2016 versus Bush in 2000, we measure it as the vote share for

[93] While the minimum value for this variable is -100, the mean is -19.7, the maximum is 1,594, and the standard deviation is 77.6.

Table 7.3 The Determinants of Trumpism: Additional Robustness Tests

PANEL A

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	*Trump vs. Bush 2000*	*Trump vs. Bush 2000*	*Trump vs. Bush 2000*	*Trump vs. Bush 2004*	*Trump vs. McCain 2008*
Patent Measurement	Patents P.C., 2008	Patents P.C., 1990	Patents P.C., 1930	Patents P.C., 2000	Patents P.C., 2000
Sample	Full	Full	Full	Full	Full
Per Capita Patents	**-2.564*** **	**-3.253*** **	**-5.477*** **	**-0.018*** **	**-0.009*** **
	[0.662]	**[1.488]**	**[1.758]**	**[0.006]**	**[0.004]**
China Trade Shock	2.649	-0.319	-0.226	0.016*	0.009
	[1.669]	[1.391]	[1.547]	[0.009]	[0.006]
Shift Share Instrument	YES	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES	YES
Autor et al. 2020 Controls	YES	YES	YES	YES	YES
Additional Controls	YES	YES	YES	YES	YES
Observations	2,653	2,787	1,607	2,630	2,628

PANEL B

	(6)	(7)	(8)	(9)	(10)
Dependent Variable	*Trump vs. Romney 2012*	*Trump vs. Bush 2000*	*Trump vs. Bush 2000*	*Trump vs. Bush 2000*	*Trump vs. Bush 2000*
Patent Measurement	Patents P.C., 2000	Patents P.C., 2000	Patents P.C., 2000	Patents P.C., 2000	Patents P.C., 2000
Sample	Full	Excluding Silicon Valley	Excluding Route 128	Excluding N.C. Res. Tri.	Excluding all big clusters
Per Capita Patents	**-0.011*** **	**-3.069*** **	**-2.561*** **	**-2.539*** **	**-3.012*** **
	[0.004]	**[0.873]**	**[0.643]**	**[0.639]**	**[0.869]**
China Trade Shock	0.009	0.644	1.297	1.378	0.744
	[0.007]	[1.406]	[1.302]	[1.267]	[1.364]
Shift Share Instrument	YES	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES	YES
Autor et al. 2020 Controls	YES	YES	YES	YES	YES
Additional Controls	YES	YES	NO	YES	YES
Observations	2,630	2,648	2,650	2,646	2,638

Notes: Significant at the .01 level (***); significant at the .05 level (**); significant at the .10 level (*). Following Autor et al. (2020), we calculate "Trumpism" by subtracting the two-party Republican vote share in 2000 from the two-party Republican vote share in different years. We exclude Alaska and Hawaii because of missing data. The patent per capita measures are logged. We estimate, but do not report, first stage regression results for each of these IV-2SLS models: the excluded instruments are Temperature, Precipitation, their interaction, and log(Population Density), all measured in 1900. We cluster the standard errors across all models by commuting zone and weigh the observations by counties' total votes in the baseline, comparison presidential election. See text for what variables are included in both the "Autor et al. 2020 Controls" and "Additional Controls."

Trump versus Bush in 2004.[94] In Column 5, we measure it as the vote share for Trump versus McCain in 2008; in Column 6, as the vote share for Trump versus Romney in 2012. The results of these experiments confirm our main results: more innovation means less statistically significant support for Trumpism, no matter how we measure the latter.

7.4 Robustness to Excluding Major Innovation Clusters

Are our results robust to excluding major innovation clusters such as Silicon Valley? To find out, we return to measuring Trumpism as the two-party vote share for Trump in 2016 versus Bush in 2000 and continue to measure innovation as log(Patents Per Capita in 2000). We also continue to use the IV-2SLS framework and unrestricted specification reported in Table 7.1, Column 8. The only difference is that, in Table 7.3, Columns 7 to 10, we experiment with excluding different innovation clusters that may have exercised an outsized effect on our results hitherto from the estimation.

These geographically censored models are as follows. In Column 7, we exclude the Silicon Valley counties from the regression (Santa Clara, San Mateo, San Francisco, Alameda, and Contra Costa). In Column 8, we exclude the Route 128 counties (Norfolk, Middlesex, and Essex). In Column 9, we exclude the North Carolina Research Triangle counties (Durham, Chatham, Franklin, Vance, Wake, Orange, and Wilson). In Column 10, we exclude all of the counties that belong to these major innovation clusters simultaneously; that is, we drop Silicon Valley, Route 128, and the North Carolina Research Triangle from the regression.

Across each of these experiments, log(Patents Per Capita) remains strongly negative associated with Trumpism, both statistically and substantively. We surmise that American voters

[94] We weigh the regression by the counties' total votes in the 2004 presidential election; for the following regressions, we adjust the weights accordingly as our baseline changes; e.g., in Column 5, we weigh the regression by the counties' total votes in the 2008 presidential election.

in innovative places rejected Trump in the 2016 presidential election across the country, even outside of major technological hubs.

7.5 Taking Stock of the Empirical Results

This chapter shows that our manuscript's main finding, that more innovative counties are negatively associated with Trumpism in 2016, is both causal and resilient. It is robust to an instrumental variable approach that exploits the exogenous sources of spatial variation outlined in Chapter 6. It also holds once we control for localized China Trade Shocks after China joined the WTO in 2001, as well as instrumenting those shocks with a so-called shift-share measure of trade exposure, as Autor et al. (2020) do. It is robust to introducing state fixed effects, a host of other control variables, including demographic variables, living standards, unemployment rates, educational levels, and how rural the county is, as well as corrections for spatial correlation. It is also robust to accounting for alternative channels by which our demographic, geographic, and climactic instrumental variables may affect electoral support for Trump in 2016. These include measures of population density today, evangelical adherence per capita, college density, student enrollment in higher education, attitudes about climate change, exposure to industrial robots, and automation risk. As in the case of localized China Trade Shocks, we instrument robot exposure with a shift-share exogenous measure of robot exposure, as Frey, Berger, and Chen (2018) do.

Additionally, the regression results hold if we measure the main variables differently. First, if we operationalize innovation differently: either as the change in patents per capita between 2000 and 2008, patents per capita in 1990, or patents per capita in 1930. Second, if we compare Trump's 2016 electoral percentage versus the share earned by other GOP presidential candidates other than George W. Bush in prior election years.

Finally, the finding that more innovation maps onto less support for Trumpism is robust to whether we relegate attention to counties outside of America's most prominent innovation clusters. In short, the regression results we report in this chapter make us confident that Trump's Neo-Luddism hurt his electoral prospects in more innovative places across the U.S. during the 2016 presidential election. We now turn to investigating the innovation retarding policies Trump adopted after he assumed the presidency and what impact this had on his electoral prospects in the 2020 presidential election.

8. Innovation, President Trump, and the 2020 Elections

In this chapter, we document President Trump's track record on innovation and look at the political consequences of his policies. First, we outline his record on immigration, education, infrastructure, R&D, basic science, and other issues bearing on U.S. technological development; we also analyze their impact on innovation and the negative reaction they engendered in the high-tech community. Second, we emulate the econometric framework introduced in the previous chapter: we systematically evaluate the relationship between innovation and Trumpism at the U.S. county level in the 2020 presidential election. We again isolate the causal effect made by spatially concentrated innovation on the difference between how Trump fared versus Bush in 2000, but now measure Trumpism as Trump's presidential vote share in 2020 versus Bush's. Third, we ask: did Trump's presidency further move the political needle against him among counties that were relatively more innovative? That is to say, we alternatively capture Trumpism as the difference between Trump's 2020 and 2016 vote shares. We then evaluate whether changes in patenting between 2016 and 2020 map onto changes between presidential elections in both electoral support for Trump and financial contributions to his campaigns.

This chapter's rich qualitative and quantitative evidence confirms that, during his presidency, Trump followed through with the Neo-Luddism he espoused during the 2016 presidential campaign. He delivered on his bid to "Make America Great Again" by enacting trade protectionism, pursuing and threatening antitrust lawsuits against Big Tech firms and similar punitive measures, including flirting with rescinding Section 230 of the Communications Decency Act, and otherwise foregoing making public investments that drive innovation. Trump also took tangible steps to reduce immigration by skilled foreign workers who are usually hired by innovative firms to help them remain globally competitive. His protectionism stressed the global supply chains and technology transfer networks relied upon by innovative U.S. firms.[95]

We find, similar to the previous chapter, that innovation is negatively associated with the 2020 version of Trumpism. This suggests that US citizens living close to innovative companies had not fully priced in Trump's negative effect on their local industries in 2016; it took his actual presidency to further alienate them politically. And this seemed to matter: the erosion of electoral support for Trumpism in innovation clusters in battleground states such as Arizona and Georgia, which had gone for Trump in 2016, contributed to him losing the presidency in 2020.

8.1 Trumpism in 2020

Figure 8.1 displays the unweighted county level change in the two-party vote share received by the Republican presidential candidate between the 2000 and 2020 elections. As in the 2016 presidential election, locations differed substantially in their reaction to Trump. For the 2,256 counties with data, the variable's mean value is a 6.98 swing (change in percentage of the two-party vote obtained by Trump versus Bush in 2000).[96]

---

[95] While on the campaign trail, Candidate Biden spoke in favor of privacy protections and personal data standards similar to those adopted by the E.U. through the General Data Protection Regulation framework by giving consumers stronger property rights over their data, including restrictions on how digital platforms use it, the reporting of security breaches, and a right to be "forgotten". President Trump, conversely, did not seem supportive of these ideas (see Finch et al. 2020). As President, Biden pushed through the reestablishment of so-called Net Neutrality, which had been rescinded under Trump's watch, thereby barring content providers from engaging in price discrimination by charging some websites more for faster internet speeds.

[96] The standard deviation is 10.8; the minimum value is -27.0; and the maximum value is 48.9. As was the case when evaluating Trumpism in 2016, a histogram of the distribution of Trumpism in 2020, juxtaposed with a normal distribution (not shown), reveals that the data resembles a bell curve. This is attested to by the fact that the mean and median are essentially identical: 7 and 7.4, respectively. If we weigh by a county's total votes in 2000, which we do in the regressions that follow, per Autor et al. (2020), the mean change between 2000 and 2020 is -1.58 and the standard deviation is 9.93. We note that the MIT Election Data and Science Lab has not yet reported observations for some states, unlike our coverage for the 2016 elections (see Chapter 7).

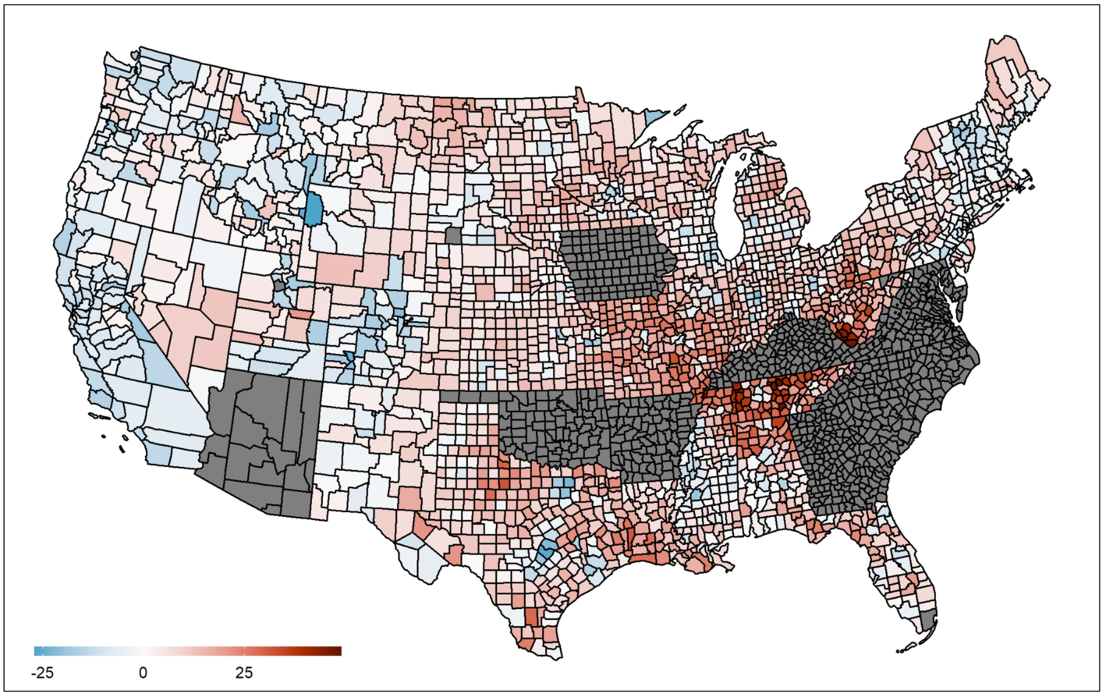

Figure 8.1. Electoral Support for Trumpism in 2020 versus 2000 across Continental U.S.

Note: Inspired by Autor et al. (2020), we calculate "Trumpism" by subtracting the two-party Republican vote share in 2000 from the two-party Republican vote share in 2020. Like they do, we exclude Alaska and Hawaii because of missing data. Unlike for the 2016 presidential elections, other states are missing data because it has not yet been reported as of the time of this writing. Source: MIT Election Data and Science Lab.

There is again, as in 2016, considerable heterogeneity within states in support for Trumpism in 2020. Notable examples include Texas, Washington, Florida, Colorado, and Utah. The 2020 presidential election results also show that Trumpism was relatively popular in red states that voted Republican in 2000. This includes Texas and Louisiana, for example, where Trump improved over Bush's 2000 vote totals by 8.73 and 10 percentage points, respectively. Conversely, Trump registered strong electoral gains in the Appalachian and Midwest regions, especially the so-called Rust Belt, vis-a-vis Bush; the average value for Trumpism in Michigan, Wisconsin, Pennsylvania, and Ohio in 2022 is 8.33 (percentage point improvement over Bush in 2000), and the median is 7.53.

However, since Trump lost the presidency in 2020, he underperformed in relation to his showing in 2016; Figure 8.2 helps us understand the geography of his electoral loss. It graphs the difference between Trump's 2020 vote percentage (as a share of the two-party vote) versus Trump's 2016 vote percentage on a county-by-county basis. The average change in his county vote share is -0.66 percentage points (the median is -.78), and the standard deviation is 2.63.

While the overall story behind these numbers is complex, two major patterns stand out. First, Trump lost considerable support in 2020 in places he managed to peel away from the Democrats in 2016. Second, Trump lost the support of innovation clusters in battleground states, which may have ultimately cost him the presidency.

The Rust Belt was no longer Trump's ace in the hole in 2016. In Michigan, Ohio, Pennsylvania, and Wisconsin, Trump received .57 percentage points fewer votes in 2020 versus 2016. And, in states with similar industrial profiles to that region, Trump also underperformed: for example, the change in his vote share in Minnesota was -1.4 percentage points; in Illinois, it was -0.04.

Therefore, to help win the presidency in 2020, Biden banked votes from white working-class men, many of whom had supported Trump in 2016 (see Williams 2020). While Trump was victorious in Ohio, and overwhelmingly won rural districts across the Midwest, Biden won with strong support in the major cities across these states. This includes Detroit, Michigan, Milwaukee, Wisconsin, and Akron, Ohio. Moreover, if we consider the Rust Belt to include cities such as Buffalo, New York, Corning, NY, Rochester, NY, Utica, NY, East Lansing, Michigan, and Flint, MI, Joe Biden also beat Trump in those places.

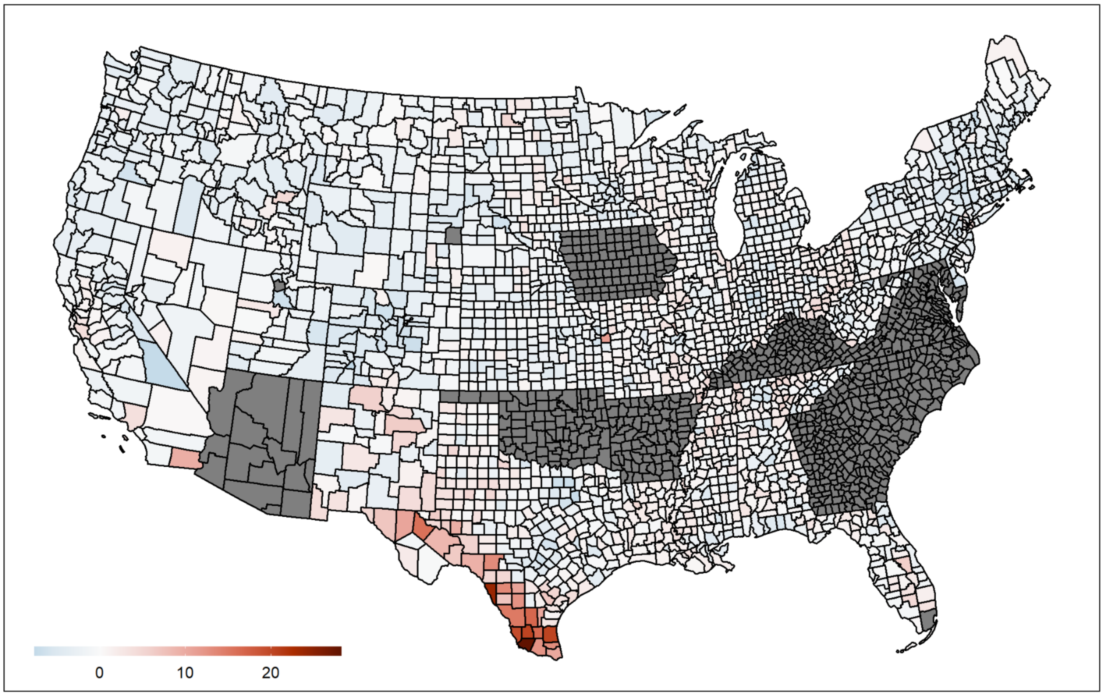

Figure 8.2. Electoral Support for Trumpism in 2020 versus 2016

Note: To obtain this measure we subtract the two-party Republican vote share in 2016 from the two-party Republican vote share in 2020. As before, we exclude Alaska and Hawaii. Unlike for the 2016 presidential elections, other states are missing data because it has not yet been reported as of the time of this writing.
Source: MIT Election Data and Science Lab.

A deeper look at the numbers confirms this picture. An election postmortem report authored by Republican pollsters affiliated with the Trump campaign in the aftermath of the 2020 presidential race evinces that the former president bled support in the Rust Belt (Fabrizio, Lee & Associates 2020).[97] The report concludes that Trump suffered great losses among demographics overrepresented in the low skilled subgroup; he experienced sizable erosion in support among white men across every age group, including males of prime working age and those entering

[97] These pollsters conducted an analysis of exit polling in several battleground states, many of them located in America's industrial heartland. They include Michigan, Wisconsin, Ohio, and Pennsylvania.

retirement age, two groups usually associated with unskilled workers. In the five states in which Biden beat Trump in 2020 after Trump won in 2016, Trump's most dramatic loss of support among these voters was in the 18 to 29 age group and the 65 and older group. This suggests that Trump's Neo-Luddism while in office may have failed to persuade these voters in 2020, notwithstanding the fact that his promise to "Make America Great Again" may have won them over in 2016.

The question now is whether this pattern, combined with further erosion of electoral support in innovative clusters in battleground states, could have cost Trump the 2020 election. Two examples of states that Trump carried in 2016, but lost in 2020, suggest that this may indeed have been the case. They are Arizona and Georgia.

First, take Arizona's so-called Easy Valley Corridor, home to a cluster of high-tech companies that has recently emerged along the Loop 101 beltway connecting Phoenix to several of its suburbs. It hosts established big tech firms such as Apple, Google, and Amazon, as well as several startups. In 2020, Trump lost Maricopa County, where this innovation cluster is situated, by almost 45,000 votes. He had previously beat Hillary Clinton there, in 2016, 747,361 to 702,907 votes. Maricopa is Arizona's most populous county and, therefore, Trump's loss sealed his defeat in the Grand Canyon state the second time around. While he lost Arizona to Biden by a bit more than 10,000 votes in 2020, his victory in Maricopa County in 2016 helped put him over the top statewide during that election, when he won Arizona by over 91,000 votes.

Second, consider Georgia's High Tech 1-85 Corridor in the northeast part of the Peach State. It includes the greater Atlanta metro area and beyond, encompassing the following counties: Fulton, Cherokee, Cobb, Forsyth, and Gwinnett, along with the north central section of Hall County. In both Gwinnett and Cobb Counties, Biden increased his share of the vote vis-a-vis

Hillary Clinton by 12 percentage points. In Cherokee County, Trump also lost 12 percentage points versus his showing in 2016; in Forsyth County, it was 16 percentage points.

We now proceed to examine whether Trump's antipathy towards innovation may have helped cost him the 2020 election nationally. We first look at how his presidency affected innovation and how some influential members of the tech community reacted to Trump's policies around immigration, trade, antitrust, and public investment.

8.2 Trump's Anti-Innovation Presidency

Soon after taking office, President-elect Trump struck a conciliatory tone towards the leaders of innovative American companies, many of whom he had butted heads with during the 2016 presidential campaign. These companies were situated in dense, diverse cities centered on high-tech that had definitively preferred Hillary Clinton. For example, San Francisco voters favored Candidate Clinton by almost 85% and Seattle voters by 87%; the wider Silicon Valley went for her by over 70% (O'Mara 2022). During a December 2016 meeting with the CEO's of major high-tech firms dubbed the "Trump tech summit", which included the leaders of Facebook, Amazon, IBM, Apple, and Microsoft, he declared that "I am here to help you folks do well", and sought to mend bridges and encourage cooperation between his administration and their companies (ibid).

Superficially, Trump seemed to champion American innovation early in his tenure, or at least railed against the putative theft of U.S. technology by Chinese firms in a manner that was ostensibly aligned with the interests of America's high-tech companies. Right out of the gate, his administration accused both the Chinese Communist Party and Chinese firms of engaging in widespread industrial espionage; compelling American firms to enter joint ventures that divulge trade secrets in exchange for market access; conducting onerous security reviews and testing requirements; and deploying trillions of dollars to acquire U.S. companies operating in high-tech industries (see Menaldo and Wittstock 2021).

But these seemingly pro high-tech gestures were not well received by his intended audience–and coupled with policies perceived by several innovative companies as harmful to their workforces, industries, and supply chains, triggered an early backlash against President Trump by the high-tech community (Lapowsky 2018). On January 27th, 2017, he issued an executive order banning travel from several majority-Muslim countries that sparked an immediate rebuke by prominent cutting-edge firms. For example, Apple CEO Tim Cook declaring that "Apple would not exist without immigration, let alone thrive and innovate the way we do" (Swisher and Fried 2017; O'Mara 2022). Google CEO Sundar Pichai, Facebook CEO Mark Zuckerberg, and other leaders of innovative U.S. firms, also publicly denounced Trump's travel ban, noting the negative effects on American technological development, including the possibility that it might precipitate a brain drain (see Romm 2017; O'Mara 2022).

This was only the beginning. The Trump administration also halted the so-called International Entrepreneur Rule, which had made it easier for non-citizen entrepreneurs to start businesses in the U.S. and issued a record number of "requests for evidence" to highly skilled H-1B visa holders, making it harder for U.S. employers to hire these immigrants (Lapowsky 2018). Moreover, early in his administration, Trump neglected to staff the Office of Science and Technology Policy (OSTP), which suffered from important vacancies, including to its director. While it took the president two years to name an OSTP director, who also serves as a U.S. president's de facto science and technology advisor, the agency shrunk from 135 personnel to 45 during Trump's tenure.

As widely expected, Trump's presidency saw an unprecedented increase in U.S. trade protectionism and clawed back globalization.[98] He introduced a host of tariff and non-tariff barriers and restrictions on certain exports.[99] In particular, Trump slapped major tariffs on Chinese goods—the Trump administration increased tariffs by 25 percent of the 2017 value of China's imports, which was equivalent to taxing $370 billion worth of Chinese goods.[100] Beijing then imposed tit-for-tat tariffs on U.S. exports and increased regulations on American firms doing business in China; for example, Chinese antitrust authorities' nixed Qualcomm's attempt to merge with Dutch chipmaker NXP in 2018. Trump also renegotiated NAFTA after taking power and squelched the TPP.

These policies hurt American innovation. Trump's tariffs on Chinese imports and China's retaliatory tariffs significantly raised the costs of doing business for American firms, especially high-tech ones (Menaldo and Wittstock 2021). Several measures in the renegotiated NAFTA, christened the so-called United States-Mexico-Canada Agreement, weakened IP protections. Walking away from the TPP foreclosed new export markets for cutting edge U.S. firms.

---

[98] A bipartisan consensus underpinned a U.S. led rules-based system after World War II, starting with the 1948 General Agreement on Tariffs and Trade (GATT) and capstoned by the 1995 World Trade Organization's (WTO) binding dispute settlement system. Irwin (2017) argues that the U.S. has used tariffs and the threat of tariffs since the 1934 Reciprocal Trade Agreements Act to ply, if not threaten, foreign governments into reciprocal trade liberalization.

[99] Between 1990 and 2017, the trade-weighted average global tariff applied under WTO rules fell by 4.2 percentage points. The drop was greatest in poorer countries: in the same period China's tariffs fell by 28 points, India's by 51 and Brazil's by 10. Bilateral and regional trade deals expanded from around 50 in the early 1990s to as many as 300 in 2019. These have cut trade weighted applied tariffs by a further 2.3 percentage points. This system supported an explosion of global trade as a share of gross output, from around 30% in the early 1970s to 60% in the early 2010s. Over the same period complex global supply chains grew from around 37% to 50% of total trade (see The Economist 2021: 3).

[100] The Trump administration also imposed import tariffs on steel and aluminum, solar panels, and an assortment of European goods.

Also, as foreshadowed during his 2016 presidential campaign, Trump weakened global supply chains in ways that harmed American high-tech companies.[101] His administration's actions against Huawei are emblematic. Trump supported the development of a so-called open architecture system for 5G centered on cloud computing and software that can bypass foreign equipment such as Huawei-made switches and routers. This followed on the heels of the Federal Communications Commission labeling both China's ZTE Corporation and Huawei national security threats, banning ZTE and Huawei from providing equipment to America's wireless communications network, and ending their federal subsidies. The Trump administration also heavily restricted semiconductor firms from selling microchips and software to Huawei, ZTE, and other Chinese firms, at first forcing the former to obtain a license and, eventually, banning some of them from doing so outright. Trump banned Huawei from America's 5G network entirely and prevented the American government and U.S. telecommunication companies from procuring and using the company's products.[102]

Though Trump's professed reason for more restrictive trade, FDI, and technology policies vis-a-vis China was to protect American national security, U.S. semiconductor industry trade groups strongly complained about the potential loss of profits and jobs associated with his administration's restrictions on microchip and software exports.[103] A 2020 report by the Boston Consulting Group, commissioned by the U.S. Semiconductor Industry Association, concludes that the Trump administration's policies undermine the competitive position of American chip

[101] This also included Trump's efforts to block some mergers and acquisitions. For example, his administration prevented Canyon Bridge Capital Partners from acquiring Lattice Semiconductor Corporation, alleging the deal would have been financed by Chinese money.
[102] To be sure, on the campaign trail during the 2020 presidential election, Candidate Biden largely agreed with Trump's circumspection towards foreign made telecommunications equipment making its way into the 5G network. See Finch et al. (2020).
[103] China is the biggest market for American semiconductors, typically purchasing about 25% of U.S. chips (amounting to hundreds of billions of dollars in sales).

companies, reducing their market shares, revenues, and employment (Varas and Varadarajan 2020). Until the Trump Administration required a license for U.S. semiconductor firms to sell chips to Huawei and other Chinese companies, Qualcomm, Broadcom, Micron, Intel, Microsoft, IBM, and Google, provided these firms with everything from microchips to software to consulting services, earning billions of dollars in the process.[104] This includes royalty revenues generated by IP licenses. Until a similar 2019 ban, several U.S. tech firms also earned a pretty penny exporting computer chips and related technologies to the Chinese government to help it power its supercomputer industry.

American companies beyond semiconductors, including some involved in AI (such as Google) and biotechnology, also objected to Chinese export bans and similar trade and capital restrictions.[105] They were worried about losing access to China's lucrative market.[106] They were also concerned about weakening transnational R&D networks that connect American and Chinese firms, research institutes, and universities (Menaldo and Wittstock 2021). In this vein, Trump constantly scolded Apple, especially on Twitter, hectoring them to make their iphones in the U.S. to avoid the increased costs of doing business borne by his Chinese import tariffs.[107] After much lobbying by Apple CEO Tim Cook, Trump ultimately agreed to exempt Apple from announced tariffs on laptops and smartphones imported from China (O'Mara 2022). A snake bitten Apple

---

[104] Indeed, Intel, Qualcomm, and other American chipmakers quietly pushed back against the U.S. government's ban on exports to Huawei, lobbying the Commerce Department to rescind them. See Nellis et al. (2019).

[105] In 2018, the U.S. Government passed the Foreign Investment Risk Review Modernization Act; it was (at least) partly intended to reduce Chinese FDI in areas that are deemed sensitive to U.S. national security.

[106] For example, in the first quarter of 2020, the Chinese market made up 20% of Apple's total sales and almost 15% of its total revenue.

[107] Only one of several examples is this Trump tweet: "Apple prices may increase because of the massive tariffs we may be imposing on china but there is an easy solution where there would be zero tax and indeed a tax incentive make your products in the united states instead of china start building new plants now. Exciting!" [TTA - Search (thetrumparchive.com)](thetrumparchive.com).

nevertheless invested in rerouting some of its manufacturing supply chain to Korea and Vietnam.[108]

Trump also took the fight to other big tech firms. He pushed the Justice Department to sue Time Warner and AT&T to prevent their vertical merger.[109] As president, he continued his 2016 presidential campaign habit of badmouthing and threatening digital platforms and their leaders. For example, he repeatedly locked horns with Amazon's Jeff Bezos, both over his ownership of the Washington Post and Amazon's tax bill. Trump also directed the U.S. Post Office (USPO) to investigate whether its delivery of Amazon packages was harming it, even though Amazon related business helped the USPO staunch record losses. He continued to badmouth and threaten other digital platforms such as Facebook, Google, and Twitter, often accusing them of peddling fake news and censoring conservative views.

Railing against "special protections" for digital platforms, Trump repeatedly called on the Federal Communications Commission to rescind Section 230.[110] While Candidate Biden agreed with Trump during the 2020 presidential campaign on this, he also stressed self-policing as a better solution for improving content moderation (see Finch et al. 2020) and shied away from doing so after becoming president. President Trump's numerous attacks on the press were also often directed towards social media companies and search engines, especially Facebook, Twitter, and

[108] Cook also visited an Apple contractor in Texas together with President Trump, who touted the reshoring of jobs to the U.S. (O'Mara 2022).
[109] The Federal Government lost the suit in court under President Trump's Justice Department.
[110] Section 230 is the lifeblood of the internet as we know it, in that it immunizes digital platforms from liability for the content posted by third party users. This reduces their exposure to lawsuits, allowing them to reach global scale economies and monetize user data. See Finch et al. (2020).

Google, which he accused of "anti-conservative bias" and of being in covert alliance with the Democratic Party (O'Mara 2022).[111]

Over his presidency, while Trump's budgets modestly increased funding for research in some targeted technology areas, especially AI and 5G, they sought overall cuts for basic research, R&D in cutting edge areas, and education (Atkinson et al. 2020).[112] This included plans to slash budgets for the National Institutes of Health, the National Science Foundation, and R&D programs run by the DOE and the National Aeronautics and Space Administration. His administration cut funding for clean energy R&D and eliminated federal programs and tax incentives for clean energy development (ibid). Trump cut funding for the Advanced Research Projects Agency-Energy, which George W. Bush had signed into law during his presidency. He also pushed for reductions in funding for so-called STEM (Science, Technology, Engineering, and Math) education while bolstering support for apprenticeship programs (Mervis 2018; Atkinson et al. 2020).

President Trump's policies not only worsened the already fraught relationship he had with the high-tech industry since the 2016 presidential elections, but they cast a shadow on his 2020 reelection bid.[113] So much so that several computer industry luminaries, including the vast majority of living Turing Award winners, departed from their typically apolitical stance and endorsed Biden over Trump during the 2020 presidential election. They declared jointly in a signed letter that

---

[111] Under the Trump Administration, the Federal Trade Commission launched probes into Facebook and the Justice Department sued Google on antitrust grounds. During his presidency, both parties converged on the idea of strengthening competition in the digital space by "cracking down" on Big Tech (see Finch et al. 2020).

[112] Trump floated the idea that the Defense Department should create a 5G network that is then leased to private network providers at different points throughout his presidency, but no telecommunications companies seemed interested in this proposal (see Finch et al. 2020).

[113] Two exceptions to this general trend may include his administration's reduction in corporate tax rates and its endorsement of flexible labor practices in relation to the gig economy, specifically, the Labor Department's decision under his presidency to continue to label workers who participate in these markets as independent contractors instead of employees, which Candidate Biden opposed during the 2020 election. See Finch et al. (2020).

“Computer Science is at its best when its learnings and discoveries are shared freely in the spirit of progress. These core values helped make America a leader in information technology, so vital in this Information Age. Joe Biden and Kamala Harris listen to experts before setting public policy, essential when science and technology may help with many problems facing our nation today”.[114]

8.3 Econometric Strategy

As we did in the previous chapter, we now evaluate the systematic, spatial relationship between innovation and Trumpism. However, we now do so for 2020 instead of 2016. Like Chapter 7, we start simply. Table 8.1, Column 1, reports the bivariate, OLS relationship between log(Patents Per Capita, in 2000) and Trumpism, where we now measure the latter as the difference in the two-party vote share earned by Trump versus Bush in 2000. Increasing Per Capita Patents by 1 percent maps onto a decrease in Trumpism of 1.36 (p-value < .001), which is stronger than the negative relationship reported in Chapter 7, where increasing Per Capita Patents by 1 percent increases the 2016 version of Trumpism by 1.19 percentage points (p-value < .001). Moreover, the r-squared for the 2020 version of the model is .16; it is .15 for its 2016 counterpart.

To ascertain whether this relationship is causal, as we submit it is for the relationship between innovation and Trumpism in 2016 reported in Chapter 7, we return to the strategy we pursued there, and estimate IV-2SLS models conducted in two stages. The first again estimates the determinants of log(Per Capita Patents) using excluded instruments. The second stage again estimates the determinants of Trumpism, but this time the 2020 version. We again follow Autor et al. (2020), and both cluster the standard errors by commuting zone (addressing spatial correlation

[114] The Turing Award is widely considered the “Nobel Prize in computing” and the recipients include leading architects of the semiconductor industry, the internet, and AI. As of 2020, there were 35 still living people who had received the award. See https://int.nyt.com/data/documenttools/the-statement-from-the-turing-award-winners-on-their-biden-endorsement/c0b01c987a946137/full.pdf

between counties in encompassing metro areas) and weigh the observations by counties' total votes in the 2000 presidential election. For the second stage regression, the most important thing to note is once again whether the predicted values of Per Capita Patents calculated from the first stage regression explain the variation in Trumpism.

As in Chapter 7, the first stage regression of our unrestricted IV- 2SLS model is:

$$y_i = \alpha_j + \beta X_i + \xi(\phi_i + \lambda_i + \phi_i \times \lambda_i) + \pi(\psi_i) + u_i \qquad (1)$$

in which y_i is the estimated value of log(Patents per Capita) for county i; α_j identifies invariant state fixed effects potentially correlated with X, a vector of k explanatory variables in 2000 associated with β estimated parameters; ξ are estimates associated with ϕ_i, county Temperature in 1900, λ_i, county Precipitation in 1900, and their interaction; π are estimates of ψ_i, county Population Density in 1900 (in logs); and u_i is an error term.

The second-stage of the unrestricted model is:

$$y_i = \alpha_j + \beta X_i + u_i \qquad (2)$$

in which y_i is the estimated value of Trumpism for county i; (first measured as the difference in vote share for Trump in 2020 versus Bush in 2000; then as the difference in vote share for Trump in 2020 versus his vote share in 2016); α_j addresses invariant state fixed effects potentially correlated with X, a vector of k explanatory variables that includes the predicted values of Patents Per Capita produced by equation (1); β are estimated parameters; and u_i is an error term.

As we did in Chapter 7, prior to estimating the unrestricted model in Table 8.1, Column 7, we discuss simpler models. We relegate attention to the second stage regressions estimated in the IV-2SLS framework; in other words, equation (2).[115] As before, we proceed in a stepwise fashion.

8.4 Stepwise Regression Approach

Let us first consider Columns 2 to 4. In Column 2, the only variable is log(Per Capita Patents). Innovation leads to less Trumpism: increasing log(Patents Per Capita) by 1% decreases Trump's share of the 2020 two-party presidential vote by 1.3 percentage points vis-a-vis Bush's vote share in 2000 (p-value = .06). The r-squared is .17. In Column 3, as we did in Chapter 7, when Trumpism is measured as the difference between Trump's vote share in 2016 and Bush's in 2000, we add China Trade Shock. Our results strengthen: log(Patents Per Capita) is now statistically significant at the 96 percent level and has a stronger magnitude. In Column 4, we instrument China Trade Shock with the Autor et al (2020) so-called shift-share instrument (see Chapter 7); the effect of log(Patents Per Capita) on Trumpism is materially unchanged.

Columns 5 to 8 perform more robustness tests. In Column 5, we introduce state fixed effects. Our results experience a three-fold rise in magnitude (increasing patents per capita by 1 percent engenders a 4.5 percentage point decrease in the Republican two-party vote share in 2020 versus 2000; p-value < .001). In Column 6, we add the same county-level variables as in Chapter 7, Table 7.1, Column 7, when we evaluated the relationship between innovation and Trumpism in 2016.[116] While the substantive effect of Patents Per Capita weakens, it is still statistically

[115] We estimate, but do not report, the first stage regression results across our models where we instrument log(Patents Per Capita) with Temperature, Precipitation and Population Density, all measured in 1900. For those results see Table 7.1, Column 2a, in Chapter 7.

[116] They include employment in the manufacturing sector; the share of occupations that involve routinized work; the share of occupations that can be outsourced overseas; census division dummies; demographic controls that measure the share of the population across different age groups, races, gender, education levels, and immigration status; and election controls that measure the Republican two-party vote share in the 1992 and 1996 presidential elections.

significant at the highest possible level; meanwhile, localized China Trade Shock is no longer statistically significant at conventional levels. Column 7 introduces more county-level controls, beyond those included in Autor et al. (2020).[117] The substantive and statistical significance of our results strengthens.[118] Column 8 reports the regression results from an LIML estimator, a linear combination of OLS and IV-2SLS estimates, with the weights (approximately) eliminating any bias introduced by an IV-2SLS regression run with weak instruments (see Hahn and Hausman 2003); the model is otherwise identical in terms of the variables included in Column 7. Compared to Column 7, Patents Per Capita is considerably stronger in magnitude.

In an effort to bias against ourselves and make it very difficult to obtain a negative relationship between innovation and Trumpism in 2020, in Column 9 we measure Trumpism as the percentage of the vote share obtained by Trump in 2020 and 2016. In terms of operationalizing innovation, we now focus on the change in the stock of patents between 2020 and 2016, which we log. Because we are now focusing on change over time for both the dependent and independent variables, we switch our econometric approach to an OLS regression, which means we no longer instrument patents with geographic or demographic variables, nor do we instrument China Trade Shock with the so-called shift-share instrument.[119] As in Columns 7 and 8, however, we continue to control for state fixed effects and the full gamut of control variables.[120]

The results of this regression are as we expected: more innovation from 2016 to 2020 means less Trumpism during this period. All else equal, places that saw increases in patenting

---

[117] We add log(Real Median Income Per Capita); Unemployment Rate; and Waldorf and Kim's (2015) Rurality Index. See Chapter 7 for a more in-depth discussion.

[118] The results are even stronger if we use Patents Per Capita in 2015 instead of 2000 and materially similar if we use Patents Per Capita in 2020.

[119] The geographic and demographic variables are county Temperature in 1900, county Precipitation in 1900, their interaction, and county Population Density in 1900 (in logs).

[120] We again cluster the standard errors by commuting zone but now weigh the regressions by the total county votes cast in the 2016 presidential election.

between 2016 and 2020 also saw lower voting percentages for Trump between presidential elections: increasing the stock of patents by 1 percent maps onto a .01 percentage point reduction in Trumpism (p-value < .001).[121] This corresponds to a one standard deviation increase in patenting inducing 3% of a standard deviation less support for Trump. We suspect that because voters had most likely priced in his Neo-Luddism by 2020, the substantive effect of greater innovation between presidential elections on changes in Trump's electoral backing is relatively muted.

What about other symptoms of anti-Trumpism? Is there evidence that innovative places further soured on Trump in ways other than a reduction in the percentage of the presidential vote he earned between 2016 and 2020? To find out, we now measure Trumpism as the change in his campaign contributions between the 2016 presidential election and 2020 election. To construct this measure, we use data from the Federal Elections Commission on all individual campaign contributions made to Trump after he obtained the share of primary election support he needed to become the presumptive Republican presidential nominee in April 2016, until the election in November 2016. Similarly, we obtain data on the individual campaign contributions made to Trump between April 2020, when he was again crowned the presumptive Republican presidential nominee, and the election in November 2020.

To create county-level observations on the total contributions made to Trump in 2016 and in 2020, we aggregate this individual-level data to the county-level.[122] We then calculate the

[121] The results are robust to controlling for the total stock of patents in 2015 to address the fact that patenting inequality between counties has decreased closer in time, which suggests that places with a higher stock of patents are less likely to experience bigger increases in patenting than places with a lower stock of patents. They are also robust to controlling for Trumpism in 2016: the difference between Trump's vote share in 2016 and Bush's in 2000.

[122] We aggregate total campaign contributions at the ZIP code level. We then aggregate the ZIP code totals to the county level by assigning dollar amounts to the latter according to the proportion of the ZIP code that is within the county in question, which we gleaned from the U.S. Postal Service crosswalk.

Table 8.1 The Determinants of Trumpism in 2020

PANEL A

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	*2020 Trumpism*	*2020 Trumpism*	*2020 Trumpism*	*2020 Trumpism*	*2020 Trumpism*
Estimation Strategy	OLS	IV (Stage 2)	IV (Stage 2)	IV (Stage 2)	IV (Stage 2)
log(Patents Per Capita, 2000)	**-1.358*** **	**-1.282***	**-1.571** **	**-1.565** **	**-4.845*** **
	[0.088]	**[0.686]**	**[0.751]**	**[0.789]**	**[0.866]**
China Trade Shock			2.625***	3.394**	4.487***
			[0.089]	[1.520]	[1.136]
Shift Share Instrument	NO	NO	NO	YES	YES
State Fixed Effects	NO	NO	NO	NO	YES
Autor et al. 2020 Controls	NO	NO	NO	NO	NO
Additional Controls	NO	NO	NO	NO	NO
Observations	2,121	1,969	1,969	1,969	1,962

PANEL B

	(5)	(7)	(8)	(9)	(10)
Dependent Variable	*2020 Trumpism*	*2020 Trumpism*	*2020 Trumpism*	*Trump '20-Trump '16*	*Trump '20-Trump '16*
Estimation Strategy	IV (Stage 2)	IV (Stage 2)	IV (Stage 2)	OLS	OLS
Innovation Measure	*P.C. Patents, 2000*	*P.C. Patents, 2000*	*P.C. Patents, 2000*	*Patents '20-Patents '16*	*Patents '20-Patents '16*
	-1.974* **	**-2.309*** **	**-4.689** **	**-0.011*** **	**-9495.138*** **
	[0 .754]	**[0 .725]**	**[2.175]**	**[0.004]**	**[2397.092]**
China Trade Shock	2.633	2.611	3.438	0.058	-321873.3***
	[1.650]	[1.659]	[2.373]	[0.112]	[34961.64]
Shift Share Instrument	YES	YES	YES	NO	NO
State Fixed Effects	YES	YES	YES	YES	YES
Autor et al. 2020 Controls	YES	YES	YES	YES	YES
Additional Controls	NO	YES	YES	YES	YES
Observations	1,962	1,957	1,957	2,246	3,092

Notes: Significant at the .01 level (***); significant at the .05 level (**); significant at the .10 level (*). Inspired by Autor et al. (2020), we calculate "Trumpism" by subtracting the two-party Republican vote share in 2000 from the two-party Republican vote share in 2020 across most models. In Column 9, we instead look at the difference between Trump's percent of the vote share in 2020 versus 2016. In Column 10, the dependent variable is the difference in Trump's campaign contributions in 2020 versus 2016. We estimate, but do not report, first stage regression results for the 2SLS models, including both the IV and LIML estimators, in which the excluded instruments are Temperature, Precipitation, their interaction, and log(Population Density), all measured in 1900. We cluster the standard errors across all models by commuting zone. See the text for how we weigh the observations for different models and for what variables are included in both difference in county-level campaign contributions for Trump between 2016 and 2020. Specifically, we subtract the total amount of Trump campaign donations per county in 2020 from the total amount in 2016 expressed in 2020 real dollars.

In Column 10, we report the results of this experiment: an OLS regression identical to

Column 9, except we now measure Trumpism as the change in Trump's campaign contributions between the 2016 presidential election and the 2020 election (in 2020 real dollars). That is to say, save for this modification of the dependent variable, we continue to measure innovation as the change in the stock of patents between 2016 and 2020, introduce the same set of controls, including state fixed effects, and cluster the standard errors similarly.[123] The results are again as we expected: increasing patents by 1% between 2016 and 2020 leads to a reduction in Trump's campaign contributions of $9,495 between 2016 and 2020 (p-value < .001).[124] As with the Column 9 results, where the outcome of interest is the change in electoral support for Trump between presidential elections, the magnitude of this effect is somewhat modest: a one standard deviation increase in patenting leads to 5 percent of a standard deviation reduction in his campaign donations.

Taken together, these results lead us to surmise that even though Trump's Neo-Luddism was probably priced in by most voters and donors by 2020, innovative places may have further rejected Trump during his reelection bid. We believe that the technology phobic policies he advanced as president had something to do with that.

8.5 The Big Picture

Like Chapter 7, this chapter again shows that our manuscript's main finding, that more innovation equals less Trumpism, is both causal and resilient. It holds when we measure Trumpism in 2020 versus Bush's votes in 2000, the change in Trump's vote share between 2016 and 2020, and the change in Trump's campaign contributions between presidential elections. Our results are

---

[123] We weigh the observations by the countywide total value of campaign contributions in 2016 expressed in 2020 dollars.

[124] We also find that more patents between 2016 and 2020 map onto a reduction in the number of donors who contributed to Trump's presidential campaign in 2020 versus 2016: increasing the patent stock by 1% during this interval leads to 12 fewer Trump donors (p-value < .05). In the regression that yields this result, we weigh the observations by the number of donors in each county in 2016.

again robust to an instrumental variable approach that exploits the exogenous sources of spatial variation in innovation outlined in Chapter 7. It also holds once we control for localized China Trade Shocks after China joined the WTO in 2001, as well as instrumenting those shocks with so-called shift-share exogenous variables, as Autor et al. (2020) do. It is robust to introducing state fixed effects, a host of other control variables, including demographics, living standards, unemployment rates, educational levels, and how rural the county is, as well as corrections for spatial correlation.

The qualitative and quantitative evidence we report in this chapter strengthens our confidence that Trump's Neo-Luddism hurt his electoral prospects in more innovative places across the U.S. Once in office, Trump was worse for innovation than he let on during his 2016 campaign, and his antipathy towards high-tech industries may have, in some ways, cost him reelection: Trump may have sacrificed battleground states such as Arizona and Georgia to Biden. In both of those states' major innovation hubs Trump lost to the 46th president in 2020, even though he had beat Clinton there in 2016.

9. Reflections on Populism and Polarization

In this manuscript, we show that relatively more innovative U.S. counties were significantly less likely to support Trump during both the 2016 and 2020 presidential elections. We also explain the reasons why. In doing so, we make several theoretical and empirical contributions. We also raise several questions for future research.

9.1 Summarizing our Main Contributions

This manuscript documents how, during the 2016 presidential election, Candidate Trump touted the economic policy preferences of voters living in places outside of America's innovation clusters. He espoused trade protectionism, restrictions on capital and technological flows, and an industrial strategy tailored to subsidize American suppliers in specific industries. Trump spoke out against so-called Big Tech companies. Unlike Candidate Clinton, he neglected innovative firms' concerns around providing access to high-speed internet access, more immigration of highly skilled foreign workers, broadly investing in science and technology, and improving higher education.

We also show how Trump then pursued several policies that harmed innovation after becoming president. We submit that this alienated the high-tech community and may have induced innovation clusters in battleground states such as Arizona and Georgia to flip their support towards the Democrats and, in turn, helped elevate Biden to the presidency. We find strong evidence that the 2016 pattern of innovation clusters rejecting Trumpism was repeated during the 2020 presidential election.

We introduce a theoretical framework that brings together several strands of ideas to help explain why Trumpist policies pose such a threat to American innovators. This includes making sense of things such as the aggregate economic benefits of trade and who supports globalization in developed countries and why. We explain why American firms operating in high-tech sectors such as software, hardware, machinery, vehicles, biotechnology, aerospace, telecommunications, diagnostics, chemicals, and green energy, benefit from trade, international capital flows, vibrant technology transfer across borders, and stronger IP globally. We extended the logic to their workers and communities. We also explain why workers outside of innovation clusters may not always benefit from policies preferred by innovative places and may be open to populist economic appeals.

We corroborate this theoretical framework empirically. The manuscript's main finding, that innovative places strongly rejected Trumpism, both in the 2016 and 2020 presidential elections, is resilient to several experiments. This includes measuring Trumpism and innovation in different ways and introducing different sets of potentially confounding variables, including controlling for Chinese import exposure shocks—and specifications where we instrument these with a so-called shift-share variable. It is also robust to introducing state fixed effects, indirectly and directly testing for whether the exclusion restriction is satisfied, for example, by controlling for exposure to robots and instrumenting this with a shift-share approach, dropping major innovation clusters, conducting adjustments for spatial correlation, and most importantly, instrumenting innovation, which we measure using patents per capita. We introduce and defend a suite of exogenous demographic, geographical, and climactic features that the literature documents as important for the origin of technology clusters in the U.S. We find as well that places with increased patenting activity between presidential elections saw reductions in Trump's campaign contributions and electoral support.

This manuscript makes additional contributions.

Following Haber, Elis, and Horrillo (2022), we provide evidence that relatively temperate climates partly determined the location of innovation clusters in the U.S. We show that these differences have endured, and that the technological gulf between less innovative and more innovative places has grown over time. We also outline the reasons for the self-reinforcing nature of American innovation clusters.

To the best of our knowledge, our manuscript is the first to show that the economic reasons why voters supported Trump across two presidential elections goes beyond the loss of jobs and income due to trade with China and increased automation and associated downward mobility and anxiety about the future. Rather, it is because of something broader and not necessarily spatially correlated with these factors: a major rift in economic policy preferences and thus support for Trump and populism in the U.S. today exists between more and less innovative areas. Regardless of their demographics, exposure to trade and robots, education and income levels, degree of urbanization, and every other potential difference between them, innovation clusters oppose Trump, and his policies, and innovation deserts support him, and his populist agenda.

9.2 Directions for Future Research

While this manuscript adduces strong path dependence in America's innovation-intensive regions over time, economic policy preferences seemed to have been more aligned across U.S. locations, irrespective of their innovativeness, in past periods. Nowadays, American voters increasingly appear to have more divergent political preferences than ever before. Perhaps growing cultural and political polarization may incline voters in less innovative places towards more reactionary politics in general: not only trade protectionism and opposition to immigration, but antipathy towards “liberal cultural issues” that may include science and technology (Bishop 2009; Abramowitz 2010; Baldasarri and Gelman 2008).

Future research may examine this question, as well as other issues raised by our findings. Does the negative relationship between innovation and populism hold for legislative elections and/or state and local level elections? Does it hold in different countries and for different time periods?

Our historical data on local U.S. innovation activity reveals some nuanced patterns that also invite new lines of inquiry. For all the evidence of path dependence in American innovation clusters we highlight in this manuscript, there has been some unconditional convergence in patenting rates as of late.[125] Therefore, while this manuscript offers reasons why more innovative clusters have historically reinforced their technological advantages vis-a-vis less innovative places, we do not explore why the pace of change in the innovation gap between U.S. locations has actually decelerated in more recent periods. Indeed, in the wake of the remote work revolution induced by the Covid-19 pandemic, key differences between U.S. locations may further attenuate into the future (Muro and You 2022). Office occupancy rates in downtown business districts across the U.S. are down by over 50% on average (Weber, Grant, and Hoffman 2022). As concerns over crime, safety, and quality of life issues such as growing commute times have exploded in cities such as New York City, Chicago, Washington, D.C., San Francisco, Los Angeles, and Seattle, alongside skyrocketing housing costs, many of their highly skilled

[125] Consider the rate of change in the Gini coefficient captured by Figure 4.2 in Chapter 4. Between 1920 and 1930, inequality in patents per capita between U.S. counties grew by 8.7%; between 1930 and 1940, it grew by 16.3%; between 1940 and 1950, the Gini coefficient shrunk by 8.8%; between 1950 and 1960, it grew by 6.1%; between 1960 and 1970, it grew by 18.8%; between 1970 and 1990, it grew by 5.7%, between 1990 and 2000, it declined by 3.9%; between 2000 and 2010, it grew by 9.5%, and, between 2010 and 2015, it declined by 0.35%.

residents have fled to Florida, Texas, and the American interior. Most have not sought out innovation clusters, but instead moved to suburbs and even rural areas with slower paces of life, predominantly in so-called red states (see Mitchell 2022).

We cannot really predict what political impacts this phenomenon may have. Perhaps a slackening in the rate of innovation inequality between American locations may reduce polarization, or at least herald the return of convergence over economic policy? Perhaps this may mirror the Cold War consensus about the government's role in promoting innovation to include both public spending and the support of markets, including globalization (O'Mara 2020)?
Of course, given that it is highly unlikely that the sharp differences between U.S. voters regarding economic policy, and especially around innovation, are entirely due to spatial divergences in technological development, this consensus is unlikely to reemerge any time soon. Trumpism may therefore continue to hold sway, with or without the former president's return to the Oval Office in 2024.

Works Cited

Abramovitz, Moses. 1993. "The Search for The Sources of Growth: Areas of Ignorance, Old and New." *The Journal of Economic History* 53(2): 217-243.

Abramowitz, Alan. 2010. *The Disappearing Center: Engaged Citizens, Polarization, and American Democracy.* New Haven: Yale University Press.

Acemoglu, Daron. 2009. *Introduction to Modern Growth Theory*. Princeton: Princeton University Press.

Acemoglu, Daron, Jacob Moscona, and James Robinson. 2016. "State capacity and American technology: evidence from the nineteenth century." *American Economic Review* 106(5): 61-67.

Acemoglu, Daron, David Autor, David Dorn, Gordon Hanson, and Brendan Price. 2016. "Import Competition and the Great Us Employment Sag of the 2000s." *Journal of Labor Economics* 34(1): 141-198.

Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and jobs: Evidence from US labor markets." *Journal of Political Economy* 128(6): 2188-2244.

Acs, Zoltan., Luc Anselin, and Attila Luc. 2002. "Patents and Innovation Counts as Measures of Regional Production of New Knowledge." *Research policy* 31(7): 1069-1085.

Anelli, Massimo, Italo Colantone, and Piero Stanig. 2019. "We Were the Robots: Automation and Voting Behavior in Western Europe." *BAFFI CAREFIN Centre Research Paper* 2019-115.

Atkinson, Robert, Mark Muro, and Jacob Whiton. 2019. "The Case for Growth Centers." *Brookings Institution:* Washington, DC, USA.

Atkinson Robert, Doug Brake, Daniel Castro, Nigel Cory, Stephen Ezell, Cale Foote, David Hart, Joe Kennedy, Robert Rozansky. 2020. "Trump vs. Biden: Comparing the Candidates' Positions on Technology and Innovation." *Information Technology and Innovation Foundation*: Washington DC.

Autor, David, David Dorn, and Gordon Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in The United States." *American Economic Review* 103(6): 2121-68.

Autor, David, David Dorn, and Gordon Hanson. 2013. "The Geography of Trade and Technology Shocks in The United States." *American Economic Review* 103(3): 220-25.

Autor, David, David Dorn, Gordon Hanson, and Jae Song. 2014. "Trade adjustment: Worker-level evidence." *The Quarterly Journal of Economics* 129(4): 1799-1860.

Autor, David, David Dorn, and Gordon Hanson. 2015. "Untangling Trade and Technology: Evidence from Local Labor Markets." *The Economic Journal* 125(584): 621-646.

Autor, David, David Dorn, and Gordon Hanson. 2016. "The China Shock: Learning from Labor-market Adjustment to Large Changes in Trade." *Annual Review of Economics* 8: 205-240.

Baccini, Leonardo, and Stephen Weymouth. 2021. "Gone for good: Deindustrialization, White Voter Backlash, and US Presidential Voting." *American Political Science Review* 115(2): 550-567.

Baccini, Leonardo, Mattia Guidi, Arlo Poletti, and Aydin B. Yildirim. 2022. "Trade liberalization and labor market institutions." *International Organization* 76(1): 70-104.

Bade, Avin. 2021. "White House Debates to Delay Biden's Plan for Tariffs on Key Chinese Industries." *Politico*. Available at: https://www.politico.com/news/2021/10/29/white-house-tariffs-china-517727

Bakker, Gerben, Nicholas Crafts, and Pieter Woltjer. 2017. "The Sources of Growth in a Technologically Progressive Economy." *GGDC Research Memorandum No. GD-156*. Groningen Growth and Development Centre, University of Groningen.

Baldassarri, Delia, and Andrew Gelman. 2008. "Partisans without constraint: Political polarization and trends in American public opinion." *American Journal of Sociology* 114(2): 408-446.

Barret, Malachi. 2020. "Biden Says Trump Failed to Bring Back Michigan Jobs and Tanked Economy with COVID Response." *MLive*. Available at: https://www.mlive.com/public-interest/2020/09/biden-says-trump-failed-to-bring-back-michigan-jobs-and-tanked-economy-with-covid-response.html

Batistich, Mary Kate, and Timothy Bond. 2019. "Stalled Racial Progress and Japanese Trade in the 1970s and 1980s." *IZA Discussion Manuscript No. 12133*.

BBC. 2016. "Trump Accuses China of 'Raping' U.S. with Unfair Trade Policy." *BBC News*. Available at: https://www.bbc.com/news/election-us-2016-36185012

Bergh, Andreas, and Therese Nilsson. 2010. "Do Liberalization and Globalization Increase Income Inequality?" *European Journal of Political Economy* 26(4): 488-505.

Bessen, James. 2015. *Learning by Doing*. New Haven: Yale University Press.

Biden, Joe, 2020. "The Biden Plan to Rebuild US Supply Chains and Ensure the US Does Not Face Future Shortages of Critical Equipment." Available at: https://joebiden.com/supplychains/

Bishop, Bill. 2009. *The Big Sort: Why the Clustering of like-minded America is Tearing us Apart.* Boston: Houghton Mifflin Harcourt.

Blau, Francine, and Christopher Mackie. 2016. "National Academies of Sciences, Engineering, and Medicine." *The Economic and Fiscal Consequences of Immigration: A Report*. Washington, D.C.

Blinken, Antony. 2021. "A Foreign Policy for the American People." Available at: https://www.state.gov/a-foreign-policy-for-the-american-people/

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

Bonacich, Edna, and Khaleelah Hardie. 2006. "WalMart and the logistics revolution." In *Wal-Mart: The face of twenty-first-century capitalism*, ed. Nelson Lichtenstein. New York: The New Press.

Breschi, Stefano, and Francesco Lissoni. 2003. "Mobility and Social networks: Localized Knowledge Spillovers Revisited." *Università commerciale Luigi Bocconi.*

Broz, Lawrence, Jeffry Frieden, and Stephen Weymouth. 2021. "Populism in Place: the Economic Geography of the Globalization Backlash." *International Organization* 75 (2): 464-494.

Carey, Kevin. 2016. "Donald Trump Doesn't Understand Common Core (and Neither Do His Rivals)". *The New York Times*. Available at: https://www.nytimes.com/2016/03/08/upshot/donald-trump-doesnt-understand-common-core-and-neither-do-his-rivals.html

Casper, Steven, 2007. "How Do Technology Clusters Emerge and Become Sustainable?: Social Network Formation and Inter-Firm Mobility within The San Diego Biotechnology Cluster." *Research Policy* 36(4): 438-455.

Çelik, Sadullah, and Ulkem Basdas. 2010. "How does Globalization Affect Income Inequality? A Panel Data Analysis." *International Advances in Economic Research* 16(4): 358-370.

Che, Lu, Justin Pierce, Peter Schott, and Zhigang Tao. 2016. "Does Trade Liberalization with China Influence US Elections?" No. w22178. *National Bureau of Economic Research*.

Choi, Jiwon, Ilyana Kuziemko, Ebonya Washington, and Gavin Wright. 2021. "Local Economic and Political Effects of Trade Deals: Evidence from NAFTA." No. w29525. *National Bureau of Economic Research*.

Clark, Paul. 2017. "Presidential Election: The Pivotal Role of Pennsylvania and the Rustbelt." *Labor Studies Journal* 42(3): 239-244.

Clinton, Hillary. 2016. "Technology and Innovation." Available at: https://www.hillaryclinton.com/issues/technology-and-innovation/

Co, Catherine, 2002. "Evolution of the Geography of Innovation: Evidence from Patent Data." *Growth and Change* 33(4): 393-423.

Cohn, Nate. 2016a. "Why Trump Won: Working-Class Whites." New York Times. Available at: https://www.nytimes.com/2016/11/10/upshot/why-trump-won-working-class-whites.html

Cohn, Nate. 2016b. "How Trump's Campaign Could Redraw Voter Allegiances." New York Times. Available at: http://www.nytimes.com/2016/06/30/upshot/ how-trumps-campaign-could-redraw-voter-allegiances.html

Colantone, Italo, and Piero Stanig. 2018a. "Global competition and Brexit." *American Political Science Review* 112(2): 201-218.

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

Conley, Brian. 2018. "Thinking What He Says: Market Research and The Making Of Donald Trump's 2016 Presidential Campaign." In *Political Marketing in the 2016 US Presidential Election*, ed., Jamie Gillies. New York: Palgrave Macmillan: 29-48.

Conley, T.G. (1999). "GMM Estimation with Cross Sectional Dependence." *Journal of Econometrics* 92(1): 1–45.

Conley, Timothy, Christian Hansen, and Peter Ross. 2012. "Plausibly Exogenous" *The Review of Economics and Statistics* 94(1): 260–272.

Corradini, Carlo, 2021. "The Geography of Innovation as Reflected by Social Media." *Environment and Planning A: Economy and Space* 53(2): 227-229.

Davidson, Adam. 2016. "Blaming Trade and Voting Trump in the Rust Belt." *New York Times Magazine*. Available at: https://www.nytimes.com/2016/07/10/magazine/blaming-trade-and-voting-trump-in-the-rust-belt.html

De Bromhead, Alan, Barry Eichengreen, and Kevin H. O'Rourke. 2013. "Political Extremism in the 1920s and 1930s: Do German Lessons Generalize?" *The Journal of Economic History* 73(2): 371-406.

Democratic Party. 2016. "2016 Democratic Party Program". Available at: https://www.presidency.ucsb.edu/documents/2016-democratic-party-platform

Diamond, Jeremy. 2016. "Trump: 'We Can't Continue to Allow China to Rape Our Country.'" *CNN Politics*. Available at: https://www.cnn.com/2016/05/01/politics/donald-trump-china-rape/index.html

Dinlersoz, Emin, and Zoltan Wolf. 2018. "Automation, Labor Share, And Productivity: Plant-Level Evidence from US Manufacturing." Unpublished Manuscript. Available at: https://ideas.repec.org/p/cen/wmanuscript/18-39.html

Dippel, Christian, Robert, Gold, Stephan Heblich and Rodrigo Pinto. 2022. "The Effect of Trade on Workers and Voters." *The Economic Journal* 132(641): 199-217.

Di Tella, Rafael, and Dani Rodrik . 2020. "Labor Market Shocks and the Demand for Trade Protection: Evidence from Online Surveys." *The Economic Journal* 130(628): 1008-1030.

Dorn, David, Gordon Hanson, and Kaveh Majlesi. 2020. "Importing political polarization? The electoral consequences of rising trade exposure." *American Economic Review* 110(10): 3139-83.

Drahos, Peter, and John Braithwaite. 2002. *Information Feudalism: Who Owns the Knowledge Economy?* New York: Routledge Press.

The Economist. 2017. "Dealing with Donald: Donald Trump's Trade Bluster." *The Economist*. Available at: https://www.economist.com/briefing/2016/12/10/donald-trumps-trade-bluster

The Economist. 2019. "America Still Leads in Technology, But China Is Catching Up Fast." *The Economist.* Available at: https://www.economist.com/special-report/2019/05/16/america-still-leads-in-technology-but-china-is-catching-up-fast

The Economist. 2021. "The New Order of Trade." *The Economist*. Available at: https://www.economist.com/special-report/2021/10/06/the-new-order-of-trade

Eriksson, Katherine, Katheryn Russ, Jay Shambaugh, and Minfei Xu. 2021. "Trade Shocks and the Shifting Landscape of US Manufacturing." *Journal of International Money and Finance* (114): 102-407.

Fabrizio, Lee & Associates. 2020. "Post-Election Exit Poll Analysis – 10 Key Target States."
Federal Communications Commission. 2021. "FCC Revokes China Telecom America's Telecom Services Authority." News Release. Available at: https://www.fcc.gov/document/fcc-revokes-china-telecom-americas-telecom-services-authority

Feler, Leo, and Mine Z. Senses. 2017. "Trade Shocks and the Provision of Local Public Goods." *American Economic Journal: Economic Policy* 9(4): 101-43.

Ferenstein, Gregory, 2016. "Tech billionaires like Democrats more than Republicans. Here's why." *The Washington Post*. Available at: https://www.washingtonpost.com/posteverything/wp/2016/05/31/tech-billionaires-like-democrats-more-than-republicans-heres-why/

Finch, Brian, Elizabeth Vella Moeller, Matthew Oresman, Deborah Thoren-Peden, Roxane Polidora, Craig Saperstein, Lee Petro, and Aimee Ghosh. 2020. Trump vs. Biden: Technology and the Internet. Pillsbury. Available at: https://www.pillsburylaw.com/en/news-and-insights/technology-policy-trump-biden-election.html

Forbes. 2022. The Global 2000. Forbes. Available at: https://www.forbes.com/lists/global2000/?sh=8db90975ac04

Freund, Caroline, and Dario Sidhu. 2017. "Global Competition and the Rise of China." *Peterson Institute for International Economics Working Manuscript* 17-3.

Frey, Carl Benedikt, Thor Berger, and Chinchih Chen. 2018. "Political Machinery: Did Robots Swing the 2016 US Presidential Election?." *Oxford Review of Economic Policy* 34(3): 418-442.

Fuller, Gregory, Alison Johnston, and Aidan Regan. 2020. "Housing Prices and Wealth Inequality in Western Europe." *West European Politics* 43(2): 297-320.

Galetovic, Alexander. 2021. "Patents in the History of the Semiconductor Industry." In *The Battle Over Patents: History and Politics of Innovation*, eds., Stephen Haber and Naomi Lamoreaux. London: Oxford University Press: 27-68.

Galetovic, Alexander, and Stephen Haber. 2017. "The Fallacies of Patent-Holdup Theory." *Journal of Competition Law & Economics* 13(1): 1-44.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review* 104(8): 2509-2526.

Grammich, Clifford, Kirk Hadaway, Richard Houseal, Dale E. Jones, Alexei Krindatch, Richie Stanley, and Richard H. Taylor. 2012. "2010 US Religion Census: Religious Congregations & Membership Study." *Association of Statisticians of American Religious Bodies*.

Grassegger, Hannes, and Mikael Krogerus. 2017. "The Data that Turned the World Upside Down." Motherboard. Available at: https://motherboard.vice.com/en_us/article/how-our-likes-helped-trump-win

Green, Joshua, and Sasha Issenberg. 2016. "Inside the Trump Bunker, with Days to Go." Bloomberg. Available at: https://www.bloomberg.com/news/articles/2016-10-27/inside-the-trump-bunker-with-12-days-to-go

Green, Jon, and Sean McElwee. 2019. "The Differential Effects of Economic Conditions and Racial Attitudes in The Election of Donald Trump." *Perspectives on Politics* 17(2): 358-379.

Greenstein, Shane. 2010. "Innovative Conduct in Computing and Internet Markets." *Handbook of the Economics of Innovation*, Vol. 1. Amsterdam: North-Holland: 477-537.

Griffin, Robert and Ruy Teixeira. 2017. "The Story of Trump's Appeal: a Portrait of Trump Voters." *The Democracy Fund Voter Group.* Available at: https://www.voterstudygroup.org/publication/story-of-trumps-appeal

Gros, Daniel. 2013. "Why Does Capital Flow from Poor to Rich Countries?" *Vox EU*. Available at: https://voxeu.org/article/why-does-capital-flow-poor-rich-countries

Gross, Daniel, and Bhaven Sampat. 2020. "Inventing the Endless Frontier: The Effects of the World War II Research Effort on Post-war Innovation." (No. w27375). *National Bureau of Economic Research*.

Goldin, Claudia, and Lawrence Katz. 2009. *The Race Between Education and Technology*. Cambridge: Harvard University Press.

Gordon, Robert. 2016. *The Rise and Fall of American Growth*. Princeton: Princeton University Press.

Guriev, Sergei, and Ellias Papaioannou. 2022. "The Political Economy of Populism." *Journal of Economic Literature* 60(3): 753-832.

Haber, Stephen, Roy Elis, and Jordan Horrillo. 2022. "The Ecological Origins of Economic and Political Systems." Available at: http://dx.doi.org/10.2139/ssrn.3958073

Hahn, Jinyong, and Jerry Hausman. 2003. "Weak instruments: Diagnosis and cures in empirical econometrics." *American Economic Review* 93(2): 118-125.

Hakobyan, Shushanik, and John McLaren. 2016. "Looking for Local Labor Market Effects of NAFTA." *Review of Economics and Statistics* 98(4): 728-741.

Hean, Oudom, and Mark Partridge. 2021. "The Impact of Metropolitan Technology on the Non-Metropolitan Labor Market: Evidence from US Patents." *Regional Studies* 56(3): 476-488.

Hejny, Jessica. 2018. "The Trump Administration and Environmental Policy: Reagan Redux?." *Journal of Environmental Studies and Sciences* 8(2): 197-211.

Hill, Seth, Daniel Hopkins, and Gregory Huber. 2019. "Local Demographic Changes and US Presidential Voting, 2012 to 2016." *Proceedings of the National Academy of Sciences* 116(50): 25023-25028.

Hiscox, Michael. 2002. "Commerce, Coalitions, and Factor Mobility: Evidence from Congressional Votes on Trade Legislation." *American Political Science Review* 96(3): 593-608.

Hope, Bradley. 2016. "Inside Donald Trump's Data Analytics Team on Election Night." *Wall Street Journal.* Available at: http://www.wsj.com/articles/inside-donald-trumps-data-analytics-team-on-election-night-1478725225

Howe, Peter D., Matto Mildenberger, Jennifer R. Marlon, and Anthony Leiserowitz. 2015. "Geographic Variation in Opinions on Climate Change at State and Local Scales in the USA." *Nature Climate Change* 5(6): 596-603.

Hull, Katy, 2020. “Lost and Found: Trump, Biden, and White Working-Class Voters.” *Atlantisch Perspectief* 44(5): 11-16.

Im, Zhen Jie, Nonna Mayer, Bruno Palier, and Jan Rovny. 2019. “The Losers of Automation’: a Reservoir of Votes for the Radical Right?” Research & Politics 6(1): 2053168018822395.

Irwin, Douglas. 2017. *Clashing Over Commerce.* Chicago: University of Chicago Press.

Iversen, Torben, and David Soskice. 2020. “Democracy and Prosperity: Reinventing Capitalism through a Turbulent Century.” Princeton: *Princeton University Press.*

Jacoby, Wade. 2020. “Surplus Germany.” *German Politics* 29(3): 498-521.

Karl, Thomas, and Walter Koss. 1984. “Regional and National Monthly, Seasonal and Annual Temperature Weighted by Area, 1895-1983.” *Historical Climatology Series 4-3.*

Kerr, William, and Ramana Nanda. 2013. “Location Choice for New Ventures: Cities.” *Harvard Business School Entrepreneurial Management Case*. Cambridge: Harvard University.

Khalifa, Sherif. 2022. *Geography and the Wealth of Nations*. Lanham: Rowman & Littlefield.

Kim, In Song. 2017. “Political Cleavages within Industry: Firm-level Lobbying for Trade Liberalization.” *American Political Science Review* 111(1): 1-20.

Lamoreaux, Naomi, and Kenneth Sokoloff. 2007. “Introduction: The Organization and Finance of Innovation in American History.” In *Financing Innovation in the United States, 1870 to Present*, eds., Naomi Lamoreaux and Kenneth Sokoloff. Cambridge: The MIT Press: 1-38.

Lapowsky, Issie. 2016. “Trump’s Plan for American-Made iPhones Would Be Disastrous.” *Wired Magazine*. Available at: https://www.wired.com/2016/03/trump-wont-get-apple-make-iphones-shouldnt/

Lapowsky, Issie. 2018. “The Lasting Impacts of Trump’s First Year.” *Wired*. Available at: https://www.wired.com/story/trump-first-year-impact-on-innovation/

Leduc, Sylvain, and Zheng Liu. 2023. “Automation, Bargaining Power, and Labor Market Fluctuations.” *Mimeo*.

Lee, Michelle. 2016. “Donald Trump Flip-flops, then Flips and Flops More on H-1B visas”. *The Washington Post*. Available at: https://www.washingtonpost.com/news/fact-checker/wp/2016/03/21/donald-trump-flip-flops-then-flips-and-flops-more-on-h-1b-visas/

Magistro, Beatrice. 2022. “The Influence of Financial and Economic Literacy on Policy Preferences in Italy.” *Economics & Politics* 34(2): 351– 381.

Mariotti, Sergio. Forthcoming. "A Warning from the Russian-Ukrainian War: Avoiding a Future that Rhymes with the Past. *Journal of Industrial and Business Economics*.

Marshall, Alfred, and Mary Paley Marshall. 1920. *The Economics of Industry.* London: Macmillan and Company.

McQuarrie, Michael. 2017. "The Revolt of The Rust Belt: Place and Politics in the Age of Anger." *The British Journal of Sociology* 68(1): 120-152.

Menaldo, Victor. 2021. "Do Patents Foster International Technology Transfer?". In *The Battle Over Patents: History and Politics of Innovation*, eds., Stephen Haber and Naomi Lamoreaux. London: Oxford University Press: 69-111.

Menaldo, Victor, and Nicolas Wittstock. 2021. "Does Technology Transfer from the US to China Harm American Firms, Workers, and Consumers? A Historical and Analytic Investigation." *Economic and Political Studies* 9(4): 417-446.

Mervis, Jeffrey. 2018. "Trump Emphasizes Workforce Training in New Vision for STEM Education." *Science*. Available at: https://www.science.org/content/article/trump-emphasizes-workforce-training-new-vision-stem-education

Mitchell, Josh. 2020. "Red States Are Winning the Post-Pandemic Economy. Wall Street Journal. Available at: https://www.wsj.com/articles/red-states-winning-post-pandemic-economy-migration-11657030536

Moretti, Enrico. 2012. *The New Geography of Jobs*. Boston: Houghton Mifflin Harcourt.

Morgan, Stephen, and Jiwon Lee. 2018. "Trump Voters and the White Working Class." *Sociological Science* 5: 234-245.

Mullins, Brody. 2023. "How Republicans and Big Business Broke Up". *The Wall Street Journal*. Available at: https://www.wsj.com/articles/republicans-corporations-donations-pacs-9b5b202b

Muro, Mark, and Yang You. 2022. "Superstars, Rising Stars, and the Rest: Pandemic Trends and Shifts in The Geography of Tech." *Brookings Institution*. Available at: https://www.brookings.edu/research/superstars-rising-stars-and-the-rest-pandemic-trends-and-shifts-in-the-geography-of-tech/

Muro, Mark, Maxim, Robert, and Whiton, Jacob, 2019. "Automation and Artificial Intelligence: How Machines are Affecting People and Places." *Brookings Institution*. Available at: https://onwork.edu.au/bibitem/2019-Muro,M-Maxim,R-etal-Automation+and+artificial+intelligence+How+machines+are+affecting+people+and+places/

Mutz, Diana. 2018. "Status Threat, Not Economic Hardship, Explains the 2016 Presidential Vote." *Proceedings of The National Academy of Sciences* 115(19): E4330-E4339.

Nellis, Stephen, Alexandra Alper, Diane Bartz, and Karen Freifeld. 2019. "US Chipmakers Quietly Lobby to Ease Huawei Ban." *Reuters*. Available at: https://www.reuters.com/article/us-huawei-tech-usa-lobbying/us-chipmakers-quietly-lobby-to-ease-huawei-ban-sources-idUSKCN1TH0VA

Nelson, Richard, and Gavin Wright. 1992. "The Rise and Fall of American Technological Leadership: the Postwar Era in Historical Perspective." *Journal of Economic Literature* 30(4): 1931-1964.

Nevo, Aviv, and Adam Rosen. 2012. "Identification with Imperfect Instruments." *Review of Economics and Statistics* 94(3): 659-671.

O'Mara, Margaret, 2020. *The Code: Silicon Valley and the Remaking of America.* New York: Penguin Press.

O'Rourke, Kevin. 2001. "Globalization and Inequality: Historical Trends. 2002." *Annual World Bank Conference on Development Economics*. Washington, D.C.: 39-67.

Osgood, Iain. 2018. "Globalizing the Supply Chain: Firm and Industrial Support for US Trade Agreements." *International Organization* 72(2): 455-484.

Pacewicz, Josh. 2016. "Here's the Real Reason Rust Belt Cities and Towns Voted for Trump." *The Washington Post*. Available at: https://www.washingtonpost.com/news/monkey-cage/wp/2016/12/20/heres-the-real-reason-rust-belt-cities-and-towns-voted-for-trump/

Palmer, Annie. 2020. "Jeff Bezos, Bill Gates, and Other Tech luminaries React to Biden's Victory". *CNBC*. Available at: https://www.cnbc.com/2020/11/07/jeff-bezos-bill-gates-and-other-tech-luminaries-react-to-biden-win.html

Perlstein, Joanna. 2016. "Techies Donate to Clinton in Droves. To Trump? Not So Much." *Wired Magazine*. https://www.wired.com/2016/08/techies-donate-clinton-droves-trump-not-much/

Petralia, Sergio, Pierre-Alexandre Balland, and David Rigby. 2016. "Unveiling the Geography of Historical Patents in The United States from 1836 To 1975." *Scientific Data* (3): 160074. 10.1038/sdata.2016.74.

Petrova, Maria, Gregor Schubert, and Pinar Yildirim. 2020. "Automation, Loss of Jobs, and Support for Populism." Mimeo, Wharton.

Piketty, Thomas. 2014. *Capital in the 21st Century*. Cambridge: Harvard University Press.

Porter, Michael. 1998. "Clusters and the New Economics of Competition" Boston: Harvard Business Review 76(6): 77-90.

The Republican National Convention. 2016. *Republican Party Platform*. https://www.presidency.ucsb.edu/documents/2016-republican-party-platform

Rho, Sungmin, and Michael Tomz. 2017. "Why Don't Trade Preferences Reflect Economic Self-Interest?" *International Organization* 71(1): 85-108.

Ritchie, Melinda, and Hye Young You. 2021. "Trump and Trade: Protectionist Politics and Redistributive Policy." *Journal of Politics* 83(2): 800-805.

Roberts, Billy. 2014. National Renewable Energy Laboratory. Solid Biomass in the United States. https://www.nrel.gov/gis/biomass.html. Accessed 3/25/2022.

Rogowski, Ronald. 1987. "Political Cleavages and Changing Exposure to Trade." *American Political Science Review* 81(4): 1121-1137.

Romer, Paul, 1993. "Idea Gaps and Object Gaps in Economic Development." *Journal of Monetary Economics* 32(3): 543-573.

Romm, Tony. 2017. "How Donald Trump Crippled US Technology and Science Policy." *Vox*. Available at: https://www.vox.com/2017/3/31/15139966/trump-white-house-technology-science-policy

Scheve, Kenneth, and Matthew Slaughter. 2001. "What Determines Individual Trade-Policy Preferences?" *Journal of International Economics* 54(2): 267-292.

Schwartz, Herman Mark. 2019. "American Hegemony: Intellectual Property Rights, Dollar Centrality, and Infrastructural Power." *Review of International Political Economy* 26(3): 490-519.

Sell, Susan. 2003. *Private Power, Public Law: the Globalization of Intellectual Property Rights.* Cambridge: Cambridge University Press.

Sherman, Ryne. 2018. "Personal Values and Support for Donald Trump During the 2016 US Presidential Primary." *Personality and Individual Differences* 128(1): 33-38.

Sherman, Gabriel. 2016. "Operation Trump: Inside the Most Unorthodox Campaign in Political History." *New York Magazine 3*. Available at: https://nymag.com/intelligencer/2016/04/inside-the-donald-trump-presidential-campaign.html

Smith, David, and Eric Hanley. 2018. "The Anger Games: Who Voted for Donald Trump in the 2016 Election, and Why?" *Critical Sociology* 44(2): 195-212.

Stanton, Katie. 2016. "An Open Letter from Technology Sector Leaders on Donald Trump's Candidacy for President." *Medium*. Available at: https://medium.com/newco/an-open-letter-from-technology-sector-leaders-on-donald-trumps-candidacy-for-president-5bf734c159e4#.nfpczjhlq

Stock, James, Jonathan Wright, and Motohiro Yogo. 2002. "A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments." *Journal of Business & Economic Statistics* 20(4): 518-529.

Stolper, Wolfgang, and Paul Samuelson. 1941. "Protection and Real Wages." *The Review of Economic Studies* 9(1): 58-73.

Swanson, Ana. 2021. "In Washington, 'Free Trade' Is NO Longer Gospel." *The New York Times*. Available at: https://www.nytimes.com/2021/03/17/business/economy/free-trade-biden-tai.html

Swisher, Kara, and Ina Fried. 2017. "Apple CEO Tim Cook on Trump's Muslim Ban: 'Apple Would Not Exist without Immigration ... It is Not a Policy we Support.'". *Vox*. Available at: https://www.vox.com/2017/1/28/14425952/tim-cook-donald-trump

Taylor, Edward, and Andreas Rinke. 2017. "Trump Threatens German Carmakers with 35 Percent US Import Tariff." *Reuters Business News*. Available at: https://www.reuters.com/article/us-usa-trump-germany-autos-idUKKBN1500VJ

U.S. Trade Representative. 2021. "2021 Trade Policy Agenda and 2020 Annual Report of The President of The United States on The Trade Agreements Program." Available at: Online PDF 2021 Trade Policy Agenda and 2020 Annual Report.pdf (ustr.gov)

Tesler, Michael. 2016. *Post-Racial or Most-Racial? Race and Politics in the Obama Era.* Chicago: University of Chicago Press.

Thewissen, Stefan, and David Rueda. 2019. "Automation and the Welfare State: Technological Change as a Determinant of Redistribution Preferences." *Comparative Political Studies 52*(2): 171-208.

Trump, Donald. 2016a. "Donald Trump: Disappearing Middle Class Needs Better Deal on Trade." *USA Today*. Available at: https://www.usatoday.com/story/opinion/2016/03/14/donald-trump-tpp-trade-american-manufacturing-jobs-workers-column/81728584/

Trump, Donald. 2016b. Declaring American Economic Independence. Trump/ Pence Campaign, June 28. Available at: https://www.donaldjtrump.com/press-releases/donald-j.-trump-addresses-re-declaring-our-american-independence

Trump, Donald. 2016c. Campaign Speech in Arizona. Donald Trump's Full Immigration Speech, Annotated. *LA Times*. Available at: https://www.latimes.com/politics/la-na-pol-donald-trump-immigration-speech-transcript-20160831-snap-htmlstory.html

The Trump Archive. https://www.thetrumparchive.com/. Accessed: 3/5/2022.

Tucker, Patrick, Michelle Torres, Betsy Sinclair, and Steven Smith. 2019. "Pathways to Trump: Republican Voters in 2016." *Electoral Studies* 61: 102035.

United States Patent and Trademark Office. 2000. *Technology Assessment and Forecast Report*. https://www.uspto.gov/web/offices/ac/ido/oeip/taf/county.pdf

U.S. Census Bureau (1931). 1930 Census: Volume 1. Population, Number and Distribution of Inhabitants. Retrieved from [https://www.census.gov/library/publications/1931/dec/1930a-vol-01-population.html].

U.S. Census Bureau (2000). 2000 Census. Retrieved from [https://www.census.gov/programs-surveys/decennial-census/decade/decennial-publications.2000.html].

U.S. Climate Divisional Database. https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/county/mapping. Accessed: 3/25/2022.

U.S. Energy Information Administration. 2022. "Biomass Explained." https://www.eia.gov/energyexplained/biomass/. Accessed: 3/27/2022

U.S. Patent and Trademark Office. Patent Technology Monitoring Team (PTMT). 2022 https://www.uspto.gov/web/offices/ac/ido/oeip/taf/reports_cbsa.htm. Accessed 3/25/2022.

U.S. Census Bureau. Historical Income Tables. Historical Income Tables: Counties (census.gov). Accessed 3/25/2022/

Varas, Antonio, and Raj Varadarajan. 2020. "How Restrictions to Trade with China Could End US Leadership in Semiconductors." *BCG Report* 9.

Viner, Jacob. 2016. *Studies in the Theory of International Trade*. New York: Routledge Press.

Waldorf, Brigitte, and Ayoung Kim. 2015. "Defining and Measuring Rurality in the US: From Typologies to Continuous Indices." In *Commissioned manuscript presented at the Workshop on Rationalizing Rural Area Classifications, Washington, DC*.

Weber, Lauren, Peter Grant, and Liz Hoffman. 2022. "Big Cities Can't Get Workers Back to the Office." *Wall Street Journal*. https://www.wsj.com/articles/office-remote-work-new-york-11657130765

Williams, Joan. 2020. "How Biden Won Back (Enough of) the White Working Class. *Harvard Business Review*: https://hbr.org/2020/11/how-biden-won-back-enough-of-the-white-working-class

Wei, Shang-Jin, and Yi Wu. 2001. "Globalization and Inequality: Evidence from within China." *National Bureau of Economic Research*. No. w8611.

White House. 2021. Press Release. Available at: https://www.whitehouse.gov/briefing-room/statements-releases/2021/06/08/statement-of-president-joe-biden-on-senate-passage-of-the-u-s-innovation-and-competition-act/

Williams, Joan. 2020. "How Biden Won Back (Enough of) the White Working Class. *Harvard Business Review*. Available at: https://hbr.org/2020/11/how-biden-won-back-enough-of-the-white-working-class

Williams, Joan. 2019. *White Working Class: Overcoming Class Cluelessness in America*. Cambridge: Harvard Business Press.

Xu, Xu, Alison Watts, and Markum Reed. 2019. "Does Access to the Internet Promote Innovation? A Look at the US Broadband Industry." *Growth and Change* 50(4): 1423-1440.