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Abstract

We study how rising market integration shaped cooperative culture and behavior in the 1850–1920 United States. Leveraging plausibly exogenous changes in county-level market access driven by railroad expansion and population growth, we show that increased market access fostered universalism, tolerance, and generalized trust—traits supporting cooperation with strangers—and shifted cooperation away from kin-based ties toward more generalized forms. Individual-level analyses of migrants reveal rapid cultural adaptation after moving to more market-integrated places, especially among those exposed to commerce. These effects are unlikely to be explained by changes in population diversity, economic development, access to information, or legal institutions.

Keywords: Markets, Trade, Cooperation, Culture, Universalism, Tolerance, Trust

JEL codes: Z10, Z13, N71, N72, R49

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"Commerce is a cure for the most destructive prejudices; for it is almost a general rule that wherever manners are gentle there is commerce; and wherever there is commerce, manners are gentle."

— Montesquieu, The Spirit of the Laws, Book 20, Chapter I

"without the assistance and co-operation of many thousands, the very meanest person in a civilized country could not be provided."

— Adam Smith, The Wealth of Nations, Chapter I

1 Introduction

How markets shape the social fabric remains a contested question. Enlightenment thinkers such as Montesquieu (1752) argued that commerce softens manners and reduces prejudice, a view echoed by Smith (1776) and Hume (1758). This *doux commerce* hypothesis is consistent with modern theories claiming that market interactions—unlike those within families or in-groups—foster impersonal prosocial norms and cooperation with out-group members (e.g., Henrich et al., 2001, 2005; Tabellini, 2008). In contrast, critics argue that expanding markets erode morality, commodify social relationships, and foster alienation and exploitation (Marx and Engels, 1848; Polanyi, 1944; Sandel, 2012; Stiglitz, 2024).

Existing evidence on this question is mainly correlational and comes primarily from small-scale or pre-industrial societies. Recent studies have found that market exchange is associated with prosocial norms (Henrich et al., 2010; Enke, 2022; Agneman and Chevrot-Bianco, 2023; Rustagi, 2024b). However, these analyses rarely address large-scale societies that experienced what Polanyi (1944) called the 'great transformation,' where expanding market integration fundamentally altered social and economic life. As a result, we know little about how markets affect culture and cooperation in such settings.

Focusing on the United States between 1850 and 1920, when the country became the world's largest and most integrated economy, this paper shows that rising market integration fostered a package of interrelated cultural traits that support cooperation with strangers and out-group members—universalism, tolerance, and generalized trust—and shifted cooperation away from kin-based toward broader and impersonal forms.

We measure market integration using a county-level measure of "market access" (Donaldson and Hornbeck, 2016). This measure combines transportation costs to all other counties with their population sizes, capturing the potential for trade. Counties' market access grew unevenly over time, driven by the expansion of the railroad network and by population growth—largely due to mass immigration.

We capture what we refer to as "generalized cooperative culture" by focusing on cultural traits that support cooperation with strangers—universalism, tolerance, and social trust. Drawing on full-count census data (Ruggles et al., 2020) and the methodology of Raz (2025), we measure universalism using the Universal Name Index (UNI), which reflects parental identification with the broader nation relative to their local community, and the rate of Extra-Community Marriage (ECM), which indicates openness to relationships beyond the in-group. Higher UNI and ECM scores reflect greater orientation toward out-group cooperation. We assess tolerance of different family-related behaviors (such as mother's age at first birth) with the Norms Tolerance Index (NTI), and of religious practices with the Religious Diversity Index (RDI), capturing openness to diverse ways of life. Finally, we construct and validate a county-level measure of social trust by applying modern Natural Language Processing techniques to a large historical corpus of US local newspapers, capturing general trust in others, including out-group members.

We develop and construct a range of indicators to measure impersonal and kin-based cooperation across different social contexts. For impersonal cooperation, we combine census data with O*NET work-style cooperation ratings to measure impersonal cooperation in local labor markets. We use patent data (Berkes, 2018) to track collaborative invention, especially among unrelated individuals, and census data to measure the share of multifamily households, capturing cooperation among unrelated individuals at home. At the community level, we use county-level tax data (Manson et al., 2020) and census data on local employment in voluntary organizations, public administration, and recreation to proxy for public goods provision and civic engagement (Putnam, 1995). Voter turnout in historical presidential elections (ICPSR, 1999) serves as an additional indicator of civicness (e.g., Alesina and La Ferrara, 2000; Rustagi, 2024a). For kin-based cooperation, we follow Ghosh et al. (2023) and use census data to measure the share of vulnerable individuals cared for by relatives at home.

Before turning to our causal analysis, we establish that our measures of generalized cooperative culture are closely linked to patterns of cooperative behavior. Counties with higher levels of generalized cooperative culture exhibit more impersonal cooperation and rely less on kin-based networks to support vulnerable individuals. These relationships hold both across counties within states and within counties over time. This evidence supports the validity of our measures and suggests that generalized cooperative culture fosters broader cooperation beyond immediate group boundaries while reducing reliance on kin-based social insurance.

We estimate the effect of increased market access on generalized cooperative culture and patterns of cooperation across counties between 1850 and 1920. Our empirical strategy, following Donaldson and Hornbeck (2016) and Hornbeck and Rotemberg (2024), controls for county fixed effects, state-by-year fixed effects, and flexible geographic trends via third-order polynomials in longitude and latitude interacted with year fixed effects. This approach identifies the impact of market integration from excess changes in counties' market access—relative to their state and broad flexible spatial patterns—driven by the expansion of the railroads and population growth across the entire network.

Our estimation yields three main results. First, increased market access boosted local commerce, validating the market access measure. A one percent increase in a county's market access led to more commerce-related content in local newspapers and a higher share of residents working in wholesale and retail, by about 13% and 14% of a standard deviation, respectively. Second, market access strengthened generalized cooperative cultural traits. A one percent increase raised universalism by 14% (Universal Name Index) and 3% (Extra-Community Marriage), tolerance by 18% (NTI, focusing on family-related norms) and 27% (RDI, focusing on religious norms), and social trust by 12%, all in standard deviation units. Third, greater market access increased impersonal cooperation and reduced kin-based cooperation. Impersonal cooperation increased by 8–14% of a standard deviation across measures. In contrast, kin-based cooperation fell by 11%, as fewer vulnerable individuals were cared for by their families at home.

To further strengthen the causal interpretation of these findings, we leverage the fact that county market access depends on the entire transportation network and population sizes in other counties, allowing us to use variation from distant rail lines and populations. Although local railroad construction and population growth may be endogenous to local culture and cooperation, our results are robust to flexible controls for both local railroad expansion and local population in and around each county. These estimates are driven by more plausibly exogenous distant changes in the rail and population network that are orthogonal to local railroad construction and population growth, as well as by shifts in how the expanding rail system complemented or substituted for earlier transport routes, such as navigable waterways.

Next, we explore *how* market access shaped generalized cooperative culture and behavior. Exploiting data on domestic migration, we test whether our results are driven by selective sorting—migrants with stronger generalized cooperative traits moving to areas with rising market access—or by cultural adaptation—individuals adapting their cultural traits and behaviors to a higher market access environment. Using the Census Linking Project (Abramitzky et al., 2022a,b,c,d,e), we compile a dataset of domestic migrants by identifying families who changed locations across censuses. Focusing on migrations across state borders, we use children's state and year of birth to infer the timing of each family's move.

To explore sorting, we test whether counties with increasing market access attracted migrants who were already more universalistic. We measure pre-migration universalism using the average UNI of children born before the migration, as well as ECM. Then, we repeat our analysis, this time focusing on the cultural traits of individuals migrating to the county rather than those of the county's population stock. Across all specifications, we find no evidence of sorting. This suggests that selective migration is unlikely to be a major driver of our main results.

To study cultural adaptation, we use a dynamic difference-in-differences. We compare families who moved to higher versus lower market access counties and track changes in parental universalism, measured by their children's Universal Name Index scores, before and after migration. We find that moving to a county with greater market access increased parents' universalism by 13% of a standard deviation. The effect appears rapidly and persists. This result is robust to alternative definitions of the Universal Name Index, including using the origin county as a reference. In a two-period difference-in-differences framework, we also find that moving to a higher market access county increases impersonal cooperation both at work (by 3%) and among non-relatives at home (by 4%). These results indicate that migrants who gain market access adapt their cooperative cultural and behavioral traits, likely by learning and adjusting to local norms.

This cultural adaptation appears to have brought economic benefits. Comparing families who moved from the same origin to the same destination county in the same decade, we find that those who became more universalistic after moving to a higher market access county experienced larger gains: a one percent increase in market access is associated with a 21% of a standard deviation increase in property values and a 12% increase in child survival rates, compared to migrants who became less universalistic. This suggests that adopting universalistic values in response to greater market access was economically beneficial, supporting the interpretation that cultural adaptation is a key driver of our main results.

We close by providing suggestive evidence on *why* market access shaped generalized cooperative culture and behavior. Because market integration fundamentally transformed many aspects of economic and social life, several channels may be at play, and, absent exogenous variation in each, we cannot fully disentangle their individual roles. Nevertheless, we provide a set of empirical tests to assess the plausibility of multiple potential channels, both direct and indirect ones.

We provide evidence in support of what we refer to as a *direct* channel. By this we mean that increased market access led to cultural adaptation primarily through greater exposure to beneficial exchanges with strangers, increasing economic interdependence beyond family and local networks. In such settings, success depends more on reputation for impersonal fairness, honesty, and trustworthiness (Smith, 1776; Tabellini, 2008; Buggle and Durante, 2021; Henrich, 2020). To explore this possibility, we use our difference-in-differences framework to study heterogeneous effects, comparing migrants working in commerce-intensive industries—such as agriculture, wholesale, and transportation—with those in more locally oriented sectors like utilities and public administration. We find that the positive impact of market access on universalism is concentrated among those in commerce-intensive sectors, with essentially no effect among those in more locally oriented sectors. Importantly, this heterogeneous treatment effect cannot be explained by pre-existing differences between individuals across the two groups, such as rural or urban origin, family size, or prior cultural traits. These results indicate that market integration shaped generalized cooperative culture directly by increasing exposure to impersonal, commerce-based interactions, rather than solely through broader shifts in the local socioeconomic environment.

We then turn to plausible *indirect* channels, as highlighted in the literature. First, market integration may increase intergroup contact and diversity, as improved transport can attract more migrants, foster broader social ties, and shift norms toward greater universalism and tolerance (e.g., Allport, 1954; Bursztyn et al., 2024). Second, it may promote income growth, urbanization and modernization, which have been linked to universalistic and tolerant values (e.g., Durkheim, 1984; Greenfield, 2009; Inglehart, 2018; Fouka and Serlin, 2024). Third, better market access could boost the flow of information and ideas, making people more tolerant towards outsiders or allowing them to learn new cultural traits related to impersonal cooperation. Fourth, market integration may support the development of local legal institutions that sustain impersonal exchange and cooperation (Greif, 1993; Cantoni and Yuchtman, 2014; Gorodnichenko and Roland, 2017; Henrich, 2020; Eruchimovitch et al., 2023).

To empirically assess these indirect channels, we conduct three complementary tests. First, we use historical data to construct proxy measures for each channel and examine whether market access had the expected impact on them. Second, we include these proxies in both our county-level and individual-level analyses to assess whether the effect of market access remains robust to controlling for these factors. Third, we horse-race gains in these factors against gains in market access in an augmented difference-in-differences analysis to explore whether migrants responded to them in the same way as to market access.

We find that although market access is associated with increases in several proxies—such as immigrant share, birthplace diversity, income, information-sector employment, and local legal professionals—most of these associations are driven by local railroad connectivity, and disappear once it is controlled for. Additionally, including these proxies as controls does not meaningfully change the main results. Importantly, our findings suggest that migrants adopted universalism in response to increased market access only, not in response to the other factors.[1] Thus, while we cannot rule out the possibility that these channels played some role, our findings suggest they are unlikely to be central mediators explaining the impact of market integration on generalized cooperative culture and cooperation.

In sum, our analyses provide evidence that market integration in 1850-1920 US shifted the scope of cooperation from local, kin-based ties to more generalized forms. This shift occurred primarily through cultural adaptation rather than selective migration, and our mechanism analysis points to the central role of exposure to impersonal, mutually beneficial exchange with strangers. Together, these results suggest that expanding opportunities for market-based interaction can promote cooperation beyond the boundaries of immediate kin and local groups.

Related Literature. Our findings contribute to several strands of literature. First, we advance the centuries-long debate about the social consequences of markets (see Hirschman, 1982). The most closely related studies in recent work include Henrich et al. (2010), which links market reliance to fairness in behavioral games across 15 mostly small-scale societies; Agneman and Chevrot-Bianco (2023), which documents a correlation between occupational choice and honesty in experiments across 13 villages in Greenland; Rustagi (2024b), which finds an impact of market proximity on civic values across 52 villages among the Oromo in Ethiopia, attributing a significant role to the demand for such values when information about goods and services is asymmetric; and Enke (2022), which shows a link between market

[1] The exception is urbanization, which is perhaps unsurprising since key features of market integration and urbanization partially overlap; both increase the likelihood of mutually beneficial interactions between strangers. However, it is important to note that, at the county level, we find that market access actually resulted in substantially less urbanization, not more. This finding is consistent with previous work (Fogel, 1964; Donaldson and Hornbeck, 2016; Chan, 2022). Therefore, while moving to a more urban environment made migrants adopt more universalistic traits, it is unlikely to explain the overall population-wide effect of market access on generalized cooperative culture and patterns of cooperation.

concepts and morality in pre-industrial folklore.

Leveraging a natural experiment and rich historical U.S. data, we contribute to this literature in four main ways. First, we focus on a period when market integration became a central organizing principle of society. Second, we identify the causal impact of market integration across a broad geography and a long time horizon. Third, we show that these effects operate through cultural adaptation, rather than selective migration. Fourth, we provide new evidence on the mechanisms linking market integration to generalized cooperative culture and the scope of cooperation. Our results support the *doux commerce* hypothesis (Montesquieu, 1752; Smith, 1776) by documenting a positive effect of market integration on impersonal cooperation and the traits that sustain it. At the same time, we find that market integration weakened kin-based social insurance, consistent with concerns raised by critics of markets (Marx and Engels, 1848; Polanyi, 1944). Thus, our findings speak to both sides of the long-standing debate.

Our paper also relates to research on markets and trade as determinants of conflict, compromise, ethnic tension, and trust (Jha, 2013; Jha and Shayo, 2019; Grosfeld et al., 2020; Margalit and Shayo, 2021; Buggle and Durante, 2021; Jha et al., 2025). Our findings suggest that the effects on these outcomes may reflect a broader transformation in what we call "generalized cooperative culture."

More broadly, our study adds to the literature on the origins and determinants of prosocial culture and cooperation. While much prior work documents persistent effects of historical shocks (Nunn and Wantchekon, 2011; Grosfeld et al., 2013; Guiso et al., 2016; Lowes et al., 2017; Moscona et al., 2020; Dell et al., 2018; Enke, 2019; Schulz et al., 2019; Buggle and Durante, 2021; Lowes and Montero, 2021; Blouin, 2022; Ramos-Toro, 2023; Rustagi, 2024a), recent evidence shows that shorter-run factors also shape cooperation and prosociality (Bauer et al., 2016; Francois et al., 2018; Rao, 2019; Kosse et al., 2020; Lowe, 2021; Raz, 2025). We highlight the dynamic role of market integration, and contribute to studies on the evolution of limited and generalized cooperation (Platteau, 2000; Tabellini, 2008, 2010; Enke, 2024; Greif et al., forthcoming), particularly complementing recent work on the American frontier (Bazzi et al., 2020, 2024), which represents the opposite end of the market-integration spectrum.

Finally, our paper complements the literature on the economic impact of railroads in the US (Fogel, 1964; Donaldson and Hornbeck, 2016; Chan, 2022; Hornbeck and Rotemberg, 2024) and elsewhere (e.g., Metzer, 1974; Donaldson, 2018). Our results suggest that trade may also promote development indirectly, by fostering cultural traits conducive to growth and innovation (Gorodnichenko and Roland, 2011, 2017; Posch et al., 2025).

Outline. The rest of this paper is organized as follows: Section 2 briefly describes the historical background. In Section 3, we explain how we measure market access, generalized cooperative culture, and both impersonal and kin-based cooperation and prosocial behavior. In Section 4, we document the correlations between generalized cooperative culture and cooperative behavior. Section 5 presents our results from the county-level analysis, while Section 6 examines selection and adaptation using the domestic-migrants design. Section 7 explores potential mechanisms. Section 8 concludes.

2 Historical Background

By the early twentieth century, the United States had undergone a profound transformation into what Polanyi (1944) termed a "market society." Market integration fundamentally reshaped both the social and economic organization of the country. Farmers and producers shifted from local subsistence to market-oriented production, interregional and long-distance trade expanded rapidly, and households across the nation grew increasingly reliant on markets to meet their consumption needs.

One vivid example comes from the agricultural Midwest. In 1890, the region produced 71% of the nation's cereal grains—roughly four times the local consumption (Fogel, 1964). This enormous surplus was shipped not only to other US regions but also to Europe and South America. A typical Midwest farmer sent grain to large primary markets within the region, from where it entered national and international trading networks, ultimately reaching about 90 secondary markets across the country before final consumption—often by individuals far removed from the farmer's own community. The scale and complexity of this distribution meant that agricultural production became fundamentally dependent on market access: as Fogel (1964) famously argued, land more than 40 miles from a railroad or navigable waterway was effectively infeasible for commercial farming.

Similar shifts occurred in household consumption. Over the course of the nineteenth and early twentieth centuries, US households transitioned from reliance on home production to purchasing a growing share of goods through markets (Gordon, 2017). The period saw a dramatic rise in the production and consumption of processed and manufactured foods—such as canned and dried fruits and vegetables, butter, cheese, and meats. By 1900, a quarter of all bread consumed in the country was baked by commercial bakeries; by 1910, Americans were consuming on average 33 cans of food per person each year. The transformation extended to clothing: whereas, at mid-century, most women made not only their own garments but also many of their children's and husbands' clothes, by the early twentieth century, mass-produced, ready-made clothing had become commonplace for urban and rural Americans alike (Gordon, 2017, p. 85–87). The growth of department stores in cities and, crucially, the spread of mail-order catalogs such as Montgomery Ward and Sears Roebuck (e.g., see Appendix Figures A.1-A.2)—facilitated by the introduction of Rural Free Delivery—brought market goods to even the most remote households.

Two key developments drove this integration. First, the period from 1850 to 1920 witnessed the explosive expansion of the US railroad network: total track mileage grew from just under 9,000 miles in 1850 to nearly 238,000 by 1920 (Appendix Figure A.3). Railroads dramatically reduced the cost of transportation nationwide. The construction of transcontinental lines integrated the Pacific Coast and the West with eastern markets, while denser rail networks in the Midwest and Northeast made local and regional transportation far more efficient. Second, the US experienced a massive population boom, rising from about 23 million in 1850 to 106 million by 1920. This "Age of Mass Migration" saw the arrival of roughly 30 million immigrants, primarily from Europe but also from Canada, Argentina, Brazil, and elsewhere (Abramitzky et al., 2014, p. 468).

The combination of a large and rapidly growing domestic market with increasingly cheap and efficient transportation greatly expanded market access for both producers and consumers throughout the country. This expansion facilitated economic development, the settlement and growth of rural areas (Donaldson and Hornbeck, 2016; Chan, 2022), and a surge in manufacturing activity and aggregate productivity (Hornbeck and Rotemberg, 2024).

3 Data

We collect data on counties' market access, prevalence of commerce, generalized cooperative cultural traits and both impersonal and kin-based cooperative behavior.

3.1 Market Access

Our measure of market integration potential follows Donaldson and Hornbeck (2016), who, building on a model of trade among U.S. counties, define an empirical first-order approximation to counties' market access as follows:

$$MA_{ot} = \sum_{d \neq o} \tau_{odt}^{-\theta} N_{dt}$$

where o denotes the county, d denotes other counties that are potential trade partners to o, and t denotes year. τ_{odt} is the trade costs between o and d in year t, expressed in proportional terms relative to the average value of the transported goods P. N_{dt} is the size of the population in county d and year t, which proxies for the size of its market, and θ is the trade elasticity. Our baseline specification follows Donaldson and Hornbeck (2016) and set $\theta = 8.22$ and $P = 35$. Our results are robust to the alternative values of P and θ used in Hornbeck and Rotemberg (2024) and to all values of θ between 1 and 13.

We use data on county-to-county transportation cost matrices (τ_{odt}) from Donaldson and Hornbeck (2016) and county-level population data (N_{dt}) from Manson et al., 2020 to calculate counties' market access for each decade between 1850-1920. The transpiration cost matrices hold the cost parameters and county borders constant at 1890 levels. Variation in county-to-county costs is therefore driven by changes in transportation infrastructure—water canals and railroads. To match the transportation cost data, we harmonize population holding county borders fixed at 1890 using the procedure in Hornbeck (2010).

Appendix Figure A.4 plots the spatial distribution of log market access for each census year between 1850-1920. Significant differences in market access across different regions of the U.S. are visible. Specifically, market access is generally the highest in the Northeast and the Midwest and lowest in the West. Panel A in Appendix Figure A.5 documents the significant increase in the average log market access during our sample period. The blue curve represents market access calculated using the contemporaneous transportation costs and population, and the dashed dark red curve fixes transportation costs to 1850. This figure shows that the main driver for the increase in market access was the decrease in transportation costs due to the expansion of the railroad network. Panel B shows that the average increase masks significant spatial heterogeneity. Areas that had lower levels of market access in 1850, which were generally the less settled and developed areas of the county, tended to experience a larger absolute increase in market access between 1850-1920.

3.2 The Prevalence of Commerce

We construct two county-level measures of the historical prevalence of commerce: commerce-related content in historical US newspapers and the share of residence working in the wholesale and retail trade industries. The outcome variables are constructed maintaining 1890 county boundaries using the harmonizing procedure in Hornbeck (2010).

Market Language in Newspapers. We develop a metric for commerce-related content in historical US newspapers. We draw on text data from *newspapers.com*, the largest online archive of historical US newspapers. This archive digitizes newspapers via optical character recognition (OCR), allowing for the retrieval of keyword frequencies by newspaper or county, rather than full text downloads.

Our methodology involves a dictionary-based measure of commerce-related content. We generate the dictionary by inputting five commerce-related seed words into *ChatGPT 4*, instructing it to augment this list to 100 keywords reflective of 19th-century U.S. newspaper language.[2] The resulting top ten keywords are: "buy", "sell", "money", "price", "trade", "market", "exchange", "goods", "services", and "commerce". For each keyword, we compute the share of pages featuring the keyword. In our main analysis, we define the dependent variable as the mean share of the top ten keywords to obtain a composite market language indicator. For validation, we extend this approach to the top 20, 50, and 100 keywords, finding a strong correlation among these indicators ($\rho > 0.94$). Additionally, our results are robust to using these alternative indicators.

Wholesale and Retail Trade Industries. We use the 1850-1920 full count censuses (Ruggles et al., 2020) to calculate the share of individuals working in the wholesale and retail trade industries, using IPUMS's *IND1950* variable. Because the empirical distribution of the wholesale and retail industries employment share is very skewed with a long right tail that also contains zeros, we winsorize it at the top 2.5% in our baseline analysis. We document robustness to using different winsorizing cutoffs and alternative ways to deal with very skewed distributions that contain zeros.

3.3 Generalized Cooperative Culture

Our hypothesis is that market integration affects the development of a package of correlated cultural traits that support cooperation with out-group members—that we refer to as a generalized cooperative culture.

[2]We use this prompt: *I want to compile a dictionary of keywords to detect content related to commerce, markets, and exchange in 19th century US newspapers. examples are "buy", "sell", "money", "price", "trade". Create a list of 100 keywords.*

Because generalized cooperative culture is a multidimensional construct, no single measure captures all its aspects. Instead, we operationalize generalized cooperative culture using multiple indicators at both the county and individual levels. Specifically, we use four measures from Raz (2025), calculated using the 1850-1920 full count censuses (Ruggles et al., 2020) and the censuses of religious bodies (Manson et al., 2020), and complement these with a novel measure obtained by applying Natural Language Processing (NLP) techniques to a corpus of U.S. local newspapers.[3] The outcome variables are constructed maintaining 1890 county boundaries, following the harmonizing procedure outlined in Hornbeck (2010).

The Universal Name Index (UNI). The UNI is focused on in-group identity, and uses children's first names to measure the extent to which the national social identity is prevalent in parents' social identity, relative to the local communal identity.[4] Following Fryer and Levitt (2004), the UNI is defined as:

$$UNI_{nlgt} = 100 \times \frac{Pr(n|-l,g,t)}{Pr(n|l,g,t) + Pr(n|-l,g,t)}$$

where n is a particular first name, l is the county, $-l$ is all other locations, g is gender, and t is the census year. The index captures the probability that a name is given to a non-local child relative to a local child. It ranges from 0-100, where values of 100 and 0 reflect distinctively non-local and local names, respectively, and a value of 50 implies that a name is equally likely to be given to local children and children elsewhere in the country.

Similar indices were recently used to study the assimilation of immigrants and nation building (e.g., Bazzi et al., 2019; Fouka, 2019; Abramitzky et al., 2020). Here, the focus is on the universal versus local component of in-group identity rather than race, ethnicity of nationality.

Panels A and B in Appendix Figure A.7 plot the spatial distribution of the UNI in 1850 and 1920, and Panel A in Appendix Figure A.8 plots the change in the UNI between those years. The spatial distribution of the UNI in 1850 and 1920 captures intuitive cultural patterns. First, in early stages of development (e.g., frontier counties in 1850), names tended to be more "local," indicating lower universalism. Second, the cultural spatial patterns in 1920 match many of the cultural patterns evident today. Specifically, the West coast, the Northeast, and large metro areas tend to be universalist, while for the South, the wheat belt, and Utah the opposite is true. Finally, locations that were in early stages of development in 1850 experienced on average a high increase in the tendency to give children universal names.

Extra-Community Marriage (ECM). The ECM focuses on in-group preference in spouse selection by measuring the tendency of individuals to marry outside their community.[5] The in-group is defined in terms of birthplace: for native-born individuals the state of birth is used and for foreign-born individuals the country of birth. The county-level ECM is the share of married couples that have a common birthplace.

Panels C and D in Appendix Figure A.7 plot the spatial distribution of the ECM in 1850 and 1920, and

[3]For more details on census-based measures and their validation, see Raz (2025).
[4]The UNI is the reverse of the LNI originally used in Raz (2025): $UNI = 100 - LNI$.
[5]The ECM is the reverse of the ICM originally used in Raz (2025): $ECM = 1 - ICM$.

Panel B in Appendix Figure A.8 plots the change. Some of the spatial patterns described above for the UNI are also evident for the ECM, however, the ECM also displays a clear East-West division, whereby the share of same-birthplace spouses in the more recently settled West tended to be much lower.

The Norms Tolerance Index (NTI). The NTI is focused on tolerance, or cultural looseness (Gelfand et al., 2006, 2011; Posch, 2021), of familial norms. The index is constructed in the following way: first, the coefficient of variance of the mother's age at first birth, the total number of children, and the number of distinct families residing in the same house are computed. Then, the first component from a PCA multiplied by -1 and standardize into z-scores within each year is defined as the NTI.[6] When computing the index, the sample is restricted to households with married mothers between the ages of 35-44 to avoid capturing variation originating from demographics rather than culture and psychology.

Panels E and F in Appendix Figure A.7 and Panel C in Appendix Figure A.8 plot the spatial distributions of the NTI in 1850, 1920, and the change between those years, respectively. Here too it seems that the level of development matters for cooperative cultural traits, as counties in early stages of settlement in 1850 tend to be highly tight. In 1920, the West and the Northeast seem to be quite loose, while Utah and much of the South and Midwest tend to be tighter. Also, large metro areas (e.g., Dallas county in Texas, Jefferson County in Alabama, or Shelby and Davidson Counties in Tennessee) tend to be more loose than surrounding counties.

The Religious Diversity Index (RDI). The RDI is focused on religious looseness, that is, tolerance of different religious identities and practices. County-level data on the number of members of religious institutions by denomination between 1850-1926 (Manson et al., 2020) is used to calculate the Herfindahl–Hirschman Index over the share of members of religious denominations. Intuitively, the index captures the degree to which multiple religious identities exist within a community. Formally:

$$RDI_{ot} = 1 - \sum_{j} s_{ojt}^2$$

where s_{ojt} is the share of members of religious denomination j in county o in year t out of the total number of members in religious institutions in county o year t. The RDI is standardize into z-scores within each year.[7]

Panels G and H in Appendix Figure A.7 and Panel D in Appendix Figure A.8 plot the spatial variation in the data.

Social Trust. We construct a novel measure of social trust using recent NLP methods, applied to a large full-text corpus provided by *newspaperarchive.com*. US newspapers historically had very local readership and often reflected their readers' values and attitudes (Gentzkow and Shapiro, 2010). This makes newspapers a useful source for studying cultural and psychological traits. Our dataset includes

[6]The NTI is the reverse of the TNI originally used in Raz (2025): $NTI = -1 \times TNI$.

[7]The RDI is the reverse of the RHI originally used in Raz (2025). Before standardization: $RDI = 1 - RHI$.

about 241 million newspaper pages, covering all US states and spanning the years 1736 to 2023.[8]

We employ a method recently developed in psychology (Atari et al., 2023). This approach measures how closely newspaper texts match psychometric questionnaire items commonly used to quantify psychological and cultural constructs in surveys. For example, the General Social Survey (GSS) has asked respondents whether "most people can be trusted" since 1972. The method involves embedding text using Sentence-BERT (SBERT), a transformer-based language model (Reimers and Gurevych, 2019) specifically designed to create embeddings at the sentence, and calculating the cosine similarity between embeddings of questionnaire items and newspaper texts.[9]

We implement this method in three steps. First, each newspaper page is embedded using the compact and efficient `all-MiniLM-L6-v2` version of SBERT. Since our data is available at the page level, we embed entire newspaper pages rather than individual articles. When a page exceeds the model's maximum context window, we split it into smaller sections, embed each section separately, and then average these embeddings to represent the page.

Second, we embed survey items measuring trust. We use two positive trust statements—"Most people can be trusted" (from the GSS) and "Most people would treat you fairly, even if they had the opportunity to take advantage of you" (adapted from the World Values Survey)—and average their embeddings. To improve precision, we also embed and average two negative statements—"You can't be too careful in dealing with people" (from the GSS) and "Most people would try to take advantage of you if they got a chance" (from the WVS)—and subtract this negative embedding from the positive embedding. This creates an "anchored" measure of trust (Kozlowski et al., 2019).

Finally, we calculate the cosine similarity between the embeddings of newspaper pages and the anchored trust embedding. Higher scores indicate greater social trust. For our analysis of market access, we aggregate the scores at the county-decade level by averaging data across all newspaper pages published in each county-year and then rounding to the nearest decade (e.g., 1855-1864 rounded to 1860). Panels G and H in Appendix Figure A.7 illustrates this variation for 1850 and 1920.

We validate our trust measure in two ways. First, we compare it with trust data from the GSS surveys between 1972 and 2014. We find two main results: (i) when aggregated by year, our newspaper-based measure closely tracks the well-documented decline in social trust since the 1970s (correlation: $\rho = 0.77$;

[8] While extensive, this data is unlikely to fully represent all segments of the population at the national, state, or county level. We will partially address this concern by including county fixed effects in our regression analysis, leveraging variation within counties over time.

[9] SBERT outperforms other transformer-based models on sentence-related tasks and greatly reduces computation time. It creates embeddings that effectively capture the core semantic meaning of sentences, ensuring sentences with similar meanings have embeddings located closely together in vector space. Higher cosine similarity between embeddings of questionnaire items and newspaper texts indicates higher levels of social trust.

This method performs significantly better than dictionary-based or simpler word embedding methods (like word2vec) and matches the performance of advanced large language models such as GPT-4 across various cultural and psychological traits (Atari et al., 2023; Abdurahman et al., 2024). A notable advantage of SBERT is its transparency—researchers have direct access to the model's parameters—and its computational efficiency, making it suitable for large textual datasets.

Appendix Figure A.9, Panel B); (ii) when aggregated by state, we find a positive and statistically significant correlation (Appendix Figure A.9, Panel C), suggesting our newspaper-based measure captures some of the variation in social trust across space and time. Second, to assess performance during the historical period of our analysis (1850–1920), we correlate social trust with generalized cooperative culture at the county level and find a strong positive association (Appendix Figure A.9, Panel D).

3.4 Impersonal and Kin-based Cooperative Behavior

We employ several county-level measures to capture historical impersonal cooperative behavior across different spheres of social life: in the labor force, in innovation, at home, and in the community. To document both the substitution between impersonal and within-kin cooperation, and the changing patterns of cooperation due to market integration, we also construct a measure of historical kin-based cooperation, focusing on care for vulnerable family members at home. All variables are constructed by maintaining 1890 county boundaries.

Cooperation in the labor force. We use data from the Occupational Information Network (O*NET) and the 1850-1920 full count censuses (Ruggles et al., 2020) to construct a county-level measure of impersonal cooperation in local labor markets. O*NET is a comprehensive database widely used by researchers (e.g., Acemoglu and Autor, 2011) that was developed by the U.S. Department of Labor to provide detailed information on job characteristics and worker attributes. The O*NET work style data, a subset of this database, focuses on personal characteristics and soft skills that are essential for successful job performance across various occupations. We focus on occupations' cooperation rating, which reflects the extent that the "[j]ob requires being pleasant with others on the job and displaying a good-natured, cooperative attitude."

We map O*NET's SOC codes to historical IPUMS's *OCC1950* codes using a combination of OCC1950-OCCSOC crosswalk and hand-coding. We then assign an O*NET cooperation score to individuals with valid occupational responses and OCC1950 codes in the historical censuses.[10] This approach assumes that the work style of occupations has remained broadly constant over time—e.g., that the current extent of cooperative behavior required from farmers, teachers, or public administrators is a good proxy for the relative degree of cooperation required from them in 1850. Finally, we compute an aggregate county-year level cooperation score by taking the weighted average O*NET cooperation scores within the county and

[10]Not all occupations have cooperation ranking in O*NET data. For example, OCC1950 "Members of the armed services" (585) and "Taxicab drivers and chauffers" (682) are missing. Depending on the year, we are able to match between 95.4% and 99.31% of individuals with a valid occupational response and OCC1950 code in the historical censuses an O*NET cooperation score. The OCC1950 occupations with the lowest cooperation ratings are "Mechanics and repairmen, office machine" (551)—3.19, "Fishermen and oystermen" (910)—3.34, "Millers, grain, flour, feed, etc." (555)—3.40, "Service workers, except private household" (790)—3.42, and "Fruit, nut, and vegetable graders, and packers, except factory" (640)—3.48. The occupations with the highest ranking are "Actors and actresses" (001)—4.72, "Ticket, station, and express agents" (380)—4.7, "Clergymen" (009)—4.66, "Officials and administrators (n.e.c.), public administration" (250)—4.61, and "Teachers (n.e.c.)" (93)—4.58. Farmers' ("Farmers (owners and tenants)" (100) and "Farm managers" (123)) cooperation ranking is 4.01, quite close to the mean (4.04) and median (4.03) cooperation ranking across OCC1950 occupations.

year, using the number of individuals in each occupation as weights. Panels A and B of Appendix Figure A.14 plot the spatial distribution of labor-force cooperation in 1850 and 1920, respectively.

Cooperation among inventors. Following Posch et al. (2025), we construct a measure of cooperation among inventors using patent data (Berkes, 2018). We focus on two different relevant aspects of cooperation: the scale of cooperation among inventors, measured by the number of inventors listed on patents, and the extent to which inventors cooperate outside their family network, measured by the entropy of patentees' surnames.[11] Because the empirical distribution of both outcomes is very skewed with a long right tail and contain zeros we winsorize them at the top 2.5% in our baseline analysis and document robustness to using different winsorizing cutoffs and alternative ways to deal with very skewed distributions that contain zeros.

A main advantage of both outcomes is that they provide a very direct measure of cooperation outside kinship networks. A disadvantage of this measure is the sparse geographical coverage of patents data, especially during the early years of our study period. Panels C-F of Appendix Figure A.14 plot the spatial distribution of cooperation among inventors, as measured by the number of co-inventors and co-inventors' diversity, in 1850 and 1920.

Residence with a non-kin. We use the 1850-1920 full count censuses (Ruggles et al., 2020) to calculate the share of multifamily households. We rely on IPUMS's *NFAMS* variable, which defines a family as "any group of persons related by blood, adoption, or marriage." Intuitively, residence with a non-kin reflects high level of cooperation outside kinship lines. Because the empirical distribution of this outcome is very skewed with a long right tail and contains zeros, we winsorize it at the top 2.5% in our baseline analysis and document robustness. Panels G and H of Appendix Figure A.14 plot the spatial distribution of the share of multifamily households in 1850 and 1920, respectively.

The provision of local public goods and services. We use county-level data from 1870-1880 on total tax revenues (Manson et al., 2020) to construct a proxy for the provision of local public goods and services. To account for the potential confounding by economic development levels, we focus on the share of local (town and county) tax revenues out of the total tax revenues (including town, county, and state taxes). Although total tax revenues may reflect local development, the share of taxes raised and allocated locally likely represents a local political decision. Panels I and J of Appendix Figure A.14 plot the spatial distribution of the local to total tax revenue ratio in 1870 and 1880, respectively.

Civic engagement. Following Putnam (1995), we examine the extent of civic activities among county residents as another outcome. We use the 1850-1920 full count censuses (Ruggles et al., 2020) to calculate the share of county residents working in industries related to local civic organizations, public adminis-

[11] For example, U.S. patent 821,393, for a "Flying Machine", granted to Orville and Wilbur Wright on May 22, 1906 has a surname entropy of zero, whereas U.S. patent 1,469,944, for Insulin, granted to Frederick Banting, Charles Best and James Collip on October 9, 1923 has a surname entropy of 1.099.

tration, and recreational activities based on IPUMS's *IND1950* variable.[12] A higher employment share in these industries suggests greater civic and social engagement at the county level. Due to the skewed distribution of this outcome with a long right tail, we winsorize it at the top 2.5% in our baseline analysis and document robustness. Panels K and L of Appendix Figure A.14 plot the spatial distribution of civic engagement in 1850 and 1920, respectively.

Voter turnout in presidential elections. Following established literature (e.g., Putnam, 1995; Alesina and La Ferrara, 2000; Rupasingha et al., 2006; Rustagi, 2024a), we use voter turnout as a measure of civicness and prosocial behavior. Voting is a form of civic engagement and political participation that, while costly for individuals, is socially beneficial.

We compute county-level turnout rates for all presidential elections from 1850 to 1920 using historical presidential elections returns (ICPSR, 1999) and estimates of the eligible voting population. For the latter, we use the full count censuses from 1850-1920 (Ruggles et al., 2020) and 1890 county-level data on male population aged 21 and over (Manson et al., 2020) to estimate the eligible voter stock in census years (round decades), taking into account historical change in women and black suffrage. We then use linear interpolation between census years. Because the true voting population can be higher than our estimate, mainly due to non-linear population growth, our proxy for the turnout rate can generally exceed 100%. However, in some cases, the estimated turnout rates are unreasonably high (e.g., 500%), suggesting data coding errors. To increase precision, we drop from the sample 338 (0.7%) observations with a turnout rate larger than 125%, which are very likely to reflect significant coding error in the data. Note that our empirical analysis below (Section 5.4) includes state-by-year fixed effects, which controls for differences in disenfranchise policies across states. Panels M and N of Appendix Figure A.14 plot the spatial distribution of voters turnout in presidential elections in 1852 and 1920, respectively.

Family Care. Finally, to capture *kin-based* cooperation, we follow Ghosh et al. (2023) and measure the share of vulnerable individuals—orphans, people with disabilities, and the elderly—cared for by relatives at home using the full count censuses from 1850-1920 (Ruggles et al., 2020). To identify orphans we focus on children below the age of 16 and rely on IPUMS's *MOMLOC* and *POPLOC* variables to identify those whose mother and father are not present in the household. To identify people with disabilities, we rely on IPUMS's *DEAF*, *BLIND*, *IDIOTIC*, *INSANE*, and *SICKNESS* variables, depending on the census year. We define old individuals as those above the age of 65. Then, we rely on IPUMS's *FAMSIZE* and *GQ* (group quarters) variables to identify the set of vulnerable individuals who are cared for by a relative at home.[13] Panels O and P of Appendix Figure A.14 plot the spatial distribution of family care in 1850 and 1920, respectively.

[12] Specifically, we include the following categories: Welfare and religious services (896), Nonprofit membership organizations (897), Local public administration (936), Eating and drinking places (679), Theaters and motion pictures (857), Bowling alleys, and billiard and pool parlors (858), Miscellaneous entertainment and recreation services (859).

[13] For orphans, we do not consider residing with a sibling orphan child as being cared for by a relative.

4 Generalized Cooperative Culture and Patterns of Cooperative Behavior

Before examining the causal impact of market integration, we first explore the relationships between our measures of generalized cooperative culture and different patterns of cooperation. This serves as a simple validation check of our measures. We expect generalized cooperative culture to be positively related to impersonal form of cooperation and negatively related to cooperation within the family (Schulz et al., 2019; Enke, 2019).

To simplify this analysis, we construct a county-year composite index of generalized cooperative culture, defined as the mean of four traits: the Universal Name Index (UNI), the Extra-Community Marriage rate (ECM), the Norms Tolerance Index (NTI), and the Religious Diversity Index (RDI).[14] Appendix Figure A.11 shows the spatial distribution of the composite index in 1850 and 1920.

We then estimate the following equation, using the same empirical approach that we will use to study the impact of market access in the next section:

$$Cooperation_{ct} = \beta \; Generalized\ Cooperative\ Culture_{ct} + \delta_{s(c)t} + \delta_c + f(x_c, y_c)\delta_t + \epsilon_{ct} \quad (1)$$

where c and t denote county and year, respectively. $\delta_{s(c)t}$ are state-by-year fixed effects, controlling for factors shared across counties within a state; δ_c are county fixed effects, absorbing persistent county-level differences and shifting the focus from levels to within-county temporal changes in cooperation and generalized cooperative culture; and $f(x_c, y_c)\delta_t$ is a cubic polynomial in longitude and latitude interacted with year, controlling for broad, time-varying smooth spatial patterns. Standard errors are clustered using arbitrary 100-mile square spatial grids to account for potential spatial autocorrelation, following the method proposed by Bester et al. (2011). The coefficient β captures the association between generalized cooperative culture and cooperation.

Figure 1 presents results for four specifications: the first without controls, followed by three that sequentially add controls. For comparability, we standardize all seven cooperation measures to z-scores. We find a strong, robust positive association between generalized cooperative culture and impersonal cooperative behavior: all coefficients are positive and significant, except for the coefficients for inventor cooperation, which lose significance in some specifications—possibly due to lower statistical power stemming from more limited spatial coverage. Most coefficients range between 0.1 and just above 0.5, indicating meaningful magnitudes. We also find a significant negative association with kin-based cooperation, with coefficients around 0.15. Appendix Table A.5 shows these results using original, non-standardized measures of cooperation.

These findings indicate that counties with stronger generalized cooperative cultural traits display higher

[14] All traits are standardized to z-scores within each year. Not all measures are available in all years: in 1880, RDI is missing and the index is constructed using UNI, ECM, and NTI; in 1890, only RDI is available. Social trust is excluded from the composite due to its limited geographic coverage (see Panels G and H in Appendix Figure A.7).

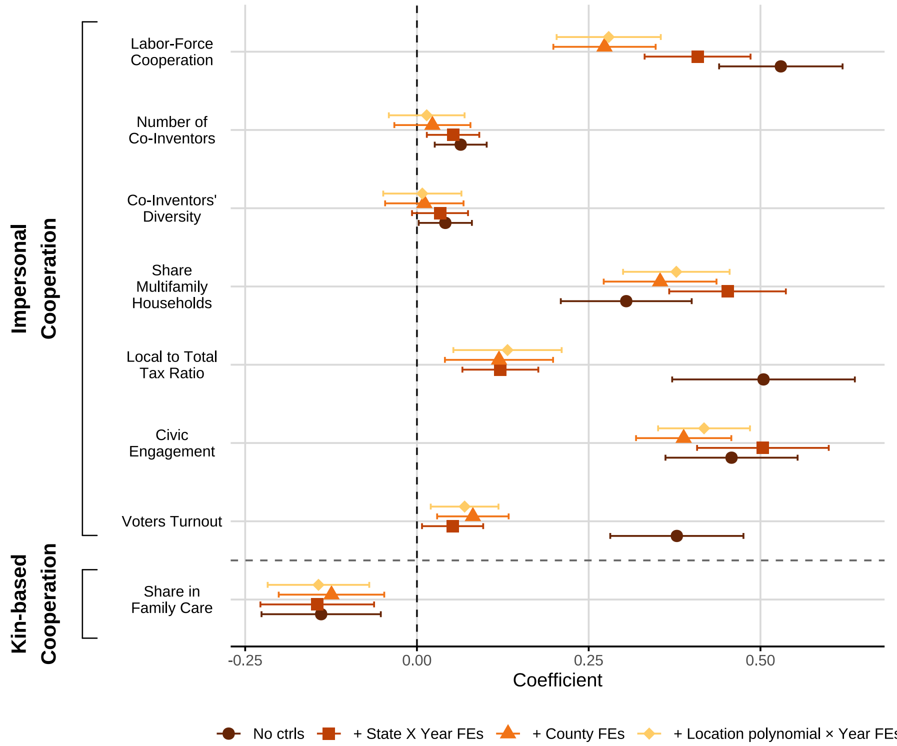

Figure 1: The Relationship Between Generalized Cooperative Culture and Cooperative Behavior

Note: This figure plots the estimates of β and 95% confidence intervals from equation (1) for all eight historical measure of cooperation, standardize into z-scores, and four different specification, sequentially adding the controls to the regression equation: without any controls, with state-by-year fixed effect $\delta_{s(c)t}$, with additional county fixed effect δ_c, and with additional cubic spatial polynomial interacted with year fixed effects $f(x_c, y_c)\delta_t$. Standard errors are clustered at arbitrary grid cells of 100 miles square (Bester et al., 2011).

levels of impersonal cooperative behavior across all domains and less reliance on kin-based social insurance. These initial correlations support the validity of our diverse—and, in some cases, novel—measures of cooperation and underscore the potential role of generalized cooperative culture in shaping the pattern of cooperation.

5 The Impact of Market Access on Generalized Cooperative Culture and Patterns of Cooperative Behavior

We now turn to our main analysis. We leverage variation in market access driven by railroad expansion and population growth between 1850 and 1920 to estimate its impact on local commerce, generalized cooperative culture, and cooperative behavior, and assess the robustness of these findings.

5.1 Empirical Strategy

We estimate the effect of market access at the county level, following the empirical strategy in Donaldson and Hornbeck (2016) and Hornbeck and Rotemberg (2024). Our regression equation is given by:

$$outcome_{ot} = \beta \ln(MA_{ot}) + \delta_o + \delta_{s(o)t} + f(x_o, y_o) \times \delta_t + X'_{ot}\gamma + \epsilon_{ot} \tag{2}$$

where o indexes counties and t indexes years. Our key explanatory variable is the log of market access, $\ln(MA_{ot})$, and the coefficient of interest is β. The equation includes county fixed effects (δ_o) to absorb all time-invariant differences across counties, and state-by-year fixed effects ($\delta_{s(o)t}$) to capture common state-level changes over time. It also accounts for smooth geographic trends by including cubic polynomials in longitude and latitude interacted with year fixed effects ($f(x_o, y_o) \times \delta_t$). Finally, X_{ot} represents additional time-varying controls, which we will add in robustness checks. Standard errors are again clustered using arbitrary 100-mile square spatial grids to account for spatial autocorrelation (Bester et al., 2011). Our results are robust to using alternative grid sizes.

The identifying assumption is conditional exogeneity: changes in market access are as good as random with respect to other unobserved determinants of the outcomes we study, conditional on the controls. County fixed effects imply that the impact is identified from counties' temporal variation in market access, after all the variation resulting from average cross-sectional differences has been partialled out. The additional state-by-year fixed effects further remove all of the temporal variation that is shared by all counties in the same state, which can relate to both geographical and institutional factors, therefore identifying the impact of *excess* changes in counties' market access relative to other counties in the state. Finally, the cubic spatial polynomial interacted with year fixed effects flexibly removes from the data all time-varying smooth geographical variation, implying that the impact of market access is identified from counties' excess changes relative to their state and broad flexible spatial patterns in the country.

There are two main threats to this identification strategy. The first is reverse causality. For example, counties that became more cooperative may have also lobbied for or attracted more railroad construction, which in turn increased their market access. Another concern is omitted variable bias: some unobserved factor (e.g., economic development) might have affected both railroad construction and our outcomes.

To address these concerns, we follow Donaldson and Hornbeck (2016) and Hornbeck and Rotemberg (2024) and leverage the fact that market access for a given county depends not just on railroad construction within that county, but also on developments in distant counties throughout the broader transportation network. By including time-varying controls for the presence and extent of local railroads in and around each county, we isolate variation in market access that is orthogonal to changes in local infrastructure. This helps ensure that our estimated effects are not simply picking up the local impact of local railroad connectivity. Moreover, following the same logic, we introduce flexible controls for local population in and around each county. This further addresses concerns that local population shifts—potentially endogenous to local culture or cooperation—could confound our estimates.[15] With these controls in place, our analysis is driven by plausibly exogenous changes in the broader rail and population network.

5.2 The Impact on the Prevalence of Commerce

We begin by exploring whether counties with greater market access became more commercially oriented. This serves both as a validation of the market access measure and as an initial test of whether the local economy responded to the increased trade potential. We focus on two outcomes: the prevalence of commerce-related content in local newspapers, and the share of residents working in the wholesale and retail trade sectors. The results are presented in Table 1.

We find that market access increases commercial orientation. Panel A focuses on the share of newspaper content related to commerce. In our baseline specification (column 2), we find that a 1 percent increase in market access increases the share of commerce-related content by 1.5 percentage points (p-value < 0.01), equivalent to about 13 percent of the standard deviation of the outcome. Appendix Figure A.6, Panel A, plots this relationship and shows that it is approximately linear and not driven by outliers.

The effect remains stable when time-varying controls for local railroad access in and around the county are included. In column 3, we add a dummy for railroad presence in the county. In column 4, we also control for a cubic polynomial in total railroad mileage in the county. Column 5 additionally controls for railroad presence and a cubic polynomial in railroad mileage within a 10-mile buffer around each county, and column 6 adds the same for 20-, 30-, and 40-mile buffers. In column 7, we further control for cubic polynomials in population size, both in the county and within 10-, 20-, 30-, and 40-mile buffers. These controls have little effect on the coefficient of interest. Appendix Table B.1 shows that our results are also robust to using different thresholds (20, 50, or 100 words) when identifying commerce-related content.

In Panel B, we turn to employment in the wholesale and retail trade sectors and find similar results. A 1 percent increase in market access raises the trade employment share by 0.51 percentage points (p-value < 0.001), or roughly 14 percent of its standard deviation. The relationship is again linear and not driven by outliers (Figure A.6, Panel B). The effect is somewhat attenuated but remains positive and statistically significant when we introduce full controls for local railroad access and population (p-value $= 0.044$). This result is robust to changes in how we handle outliers and skewness in the data (see Appendix Tables B.2 and B.3), and to whether or not we include immigrants and non-whites in the calculation of employment shares (Appendix Table B.4).

We view these results as important sanity checks. First, they validate market access as a proxy for counties' integration into broader markets. Second, they validate the empirical strategy by showing that the local commerce environment is responding to changes in market access, and that this response can be identified even from counties' excess changes in market access that are orthogonal to local expansions of the railroad network and population growth.

[15] However, note that the size of a county's own population does not enter the market access measure. See Section 3.1.

Table 1: Market Access and the Local Prevalence of Commerce

	Dependent variable:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Mean top 10 market terms share (mean = 0.466 , sd = 0.116)						
Log market access	0.0180***	0.0146***	0.0106**	0.0158***	0.0156***	0.0154***	0.0145**
	(0.0043)	(0.0045)	(0.0050)	(0.0053)	(0.0055)	(0.0058)	(0.0058)
Observations	8,625	8,625	8,625	8,625	8,625	8,625	8,625
R^2	0.629	0.633	0.630	0.635	0.636	0.637	0.639
	Panel B: Wholesale and Retail Share (mean = 0.055 , sd = 0.036)						
Log market access	0.0043***	0.0051***	0.0038***	0.0025***	0.0021**	0.0016*	0.0018**
	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Observations	18,266	18,266	18,266	18,266	18,266	18,266	18,266
R^2	0.771	0.780	0.781	0.789	0.790	0.790	0.793
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year		Yes	Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes	Yes
Railroads within further buffers						Yes	Yes
Population within further buffers							Yes

Note: This table reports estimates of equation (2) with additional controls for local railroad infrastructure and population. The dependent variables are proxy measures of the local prevalence of commerce. In Panel A, the dependent variable is the mean share of the keywords "buy", "sell", "money", "price", "trade", "market", "exchange", "goods", "services", and "commerce". In Panel B, it is the share of residence working in the wholesale and retail trade industries. Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 The Impact on Generalized Cooperative Culture

We now turn to the impact of market access on generalized cooperative culture, using all five county-level measures of cultural traits that support cooperation with strangers: universalism, tolerance, and social trust. The results are shown in Table 2.

Panel A focuses on the Universal Name Index (UNI), which reflects parental orientation toward national rather than local identity. According to column 2, a 1 percent increase in market access increases the average UNI by 0.925 points (p-value < 0.001), or about 14 percent of a standard deviation. Appendix

Figure A.10, Panel A, shows the relationship is linear and not driven by outliers. Although the coefficient attenuates when we control for the presence and extent of local railroads and local population growth, it remains meaningful (over 6% of a standard deviation) and statistically significant (p-value = 0.019) even with the most comprehensive controls.

Panel B reports results for Extra-Community Marriage (ECM), which captures openness to out-group relationships. The estimated coefficient is smaller and less precise. A 1 percent increase in market access increases the likelihood of marrying someone born outside the community by 0.69 percentage points (p-value = 0.081), which is about 3 percent of a standard deviation (column 2). The estimates are similar but become statistically insignificant when controlling for local railroad exposure and population growth (columns 3–7). Still, the relationship is positive and not driven by outliers (Appendix Figure A.10, Panel B).

Panels C and D show strong results for cultural tolerance. A 1 percent increase in market access increases the Norm Tolerance Index (NTI) and Religious Diversity Index (RDI) by 0.18 and 0.27 standard deviations, respectively (p-value < 0.001 in both cases, column 2). These are sizable effects. The relationships are linear (Appendix Figure A.10, Panels C–D) and robust to the inclusion of local railroad and population controls (Columns 3–7).

Finally, Panel E reports the effects on social trust. We find that a 1 percent increase in market access increases social trust by 0.12 standard deviations (p-value = 0.014). The estimate is stable across all specifications. Appendix Figure A.10, Panels E visualizes the relationship.

Robustness. We conduct a range of robustness checks. Appendix Table B.5 shows that the results are not sensitive to the inclusion or exclusion of immigrants and non-whites in constructing county-level cultural indicators, suggesting that they are not driven by demographics or population diversity. Appendix Figure B.1 documents robustness to alternative methods for clustering standard errors to account for spatial autocorrelation. Our results are also robust to using alternative parameters when calculating market access. Appendix Table B.6 shows that the results hold under different values of trade elasticity (θ) and the price of transported goods (P), including those used by Hornbeck and Rotemberg (2024).[16] Finally, Appendix Table B.7 confirms that no single region drives the results. We also find similar effects when using a composite index of generalized cooperative culture (Appendix A.5).

5.4 The Impact on Impersonal and Kin-based Cooperative Behavior

Having established a positive causal impact of market access on generalized cooperative culture, we proceed to examine how market access affected cooperative behavior—specifically, whether it increased impersonal cooperation and reduced provision of kin-based support. We use seven indicators of impersonal

[16] In our baseline analysis, we follow Donaldson and Hornbeck (2016) in setting the trade elasticity to $\theta = 8.22$ and the average value of transported goods per ton to $P = 35$. The robustness check shows that our results are robust to using the alternative parameter values in Hornbeck and Rotemberg (2024)—$P = 38.7$ and $\theta = 3.05$—and any value for θ between 1 and 13. While the point estimates naturally vary with the parameters, we consistently find positive and significant effects.

Table 2: Market Access and Generalized Cooperative Cultural Traits

	Dependent variable:						
	(1)	(2)	(3)	(4)	(5)	(6)	(6)
	Panel A: Universal Name Index (mean = 32.18 , sd = 6.6)						
Log market access	1.137***	0.9250***	0.7035***	0.5531***	0.4657***	0.3572**	0.4051**
	(0.1606)	(0.1610)	(0.1681)	(0.1695)	(0.1737)	(0.1713)	(0.1724)
Observations	18,182	18,182	18,182	18,182	18,182	18,182	18,182
R^2	0.795	0.805	0.806	0.809	0.810	0.813	0.816
	Panel B: Extra-Community Marriage (mean = 0.382 , sd = 0.2)						
Log market access	0.0061*	0.0069*	0.0072*	0.0044	0.0056	0.0056	0.0065
	(0.0037)	(0.0037)	(0.0039)	(0.0040)	(0.0040)	(0.0041)	(0.0041)
Observations	18,179	18,179	18,179	18,179	18,179	18,179	18,179
R^2	0.904	0.908	0.908	0.909	0.910	0.910	0.911
	Panel C: Norms Tolerance Index (mean = 0 , sd = 1)						
Log market access	0.1866***	0.1785***	0.1753***	0.1753***	0.1610***	0.1465***	0.1496***
	(0.0277)	(0.0321)	(0.0333)	(0.0333)	(0.0339)	(0.0347)	(0.0346)
Observations	18,098	18,098	18,098	18,098	18,098	18,098	18,098
R^2	0.692	0.698	0.698	0.698	0.699	0.700	0.701
	Panel D: Religious Diversity Index (mean = 0 , sd = 1)						
Log market access	0.2907***	0.2681***	0.2306***	0.2180***	0.2031***	0.1909***	0.1893***
	(0.0374)	(0.0347)	(0.0362)	(0.0383)	(0.0382)	(0.0383)	(0.0384)
Observations	17,303	17,303	17,303	17,303	17,303	17,303	17,303
R^2	0.674	0.681	0.682	0.683	0.684	0.687	0.689
	Panel E: Social Trust (mean = 0.002 , sd = 0.998)						
Log market access	0.1307***	0.1201**	0.1258**	0.1229**	0.1373**	0.1291**	0.1291**
	(0.0449)	(0.0485)	(0.0534)	(0.0587)	(0.0616)	(0.0631)	(0.0631)
Observations	6,821	6,821	6,821	6,821	6,821	6,821	6,821
R^2	0.678	0.681	0.680	0.681	0.681	0.683	0.685
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year		Yes	Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes	Yes
Railroads within further buffers						Yes	Yes
Population within further buffers							Yes

Note: This table reports estimates of equation (2) with additional controls for local railroad infrastructure and population. The dependent variables are different historical generalized cooperative cultural traits: the UNI (Panel A), the ECM (Panel B), the NTI (Panel C), the RDI (Panel D), and Social Trust (Panel E). Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Market Access and Impersonal and Kin-based Cooperative Behavior

	Dependent variable:							
	Impersonal							Kin-based
	Labor-force cooperation	Number of co-inventors	Diversity of co-inventors	Residence with a non-kin	Provision of public goods	Engagement in civic activities	Voter turnout	Share in Family Care
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log market access	0.0058***	0.0114***	0.0111***	0.0083***	0.0185***	0.0008***	0.0340***	-0.0121***
	(0.0012)	(0.0037)	(0.0034)	(0.0022)	(0.0060)	(0.0002)	(0.0060)	(0.0032)
DV mean	3.996	1.092	0.0760	0.1510	0.6700	0.0120	0.6300	0.7780
DV sd	0.0590	0.1160	0.1060	0.0840	0.1980	0.0090	0.2400	0.1110
Observations	18,267	17,360	17,360	18,277	4,942	18,266	45,308	18,173
R^2	0.680	0.241	0.241	0.782	0.908	0.688	0.795	0.721
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × State Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation (2). The dependent variables are seven different historical measure of impersonal cooperation: labor-force cooperation (column 1), the average number of patents co-inventors (column 2), the diversity of patents co-inventors (column 3), the share of multifamily households (column 4), share of local tax revenues (column 5), the share employed in civic activities (column 6), and voters turnout in presidential elections (column 7); and one measure of historical kin-based cooperation: the share of vulnerable individuals in family care (column 8). Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

cooperation, along with one measure of kin-based social insurance. The results are presented in Table 3.

Across all seven measures, we find that market access increased impersonal cooperative behavior. Column 1 shows that a 1 percent increase in market access raises the average labor-force cooperation rating by 0.0058 points (p-value < 0.001), or about 10 percent of a standard deviation. Columns 2 and 3 show similar effects for collaborative invention. Market access increases both the number and diversity of co-inventors by 0.011 points (p-value < 0.01 for both), which amounts to approximately 10 percent of a standard deviation in each outcome. Market access also increases the share of multifamily households, the share of the population involved in public collective action, and civic engagement by about 8 to 10 percent of a standard deviation (p-value < 0.01 for all). The effect on presidential election turnout is especially large: a 1 percent increase in market access raises turnout by 0.034 points, or 14 percent of a standard deviation (p-value < 0.001).

By contrast, Column 8 shows that provision of kin-based social insurance falls. A 1 percent increase in market access reduces the share of vulnerable individuals cared for by relatives by 0.012 points (p-value < 0.001), an effect size of about 11 percent of a standard deviation. In all cases, the relationship between market access and the outcome is linear and not driven by a few outliers (Appendix Figure A.15).

To support a causal interpretation of these findings, we again rely on the network structure of market access and identify effects using only changes in market access that are orthogonal to railroad construction and population growth in and around each county. Appendix Table A.4 shows that all coefficients remain positive for impersonal cooperation and negative for kin-based cooperation, and statistically significant for six of the eight outcomes even with the most demanding set of controls. In addition, the effects sizes remain stable: for most outcomes, the baseline estimates and those with full railroad controls are statistically indistinguishable.

Robustness. These findings are also robust to a wide range of robustness checks. The main results are not sensitive to the way spatial autocorrelation is accounted for (Appendix Figure B.2), to the parameters used to calculate market access (Appendix Table B.8), or to the handling of skewed outcome distributions (Appendix Tables B.9, B.10, B.11). The results also hold when we drop any one census region at a time (Appendix Table B.12).

Overall, our analysis demonstrates that market integration had a widespread and robust impact on both culture and behavior, increasing the prevalence of both generalized cooperative culture and impersonal cooperation, and reducing the provision of kin-based social insurance.

6 Adaptation vs. Sorting: Evidence from Domestic Migrants

In this section, we use individual-level data on domestic migrants to explore *how* market access strengthened generalized cooperative culture and behavior. Specifically, we ask: Did people with generalized cooperative cultural traits move to areas with rising market access (selective sorting), or did people adapt their culture and behavior (cultural adaptation), or was it some combination of both?

To answer these questions, we draw on the Census Linking Project (Abramitzky et al., 2022a,b,c,d,e) to construct a sample of domestic migrants. By connecting male household heads from one census to the next, this source allows us to follow households over time. We focus on families that moved across state lines and estimate the year of migration as the midpoint between the last child born in the state of origin and the first child born in the destination state. Because county boundaries changed over time, we use a fuzzy matching approach to assign families to 1890 county boundaries, sometimes assigning them to more than one possible county, weighting each assignment by how likely it is to be correct based on the geographical overlap of counties' boundaries. Each household is then linked to the level of market access in both their origin and destination counties at the time of the later census.

6.1 Selective Sorting

One possibility is that people with stronger generalized cooperative cultural traits were more likely to move to areas that were becoming more market-integrated. If this is the case, the positive relationship between market access and generalized cooperative culture might simply reflect selective sorting, that is, where people chose to move.

To test for this possibility, we aggregate the individual-level data of incoming domestic migrants to the county-year level and use Equation (2) to estimate whether counties that experienced increases in market

Table 4: No Selective Sorting of Domestic Migrants on Generalized Cooperative Cultural Traits

	Dependent variable:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Universal Name Index (mean = 44.24 , sd = 7.915)						
Log market access	-0.0616	0.1377	0.2003	0.2245	0.1986	0.2574	0.2766
	(0.3858)	(0.3501)	(0.4055)	(0.4275)	(0.4517)	(0.4699)	(0.4681)
Observations	8,748	8,748	8,748	8,748	8,748	8,748	8,748
R^2	0.366	0.368	0.368	0.368	0.368	0.369	0.369
	Panel B: Extra-Community Marriage (mean = 0.407 , sd = 0.286)						
Log market access	-0.0125	-0.0184	-0.0223	-0.0206	-0.0207	-0.0165	-0.0171
	(0.0116)	(0.0127)	(0.0146)	(0.0151)	(0.0158)	(0.0162)	(0.0163)
Observations	8,872	8,872	8,872	8,872	8,872	8,872	8,872
R^2	0.405	0.407	0.407	0.407	0.407	0.408	0.408
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year		Yes	Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes	Yes
Railroads within further buffers						Yes	Yes
Population within further buffers							Yes

Note: This table reports estimates of equation (2) with additional controls for local railroad infrastructure and population. The dependent variables are the average UNI (Panel A) and ECM (Panel B) of incoming domestic migrants. Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

access attracted migrants with higher pre-migration universalism, as measured by the average Universal Name Index (UNI) of children born before migration and Extra-Community Marriage (ECM).

Table 4 shows that, in contrast to our main county-level findings, which focus on the cultural traits of the entire population in the county (Section 5.3), there is no significant association between excess changes in market access and the universalistic cultural traits of incoming migrants. Thus, we do not find evidence that selective migration is responsible for the positive link between market access and generalized cooperative culture found in the broader population.

6.2 Cultural Adaptation

6.2.1 Generalized Cooperative Culture

To explore the possibility that people adapt their generalized cooperative cultural trait to the changing market access environment, we examine changes in parental universalism using a dynamic difference-in-differences framework, following the approach in Raz (2025). We compare UNI scores among siblings born before and after migration in families that moved to higher versus lower market access counties.

Empirical strategy. We estimate the following equation:

$$UNI_i = \delta_{b(i)} + \theta_{f(i)} + \sum_{b \neq 0} \beta_b \cdot \mathbb{1}\left[b(i) = b\right] \cdot \mathbb{1}\left[MA_{d(i)} > MA_{o(i)}\right] + X_i\Omega + \epsilon_i \tag{3}$$

where UNI_i is the Universal Name Index score for child i, currently residing in county $d(i)$ and born $b(i)$ years relative to the year the family $f(i)$ migrated from county $o(i)$ to county $d(i)$. $\delta_{b(i)}$ is a set of relative-year-of-birth fixed effects, absorbing any changes in universal identification relative to the year of migration in families that migrated to a lower market access county. Crucially, $\theta_{f(i)}$ is a family fixed effect, removing any unobserved factor that is common among siblings, including the family's migration path and permanent cultural and economic characteristics, so we compare only within family over time. X_i is a vector of child i characteristics—gender, birth order and a 5-year cohort fixed effect—and is included when we assess the robustness of the estimates. β_b are the coefficients of interest, capturing the impact of moving to a higher versus lower market access county on universal identification over time. We normalize β_{-1} to zero so that β_b can be interpreted as the effect relative to the year just before the migration.[17]

We cluster standard errors ϵ_i at the county-of-destination level (Bertrand et al., 2004), but results are robust to two-way clustering. When families are matched to multiple 1890 counties, we weight observations by the matching probabilities, such that the total weight per child sums to one.

Results. We find that migration to a higher market access county rapidly increases universalism. Figure 2 shows that there are no differential trends in UNI prior to migration between families who moved to counties with higher versus lower market access, validating the empirical design. In the first year after migration, the UNI of a child born to a family that moved to a higher market access county jumps by 2.45 points (p-value < 0.001) relative to a child born to a family that experienced a decline in market access, and this effect persists for at least ten years. Estimating a static version of Equation (3) yields similar results: Table 5, column 1, shows that the UNI of children born to families that gained market access through migration was about 2.35 points higher (p-value < 0.001) than that of children whose families

[17] Our specification uses event time rather than calendar time, which means that all families are first treated between $b = 0$ and $b = 1$. As a result, concerns about negative weights in two-way fixed effects regressions with staggered treatment timing (e.g. Borusyak et al., 2024; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021)—or more generally, in designs where groups experience different evolution of their exposure to treatment over time—do not arise.

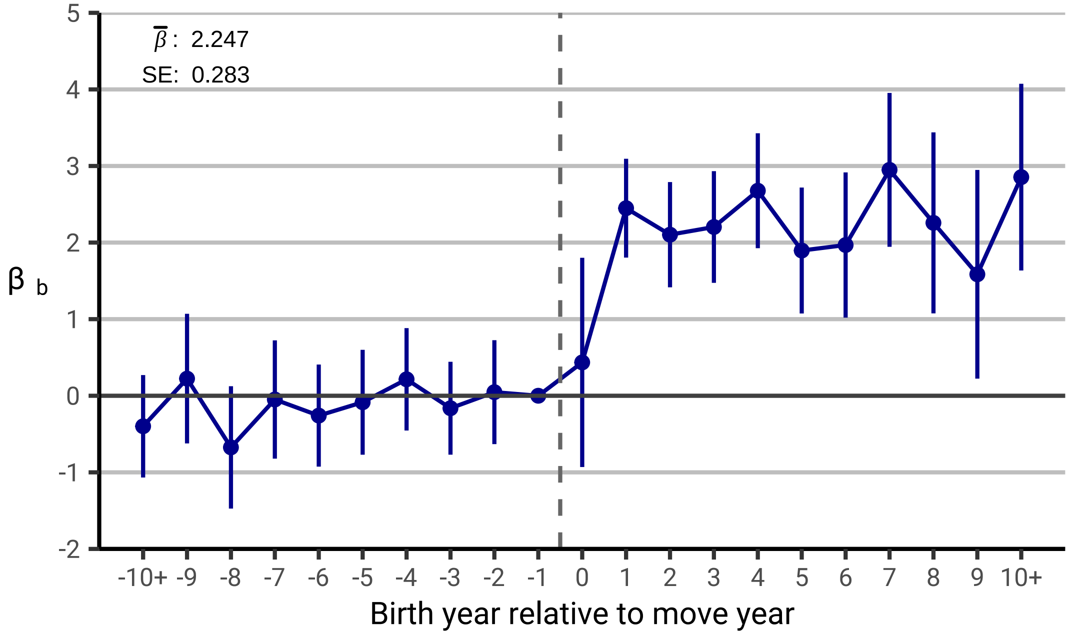

Figure 2: The Impact of Moving to a Higher Market Access County on Universalism

Note: This figure plots the estimates of β_b and 95% confidence intervals from the dynamic difference-in-differences equation (3). $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

lost market access after moving.

One concern in interpreting the results as indicating a positive impact of market access on universal versus local identity is that migration implies a change in the definition of "local". That is, UNI measures the degree to which national social identity is prevalent in parents' social identity relative to the local or communal identity, but because here we are focusing on migrants, maintaining a higher degree of social identification with the origin is likely to imply a lower degree of social identification with the destination. If that is the case, then a relative increase in the UNI may reflect a decrease in universalism rather than an increase. To explore this possibility, we also compute a version of the UNI in which we fix the definition of "local" at the county of origin. That is, for children born after migration, the UNI is *not* computed for their county of birth, but for their family's previous county of residence. We then use this version of the UNI and Equation 3 to estimate the impact of moving to a higher versus lower market access county on universal identification relative to the *previous* community. Column 3 in Table 5 and Appendix Figure A.16 present the results. The findings are qualitatively similar, documenting a positive and highly significant causal impact of market access on universal identification. Quantitatively, the impact is smaller.

Robustness. This finding is robust to variation in specification, treatment definition, sample, and inference. Appendix Figure B.3 and columns 2 and 4 in Table 5 document that the finding is robust to controlling for gender, birth order, and a 5-year cohort fixed effects. Appendix Figure B.4 documents that

Table 5: Cultural Adaptation to a Higher Market Access Environment

	Dependent variable: Universal Name Index			
Local is:	Birth County (mean = 41.146 , sd = 18.225)		Origin County (mean = 44.665 , sd = 16.591)	
	(1)	(2)	(3)	(4)
Post Migration × Higher Market Access	2.349*** (0.2250)	1.995*** (0.2130)	0.5192*** (0.1284)	0.3779*** (0.1301)
Observations	470,998	470,998	431,765	431,765
R^2	0.321	0.323	0.336	0.337
Family Fixed-Effects	Yes	Yes	Yes	Yes
Relative-year-of-birth Fixed-Effects	Yes	Yes	Yes	Yes
Individual Controls		Yes		Yes

Note: This table reports estimates of the static version of equation (3). The dependent variable is children's UNI of domestic migrants. In columns 1-2, "local" is defined as the county of origin for children born before the migration and the county of destination for children born after it. In columns 3-4, "local" is always defined as the county of origin. Individual controls include gender, birth order, and a 5-year cohort fixed effects. Standard errors clustered at the county of destination in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the finding is robust to two-way clustering at the counties of destination and origin. Appendix Figure B.5 documents that the finding is robust to using a continuous definition of treatment—the difference in log market access, instead of a binary one. Finally, Appendix Figure B.6 documents that the finding is not driven by demography, as the finding is robust to the exclusion of immigrants and non-Whites.

6.2.2 Adaptation in Cooperative Behavior

We also examine whether this adaptation extends to actual cooperative behavior, focusing on the two indicators that we can measure at the family level before and after migration: the father's labor-force cooperation score and residing with non-kin.

Empirical strategy. We use a simple two-period difference-in-differences framework to identify the causal impact of market access on impersonal cooperation:

$$cooperation_{ft} = \theta_f + Post_t + \beta \cdot \mathbb{1}\left[MA_{d(f)} > MA_{o(f)}\right] \cdot Post_t + \epsilon_{ft}. \tag{4}$$

Here, $cooperation_{ft}$ is the degree of cooperation for family f, measured at time t, either before or after their move from county $o(f)$ to county $d(f)$. $Post_t$ is an indicator for the post-migration period, and θ_f is a family fixed effect. The coefficient β captures the effect of moving to a county with higher (versus lower) market access on cooperation. Standard errors ϵ_{ft} are clustered at the county of destination d, or

Table 6: The Impact of Moving to a Higher Market Access County on Impersonal Cooperative Behavior

	Dependent variable:					
	Labor-force cooperation (mean = 4.036 , sd = 0.171)			Residence with non-kin (mean = 0.144 , sd = 0.351)		
Treatment:	Binary	Binary	Continuous	Binary	Binary	Continuous
Clustering:	Destination	Two-way	Destination	Destination	Two-way	Destination
	(1)	(2)	(3)	(4)	(5)	(6)
Post Migration × Higher Market Access	0.0051*** (0.0018)	0.0051** (0.0020)	0.0034*** (0.0013)	0.0138*** (0.0039)	0.0138*** (0.0042)	0.0050* (0.0028)
Observations	189,588	189,588	189,588	189,588	189,588	189,588
R^2	0.669	0.669	0.669	0.544	0.544	0.544
Family Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Post	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation (4). The dependent variables are labor-force cooperation (columns 1-3) and residence with a non-kin (columns 4-6). Higher market access is coded as binary in columns 1-2 and 4-5, and continuously in columns 3 and 6. Standard errors in parentheses are clustered at the county of destination in columns 1, 3-4, and 6, and two-way clustered at county of destination and the county of origin in columns 2 and 5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

two-way clustered (Bertrand et al., 2004). As before, we weight observations by matching probabilities to account for families that are matched to multiple 1890 counties.

Results. We find that families moving to higher market access counties experienced a statistically significant increase in both measures of impersonal cooperation. Specifically, Table 6 shows that the labor-force cooperation score increased by 0.005 points (p-value < 0.01), about 3 percent of a standard deviation, and the probability of living with a non-kin rose by 0.0138 points (p-value < 0.001), about 4 percent of a standard deviation, relative to families moving to lower market access counties. These results are robust to two-way clustering at the destination- and origin-county level (columns 2 and 5) and to using a continuous definition of treatment (columns 3 and 6).

Together, these findings reinforce our main result: market integration increases generalized cooperative culture and impersonal cooperation. They also suggest that this effect is driven mainly by cultural adaptation to a higher market access environment, rather than by selective migration.

6.3 The Returns to Adaptation

Finally, we ask whether adapting to a more market-integrated environment actually benefited migrants and their families. To do this, we compare families that moved from the same origin to the same destination in the same decade—therefore experiencing the same change in environment—but differed in whether they became more universalistic after the move. While this test is informative, it provides only suggestive evidence and does not causally identify the returns to adaptation.

Empirical strategy. We estimate the following equation:

$$success_i = \gamma Adapted_i + \beta Adapted_i \cdot \mathbb{1}\left[MA_d > MA_o\right] + \delta_{dot} + X_i\Omega + \epsilon_i \tag{5}$$

where $success_i$ denotes two measures of success that are available in the historical censuses: the survival rate of children (available for 1900–1910)[18] and the value of real property owned (available for 1850–1870).[19] $Adapted_i$ is a dummy variable equal to one if the mean UNI score of children born to migrant i after the move was higher than the mean score of children born before migration—that is, if the migrant became more universalistic. δ_{dot} is a origin-by-destination-by-year fixed effect, which also captures the main effect of moving to a county with higher market access. X_i is a vector of migrant characteristics, including fixed effects for age, race, birthplace, ECM and urban origin. β, the coefficient on the interaction between moving to a higher market access county and becoming more universalistic, is our target of interest. It captures the return to cultural adaptation.[20] We cluster standard errors ϵ_i at the county of destination d.

Results. We find that families that became more universalistic after moving to a higher market access county had better outcomes. Table 7 shows a strong and significant positive association between cultural adaptation and both measures of economic success. Column 1 suggests that children of migrants who gained market access and became more universalistic had a 1.9% (p-value = 0.032) higher survival rate compared to children of migrants who became less universalistic, or 12% of a standard deviation. This result remains stable when we add fixed effects for age, race, and birthplace (column 2), and when we further control for pre-existing cooperative traits (as measured by ECM) and urban versus rural origin (column 3). Column 4 shows a similar pattern for real property value: migrants who culturally adapted to a higher market access environment owned \$559 more in real property (p-value = 0.026) than those who did not adapt, or roughly 21% of a standard deviation. This finding also holds when we include individual-level controls (columns 5 and 6).[21] These patterns are consistent with the idea that people adapt their cultural traits to better fit the market access environment.

Robustness. Appendix Table B.14 shows that the result is robust to two-way clustering at the county of destination and county of origin. In our baseline, we winsorize real property values at the top 2.5%; however, Appendix Table B.15 shows that the finding also holds when we winsorize at different top

[18]To calculate children survival rate, we rely on IPUMS's *CHBORN* and *CHSURV* variables.

[19]We rely on IPUMS's *REALPROP* variable (available for 1850-1870).

[20]Note that in this framework, β is estimated from several thousand cases where there are multiple migrants within the same origin-destination-decade cell.

[21]Interestingly, we find no evidence for a similar effect on personal property. When we use total property value (real plus personal property) as the dependent variable, the effect is only marginally significant. See Appendix Table B.13.

Table 7: The Returns to Cultural Adaptation

	Dependent variable:					
	Children Survival Rate (mean = 0.879 , sd = 0.163)			Real Property Value (mean = 2321.0 , sd = 2711.7)		
	(1)	(2)	(3)	(4)	(5)	(6)
More Universalistic	-0.0031	-0.0018	-0.0018	-106.0	-93.20	-93.92
	(0.0064)	(0.0066)	(0.0066)	(117.5)	(115.4)	(114.6)
Higher Market Access × More Universalistic	0.0192**	0.0194**	0.0195**	559.0**	606.2**	599.7**
	(0.0090)	(0.0095)	(0.0095)	(250.9)	(240.2)	(238.6)
Observations	25,432	25,432	25,432	24,835	24,835	24,835
R^2	0.777	0.789	0.789	0.883	0.892	0.892
Origin × Destination × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Ctrls. (demographics)	No	Yes	Yes	No	Yes	Yes
Individual Ctrls. (traits)	No	No	Yes	No	No	Yes

Note: This table reports estimates of equation (5). The dependent variables are different measures of success: children survival rate (columns 1-3) and real property value (columns 4-6). Individual demographic controls includes age, race, and birthplace fixed effects. Individual traits controls include fixed effects of ECM and an urban origin. Standard errors clustered at the county of destination in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

percentiles, or do not winsorize at all. Appendix Table B.16 demonstrates that the results for real property values are robust to different methods of addressing skewed distributions with a long right tail.

7 Mechanisms: Why Did Market Access Transform Generalized Cooperative Culture?

In this section, we explore *why* greater market access transformed cooperative generalized culture and patterns of cooperation. We consider both the direct channel—exposure to beneficial exchanges and increased economic dependence on strangers and out-group members—and a set of indirect channels, operating through certain features of the environment such as population diversity and economic development, which may in turn influence culture and behavior.

7.1 Direct Channel: Exposure to Commerce and Market Interactions

A central hypothesis in both economics and cultural evolution is that direct exposure to markets—everyday economic interdependence and mutually beneficial interactions and exchanges with strangers and out-group individuals—can shape people's psychology and norms. This argument goes back to Enlightenment thinkers like Montesquieu (1752) and Smith (1776), and is central to modern theories (e.g., Tabellini, 2008; Henrich et al., 2010; Henrich, 2020). The idea is that as individuals become more economically interdependent with people outside their family or group, they have stronger incentives to internalize universalistic values, generalized trust and tolerance for diverse norms. These traits support cooperation with strangers and are seen as adaptive in large-scale integrated societies (Henrich et al. 2005; Ensminger and Henrich, eds 2014; Henrich and Muthukrishna 2021).

We present evidence suggesting that the impact of market access on generalized cooperative culture stem from engagement in commerce. Our analysis leverages a key intuition: If market integration shapes culture through direct exposure to commerce, then individuals whose livelihoods depend more heavily on commerce should be more strongly affected. Conversely, people working in industries that are more insulated from broader markets—serving only the local community—should be less affected.

To operationalize this, we categorize migrants' industries into two broad groups: *commerce-intensive*, which are sectors that either sell to distant markets—like manufacturing and agriculture—or that are essential to the broader functioning of markets—such as wholesale, retail and transportation; and *commerce-moderate*, which include industries mostly serving local markets and community needs, such as construction, utilities, entertainment and recreation, and public administration.[22] Then, using our dynamic difference-in-differences framework, we limit the sample to households where the father remained in the same broad industry category before and after migration, and estimate the impact of moving to a county with higher market access separately for each category.

Figure 3 presents the results. For those in commerce-intensive industries, moving to a county with higher market access leads to an immediate and persistent increase in universalistic traits, relative to moving to a lower market access county (Panel A). This pattern closely mirrors the findings from the full sample of migrants. By contrast, for individuals working in commerce-moderate industries, there is no discernible impact: moving to a county with greater market access has essentially no effect on universalism (Panel B).

This heterogeneity in how individuals working in different industrial groups respond to market access supports the hypothesis that direct exposure to commerce—as opposed to simply living in a more market-oriented place—shapes generalized cooperative cultural traits. The fact that the effect is concentrated among commerce-intensive migrants also makes it unlikely that the association is being driven by county-

[22] Specifically, we classify the following IPUMS *IND1950* codes as commerce-intensive: Agriculture, Forestry, and Fishing (105-126), Mining (206-239), Manufacturing (306-499), Transportation (506-568), Telecommunications (578-579), Wholesale Trade (606-627), Retail Trade (636-699, except 679 - Eating and drinking places), Banking and credit agencies (716), Security and commodity brokerage and investment companies (726), Insurance (736), Advertising (806), Accounting, auditing, and bookkeeping services (807), and Miscellaneous business services (808); and the following codes as commerce-moderate: Construction (246), Utilities and Sanitary Services (586-598), Eating and drinking places (679), Real estate (746), Real estate-insurance-law offices (756), Auto repair services and garages (816), Miscellaneous repair services (817), Personal services (826-849), Entertainment and Recreation Services (856-859), Professional and Related Services (868-899), and Public Administration (906-946).

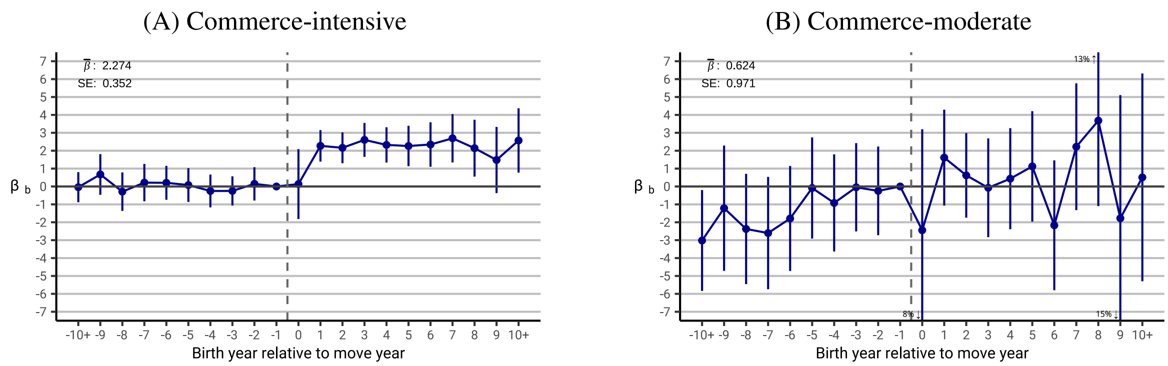

Figure 3: Market Access Affects Individuals Working in Commerce-Intensive Industries Only

Note: This figure plots the estimates of β_b and 95% confidence intervals from the dynamic difference-in-differences equation (3). In Panel A, the sample is restricted to households in which the father was working in a commerce-intensive industry before and after the migration. In Panel B, the sample is restricted to households in which the father was working in a commerce-moderate industry before and after the migration. $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

level changes or indirect channels that affect all residents equally.

We perform several additional analyses to address possible concerns. One might worry that the effect is driven primarily by farmers, who make up about 53% of the commerce-intensive sample, or by the much larger sample size in this category (266,028 observations, compared to 25,402 in the commerce-moderate group). To explore this, we further split the commerce-intensive category into farmers and non-farmers and repeat the analysis (Appendix Figure A.17).[23] The positive effect of market access on universalism is present in both subgroups. Even among non-farmers, where the sample is much smaller (50,448 observations), the effect remains statistically significant, showing that the result is not simply driven by farming. Sample size differences are also unlikely to explain the null effect for commerce-moderate jobs. In Appendix Figure A.18, we take 1,000 random draws of 5,985 families (the same number of families as in the commerce-moderate group) from the commerce-intensive group and re-estimate the impact in each of these random samples. We find a stronger effect in 96.2% of these draws than in the commerce-moderate group.

A more general concern is that families in the two industrial categories might differ in other important ways that could explain the results. In particular, we find that families in commerce-intensive industries tend to have weaker generalized cooperative cultural traits to begin with: they have more children, are less likely to originate from urban areas, are less likely to be in extra-community marriages, and are less likely to have given their children universal names before migrating (Appendix Table A.6). However, our analyses suggest that these differences do not explain the pattern of heterogeneous effects. Appendix

[23]Note that some individuals change their occupation after migrating, so the combined size of the two sub-groups is smaller than the total number in the commerce-intensive group. The analysis includes 152,317 observations for farmers and 50,448 for commerce-intensive non-farmers.

Figures A.19–A.21 show similar impacts across small and large families, rural and urban origins, and different types of marriage. Appendix Figure A.22, Panels A and B show that while both families with high and low average prior UNI scores were affected, the impact on families with high UNI scores was stronger. Since UNI scores are lower in the commerce-intensive group, if anything, this pattern works against finding an effect only in that group. Moreover, even individuals in commerce-moderate industries with high initial universalism show no response to market access, while those in commerce-intensive industries do (Appendix Figure A.22, Panels C and D).

Together, these results provide evidence that an important driver of the effect is the nature of everyday economic interaction and interdependence. It appears to be linked to the direct and repeated experience of engaging in impersonal, market-based exchange with strangers and out-group members, or being dependent on them, that encourages people to adopt more generalized cooperative cultural traits.

7.2 Indirect Channels: Testing Alternative Pathways

While our results suggest a direct link between market access and generalized cooperative culture, we also consider whether more indirect pathways could explain the patterns we observe. In this section, we provide a few tests to evaluate the potential role of four major candidate channels: population diversity, economic development, access to information, and the development of legal institutions. We first report the results for each channel individually, and then present a final test that compares them jointly.

Population diversity. One prominent idea in social science is that population diversity—created by migration and mixing of groups—can help foster more universalistic, tolerant and trusting cultures. This theory, going back to classic work by Allport (1954), holds that repeated contact with people from different backgrounds can reduce prejudice and encourage broader cooperative norms. In our context, it is plausible that the arrival of railroads brought new people and more diverse populations to many counties.

Before discussing the additional analysis exploring this possibility, it is useful to recall that our results from both the county-level and individual-level analyses are robust to including or excluding immigrants and non-Whites from the sample (see Appendix Table B.5 and Appendix Figure B.6). This gives us some initial reason to suspect that diversity is not a central mediating factor in our results.

To further examine this potential channel, we construct two measures of local diversity for each county and decade: the share of immigrants in the population and a birthplace diversity index (calculated as one minus the Herfindahl-Hirschman Index over birthplaces), both from the full-count census data (Ruggles et al., 2020). We then conduct three sets of empirical tests.

First, we estimate the effect of market access on each diversity measure using our county-level regression Eq. 2). In our baseline specification, we find that market access is positively associated with both immigrant share and birthplace diversity (Appendix Table A.7, Panels A and B, column 2). However, when we add flexible controls for local railroad expansion and population growth (columns 3–7), these associations shrink and lose statistical significance. This suggests that, unlike generalized cooperative culture and behavior, increases in diversity are driven by local railroad connectivity, and not market access itself.

Second, we ask whether the estimated effects of market access on generalized cooperative culture and behavior remain robust when we control for diversity. If increased diversity is an important mediator, we would expect the relationship between market access and generalized cooperative culture and behavior to weaken once diversity is included as a control.[24] We repeat our main regressions but now add each diversity measure as an additional control variable. We find that the estimated effects of market access on our cultural outcomes are virtually unchanged by the inclusion of these controls (Table 8, Columns 2–3), and the same holds for our measures of cooperative behavior (Appendix Table A.8).

Third, we extend this logic to our individual-level migrant analysis by augmenting the difference-in-differences framework (Eq. 3) to also account for the dynamic impact of moving to a county with higher versus lower population diversity. Specifically, we include dynamic controls for the difference in each measure of diversity between the origin county (o) and the destination county (d). We then examine how controlling for these differences affects the estimated impact of moving to a county with higher market access on universal identification.[25] Again, the estimated impact of moving to a higher market access county on universalism is essentially unchanged (Appendix Figure A.23, Panels A–B).

Finally, we also consider whether the heterogeneous impact across commerce-intensive and commerce-moderate migrants could be explained by differences in how these groups respond to diversity. We find that even after controlling for the dynamic effect of moving to a county with higher versus lower population diversity, the impact of market access remains limited to migrants working in commerce-intensive industries (Appendix Figure A.25, Panels A–D).

Taken together, these results indicate that population diversity, while plausibly affected by local railroad connectivity, is unlikely to play a central role in mediating the impact of market access on generalized cooperative culture or behavior.

Economic development. Another influential set of theories argues that economic development is a key driver of cultural change. As societies become wealthier and move away from subsistence agriculture toward industrial and service sectors, people's lives become less vulnerable to existential threats and daily survival pressures. This rising security may foster a more universalistic outlook and greater tolerance for diversity, as people feel less dependent on tight-knit family and local networks for support (e.g., Inglehart, 2018; Gelfand et al., 2011; Posch, 2021). At the same time, modernization typically involves urbanization

[24] It is important to emphasize that diversity is itself a potential outcome of market access, making it a "bad control." Thus, the coefficients from this type of exercise should not be interpreted causally, but rather as suggestive evidence on the possible mediating role of diversity.

[25] The additional controls take the following form:

$$\sum_{b\neq 0} \gamma_b \cdot \mathbb{1}\left[b(i)=b\right] \cdot \mathbb{1}\left[Mediator_{d(i)} > mediator_{o(i)}\right]$$

Table 8: Market Access and Generalized Cooperative Traits: Controlling for Proxies of Indirect Channels

	Dependent variable:									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Universal Name Index									
logMA	0.9250***	0.8771***	0.8021***	0.9802***	1.397***	0.8630***	1.181***	0.9173***	0.8367***	1.268***
	(0.1610)	(0.1582)	(0.1546)	(0.1588)	(0.1973)	(0.1586)	(0.1680)	(0.1605)	(0.1595)	(0.2057)
Observations	18,182	18,182	18,182	18,179	12,683	18,168	17,267	18,168	18,168	12,268
R^2	0.805	0.807	0.812	0.806	0.831	0.808	0.806	0.805	0.808	0.837
	Panel B: Extra-Community Marriage									
logMA	0.0069*	0.0080**	0.0064*	0.0077**	0.0125***	0.0051	0.0060	0.0059	0.0060	0.0051
	(0.0037)	(0.0037)	(0.0036)	(0.0037)	(0.0046)	(0.0036)	(0.0037)	(0.0036)	(0.0036)	(0.0040)
Observations	18,179	18,179	18,179	18,176	12,674	18,165	17,262	18,165	18,165	12,257
R^2	0.908	0.910	0.908	0.909	0.923	0.911	0.929	0.910	0.909	0.946
	Panel C: Norms Tolerance Index									
logMA	0.1785***	0.1784***	0.1783***	0.1806***	0.1901***	0.1741***	0.1527***	0.1797***	0.1738***	0.1638***
	(0.0321)	(0.0323)	(0.0324)	(0.0320)	(0.0400)	(0.0326)	(0.0330)	(0.0321)	(0.0323)	(0.0420)
Observations	18,098	18,098	18,098	18,095	12,634	18,084	17,233	18,084	18,084	12,233
R^2	0.698	0.698	0.698	0.700	0.718	0.699	0.701	0.698	0.699	0.716
	Panel D: Religious Diversity Index									
logMA	0.2681***	0.2438***	0.2346***	0.2703***	0.2362***	0.2241***	0.2681***	0.2429***	0.2382***	0.2045***
	(0.0347)	(0.0359)	(0.0357)	(0.0343)	(0.0374)	(0.0365)	(0.0380)	(0.0363)	(0.0367)	(0.0424)
Observations	17,303	14,626	14,626	17,301	12,248	14,612	16,755	14,612	14,612	9,358
R^2	0.681	0.708	0.709	0.683	0.710	0.709	0.677	0.706	0.707	0.740
	Panel E: Social Trust									
logMA	0.1201**	0.1013*	0.1040*	0.1191**	0.1039*	0.0988*	0.1101**	0.0962*	0.0894*	0.0630
	(0.0485)	(0.0538)	(0.0538)	(0.0485)	(0.0563)	(0.0537)	(0.0521)	(0.0528)	(0.0530)	(0.0685)
Observations	6,821	5,861	5,861	6,820	5,256	5,853	6,736	5,853	5,853	4,249
R^2	0.681	0.683	0.684	0.681	0.704	0.684	0.682	0.684	0.684	0.710
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Share Immigrants		Yes								Yes
Birthplace Diversity			Yes							Yes
Share Urban				Yes						Yes
Manufacturing Est. PC					Yes					Yes
Occupational Income Score						Yes				Yes
Log Real GDP PC							Yes			Yes
Information Workers per 1,000								Yes		Yes
Lawyers and Judges per 1,000									Yes	Yes

Note: This table reports estimates of equation (2) with additional controls for proxies of potential indirect channels. The dependent variables are different historical generalized cooperative cultural traits: the UNI (Panel A), the ECM (Panel B), the NTI (Panel C), the RDI (Panel D), and Social Trust (Panel E). Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and a greater division of labor (e.g., Durkheim, 1984; Greenfield, 2009). As cities grow and economies industrialize, individuals interact more frequently with strangers and people from diverse backgrounds, and must rely on impersonal forms of trust and cooperation to navigate the workplace, civic life, and public institutions. Some of these dynamics may overlap with the direct channel—everyday mutually beneficial interactions and exchanges with strangers and out-group individuals.

To test whether economic development and urbanization can explain the relationship between market access and generalized cooperative culture and behavior in our setting, we assemble several county-level measures of development, modernization and urbanization. These include the share of the population living in urban areas, defined as incorporated places of at least 2,500 inhabitants, and the number of manufacturing establishments per capita (both from Manson et al., 2020), the mean occupational income score (a proxy for wage levels) calculated using the full-count censuses (Ruggles et al., 2020), and county-level real GDP per capita from Fulford et al. (2020), all harmonized to 1890 county boundaries using the procedure in Hornbeck 2010.[26] We then conduct the same three tests as before.

When we estimate the effect of market access on these outcomes, the results are mixed (Panels C–F of Appendix Table A.7). Contrary to standard modernization theory, we find that increased market access actually *reduced* urbanization and had no statistically significant effect on manufacturing establishments per capita. At the same time, we do find a positive effect of market access on both mean occupational income scores and real GDP per capita, although the effect on income scores becomes statistically insignificant when we flexibly control for local railroad connectivity and population. These results suggest that while market access increased economic output and perhaps income, it did not necessarily drive urbanization or a shift from agriculture to manufacturing in this period. These findings are consistent with previous studies showing that increases in county market access led to increased farmland settlement and agricultural production (Fogel, 1964; Donaldson and Hornbeck, 2016; Chan, 2022) and a general expansion of county economic activity, rather than a shift toward local manufacturing or urbanization (Hornbeck and Rotemberg, 2024).

When we add these proxies for economic development as controls to our main regression the estimated effect of market access on generalized cooperative culture remains stable (columns 4-7 in Table 8). The same holds when we look at impersonal and kin-based cooperative behavior (Appendix Table A.8). Similarly, when we control for moving to a county with higher values in these economic development proxies in our dynamic difference-in-differences framework (Eq. 3), the impact of market access on universalism remains robust, and the differential impact by commerce-intensive versus commerce-moderate industries is likewise unaffected (Appendix Figure A.23, Panels C–F, and Appendix Figure A.25, Panels E–L).

Access to Information. The spread of new ideas, information, and communication technologies is another potential channel. As railroads and markets expanded, so too did the reach of newspapers, the telegraph, and the postal service. Places with better access to information might be more likely to learn about new and diverse cultural norms, making them more open-minded to diverse ways of life.

To explore this possibility, we use census data (Ruggles et al., 2020) to calculate the number of workers in information-related occupations (e.g., editors, reporters, newsboys, mail carriers, and telegraph operators) per 1,000 workers in each county (winsorized at the top 2.5% to mitigate the effect of outliers in

[26] Fulford et al. (2020) provides their data at 1980 county-group levels.

the regressions).[27] When we regress this measure on market access, we find a significant positive effect (Appendix Table A.7, Panel G). This is intuitive: more connected places supported a larger information sector.

However, when we control for access to information in the county-level analysis (Eq. 2), the relationship between market access and generalized cooperative culture remains stable (Table 8, column 8), as does the effect on cooperative behavior (Appendix Table A.8). Our individual-level finding and the differential impact across commerce-intensive vs. commerce-moderate industries are likewise robust to controlling for moving to a county with greater information access (Appendix Figure A.23, Panel G; Appendix Figure A.25, Panels M–N).

Legal Institutions. Finally, increasing trade due to higher market access may contribute to the emergence and strengthening of local legal institutions that solve the "fundamental problem of [impersonal] exchange" (Greif, 1993, 2000; Cantoni and Yuchtman, 2014). This, in turn, may foster generalized cooperative cultural traits and broaden the scope of cooperation (Gorodnichenko and Roland, 2017; Henrich, 2020; Eruchimovitch et al., 2023).

To investigate this, we use census data (Ruggles et al., 2020) to calculate the number of lawyers and judges per 1,000 workers in each county (again, winsorized at the top 2.5%) as a proxy for local legal institutional development. We find a significant positive effect of market access on this measure, even after controlling for local railroads (Appendix Table A.7, Panel H). This reinforces the idea that market integration and the development of local legal institutions go hand in hand.

Yet, here as well, including this variable as a control in our main regressions has little impact on the effect of market access on generalized cooperative culture and behavior (Table 8, column 9; Appendix Table A.8). The results also remain stable in our individual-level and commerce intensive vs. moderate analyses (Appendix Figure A.23, Panel H; Appendix Figure A.25, Panels O–P).

Thus, while market access did support the development of local legal institutions, the estimated impact of market access on generalized cooperative culture and patterns of cooperation is robust to controlling for our proxy measure of this potential mediator.

Horse race. We close our examination of potential indirect channels by "horse racing" all of them against each other and market access. Previously, we showed that adding each proxy variable one at a time to our regressions had little impact on the estimated effect of market access. Here, we take a more demanding approach by including all of them at once to provide suggestive evidence on the key factors driving the adoption of generalized cooperative cultural traits.

First, we include all of these proxy measures together in our county-level and individual-level regressions to see if the estimated effect of market access on generalized cooperative culture and behavior still

[27] Specifically, we include the following *OCC1950* categories: Editors and reporters (36), Newsboys (460), Pressmen and plate printers, printing (575), Apprentices, printing trades (613), Postmasters (270), Express messengers and railway mail clerks (325), Mail carriers (335), Telegraph messengers (360), and Telegraph operators (365).

holds. We find that it does—the estimated effects of market access hardly change, even when all potential mediators are controlled for at once (see Table 8, column 10; Appendix Table A.8, column 10; Appendix Figure A.24, Panel A; and Appendix Figure A.25, Panels Q–R).

Second, we look directly at the coefficients on these mediators in the migrant-level difference-in-differences regression. We find that only market access and urbanization have a significant effect on migrants' universalism (Appendix Figure A.24, Panels A-I). The positive effect of urbanization is perhaps not surprising, since both urbanization and market access work through related channels: they increase the chances for mutually beneficial exchanges and deeper economic ties among people who do not know each other. That said, it is important to note that, at the county level, increased market access resulted in lower urbanization. As a result, while urbanization might have also affected migrants' universalism, it cannot explain the overall population-level effect of market access on generalized cooperative culture and patterns of cooperation.

In summary: Across all these tests, none of the indirect channels—population diversity, economic development, access to information, or local legal development—appear to account for the robust link between market access and generalized cooperative culture, as well as both impersonal and kin-based cooperation. While we cannot rule out that some of these factors played a role, our findings suggest that direct exposure to impersonal exchange and commerce itself is the key driver.

8 Conclusions

We provide new evidence that rising market integration in the United States between 1850 and 1920 fundamentally transformed key aspects of social life. Using county-level market access—driven by the expansion of the railroad network and mass immigration—as a measure of integration into broader markets, we show that increased market integration fostered a set of interrelated cultural traits: universalism, tolerance and generalized trust. Hand-in-hand with this cultural change, market access also shifted the scope of cooperation, moving it away from kin-based networks and toward more impersonal, generalized forms—enabling greater cooperation with strangers and out-group individuals.

Our approach leverages rich historical data from the full-count U.S. census, newspapers, and other sources to assemble and develop a range of measures of generalized cooperative culture and both impersonal and kin-based cooperation. We validate that counties with higher levels of such cultural traits do indeed display more impersonal cooperation—whether at work, at home, or in civic life—and are less reliant on kin-based support systems.

To establish causality, we first exploit the uneven, network-driven changes in county market access across space and time, using a research design that accounts for local railroad construction and population shifts. The evidence shows that increases in market access led not only to greater commerce, but also to substantial and persistent increases in universalism, tolerance, social trust, and impersonal cooperation, alongside a decline in kin-based cooperation.

We then leverage linked individual-level census data to examine the experiences of domestic migrants who moved between counties with differing market access. These results rule out selective sorting as the main explanation: migrants to higher-access counties were not already more universalistic before moving. Instead, we find evidence of cultural adaptation: families who moved to places with greater market access rapidly adopted more universalistic names for their children, and became more likely to engage in impersonal cooperation both at work and at home. Importantly, these adaptive changes were associated with real benefits—migrants who adapted culturally saw higher property values and child survival rates.

To shed light on the deep mechanisms, we show that the effect of market access on generalized cooperative culture is concentrated among individuals working in commerce-intensive industries, such as manufacturing, agriculture, wholesale, and transportation—those whose livelihoods depended most on interactions with strangers and market-based exchange. By contrast, we find no such effect among those in more locally oriented sectors. Our analysis also tests, and largely rules out, the possibility that the main effects operate through indirect channels such as increased population diversity, economic development, urbanization, access to information, or the growth of local legal institutions. Even when all potential mediators are included in the regressions, the effect of market access remains robust and substantial.

Taken together, our findings provide new support for the *doux commerce* hypothesis—that expanding market integration can foster impersonal prosocial norms, generalized trust, and broader patterns of cooperation. At the same time, we show that this shift toward impersonal cooperation comes with a decline in traditional kin-based social insurance, echoing concerns from critics of markets such as Polanyi (1944) and Marx and Engels (1848).

The historical experience of the United States shows that markets can play a powerful role not only in driving economic growth but also in reshaping the psychological and cultural boundaries of cooperation. As debates about the social consequences of markets and globalization continue, our findings highlight the dynamic, medium- and long-run potential of market integration to expand the scope of prosocial norms and foster cooperation beyond the boundaries of immediate kin and local groups.

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Online Appendices

A Further Figures, Analysis and Results

A.1 A “Market Society” - Examples from Mail-Order Catalogs

Figure A.1: Pages from the Montgomery Ward & Co. Catalog No. 13, spring and summer, 1875

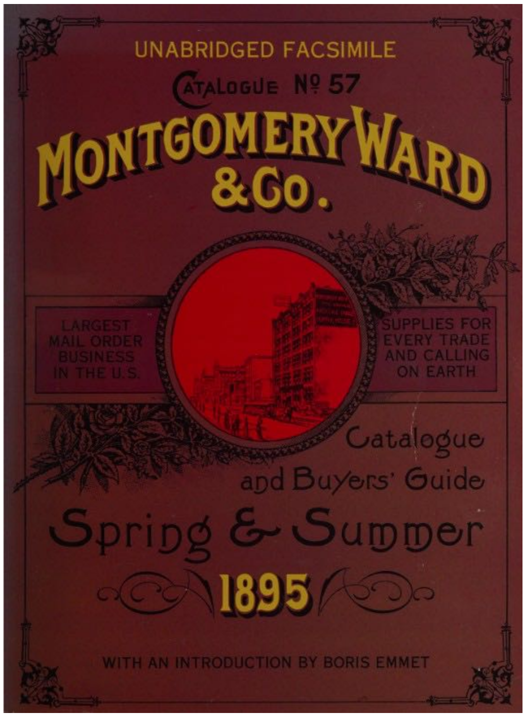


Figure A.2: Pages from the Montgomery Ward & Co. Catalog No. 57, spring and summer, 1895

A.2 The Development of the Railroad Network and Market Access

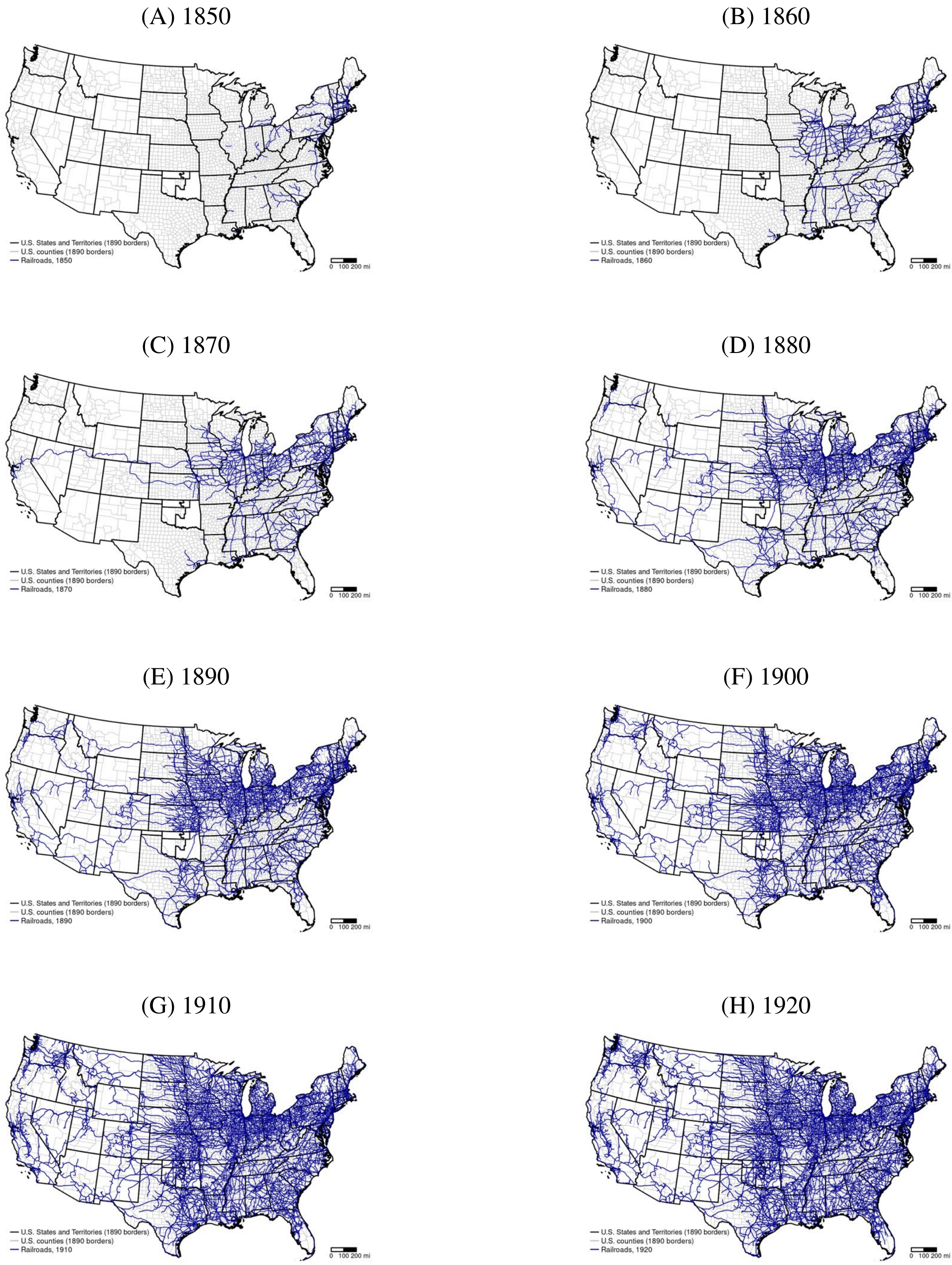


Figure A.3: The Railroad Network, 1850-1920

Note: This figure plots the railroad network for each decade between 1850-1920.

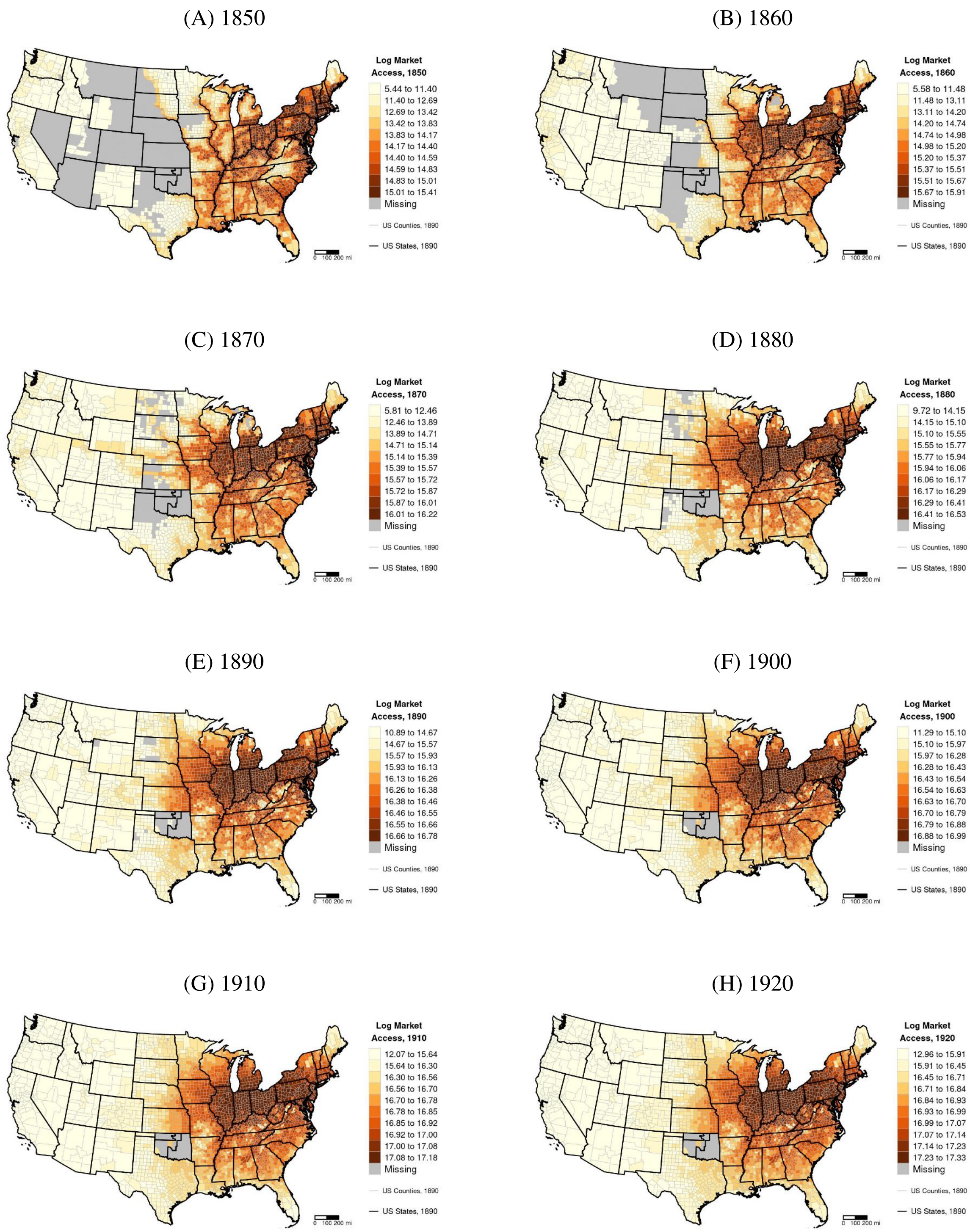


Figure A.4: Log Market Access, 1850-1920

Note: This figure plots the spatial distributions of log market access for each decade between 1850-1920. Within each decade, a darker color implies a higher market access.

(A) Average log market access by year

(B) Change in log market access, 1850-1920

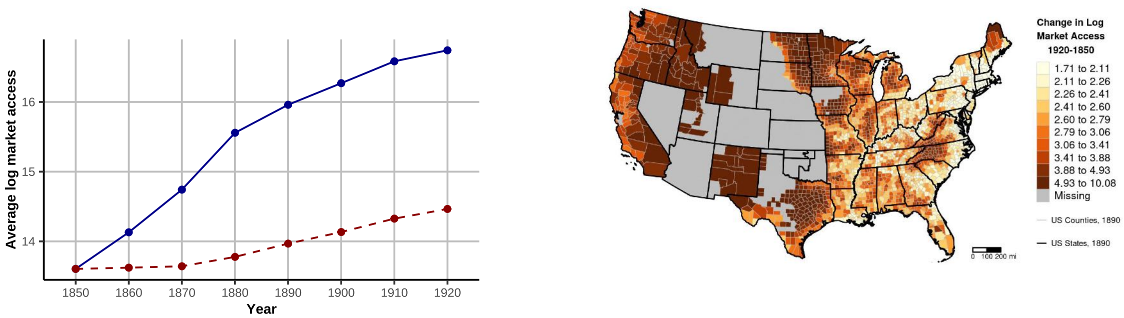


Figure A.5: The Change in log Market Access, 1850-1920

Note: This figure plots the changes in log market access over time. Panel A plots the average log market access by decade. The blue curve represents market access calculated using the contemporaneous transportation costs and population, and the dashed dark red curve fixes transportation costs to 1850. Panel B maps the difference between log market access in 1920 and 1850.

A.3 The Prevalence of Commerce

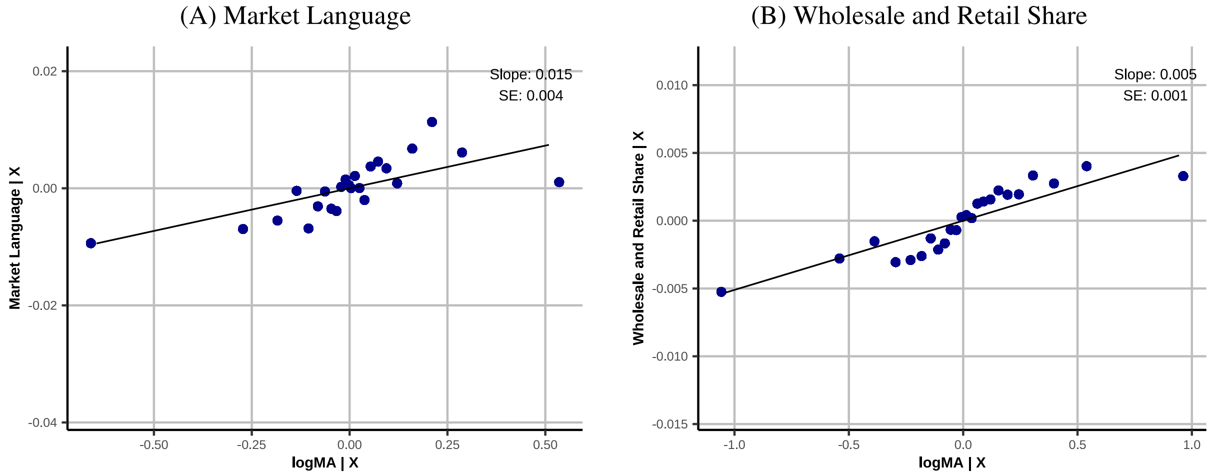
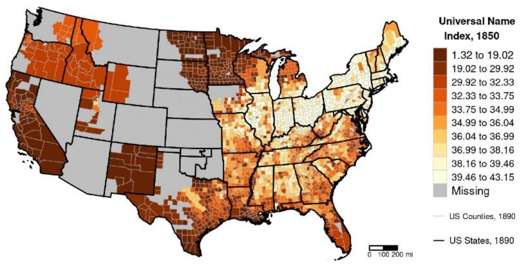


Figure A.6: Market Access and the Prevalence of Commerce: County-level Bin Scatter Plots

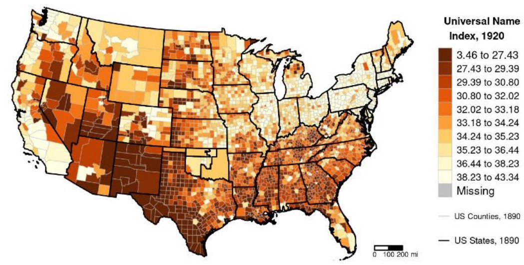
Note: This figure presents bin scatter plots of the relationship between log market access and cooperation and the prevalence of commerce, using equation (2). The plots present the conditional relationship after partialling out the baseline controls, corresponding to column 2 in Table 1. All bins have the same number of observations.

A.4 Generalized Cooperative Cultural Traits

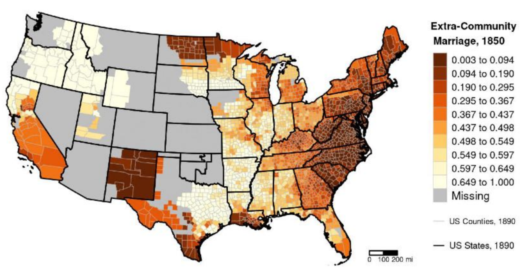
(A) Universal Name Index, 1850



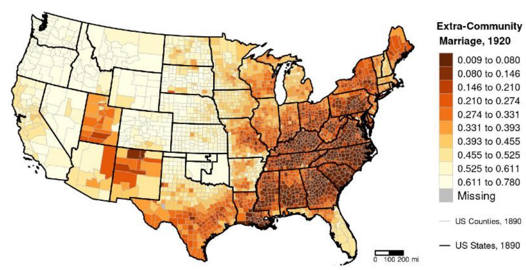
(B) Universal Name Index, 1920



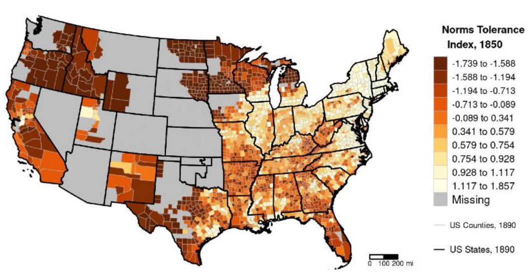
(C) Extra-Community Marriage, 1850



(D) Extra-Community Marriage, 1920



(E) Norms Tolerance Index, 1850



(F) Norms Tolerance Index, 1920

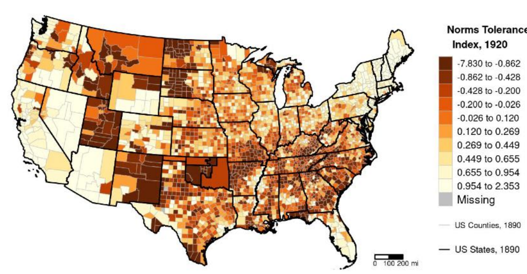
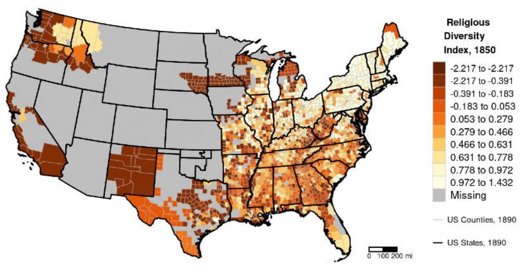


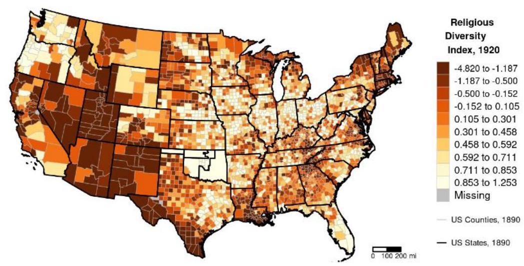
Figure A.7: Generalized Cooperative Cultural Traits, 1850 and 1920

Note: This figure plots the spatial distributions of our measures of generalized cooperative cultural traits: the UNI, the ECM, the NTI, the RDI, and social trust, in 1850 (left column) and in 1920 (right column). A lighter color implies a higher prevalence of cooperative traits. The figure continues to the next page.

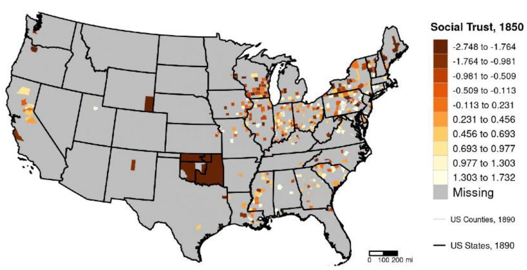
(G) Religious Diversity Index, 1850



(H) Religious Diversity Index, 1920



(I) Social Trust, 1850



(J) Social Trust, 1920

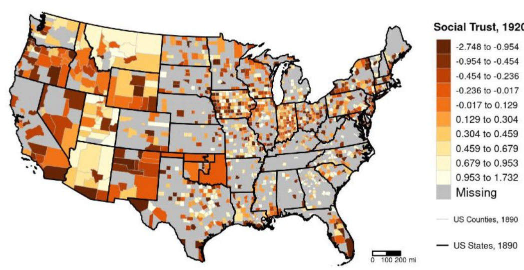
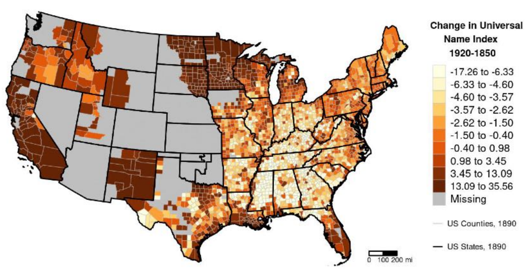


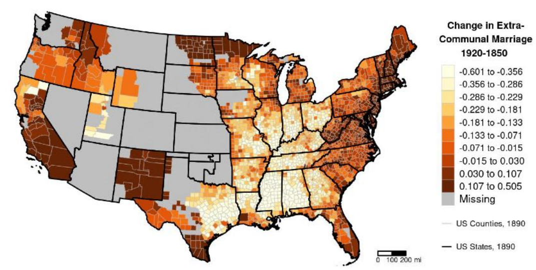
Figure A.7: Generalized Cooperative Cultural Traits, 1850 and 1920 (cont.)

Note: This figure plots the spatial distributions of our measures of generalized cooperative cultural traits: the UNI, the ECM, the NTI, the RDI, and social trust, in 1850 (left column) and in 1920 (right column). A lighter color implies a higher prevalence of cooperative traits.

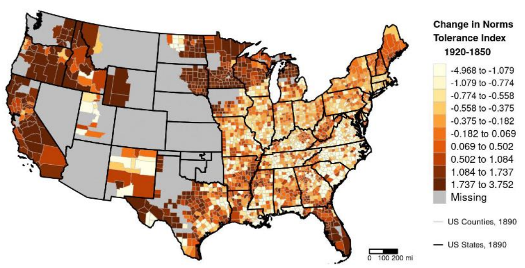
(A) Universal Name Index



(B) Extra-Communal Marriage



(C) Norms Tolerance Index



(D) Religious Diversity Index

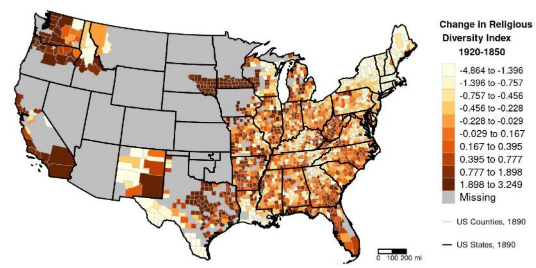


Figure A.8: The Change in Generalized Cooperative Cultural Traits Between 1850-1920

Note: This figure plots the difference in four generalized cooperative cultural traits between 1920 and 1850: the UNI, the ECM, the NTI, and the RDI.

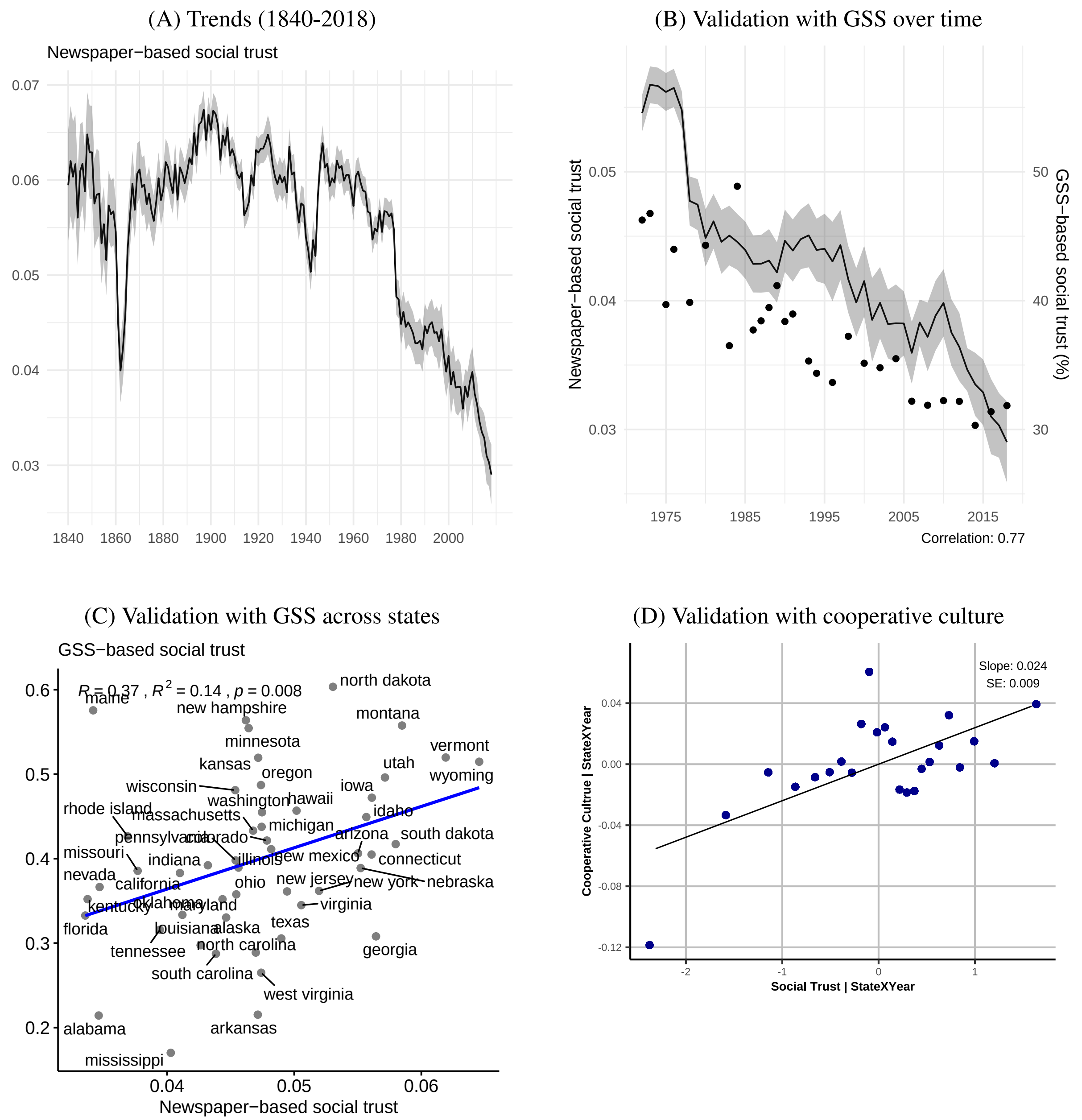


Figure A.9: Newspaper-based Social Trust: Trends and Validation

Note: This figure presents descriptive and validation results for the newspaper-based measure of social trust. Top row: national-trends in trust from 1840 to 2018 (left plot) and 1972 to 2018 (right plot). The dots depict trust data from the GSS (labeled on right y-axis). Bottom row: State-level correlation between newspaper and GSS-based trust from 1972 to 2014, net of year fixed effects before aggregation (right plot), and relationship between newspaper-based trust and our measure of generalized cooperative culture net of state-by-year fixed effect $\delta_{s(c)t}$.

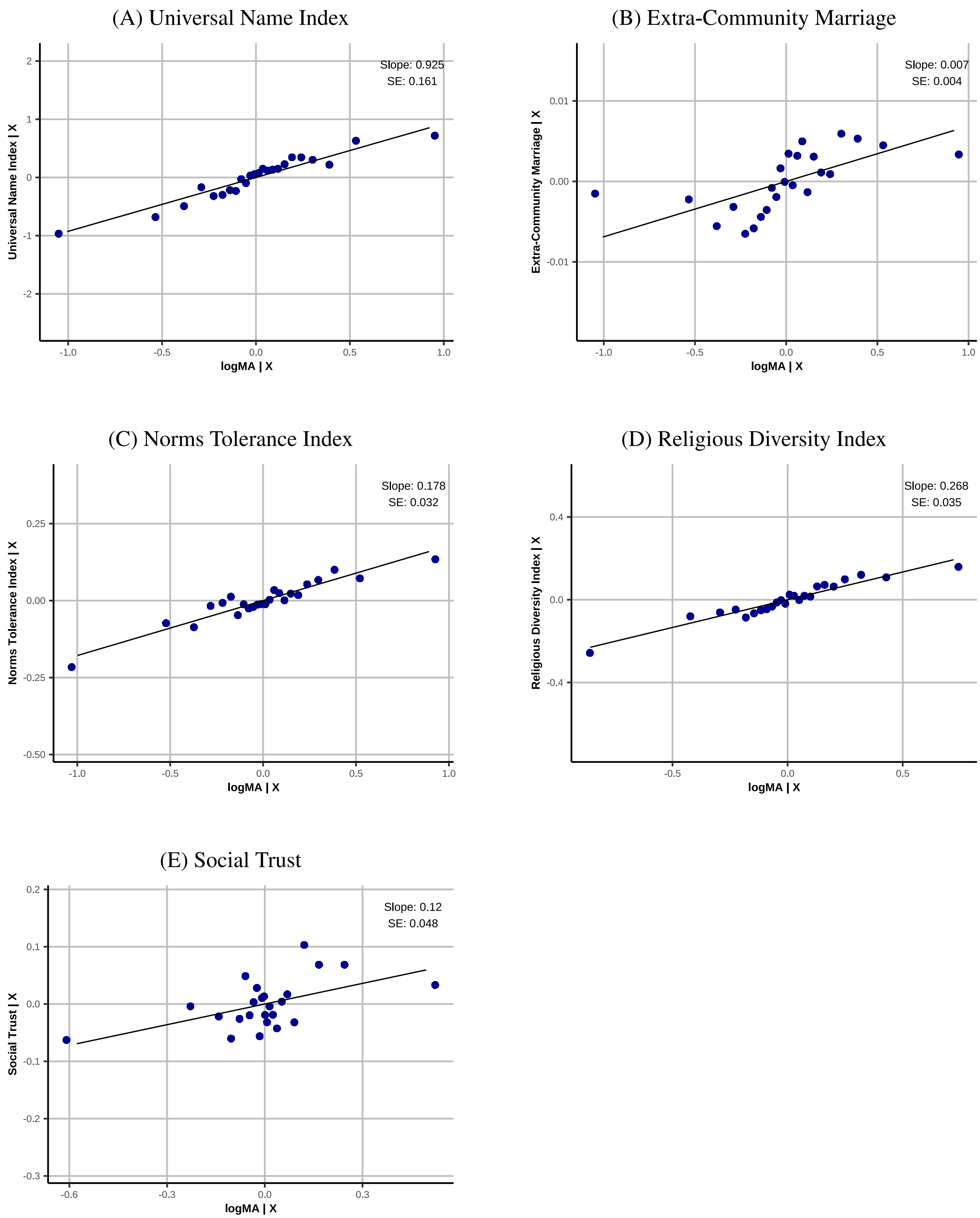


Figure A.10: Market Access and Generalized Cooperative Traits: County-level Bin Scatter Plots

Note: This figure presents bin scatter plots of the relationship between log market access and generalized cooperative cultural traits, using equation (2). The plots present the conditional relationship after partialling out the baseline controls, corresponding to column 2 in Table 2. All bins have the same number of observations.

A.5 Generalized Cooperative Culture

(A) Generalized Cooperative Culture, 1850

(B) Generalized Cooperative Culture, 1920

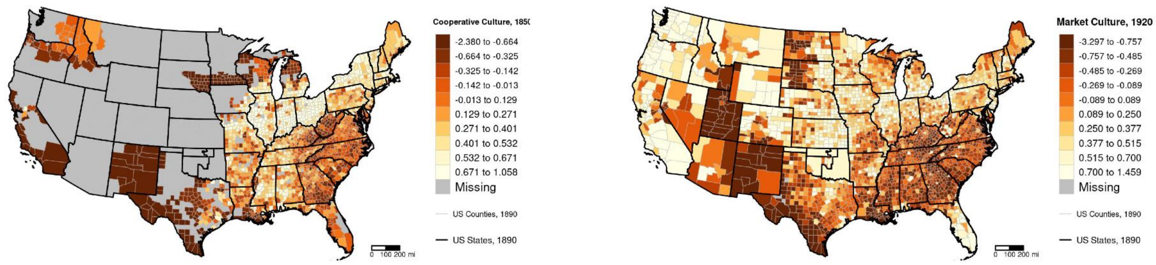


Figure A.11: Generalized Cooperative Culture, 1850 and 1920

Note: This figure plots the spatial distributions of the composite generalized cooperative culture index, in 1850 (left column) and in 1920 (right column). A lighter color implies a higher prevalence of generalized cooperative culture.

Table A.1: Market Access and Generalized Cooperative Culture

	Dependent variable: Generalized Cooperative Culture Index (mean = 0.024, sd = 0.64)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log market access	0.1585***	0.1461***	0.1265***	0.1059***	0.0971***	0.0868***	0.0917***
	(0.0170)	(0.0178)	(0.0171)	(0.0175)	(0.0173)	(0.0175)	(0.0174)
Observations	19,912	19,912	19,912	19,912	19,912	19,912	19,912
R^2	0.747	0.737	0.755	0.758	0.758	0.759	0.762
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year		Yes	Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes	Yes
Railroads within further buffers						Yes	Yes
Population within further buffers							Yes

Note: This table reports estimates of equation 2 with additional controls for local railroad infrastructure and population when the dependent variable is the composite generalized cooperative culture index. Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

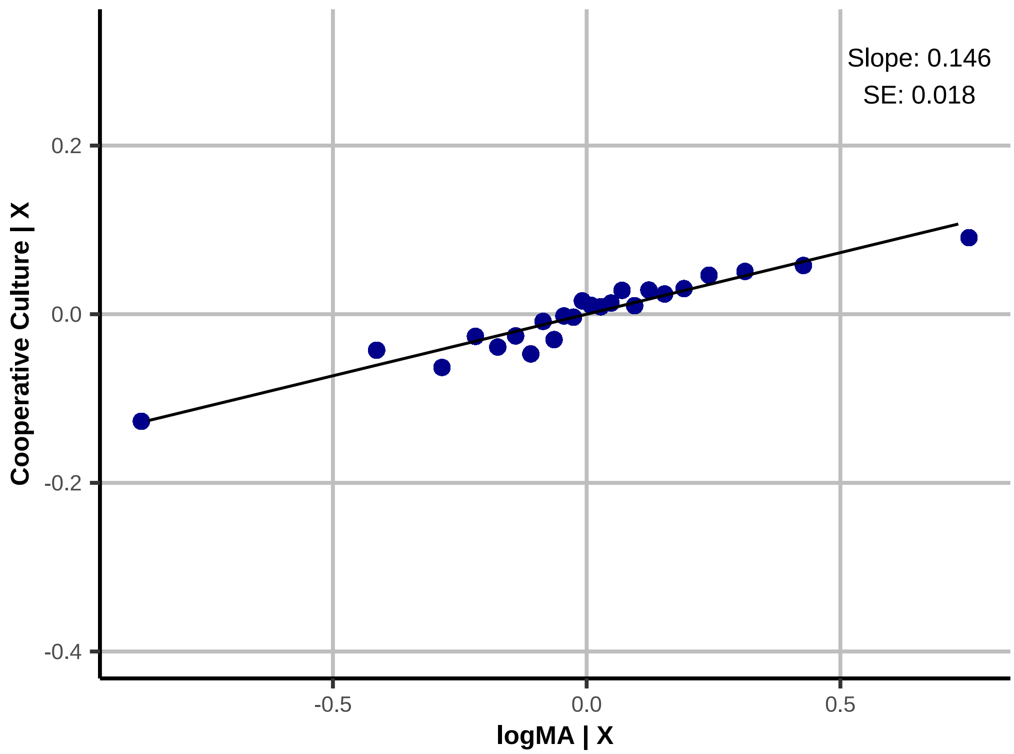


Figure A.12: Market Access and Generalized Cooperative Culture: County-level Bin Scatter Plots

Note: This figure presents bin scatter plots of the relationship between log market access and the composite generalized cooperative culture index, using equation (2). The plots present the conditional relationship after partialling out the baseline controls, corresponding to column 2 in Table A.1. All bins have the same number of observations.

Table A.2: Generalized Cooperative Culture: Exclusion of Immigrants and Non-Whites

	Dependent variable: Generalized Cooperative Culture Index			
Sample:	Baseline	Exclude foreign-born	Exclude non-whites	Exclude non-whites and foreign-born
	(1)	(2)	(3)	(4)
logMA	0.1461***	0.1457***	0.1427***	0.1471***
	(0.0178)	(0.0173)	(0.0178)	(0.0173)
Observations	19,912	19,899	19,912	19,896
R^2	0.737	0.745	0.740	0.751
County Fixed-Effects	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes
Location cubic polynomial × Year	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation 2 when the dependent variable is the composite generalized cooperative culture index. The base sample used to calculate the county-level measures in column 1 includes all of the population not residing in group quarters. In column 2 the sample excludes foreign-born, in column 3 it excludes non-whites, and in column 4 it excludes all non-whites and foreign-born.

Table A.3: Generalized Cooperative Culture: Different Market Access Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Baseline and Robustness							
	Baseline	Robustness						
	$P = 35$	$P = 38.7$		$P = 35$				
	$\theta = 8.22$	$\theta = 3.05$	$\theta = 8.22$	$\theta = 1$	$\theta = 2$	$\theta = 3$	$\theta = 4$	$\theta = 5$
Cooperative Culture	0.146***	0.393***	0.154***	1.14***	0.569***	0.379***	0.285***	0.229***
	(0.018)	(0.049)	(0.018)	(0.140)	(0.070)	(0.046)	(0.040)	(0.028)
	Panel B: Robustness							
	$P = 35$							
	$\theta = 6$	$\theta = 7$	$\theta = 8$	$\theta = 9$	$\theta = 10$	$\theta = 11$	$\theta = 12$	$\theta = 13$
Cooperative Culture	0.193***	0.168***	0.149***	0.135***	0.124***	0.115***	0.108***	0.102***
	(0.024)	(0.020)	(0.018)	(0.016)	(0.014)	(0.013)	(0.012)	(0.011)

Note: This table reports estimates of β from equation 2 when the dependent variable is the composite generalized cooperative culture index and market access is calculated using different average costs P and different trade elasticities θ. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

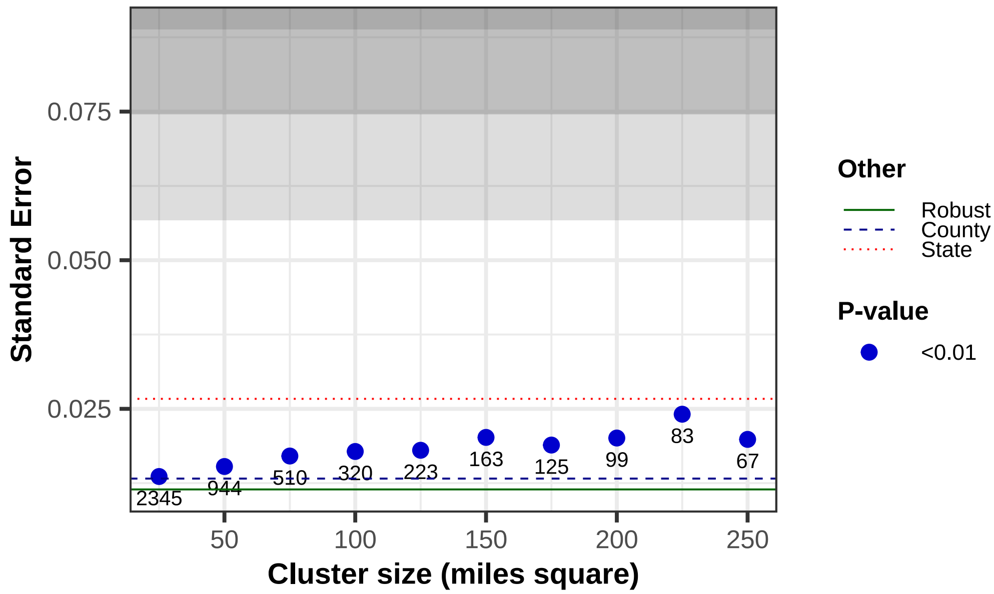
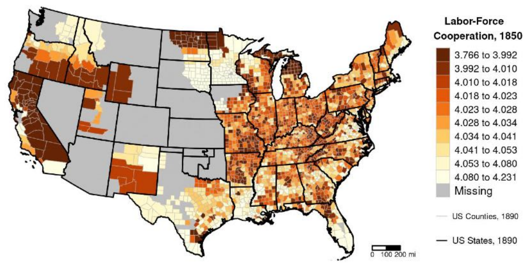


Figure A.13: Generalized Cooperative Culture: Different Standard Errors

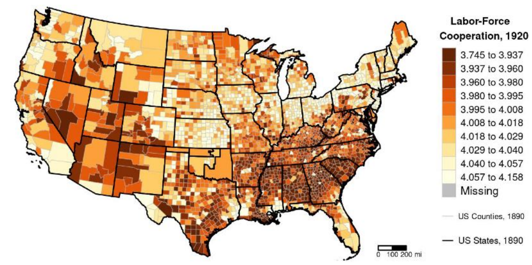
Note: This figure plots the standard errors of β from the preferred specification of equation (2) using different approaches for inference. The blue dots represent the standard errors (on the y-axis) using arbitrary grid-cell of different sizes (on the x-axis), as proposed by Bester et al. (2011). The numeric label under each dot indicates the number of spatial clusters. The dotted dark green horizontal line plots the HC robust standard errors, the dashed dark blue horizontal line plots the standard errors when clustering at the county level, and the dash-dotted red horizontal line plots the standard errors when clustering at the state level. The background color is indicative of the level of statistical significance. The p-value is < 0.01 in the white area, and < 0.05, < 0.1 and > 0.1 in the light to dark shades of gray.

A.6 Impersonal and Kin-based Cooperation

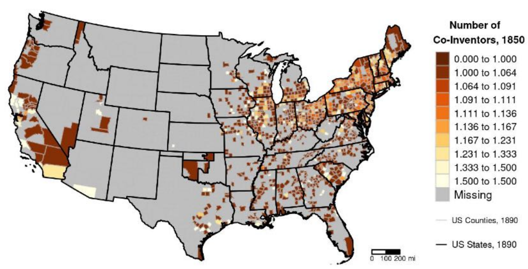
(A) Labor-force Cooperation, 1850



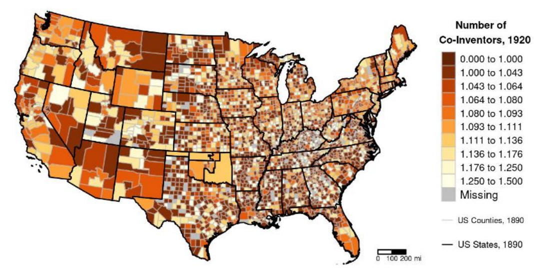
(B) Labor-force Cooperation, 1920



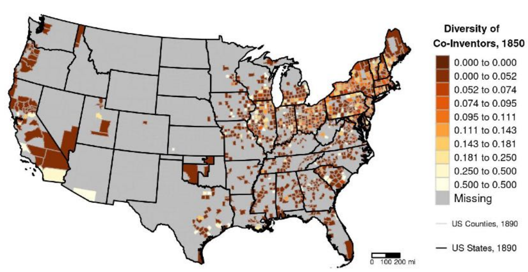
(C) Number of Co-Inventors, 1850



(D) Number of Co-Inventors, 1920



(E) Co-Inventors' Diversity, 1850



(F) Co-Inventors' Diversity, 1920

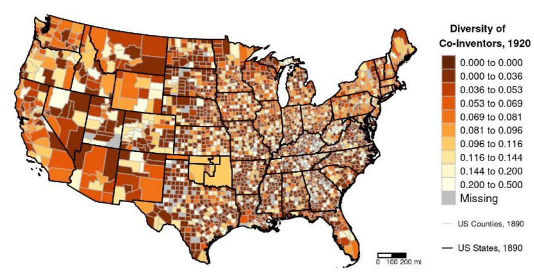
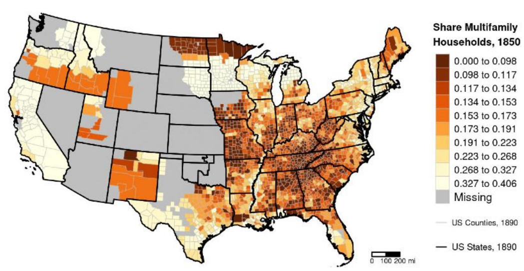


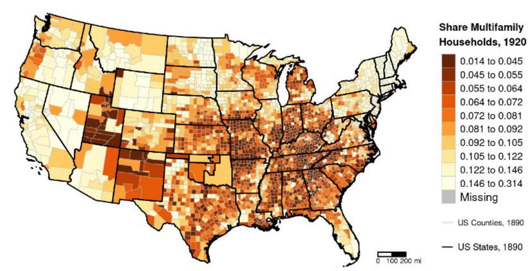
Figure A.14: Measures of Impersonal and Kin-based Cooperation, 1850 and 1920

Note: This figure plots the spatial distributions of seven measures of impersonal cooperation and one measure of kin-based cooperation in the earlier period (left column) and the later period (left column). Exact periods vary my outcome. A lighter color implies a higher degree of impersonal cooperation.

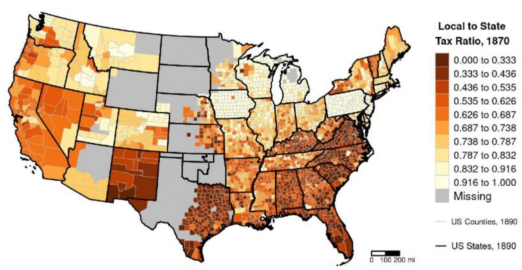
(G) Share Multifamily Households, 1850



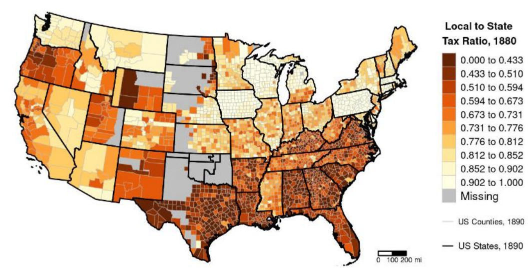
(H) Share Multifamily Households, 1920



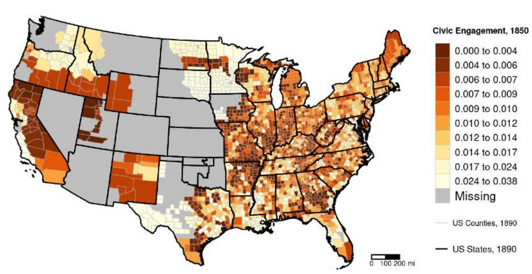
(I) Local to Total Taxes Ratio, 1870



(J) Local to Total Taxes Ratio, 1880



(K) Civic Engagement, 1850



(L) Civic Engagement, 1920

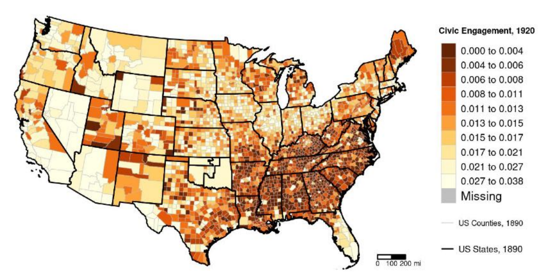
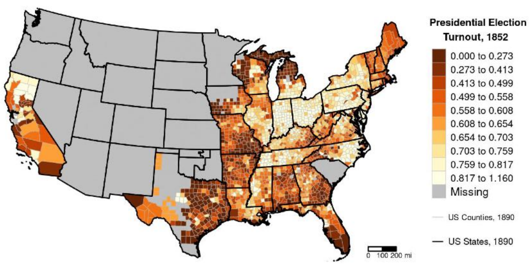


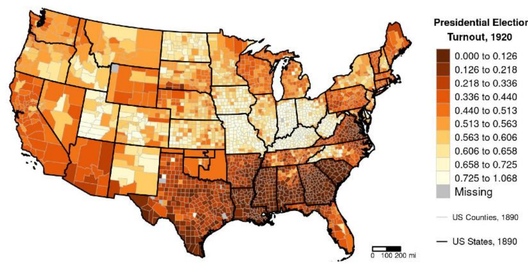
Figure A.14: Measures of Impersonal and Kin-based Cooperation, 1850 and 1920 (cont.)

Note: This figure plots the spatial distributions of seven measures of impersonal cooperation and one measure of kin-based cooperation in the earlier period (left column) and the later period (left column). Exact periods vary my outcome. A lighter color implies a higher degree of impersonal cooperation.

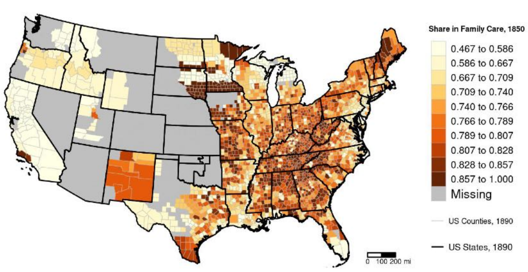
(M) Voters Turnout, 1852



(N) Voters Turnout, 1920



(O) Family Care, 1852



(P) Family Care, 1920

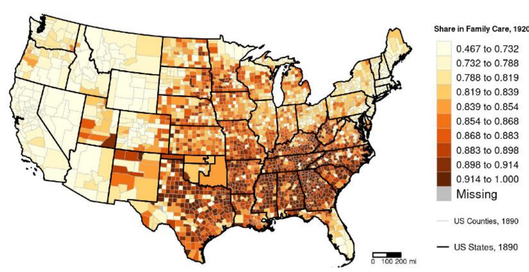


Figure A.14: Measures of Impersonal and Kin-Based Cooperation, 1850 and 1920 (cont.)

Note: This figure plots the spatial distributions of seven measures of impersonal cooperation and one measure of kin-based cooperation in the earlier period (left column) and the later period (left column). Exact periods vary my outcome. A lighter color implies a higher degree of impersonal cooperation.

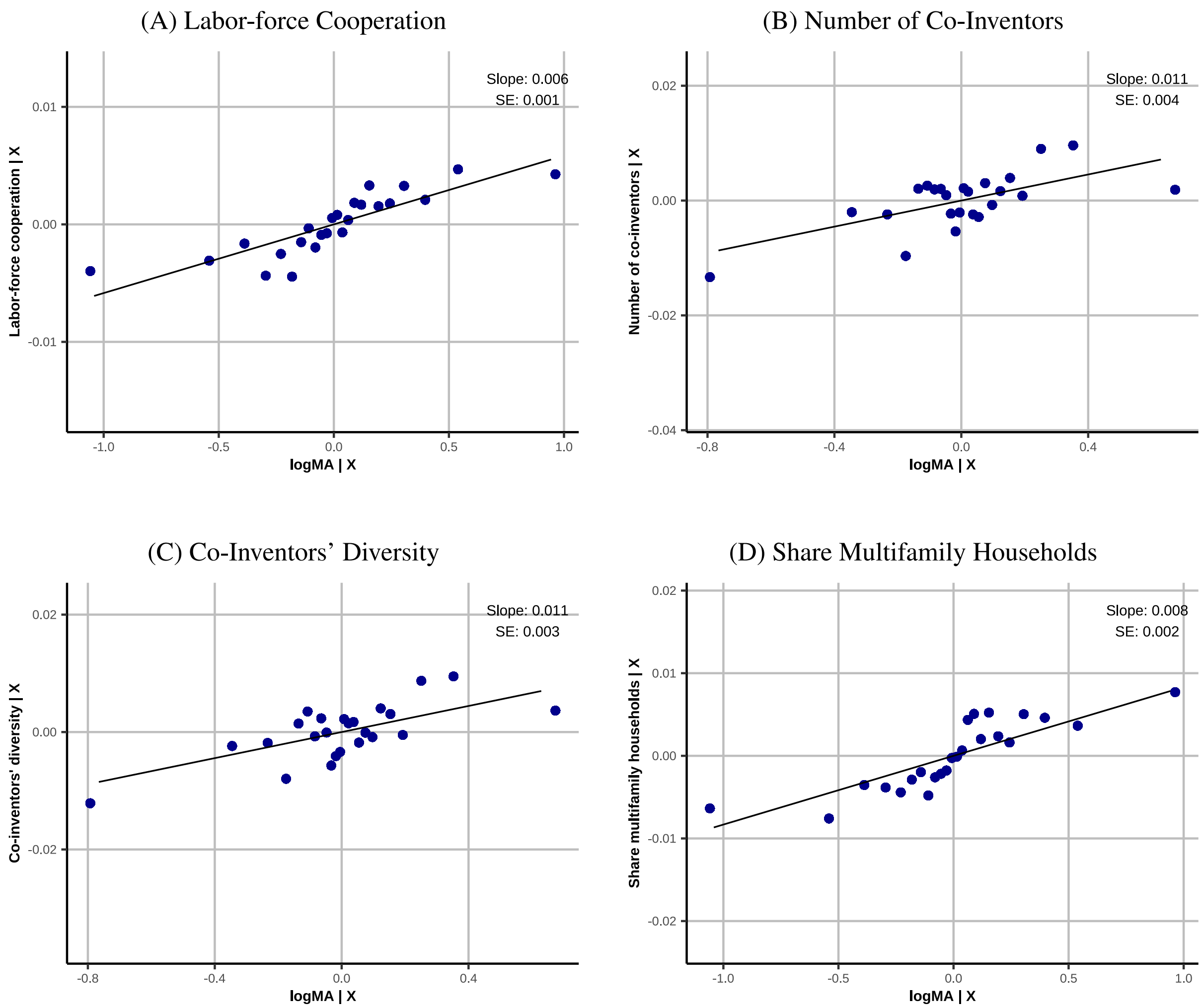


Figure A.15: Market Access and Patterns of Cooperation: County-level Bin Scatter Plots

Note: This figure presents bin scatter plots of the relationship between log market access and both impersonal and kin-based cooperation, using equation (2). The plots present the conditional relationship after partialling out the baseline controls, corresponding to column 2 in Table 3. All bins have the same number of observations. The figure continues to the next page.

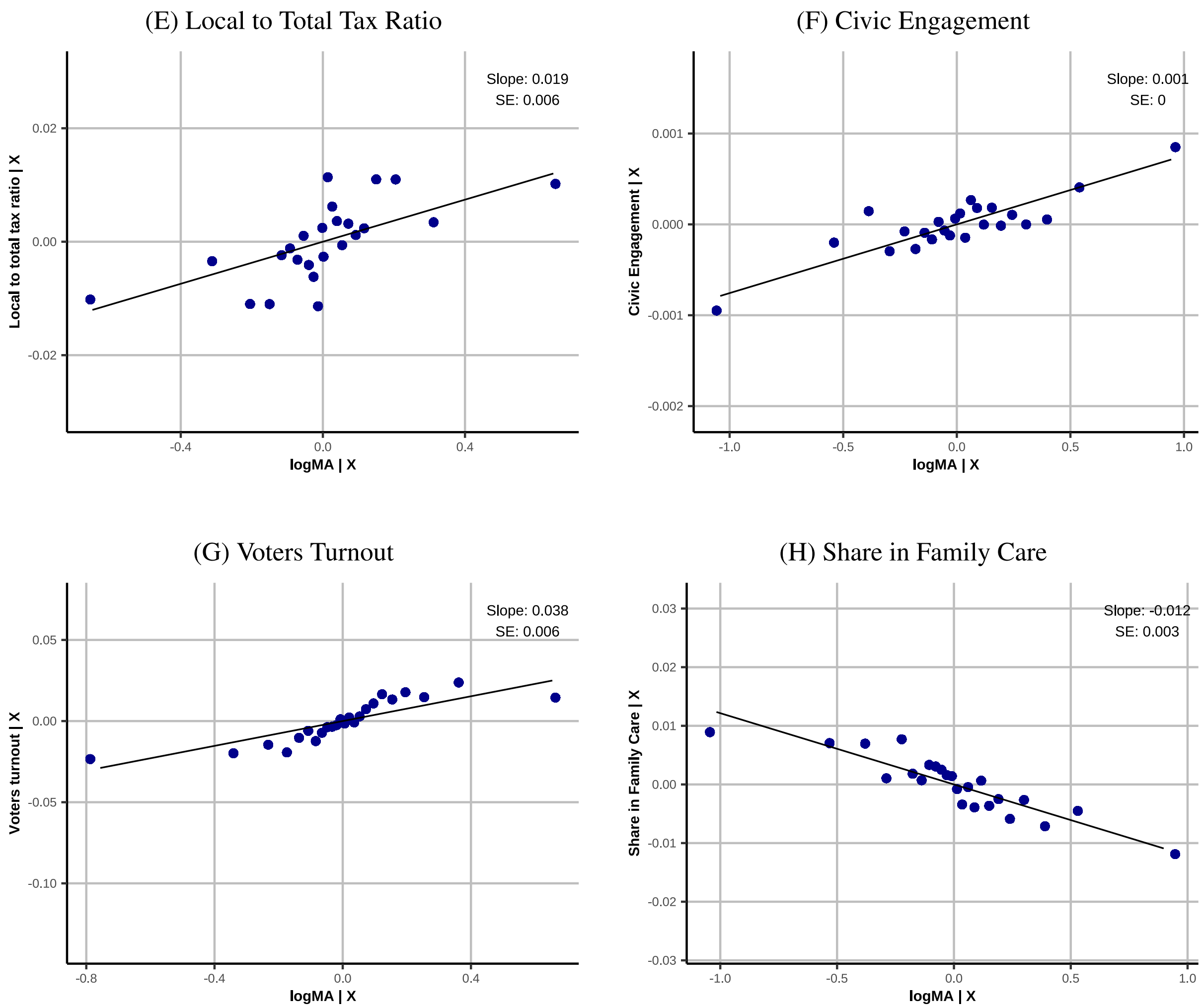


Figure A.15: Market Access and Patterns of Cooperation: County-level Bin Scatter Plots (cont.)

Note: This figure presents bin scatter plots of the relationship between log market access and both impersonal and kin-based cooperation, using equation (2). The plots present the conditional relationship after partialling out the baseline controls, corresponding to column 2 in Table 3. All bins have the same number of observations.

Table A.4: Market Access and Patterns of Cooperation: Railroad and Population Controls

	Dependent variable:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Labor-Force Cooperation (mean = 3.996 , sd = 0.059)						
Log market access	0.0055***	0.0058***	0.0048***	0.0037***	0.0034***	0.0025*	0.0026**
	(0.0013)	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Observations	18,267	18,267	18,267	18,267	18,267	18,267	18,267
R^2	0.670	0.680	0.680	0.683	0.682	0.684	0.686
	Panel B: Number of Co-Inventors (mean = 1.092 , sd = 0.116)						
Log market access	0.0118***	0.0114***	0.0082**	0.0098**	0.0098**	0.0090**	0.0094**
	(0.0035)	(0.0037)	(0.0041)	(0.0042)	(0.0044)	(0.0045)	(0.0045)
Observations	17,360	17,360	17,360	17,360	17,360	17,360	17,360
R^2	0.237	0.241	0.241	0.242	0.242	0.242	0.242
	Panel C: Co-Inventors' Diversity (mean = 0.076 , sd = 0.106)						
Log market access	0.0099***	0.0111***	0.0078**	0.0088**	0.0088**	0.0084*	0.0087**
	(0.0032)	(0.0034)	(0.0038)	(0.0039)	(0.0041)	(0.0043)	(0.0043)
Observations	17,360	17,360	17,360	17,360	17,360	17,360	17,360
R^2	0.238	0.241	0.242	0.242	0.242	0.243	0.243
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year		Yes	Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes	Yes
Railroads within further buffers						Yes	Yes
Population within further buffers							Yes

Note: This table reports estimates of equation 2 with additional controls for local railroad infrastructure and population when the dependent variables are different historical measure of impersonal or kin-based cooperation. Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). The table continues to the next page. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Market Access and Patterns of Cooperation: Railroad and Population Controls (cont.)

	Dependent variable:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel D: Share Multifamily Households (mean = 0.151 , sd = 0.084)						
Log market access	0.0050^{*}	0.0083^{***}	0.0062^{**}	0.0051^{**}	0.0048^{*}	0.0051^{**}	0.0055^{**}
	(0.0025)	(0.0022)	(0.0024)	(0.0025)	(0.0025)	(0.0025)	(0.0026)
Observations	18,277	18,277	18,277	18,277	18,277	18,277	18,277
R^2	0.769	0.782	0.783	0.784	0.784	0.786	0.787
	Panel E: Local to Total Tax Ratio (mean = 0.67 , sd = 0.198)						
Log market access	0.0169^{***}	0.0185^{***}	0.0144^{**}	0.0153^{**}	0.0131^{*}	0.0106	0.0105
	(0.0059)	(0.0060)	(0.0065)	(0.0067)	(0.0069)	(0.0067)	(0.0067)
Observations	4,942	4,942	4,942	4,942	4,942	4,942	4,942
R^2	0.907	0.908	0.908	0.908	0.908	0.909	0.910
	Panel F: Civic Engagement (mean = 0.012 , sd = 0.009)						
Log market access	0.0006^{***}	0.0008^{***}	0.0007^{***}	0.0004^{*}	0.0003	0.0002	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	18,266	18,266	18,266	18,266	18,266	18,266	18,266
R^2	0.680	0.688	0.688	0.697	0.698	0.699	0.707
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year		Yes	Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes	Yes
Railroads within further buffers						Yes	Yes
Population within further buffers							Yes

Note: This table reports estimates of equation 2 with additional controls for local railroad infrastructure and population when the dependent variables are different historical measure of impersonal or kin-based cooperation. Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). The table continues to the next page. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Market Access and Patterns of Cooperation: Railroad and Population Controls (cont.)

	Dependent variable:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel G: Voters Turnout (mean = 0.63 , sd = 0.24)						
Log market access	0.0442***	0.0382***	0.0290***	0.0372***	0.0293***	0.0211***	0.0205***
	(0.0061)	(0.0061)	(0.0064)	(0.0068)	(0.0066)	(0.0064)	(0.0064)
Observations	45,308	45,308	45,308	45,308	45,308	45,308	45,308
R^2	0.792	0.800	0.801	0.803	0.794	0.803	0.806
	Panel H: Share in Family Care (mean = 0.778 , sd = 0.111)						
Log market access	-0.0084**	-0.0121***	-0.0113***	-0.0107***	-0.0103***	-0.0104***	-0.0104**
	(0.0033)	(0.0032)	(0.0036)	(0.0037)	(0.0039)	(0.0040)	(0.0040)
Observations	18,173	18,173	18,173	18,173	18,173	18,173	18,173
R^2	0.715	0.721	0.721	0.722	0.722	0.722	0.722
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year		Yes	Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes	Yes
Railroads within further buffers						Yes	Yes
Population within further buffers							Yes

Note: This table reports estimates of equation 2 with additional controls for local railroad infrastructure and population when the dependent variables are different historical measure of impersonal or kin-based cooperation. Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Generalized Cooperative Culture and Cooperative Behavior

	Dependent variable:			
	(1)	(2)	(3)	(4)
	Panel A: Labor-Force Cooperation (mean = 3.996 , sd = 0.059)			
Cooperative Culture	0.0283***	0.0211***	0.0134***	0.0135***
	(0.0026)	(0.0021)	(0.0019)	(0.0020)
Observations	17,249	17,249	17,249	17,249
R^2	0.083	0.500	0.704	0.711
	Panel B: Number of Co-Inventors (mean = 1.092 , sd = 0.116)			
Cooperative Culture	0.0066***	0.0057**	0.0025	0.0014
	(0.0022)	(0.0022)	(0.0034)	(0.0033)
Observations	16,966	16,966	16,966	16,966
R^2	0.001	0.048	0.241	0.244
	Panel C: Co-Inventors' Diversity (mean = 0.076 , sd = 0.106)			
Cooperative Culture	0.0041**	0.0033	0.0009	0.0005
	(0.0020)	(0.0021)	(0.0031)	(0.0031)
Observations	16,966	16,966	16,966	16,966
R^2	0.0006	0.048	0.242	0.244
State × Year Fixed-Effects		Yes	Yes	Yes
County Fixed-Effects			Yes	Yes
Location cubic polynomial × Year				Yes

Note: This table reports estimates of equation 1 when the dependent variables are seven different historical measure of impersonal cooperation: labor-force cooperation (Panel A), the average number of patents co-inventors (Panel B), the diversity of of patents co-inventors (Panel C), the share of multifamily households (Panel D), share of local tax revenues (Panel E), the share employed in civic industries (Panel F), and voters turnout in presidential elections (Panel G), and one measure of historical kinship-based cooperation: the share of vulnerable individuals in family care (Panel H). Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). The table continues to the next page. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Generalized Cooperative Culture and Cooperative Behavior (cont.)

	Dependent variable:			
	(1)	(2)	(3)	(4)
	Panel D: Share Multifamily Households (mean = 0.151 , sd = 0.084)			
Cooperative Culture	0.0171***	0.0257***	0.0168***	0.0184***
	(0.0035)	(0.0027)	(0.0026)	(0.0024)
Observations	17,263	17,263	17,263	17,263
R^2	0.017	0.645	0.814	0.824
	Panel E: Local to Total Tax Ratio (mean = 0.67 , sd = 0.198)			
Cooperative Culture	0.0975***	0.0235***	0.0216***	0.0243***
	(0.0128)	(0.0054)	(0.0081)	(0.0081)
Observations	4,804	4,804	4,804	4,804
R^2	0.073	0.748	0.918	0.918
	Panel F: Civic Engagement (mean = 0.012 , sd = 0.009)			
Cooperative Culture	0.0039***	0.0044***	0.0034***	0.0036***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Observations	17,249	17,249	17,249	17,249
R^2	0.071	0.432	0.738	0.743
State × Year Fixed-Effects		Yes	Yes	Yes
County Fixed-Effects			Yes	Yes
Location cubic polynomial × Year				Yes

Note: This table reports estimates of equation 1 when the dependent variables are seven different historical measure of impersonal cooperation: labor-force cooperation (Panel A), the average number of patents co-inventors (Panel B), the diversity of of patents co-inventors (Panel C), the share of multifamily households (Panel D), share of local tax revenues (Panel E), the share employed in civic industries (Panel F), and voters turnout in presidential elections (Panel G), and one measure of historical kinship-based cooperation: the share of vulnerable individuals in family care (Panel H). Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). The table continues to the next page. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Generalized Cooperative Culture and Cooperative Behavior (cont.)

	Dependent variable:			
	(1)	(2)	(3)	(4)
	Panel G: Voters Turnout (mean = 0.63 , sd = 0.24)			
Cooperative Culture	0.0924***	0.0100**	0.0169***	0.0143***
	(0.0118)	(0.0050)	(0.0057)	(0.0054)
Observations	44,405	44,405	44,405	44,405
R^2	0.053	0.725	0.805	0.807
	Panel H: Share in Family Care (mean = 0.778 , sd = 0.111)			
Cooperative Culture	-0.0141***	-0.0136***	-0.0107***	-0.0126***
	(0.0042)	(0.0038)	(0.0035)	(0.0034)
Observations	17,255	17,255	17,255	17,255
R^2	0.006	0.568	0.766	0.771
State × Year Fixed-Effects		Yes	Yes	Yes
County Fixed-Effects			Yes	Yes
Location cubic polynomial × Year				Yes

Note: This table reports estimates of equation 1 when the dependent variables are seven different historical measure of impersonal cooperation: labor-force cooperation (Panel A), the average number of patents co-inventors (Panel B), the diversity of of patents co-inventors (Panel C), the share of multifamily households (Panel D), share of local tax revenues (Panel E), the share employed in civic industries (Panel F), and voters turnout in presidential elections (Panel G), and one measure of historical kinship-based cooperation: the share of vulnerable individuals in family care (Panel H). Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.7 Cultural Adaptation

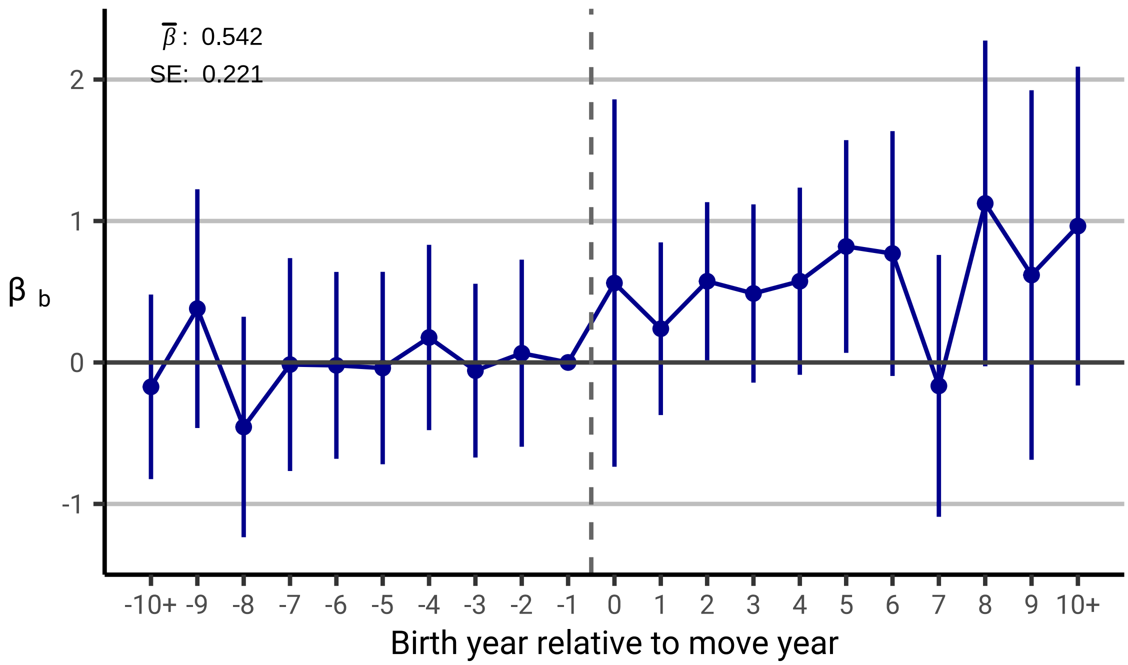


Figure A.16: The Impact of Moving to a Higher Market Access County on Universalism

Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences equation (3), with an UNI measure in which "local" is always the county of origin. $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

A.8 Channels

A.8.1 The Direct Impact of Commerce

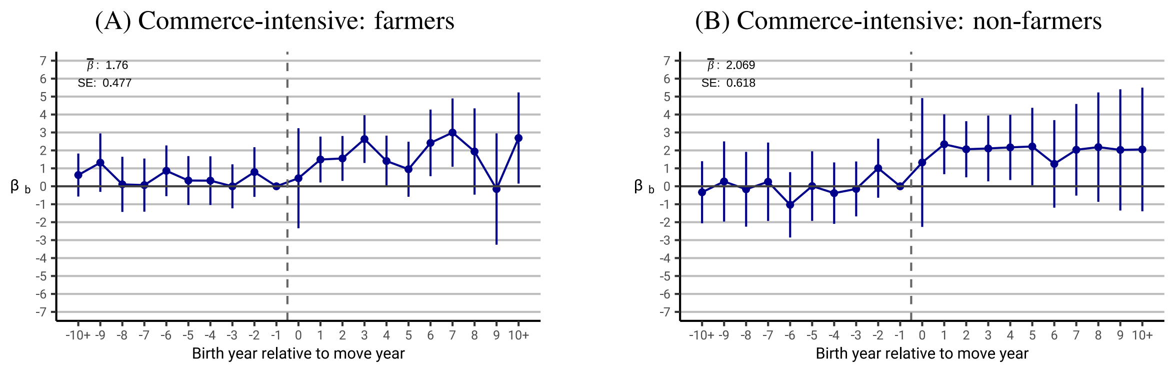


Figure A.17: DID: The Impact on Farmers and Migrants Working in Other Commerce-intensive Industries

Note: This figure plots the estimates of β_b and 95% confidence intervals from equation (3). The sample in Panel A is restricted to migrants' households in which the father worked as a farmer before and after the migration. In Panel b, is restricted to migrants' households in which the father worked in a non-farming commerce-intensive industry before and after the migration. $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

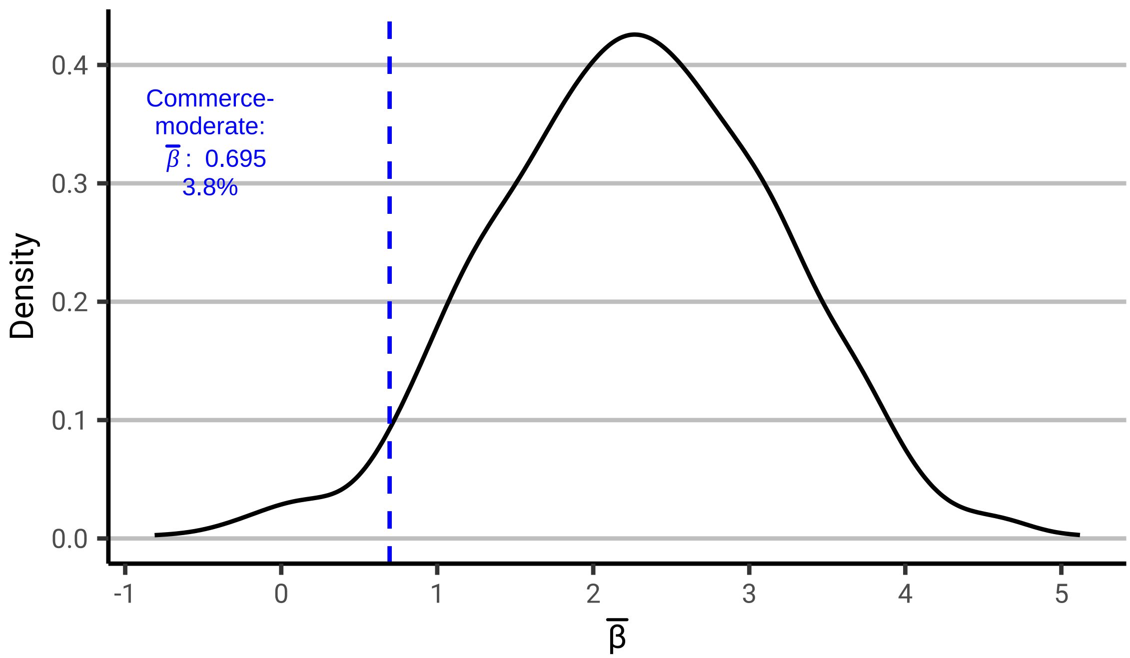


Figure A.18: Heterogeneous Impact is Not Driven by Sample Size

Note: This figure plots the distribution of estimates of $\bar{\beta}$, the average treatment effects from the difference-in-differences equation (3), estimated on 1,000 random sample draws without replacements of 5,985 families from the commerce-intensive group. The blue dashed vertical line plots the estimation of $\bar{\beta}$ for the commerce-moderate group (Figure 3, Panel B).

Table A.6: Characteristics of Families in Commerce-Intensive and Commerce-Moderate Categories

	Category:		
	Commerce intensive N=54,456	Commerce moderate N=5,985	Difference p-value
	(1)	(2)	(3)
Father's Age	31.7 (7.01)	31.6 (6.29)	0.303
Number of Children (0-10)	4.83 (1.90)	4.11 (1.69)	<0.001
Origin is Urban	0.15 (0.35)	0.44 (0.50)	0.000
Extra-Community Marriage	0.42 (0.49)	0.47 (0.50)	<0.001
Avg. Pre-migration UNI score	43.8 (13.0)	44.6 (13.2)	<0.001

Note: This table reports the mean characteristics of domestic out-of-state migrant households in the commerce-intensive and commerce-moderate categories. Standard errors in parenthesis.

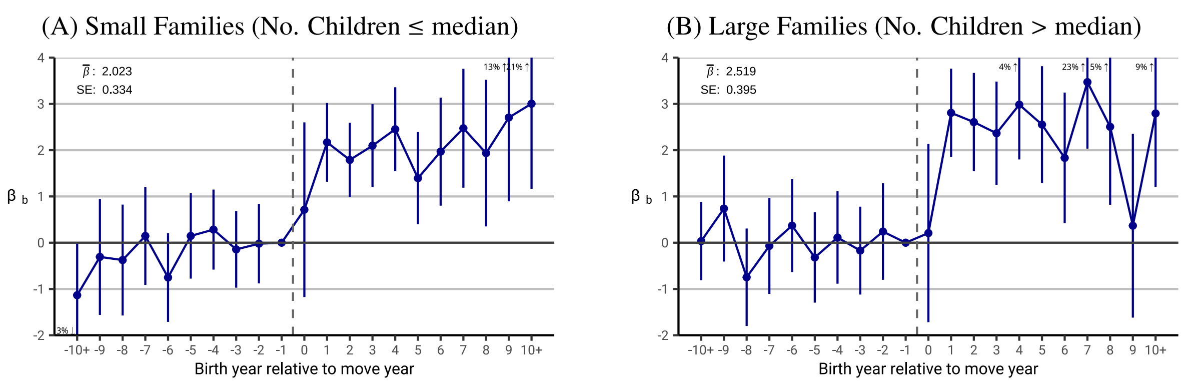


Figure A.19: Heterogeneous Impact is Not Driven by Family Size

Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences equation (3). In Panel A, the sample is restricted to households in which the number of children is below or equal to the median. In Panel B, the sample is restricted to households in which the number of children is above the median. $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

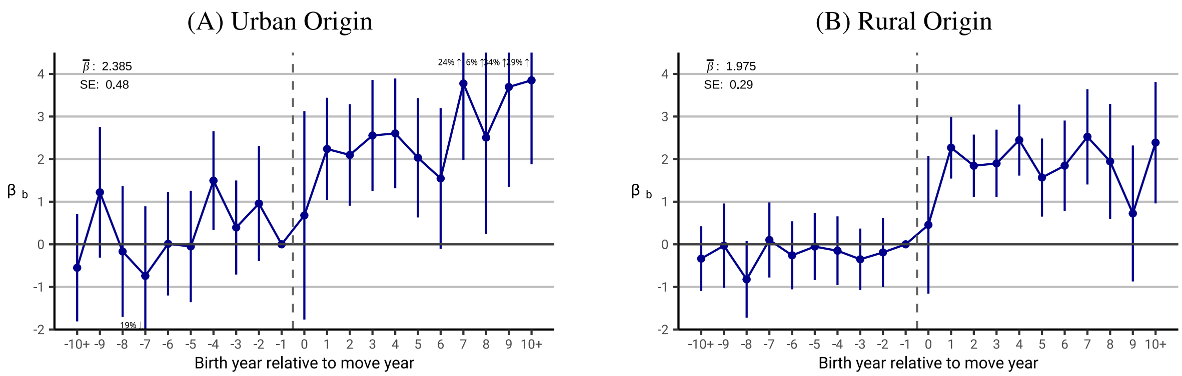


Figure A.20: Heterogeneous Impact is Not Driven by Urban vs. Rural Origins

Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences equation (3). In Panel A, the sample is restricted to households that originated from urban location. In Panel B, the sample is restricted to households that originated from rural locations. $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

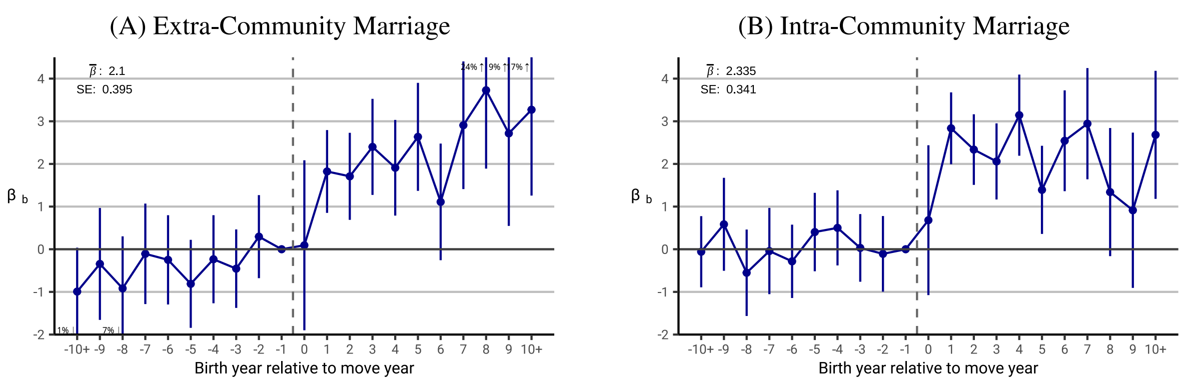


Figure A.21: Heterogeneous Impact is Not Driven by Intra- vs. Extra-Community Marriage

Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences equation (3). In Panel A, the sample is restricted to households in extra-community marriage. In Panel B, the sample is restricted to households in intra-community marriage. $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

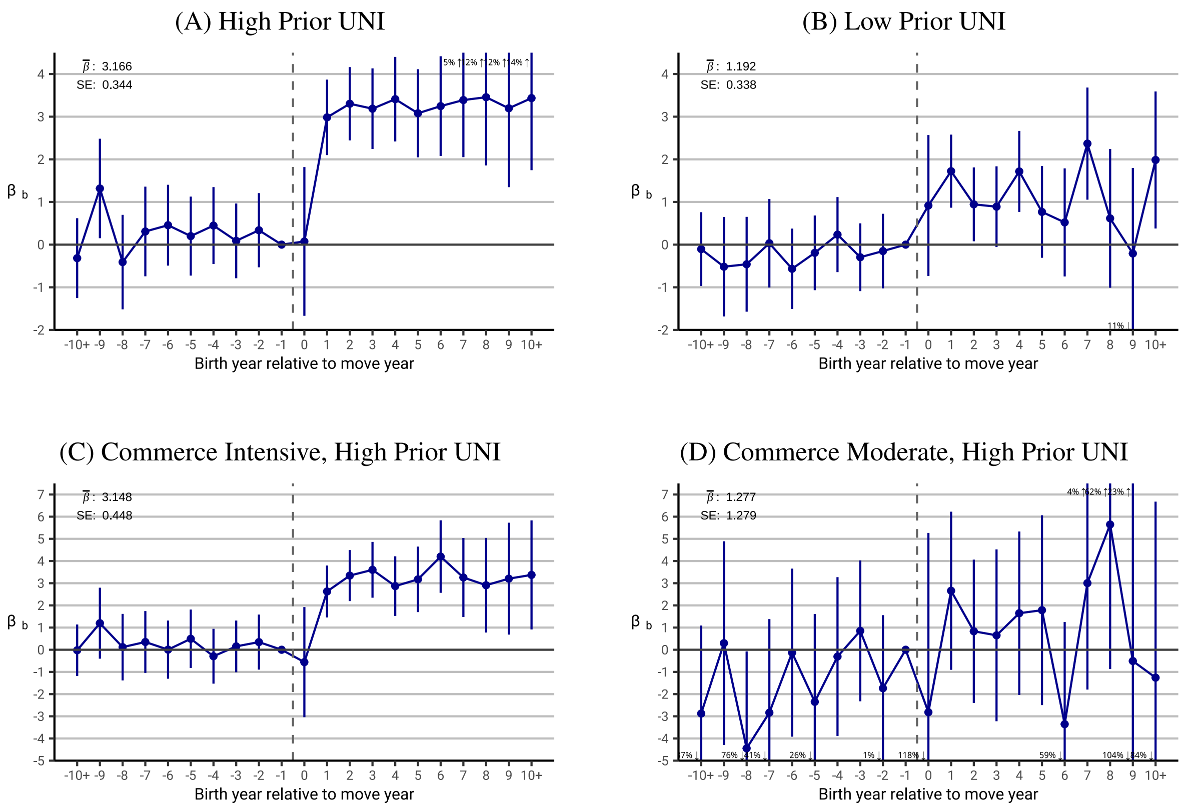


Figure A.22: Heterogeneous Impact is Not Driven by High vs. Low Prior Universalism Identification

Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences equation (3). In Panel A, the sample is restricted to households in which the average UNI of children born before the migration is above the median. In Panel B, the sample is restricted to households in which the average UNI of children born before the migration is below the median. In Panels C-D, the sample is further restricted to households with high pre-migration UNI. Additionally, in Panel C the sample is further restricted to households in which the father was working in a commerce-intensive industry before and after the migration, while in Panel D it is further restricted to households in which the father was working in a commerce-moderate industries. $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

A.8.2 Indirect Channels

Table A.7: Market Access and Proxy Measures of Possible Indirect Channels

	Dependent variable:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Share Immigrants (mean = 0.166 , sd = 0.193)						
Log market access	0.0074**	0.0075***	0.0040	0.0021	0.0009	-0.0001	-0.0003
	(0.0035)	(0.0028)	(0.0031)	(0.0032)	(0.0032)	(0.0033)	(0.0033)
Observations	18,282	18,282	18,282	18,282	18,282	18,282	18,282
R^2	0.899	0.903	0.904	0.904	0.905	0.906	0.907
	Panel B: Birthplace Diversity (mean = 0.249 , sd = 0.247)						
Log market access	0.0133***	0.0143***	0.0094***	0.0068*	0.0054	0.0045	0.0047
	(0.0039)	(0.0033)	(0.0035)	(0.0036)	(0.0037)	(0.0036)	(0.0036)
Observations	18,282	18,282	18,282	18,282	18,282	18,282	18,282
R^2	0.923	0.925	0.926	0.926	0.927	0.928	0.929
	Panel C: Share Urban (mean = 0.106 , sd = 0.198)						
Log market access	-0.0108***	-0.0087***	-0.0067*	-0.0169***	-0.0174***	-0.0186***	-0.0159***
	(0.0033)	(0.0032)	(0.0036)	(0.0035)	(0.0036)	(0.0037)	(0.0036)
Observations	21,207	21,207	21,207	21,207	21,207	21,207	21,207
R^2	0.804	0.808	0.808	0.824	0.824	0.822	0.828
	Panel D: Manufacturing Est. PC (mean = 0.352 , sd = 0.313)						
Log market access	-0.0027	-0.0037	-0.0127	-0.0179	-0.0209*	-0.0100	-0.0103
	(0.0092)	(0.0094)	(0.0106)	(0.0110)	(0.0118)	(0.0133)	(0.0132)
Observations	15,622	15,622	15,622	15,622	15,622	15,622	15,622
R^2	0.604	0.611	0.611	0.612	0.612	0.614	0.614
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year		Yes	Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes	Yes
Railroads within further buffers						Yes	Yes
Population within further buffers							Yes

Note: This table reports estimates of equation (2) with additional controls for local railroad infrastructure and population. The dependent variables are proxy measures of potential indirect channels: population diversity (Panels A-B), urbanization (Panels C), economic development (Panels D-F), access to new information (Panel G), and legal institutions (Panel H). Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Market Access and Proxy Measures of Possible Indirect Channels (cont.)

	Dependent variable:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel E: Mean Occupational Income Score (mean = 17.378 , sd = 3.262)						
Log market access	0.2469***	0.3122***	0.2370***	0.1258	0.0996	0.0413	0.0712
	(0.0783)	(0.0761)	(0.0798)	(0.0815)	(0.0814)	(0.0803)	(0.0800)
Observations	18,268	18,268	18,268	18,268	18,268	18,268	18,268
R^2	0.746	0.751	0.752	0.759	0.760	0.762	0.766
	Panel F: Log Real GDP PC (mean = 7.554 , sd = 0.632)						
Log market access	0.0600***	0.0585***	0.0541***	0.0436***	0.0415**	0.0370**	0.0394**
	(0.0148)	(0.0158)	(0.0160)	(0.0163)	(0.0169)	(0.0169)	(0.0168)
Observations	20,065	20,065	20,065	20,065	20,065	20,065	20,065
R^2	0.901	0.894	0.905	0.906	0.906	0.907	0.908
	Panel G: Information Workers per 1,000 (mean = 3.154 , sd = 2.919)						
Log market access	0.1748***	0.1756***	0.1673***	0.0994*	0.1078*	0.1050*	0.1008*
	(0.0549)	(0.0576)	(0.0580)	(0.0595)	(0.0585)	(0.0556)	(0.0559)
Observations	18,268	18,268	18,268	18,268	18,268	18,268	18,268
R^2	0.751	0.756	0.756	0.759	0.760	0.762	0.763
	Panel H: Lawyers and Judges per 1,000 (mean = 3.093 , sd = 2.412)						
Log market access	0.4615***	0.3835***	0.3656***	0.3951***	0.3537***	0.3305***	0.3319***
	(0.0727)	(0.0788)	(0.0837)	(0.0849)	(0.0839)	(0.0844)	(0.0843)
Observations	18,268	18,268	18,268	18,268	18,268	18,268	18,268
R^2	0.545	0.553	0.553	0.554	0.558	0.562	0.562
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year		Yes	Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes	Yes
Railroads within further buffers						Yes	Yes
Population within further buffers							Yes

Note: This table reports estimates of equation (2) with additional controls for local railroad infrastructure and population. The dependent variables are proxy measures of potential indirect channels: population diversity (Panels A-B), urbanization (Panels C), economic development (Panels D-F), access to new information (Panel G), and legal institutions (Panel H). Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Market Access and Patterns of Cooperative Behavior: Controlling for Possible Channels

	Dependent variable:									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Labor-force cooperation									
logMA	0.0058***	0.0059***	0.0058***	0.0063***	0.0078***	0.0025**	0.0084***	0.0053***	0.0042***	0.0032**
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0016)	(0.0011)	(0.0013)	(0.0012)	(0.0012)	(0.0016)
Observations	18,267	18,267	18,267	18,264	12,739	18,267	17,304	18,267	18,267	12,307
R^2	0.680	0.680	0.675	0.686	0.692	0.765	0.701	0.687	0.693	0.800
	Panel B: Number of co-inventors									
logMA	0.0114***	0.0096**	0.0097**	0.0114***	0.0118***	0.0101***	0.0101***	0.0103***	0.0103***	0.0061
	(0.0037)	(0.0038)	(0.0038)	(0.0037)	(0.0043)	(0.0038)	(0.0038)	(0.0038)	(0.0039)	(0.0051)
Observations	17,360	14,781	14,781	17,357	13,421	14,768	17,018	14,768	14,768	10,664
R^2	0.241	0.266	0.266	0.241	0.286	0.267	0.244	0.266	0.267	0.327
	Panel C: Diversity of co-inventors									
logMA	0.0111***	0.0100***	0.0101***	0.0112***	0.0125***	0.0104***	0.0092***	0.0105***	0.0103***	0.0073
	(0.0034)	(0.0035)	(0.0035)	(0.0034)	(0.0040)	(0.0036)	(0.0035)	(0.0035)	(0.0036)	(0.0047)
Observations	17,360	14,781	14,781	17,357	13,421	14,768	17,018	14,768	14,768	10,664
R^2	0.241	0.269	0.269	0.242	0.287	0.269	0.245	0.269	0.269	0.328
	Panel D: Residence with a non-kin									
logMA	0.0083***	0.0080***	0.0072***	0.0088***	0.0131***	0.0070***	0.0085***	0.0083***	0.0080***	0.0083***
	(0.0022)	(0.0022)	(0.0021)	(0.0023)	(0.0030)	(0.0022)	(0.0020)	(0.0022)	(0.0022)	(0.0026)
Observations	18,277	18,277	18,277	18,274	12,749	18,263	17,317	18,263	18,263	12,306
R^2	0.782	0.783	0.786	0.785	0.810	0.789	0.801	0.783	0.783	0.825
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Share Immigrants		Yes								Yes
Birthplace Diversity			Yes							Yes
Share Urban				Yes						Yes
Manufacturing Est. PC					Yes					Yes
Occupational Income Score						Yes				Yes
Log Real GDP PC							Yes			Yes
Information Workers per 1,000								Yes		Yes
Lawyers and Judges per 1,000									Yes	Yes

Note: This table reports estimates of equation 2 with additional controls for potential indirect channels, when the dependent variables are different historical measures of impersonal or kin-based cooperative behavior: labor-force cooperation (Panel A), the number of co-inventors (Panel B), co-inventors' diversity (Panel C), the share of multifamily households (Panel D), local to state tax ratio (Panel E), civic engagement (Panel F), voters turnout (panel G), and family care (Panel H). Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). The table continues of the next page. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Market Access and Patterns of Cooperative Behavior: Controlling for Possible Channels (cont.)

	Dependent variable:									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel E: Provision of public goods									
logMA	0.0185***	0.0174***	0.0158**	0.0197***	0.0186***	0.0183***	0.0209***	0.0178***	0.0173***	0.0190***
	(0.0060)	(0.0061)	(0.0062)	(0.0060)	(0.0060)	(0.0060)	(0.0068)	(0.0059)	(0.0061)	(0.0072)
Observations	4,942	4,942	4,942	4,940	4,940	4,929	4,799	4,929	4,929	4,782
R^2	0.908	0.908	0.908	0.908	0.908	0.908	0.909	0.908	0.908	0.911
	Panel F: Engagement in civic activities									
logMA	0.0008***	0.0007***	0.0006***	0.0009***	0.0010***	0.0003*	0.0006***	0.0006***	0.0005**	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	18,266	18,266	18,266	18,263	12,739	18,266	17,303	18,266	18,266	12,306
R^2	0.688	0.690	0.693	0.716	0.731	0.749	0.715	0.700	0.705	0.815
	Panel G: Voter turnout									
logMA	0.0382***	0.0412***	0.0417***	0.0367***	0.0465***	0.0387***	0.0460***	0.0394***	0.0357***	0.0482***
	(0.0061)	(0.0064)	(0.0064)	(0.0060)	(0.0066)	(0.0063)	(0.0068)	(0.0064)	(0.0059)	(0.0071)
Observations	45,308	40,242	40,242	45,304	36,915	40,213	44,713	40,213	40,213	31,535
R^2	0.800	0.804	0.803	0.802	0.801	0.803	0.807	0.803	0.807	0.799
	Panel H: Share in Family Care									
logMA	-0.0121***	-0.0115***	-0.0107***	-0.0127***	-0.0168***	-0.0114***	-0.0133***	-0.0119***	-0.0116***	-0.0117***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0033)	(0.0032)	(0.0028)	(0.0032)	(0.0032)	(0.0033)
Observations	18,173	18,173	18,173	18,170	12,674	18,159	17,267	18,159	18,159	12,263
R^2	0.721	0.724	0.725	0.723	0.780	0.723	0.751	0.722	0.722	0.794
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Share Immigrants		Yes								Yes
Birthplace Diversity			Yes							Yes
Share Urban				Yes						Yes
Manufacturing Est. PC					Yes					Yes
Occupational Income Score						Yes				Yes
Log Real GDP PC							Yes			Yes
Information Workers per 1,000								Yes		Yes
Lawyers and Judges per 1,000									Yes	Yes

Note: This table reports estimates of equation 2 with additional controls for local railroad infrastructure and potential indirect channels, when the dependent variables are different historical measures of impersonal or kin-based cooperative behavior: labor-force cooperation (Panel A), the number of co-inventors (Panel B), co-inventors' diversity (Panel C), the share of multifamily households (Panel D), local to state tax ratio (Panel E), civic engagement (Panel F), voters turnout (panel G), and family care (Panel H). Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

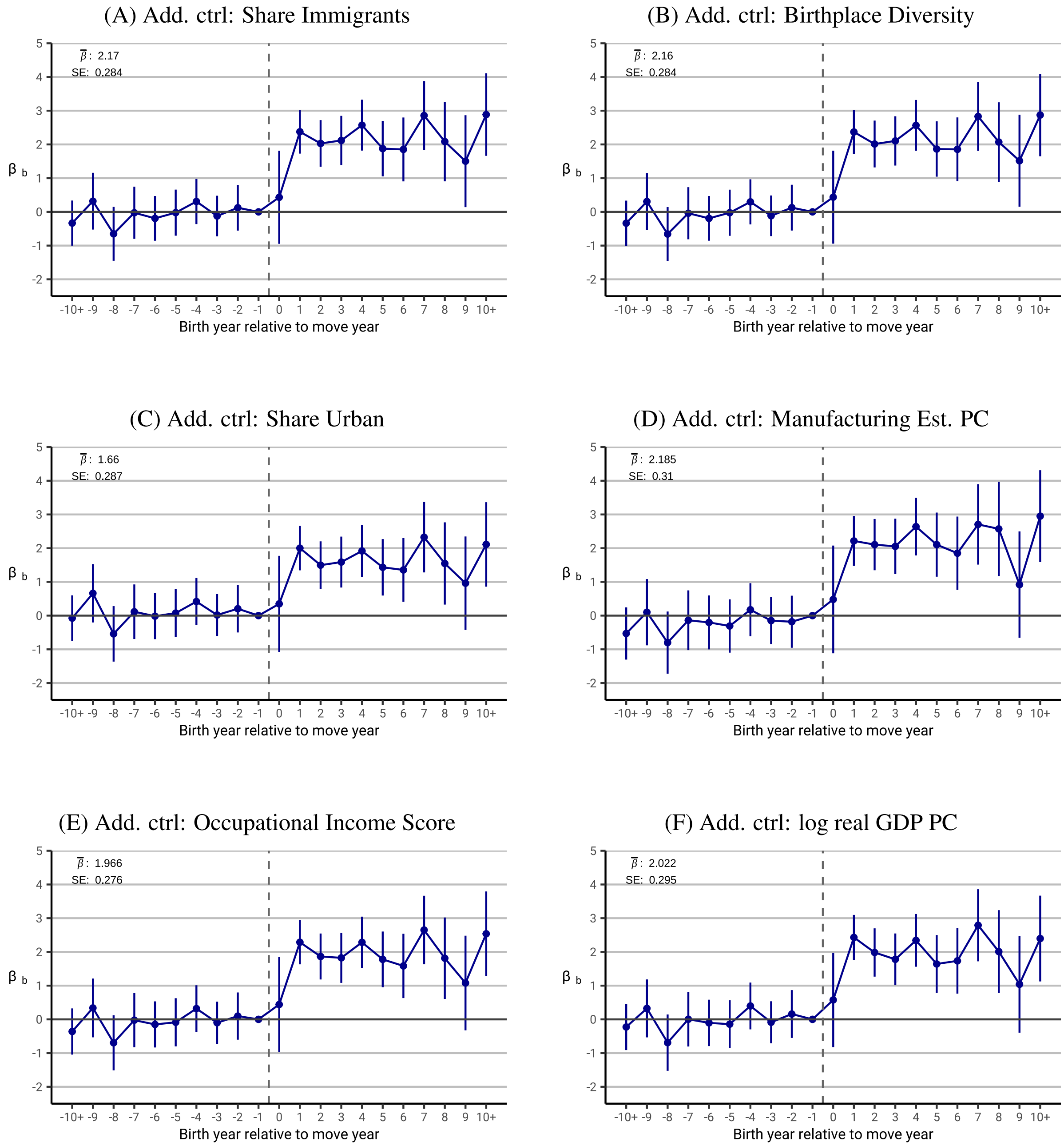


Figure A.23: The Impact is Not Driven by Indirect Channels

Note: This figure plots the estimates of β_b and 95% confidence intervals from an augmented version of the difference-in-differences equation (3) that also controls for the dynamic impact of potential mediators, defined as the differences in the levels of the potential mediator between origin county o and destination county d. The potential mediators considered are: the share of immigrants (Panel A), birthplace diversity (Panel B), the share urban (Panel C), the number of manufacturing establishments per capita (Panel D), the mean occupational income score (Panel E), log real GDP per capita (Panel F), the number of information workers per 1,000 (Panel G), and the number of lawyers and judges per 1,000 (Panel G). $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year. The figure continues to the next page.

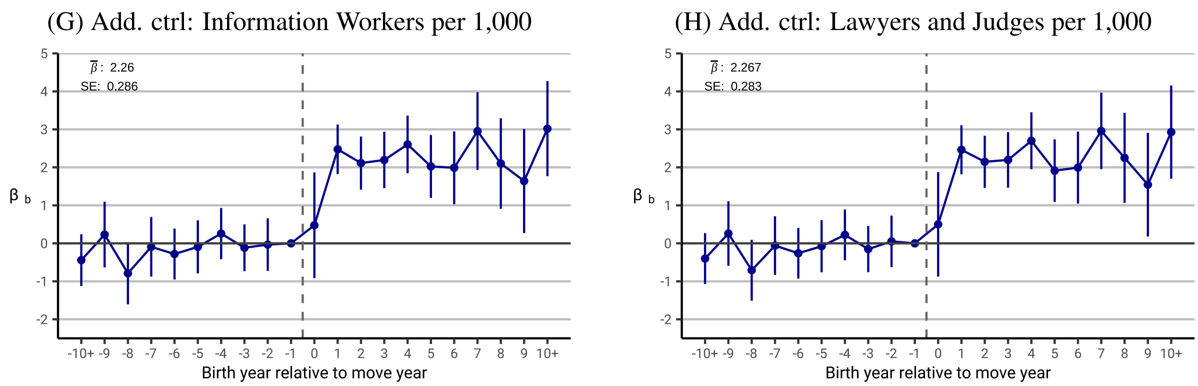


Figure A.23: The Impact is Not Driven by Indirect Channels (cont.)

Note: This figure plots the estimates of β_b and 95% confidence intervals from an augmented version of the difference-in-differences equation (3) that also controls for the dynamic impact of potential mediators, defined as the differences in the levels of the potential mediator between origin county o and destination county d. The potential mediators considered are: the share of immigrants (Panel A), birthplace diversity (Panel B), the share urban (Panel C), the number of manufacturing establishments per capita (Panel D), the mean occupational income score (Panel E), log real GDP per capita (Panel F), the number of information workers per 1,000 (Panel G), and the number of lawyers and judges per 1,000 (Panel H). $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

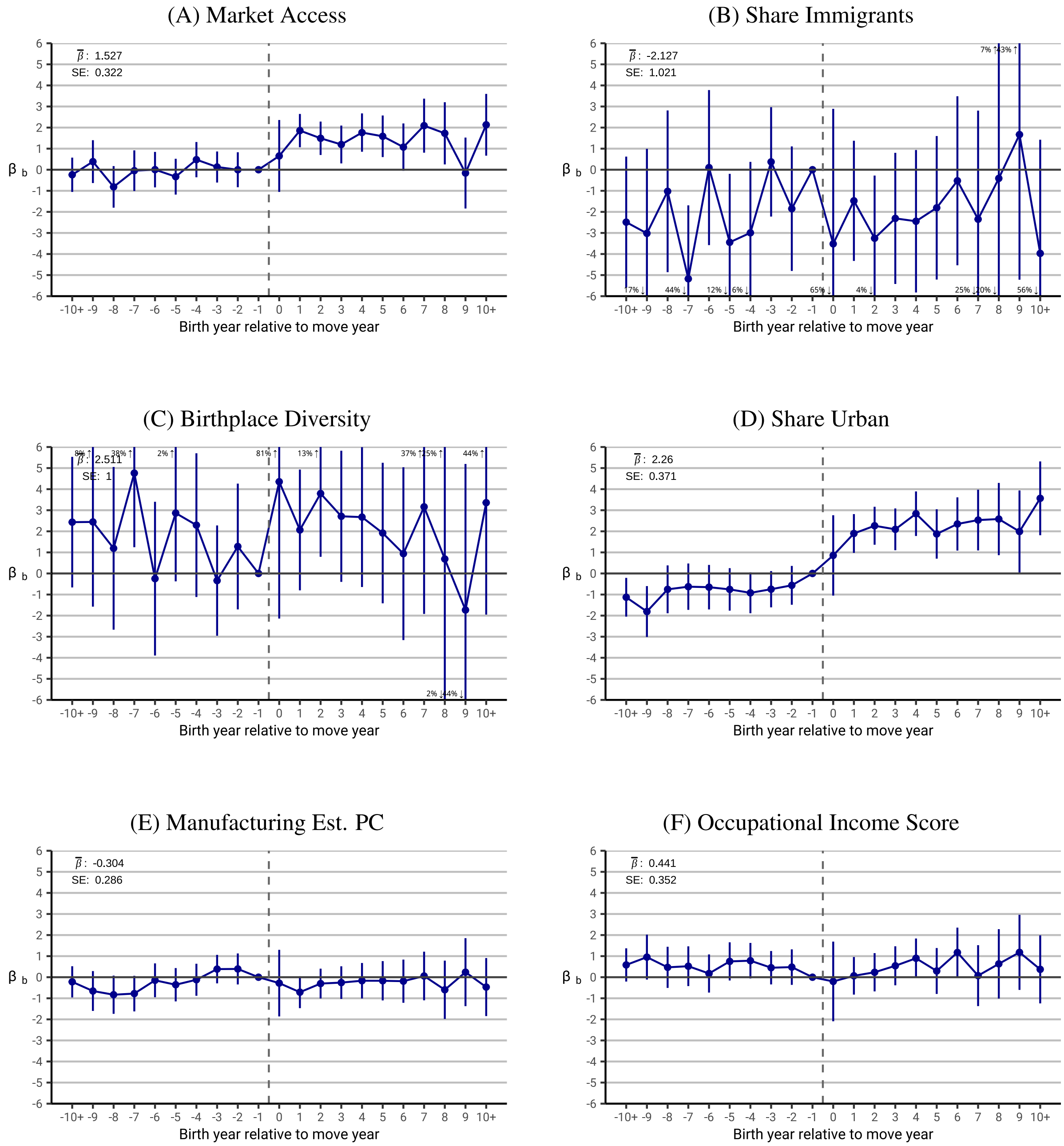
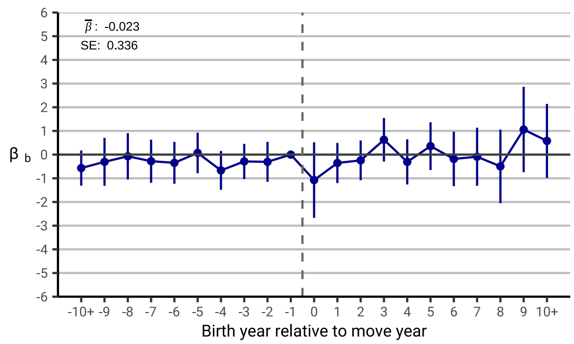


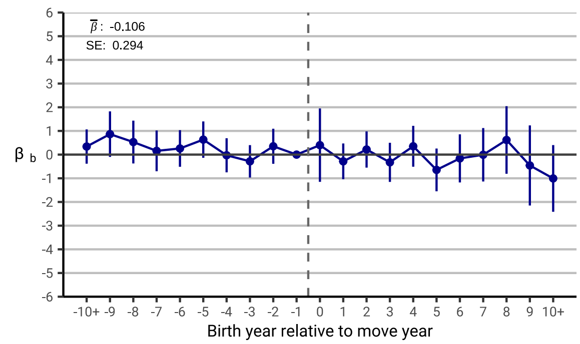
Figure A.24: Adaptation is Driven by Economic Interdependence Between Strangers

Note: This figure plots the estimates of the dynamic impact of different features of the environment from an augmented version of the difference-in-differences equation (3) that also controls for the dynamic impact of all potential mediators, defined as the differences in the levels of the potential mediator between origin county o and destination county d. Each panel plots the coefficients and 95% confidence intervals of different features: log market access (Panel A), the share of immigrants (Panel B), birthplace diversity (Panel C), the share urban (Panel D), the number of manufacturing establishments per capita (Panel E), the mean occupational income score (Panel F), log real GDP per capita (Panel G), the number of information workers per 1,000 (Panel H), and the number of lawyers and judges per 1,000 (Panel I). $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year. The figure continues to the next page.

(G) log real GDP PC



(H) Information Workers per 1,000



(I) Lawyers and Judges per 1,000

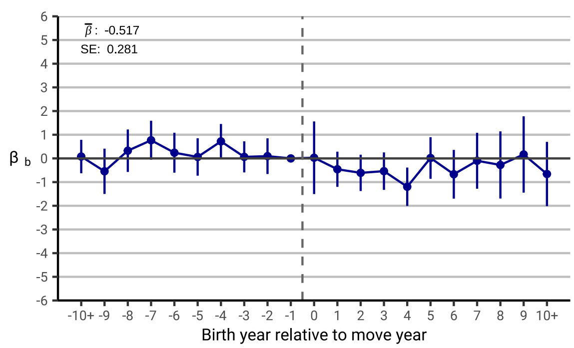


Figure A.24: Adaptation is Driven by Economic Interdependence Between Strangers (cont.)

Note: This figure plots the estimates of the dynamic impact of different features of the environment from an augmented version of the difference-in-differences equation (3) that also controls for the dynamic impact of all potential mediators, defined as the differences in the levels of the potential mediator between origin county o and destination county d. Each panel plots the coefficients and 95% confidence intervals of different features: log market access (Panel A), the share of immigrants (Panel B), birthplace diversity (Panel C), the share urban (Panel D), the number of manufacturing establishments per capita (Panel E), the mean occupational income score (Panel F), log real GDP per capita (Panel G), the number of information workers per 1,000 (Panel H), and the number of lawyers and judges per 1,000 (Panel I). $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

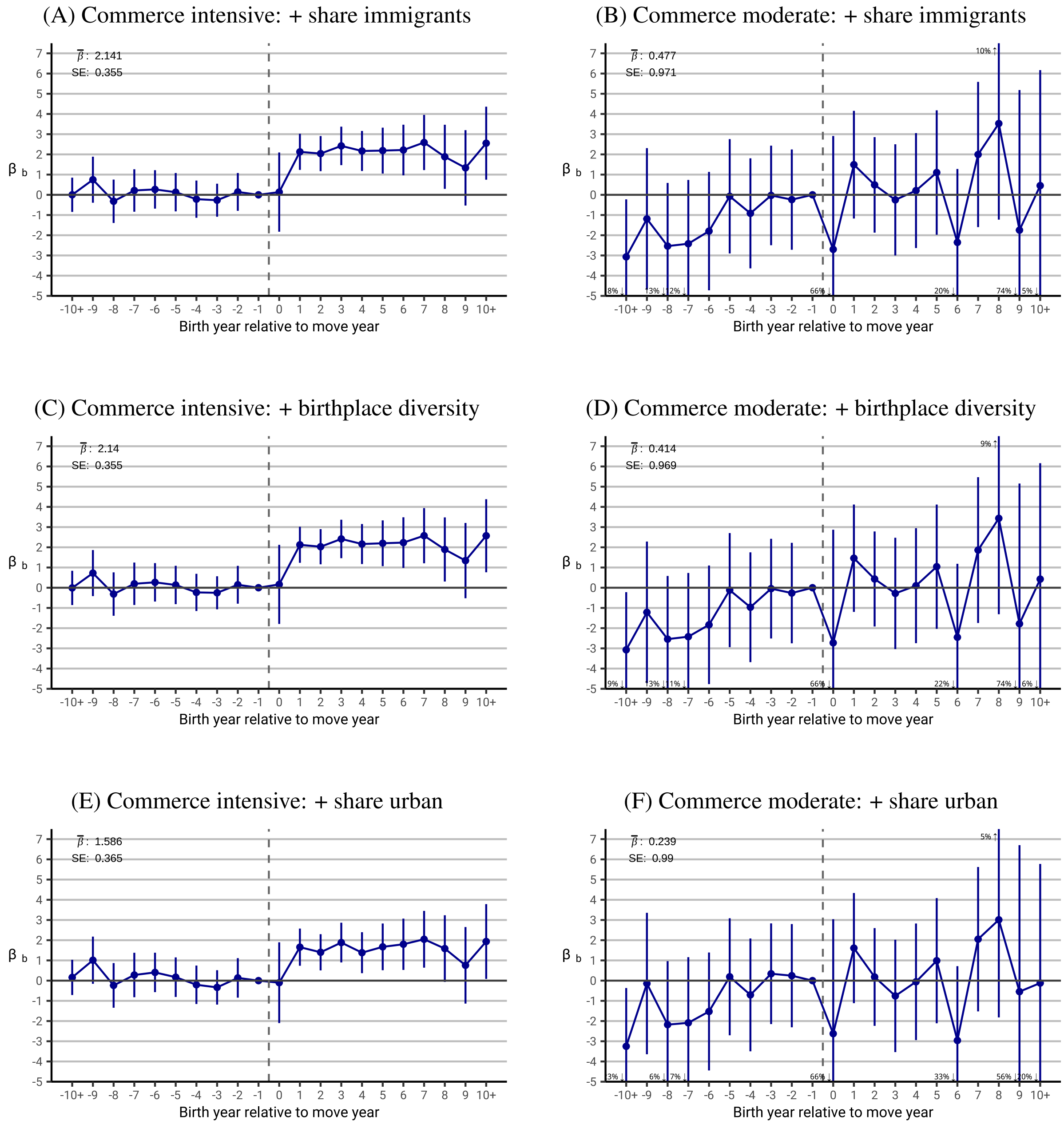
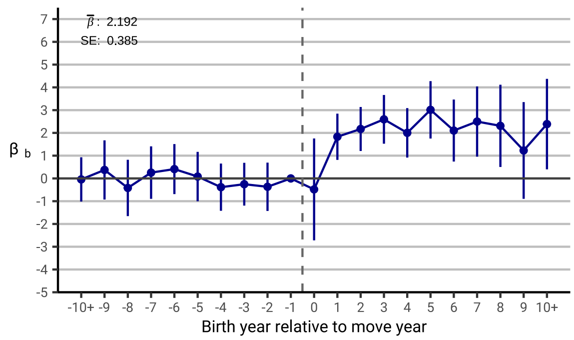


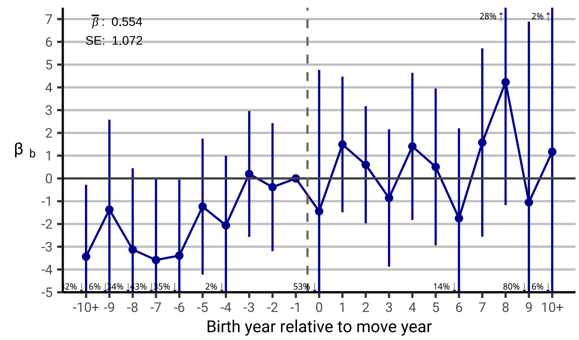
Figure A.25: The Differential Impact is Not Driven by Indirect Channels

Note: This figure plots the estimates of β_b and 95% confidence intervals from an augmented version of the difference-in-differences equation (3) that also controls for the dynamic impact of potential mediators, defined as the differences in the levels of the potential mediator between origin county o and destination county d. In the left column the sample is restricted to households in which the father was working in a commerce-intensive industry before and after the migration. In right column the sample is restricted to households in which the father was working in a commerce-moderate industry before and after the migration. The potential mediators considered are: the share of immigrants (Panels A-B), birthplace diversity (Panels C-D), the share urban (Panels E-F), the number of manufacturing establishments per capita (Panels g-h), the mean occupational income score (Panels I-J), log real GDP PC (Panels K-L), the number of information workers per 1,000 (Panels M-N), the number of lawyers and judges per 1,000 (Panels O-P), and all potential mediators (Panels Q-R). $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year. The figure continues to the next page.

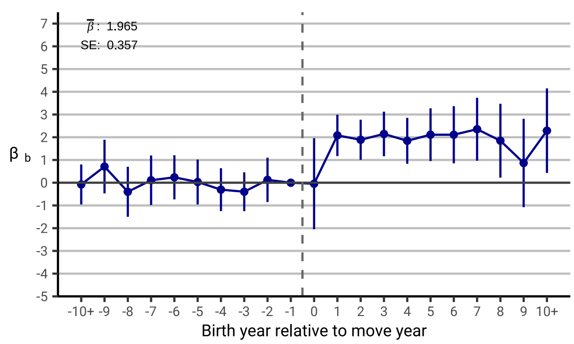
(G) Commerce intensive: + manufacturing est. pc



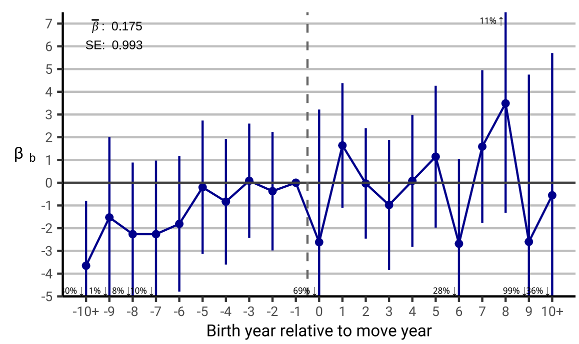
(H) Commerce moderate: + manufacturing est. pc



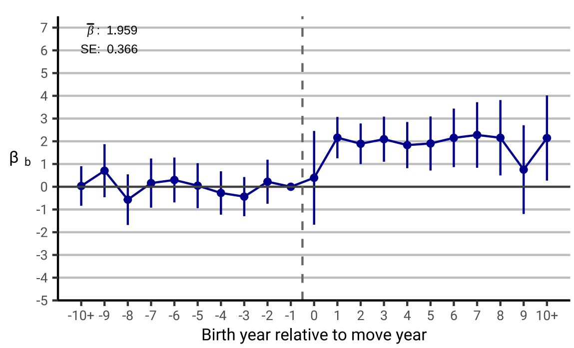
(I) Commerce intensive: + occ. income score



(J) Commerce moderate: + occ. income score



(K) Commerce intensive: + log real GDP pc



(L) Commerce moderate: + log real GDP pc

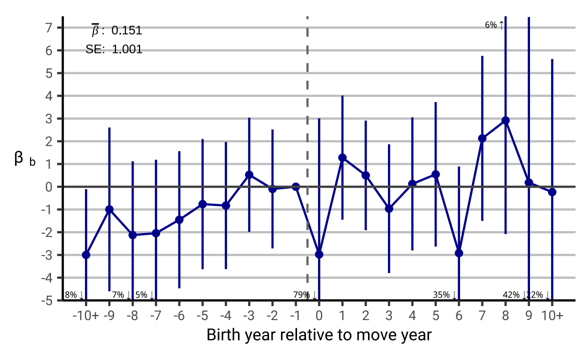


Figure A.25: The Differential Impact is Not Driven by Indirect Channels (cont.)

Note: This figure plots the estimates of β_b and 95% confidence intervals from an augmented version of the difference-in-differences equation (3) that also controls for the dynamic impact of potential mediators, defined as the differences in the levels of the potential mediator between origin county o and destination county d. In the left column the sample is restricted to households in which the father was working in a commerce-intensive industry before and after the migration. In right column the sample is restricted to households in which the father was working in a commerce-moderate industry before and after the migration. The potential mediators considered are: the share of immigrants (Panels A-B), birthplace diversity (Panels C-D), the share urban (Panels E-F), the number of manufacturing establishments per capita (Panels g-h), the mean occupational income score (Panels I-J), log real GDP PC (Panels K-L), the number of information workers per 1,000 (Panels M-N), the number of lawyers and judges per 1,000 (Panels O-P), and all potential mediators (Panels Q-R). $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year. The figure continues to the next page.

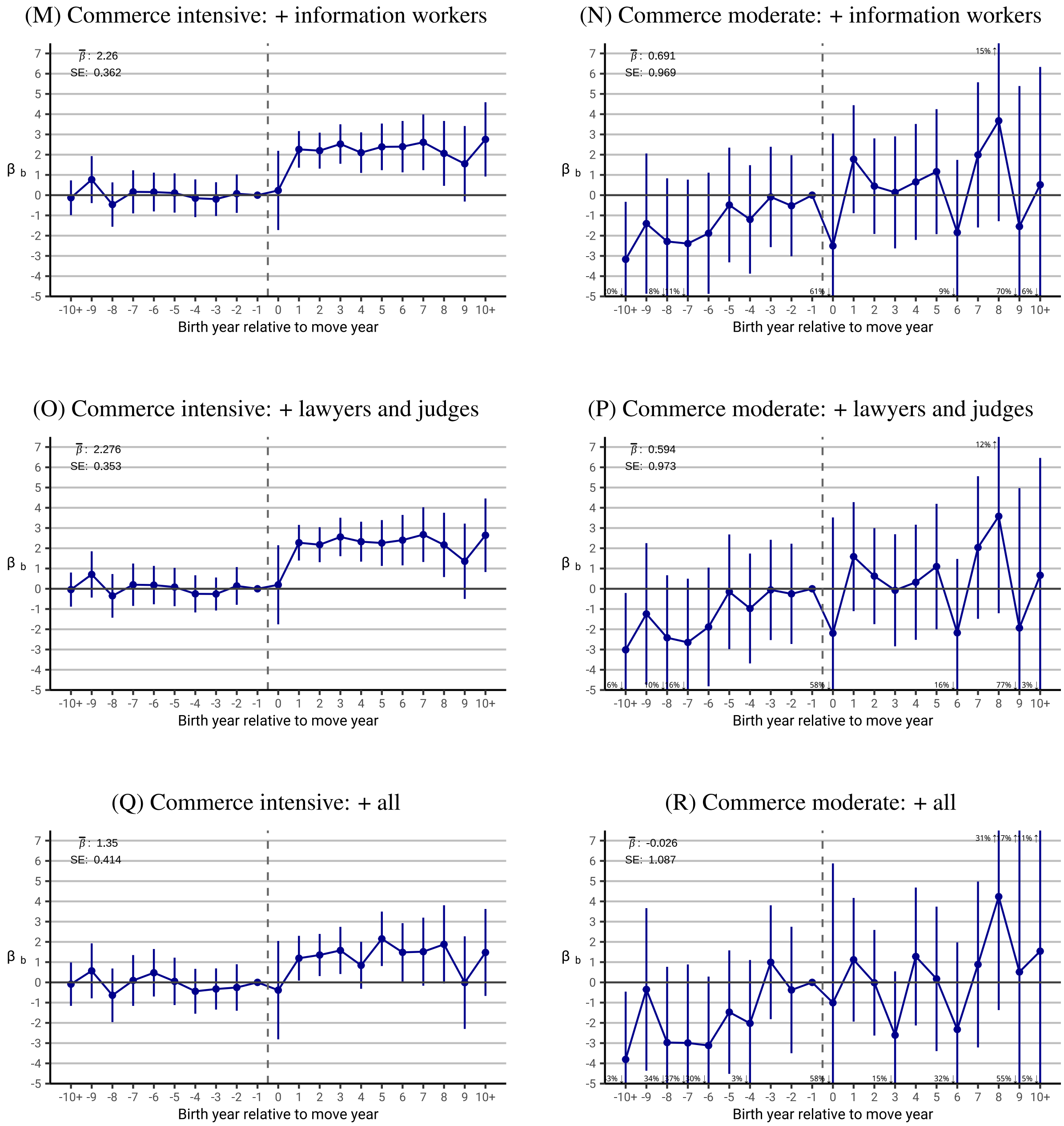


Figure A.25: The Differential Impact is Not Driven by Indirect Channels (cont.)

Note: This figure plots the estimates of β_b and 95% confidence intervals from an augmented version of the difference-in-differences equation (3) that also controls for the dynamic impact of potential mediators, defined as the differences in the levels of the potential mediator between origin county o and destination county d. In the left column the sample is restricted to households in which the father was working in a commerce-intensive industry before and after the migration. In right column the sample is restricted to households in which the father was working in a commerce-moderate industry before and after the migration. The potential mediators considered are: the share of immigrants (Panels A-B), birthplace diversity (Panels C-D), the share urban (Panels E-F), the number of manufacturing establishments per capita (Panels g-h), the mean occupational income score (Panels I-J), log real GDP PC (Panels K-L), the number of information workers per 1,000 (Panels M-N), the number of lawyers and judges per 1,000 (Panels O-P), and all potential mediators (Panels Q-R). $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

B Robustness Checks

B.1 The Impact on Generalized Cooperative Culture and Behavior

B.1.1 The Prevalence of Commerce

Table B.1: Market Access and Market Language: More Market Terms

	Dependent variable:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Mean top 20 market terms share (mean = 0.365 , sd = 0.097)						
Log market access	0.0140***	0.0121***	0.0087**	0.0126***	0.0124***	0.0122**	0.0113**
	(0.0036)	(0.0038)	(0.0043)	(0.0045)	(0.0046)	(0.0049)	(0.0049)
Observations	8,625	8,625	8,625	8,625	8,625	8,625	8,625
R^2	0.642	0.646	0.643	0.648	0.649	0.650	0.652
	Panel B: Mean top 50 market terms share (mean = 0.226 , sd = 0.062)						
Log market access	0.0098***	0.0080***	0.0059**	0.0081***	0.0078***	0.0076**	0.0072**
	(0.0023)	(0.0024)	(0.0027)	(0.0028)	(0.0029)	(0.0030)	(0.0030)
Observations	8,625	8,625	8,625	8,625	8,625	8,625	8,625
R^2	0.642	0.646	0.636	0.648	0.649	0.651	0.652
	Panel C: Mean top 100 market terms share (mean = 0.169 , sd = 0.047)						
Log market access	0.0072***	0.0058***	0.0042**	0.0057***	0.0054**	0.0053**	0.0051**
	(0.0018)	(0.0019)	(0.0020)	(0.0022)	(0.0022)	(0.0023)	(0.0023)
Observations	8,625	8,625	8,625	8,625	8,625	8,625	8,625
R^2	0.642	0.646	0.639	0.647	0.648	0.650	0.652
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year		Yes	Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes	Yes
Railroads within further buffers						Yes	Yes
Population within further buffers							Yes

Note: This table reports estimates of equation (2) with additional controls for local railroad infrastructure and population when the dependent variables are the mean shares of top market words: top 20 (Panel A), top 50 (Panel B), and top 100 (Panel C). Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Wholesale and Retail Share: Winsorize at Different Percentiles

	Dependent variable: Wholesale and Retail Share					
	p(96)	p(96.5)	p(97)	p(98)	p(98.5)	p(99)
	(1)	(2)	(3)	(4)	(5)	(6)
Log market access	0.0050***	0.0051***	0.0051***	0.0051***	0.0052***	0.0052***
	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0010)
Observations	18,266	18,266	18,266	18,266	18,266	18,266
R^2	0.780	0.781	0.781	0.778	0.777	0.773
DV mean	0.0540	0.0540	0.0550	0.0550	0.0550	0.0560
DV sd	0.0340	0.0340	0.0350	0.0370	0.0380	0.0390
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation (2) when the dependent variable is the winsorized share of individuals working in the wholesale and retail trade industries. In each column that outcome is winsorizied at different percentile at the top, between 4% (column 1) and 1% (column 6). Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Wholesale and Retail Share: Alternative Ways to Address Skewed Distributions With Zeros

	Dependent variable: Wholesale and Retail Share (mean = 0.056, sd = 0.041)			
	Poisson Regression	asinh(y)	log(1+y)	log(0.0001+y)
	(1)	(2)	(3)	(4)
Log market access	0.0843***	0.0045***	0.0044***	0.2271***
	(0.0209)	(0.0013)	(0.0011)	(0.0325)
Observations	18,260	18,266	18,266	18,266
R^2		0.73831	0.74762	0.61193
Pseudo R^2	0.054			
County Fixed-Effects	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes
Location cubic polynomial × Year Fixed-Effects	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation (2) when the dependent variable is the share of individuals working in the wholesale and retail trade industries. Each columns deals with the skewness of the outcome that contains zeros differently: column 1 uses a Poisson regression, columns 2 uses inverse hyperbolic sine transformation of the dependent variable, and columns 3-4 use log transformations. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4: Wholesale and Retail Share: Exclusion of Immigrants and Non-Whites

	Dependent variable: Wholesale and Retail Share			
Sample:	Baseline	Exclude foreign-born	Exclude non-whites	Exclude non-whites and foreign-born
	(1)	(2)	(3)	(4)
Log market access	0.0051***	0.0048***	0.0041***	0.0038***
	(0.0008)	(0.0008)	(0.0009)	(0.0009)
DV mean	0.0550	0.0550	0.0620	0.0630
DV sd	0.0360	0.0370	0.0400	0.0400
Observations	18,266	18,212	18,257	18,197
R^2	0.780	0.790	0.781	0.784
County Fixed-Effects	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes
Location cubic polynomial × Year	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation (2) when the dependent variable is the share of individuals working in the wholesale and retail trade industries. The base sample used to calculate the county-level measures in column 1 includes all of the population not residing in group quarters. In column 2 the sample excludes foreign-born, in column 3 it excludes non-whites, and in column 4 it excludes all non-whites and foreign-born.

B.1.2 Generalized Cooperative Culture

Table B.5: Generalized Cooperative Cultural Traits: Exclusion of Immigrants and Non-Whites

	Dependent variable:			
Sample:	Baseline	Exclude foreign-born	Exclude non-whites	Exclude non-whites and foreign-born
	(1)	(2)	(3)	(4)
	Panel A: Universal Name Index			
logMA	0.9250***	0.8057***	1.004***	0.8976***
	(0.1610)	(0.1678)	(0.1650)	(0.1740)
Observations	18,182	18,182	18,182	18,182
R^2	0.805	0.812	0.810	0.815
	Panel B: Extra-Community Marriage			
logMA	0.0069*	0.0145***	0.0011	0.0081*
	(0.0037)	(0.0044)	(0.0035)	(0.0042)
Observations	18,179	18,170	18,178	18,162
R^2	0.908	0.912	0.909	0.917
	Panel C: Norms Tolerance Index			
logMA	0.1785***	0.1652***	0.1945***	0.1823***
	(0.0321)	(0.0306)	(0.0323)	(0.0305)
Observations	18,098	17,997	18,076	17,969
R^2	0.698	0.697	0.698	0.696
County Fixed-Effects	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes
Location cubic polynomial × Year	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation (2) when the dependent variables are the UNI (Panel A), the share of ECM (Panel B), and the NTI (Panel C). The base sample used to calculate the county-level measures in column 1 includes all of the population not residing in group quarters. In column 2 the sample excludes foreign-born, in column 3 it excludes non-whites, and in column 4 it excludes all non-whites and foreign-born.

Table B.6: Generalized Cooperative Cultural Traits: Different Market Access Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Baseline and Robustness							
	Baseline	Robustness						
	$P = 35$	$P = 38.7$		$P = 35$				
	$\theta = 8.22$	$\theta = 3.05$	$\theta = 8.22$	$\theta = 1$	$\theta = 2$	$\theta = 3$	$\theta = 4$	$\theta = 5$
UNI	0.925***	2.43***	0.963***	7.08***	3.54***	2.37***	1.78***	1.44***
	(0.161)	(0.450)	(0.171)	(1.30)	(0.647)	(0.430)	(0.322)	(0.258)
ECM	0.007*	0.018*	0.007*	0.052*	0.026*	0.017*	0.013*	0.011*
	(0.004)	(0.010)	(0.004)	(0.030)	(0.015)	(0.010)	(0.007)	(0.006)
NTI	0.178***	0.485***	0.189***	1.40***	0.699***	0.465***	0.350***	0.281***
	(0.032)	(0.090)	(0.034)	(0.260)	(0.130)	(0.086)	(0.065)	(0.052)
RDI	0.268***	0.732***	0.282***	2.13***	1.06***	0.705***	0.529***	0.425***
	(0.035)	(0.097)	(0.037)	(0.280)	(0.140)	(0.093)	(0.070)	(0.056)
Trust	0.120**	0.341**	0.127**	0.998**	0.495**	0.329**	0.246**	0.197**
	(0.049)	(0.139)	(0.052)	(0.398)	(0.199)	(0.132)	(0.099)	(0.079)

Note: This table reports estimates of β from equation (2) when the dependent variables are different historical generalized cooperative cultural traits: the UNI, the ECM, the NTI, the RDI, and social trust, and market access is calculated using different average costs P and different trade elasticities θ. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). The table continues to the next page. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.6: Generalized Cooperative Cultural Traits: Different Market Access Measures (cont.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel B: Robustness							
	$P = 35$							
	$\theta = 6$	$\theta = 7$	$\theta = 8$	$\theta = 9$	$\theta = 10$	$\theta = 11$	$\theta = 12$	$\theta = 13$
UNI	1.21***	1.06***	0.946***	0.858***	0.789***	0.737***	0.699***	0.672***
	(0.217)	(0.187)	(0.165)	(0.148)	(0.134)	(0.123)	(0.114)	(0.107)
ECM	0.009*	0.008*	0.007*	0.006*	0.006*	0.005*	0.005*	0.005**
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
NTI	0.237***	0.206***	0.183***	0.165***	0.150***	0.138***	0.129***	0.121***
	(0.043)	(0.037)	(0.033)	(0.029)	(0.027)	(0.025)	(0.023)	(0.021)
RDI	0.357***	0.309***	0.275***	0.248***	0.228***	0.213***	0.200***	0.190***
	(0.047)	(0.040)	(0.035)	(0.032)	(0.029)	(0.026)	(0.025)	(0.023)
Trust	0.164**	0.141**	0.123**	0.110**	0.100**	0.092**	0.087**	0.082***
	(0.066)	(0.057)	(0.050)	(0.044)	(0.040)	(0.037)	(0.034)	(0.031)

Note: This table reports estimates of β from equation (2) when the dependent variables are different historical generalized cooperative cultural traits: the UNI, the ECM, the NTI, the RDI, and social trust, and market access is calculated using different average costs P and different trade elasticities θ. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

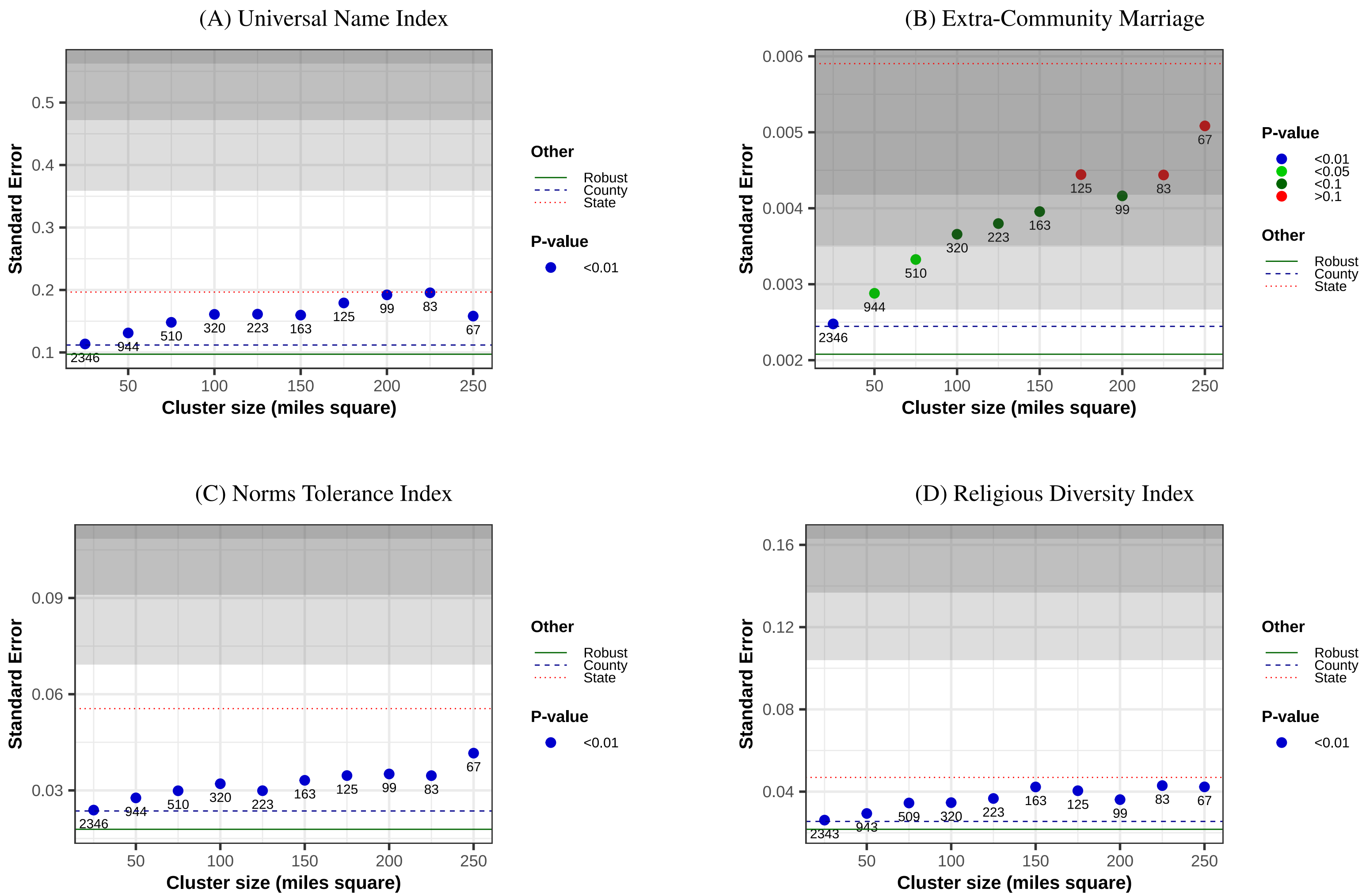


Figure B.1: Generalized Cooperative Cultural Traits: Different Standard Errors

Note: This figure plots the standard errors of β from the preferred specification of equation (2) using different approaches for inference. The blue dots represent the standard errors (on the y-axis) using arbitrary grid-cell of different sizes (on the x-axis), as proposed by Bester et al. (2011). The numeric label under each dot indicates the number of spatial clusters. The dotted dark green horizontal line plots the HC robust standard errors, the dashed dark blue horizontal line plots the standard errors when clustering at the county level, and the dash-dotted red horizontal line plots the standard errors when clustering at the state level. The background color is indicative of the level of statistical significance. The p-value is < 0.01 in the white area, and < 0.05, < 0.1 and > 0.1 in the light to dark shades of gray. The figure continues to the next page.

(E) Social Trust

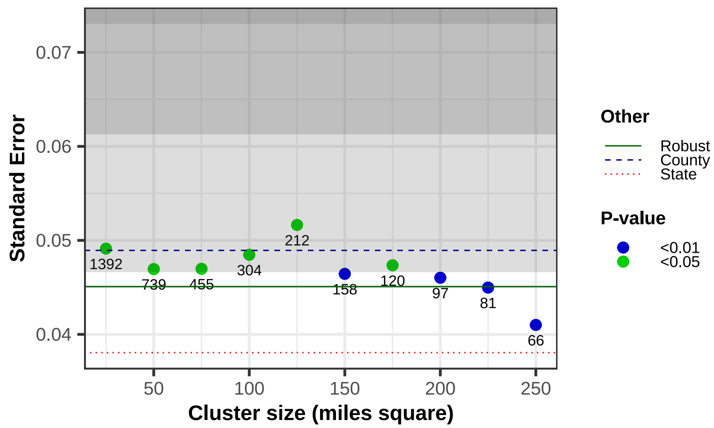


Figure B.1: Generalized Cooperative Cultural Traits: Different Standard Errors (cont.)

Note: This figure plots the standard errors of β from the preferred specification of equation (2) using different approaches for inference. The blue dots represent the standard errors (on the y-axis) using arbitrary grid-cell of different sizes (on the x-axis), as proposed by Bester et al. (2011). The numeric label under each dot indicates the number of spatial clusters. The dotted dark green horizontal line plots the HC robust standard errors, the dashed dark blue horizontal line plots the standard errors when clustering at the county level, and the dash-dotted red horizontal line plots the standard errors when clustering at the state level. The background color is indicative of the level of statistical significance. The p-value is < 0.01 in the white area, and < 0.05, < 0.1 and > 0.1 in the light to dark shades of gray.

Table B.7: Generalized Cooperative Cultural Traits: Exclusion of Regions

	Dependent variable:				
Sample:	Baseline	Exclude Northeast	Exclude Midwest	Exclude South	Exclude West
	(1)	(2)	(3)	(4)	(5)
	Panel A: Universal Name Index				
logMA	0.9250***	0.9084***	0.9096***	0.8586***	1.016***
	(0.1610)	(0.1613)	(0.1930)	(0.1944)	(0.1871)
Observations	18,182	16,677	11,573	9,882	16,414
R^2	0.805	0.789	0.813	0.830	0.799
	Panel B: Extra-Community Marriage				
logMA	0.0069*	0.0074**	0.0038	0.0085**	0.0034
	(0.0037)	(0.0037)	(0.0051)	(0.0042)	(0.0039)
Observations	18,179	16,674	11,565	9,884	16,414
R^2	0.908	0.904	0.927	0.865	0.906
	Panel C: Norms Tolerance Index				
logMA	0.1785***	0.1791***	0.0711**	0.2389***	0.1856***
	(0.0321)	(0.0324)	(0.0355)	(0.0403)	(0.0404)
Observations	18,098	16,593	11,541	9,820	16,340
R^2	0.698	0.686	0.656	0.755	0.698
	Panel D: Religious Diversity Index				
logMA	0.2681***	0.2656***	0.2258***	0.2922***	0.3026***
	(0.0347)	(0.0350)	(0.0404)	(0.0386)	(0.0398)
Observations	17,303	15,798	11,203	9,191	15,717
R^2	0.681	0.676	0.703	0.739	0.616
	Panel E: Social Trust				
logMA	0.1201**	0.1117**	0.0851	0.1055*	0.1959***
	(0.0485)	(0.0490)	(0.0657)	(0.0556)	(0.0586)
Observations	6,821	5,893	3,762	4,814	5,994
R^2	0.681	0.679	0.712	0.664	0.676
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year	Yes	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation (2) when the dependent variables are the UNI (Panel A), the share of ECM (Panel B), the NTI (Panel C), the RDI (Panel D), and social trust (Panel E). Column 1 reports the baseline estimate. Columns 2-5 exclude different regions of the country: the Northeast, the Midwest, the South, and the West.

B.1.3 Impersonal and Kin-based Cooperative Behavior

Table B.8: Patterns of Cooperation: Different Market Access Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Baseline and Robustness							
	Baseline	Robustness						
	$P = 35$	$P = 38.7$		$P = 35$				
	$\theta = 8.22$	$\theta = 3.05$	$\theta = 8.22$	$\theta = 1$	$\theta = 2$	$\theta = 3$	$\theta = 4$	$\theta = 5$
Cooperation	0.006***	0.016***	0.006***	0.047***	0.024***	0.016***	0.012***	0.009***
	(0.001)	(0.004)	(0.002)	(0.010)	(0.005)	(0.004)	(0.003)	(0.002)
No. Co-Inventors	0.011***	0.033***	0.012***	0.095***	0.048***	0.032***	0.024***	0.019***
	(0.004)	(0.011)	(0.004)	(0.031)	(0.016)	(0.010)	(0.008)	(0.006)
Co-Inventors' Div.	0.011***	0.033***	0.012***	0.095***	0.047***	0.032***	0.024***	0.019***
	(0.003)	(0.010)	(0.004)	(0.029)	(0.015)	(0.010)	(0.007)	(0.006)
Multifamily Households	0.008***	0.025***	0.009***	0.071***	0.036***	0.024***	0.018***	0.014***
	(0.002)	(0.006)	(0.002)	(0.018)	(0.009)	(0.006)	(0.005)	(0.004)
Local Taxes	0.018***	0.051***	0.019***	0.149***	0.074***	0.049***	0.037***	0.030***
	(0.006)	(0.017)	(0.006)	(0.049)	(0.025)	(0.016)	(0.012)	(0.010)
Civic Engagement	0.0008***	0.002***	0.0008***	0.006***	0.003***	0.002***	0.001***	0.001***
	(0.0002)	(0.0006)	(0.0002)	(0.002)	(0.0008)	(0.0005)	(0.0004)	(0.0003)
Voters Turnout	0.038***	0.109***	0.041***	0.314***	0.157***	0.104***	0.078***	0.062***
	(0.006)	(0.018)	(0.007)	(0.051)	(0.025)	(0.017)	(0.013)	(0.010)
Family Care	-0.012***	-0.035***	-0.013***	-0.101***	-0.050***	-0.033***	-0.025***	-0.020***
	(0.003)	(0.009)	(0.003)	(0.026)	(0.013)	(0.009)	(0.006)	(0.005)

Note: This table reports estimates of β from equation (2) when the dependent variables are different measures of historical impersonal or kin-based cooperation and market access is calculated using different average costs P and different trade elasticities θ. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). The table continues to the next page. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.8: Patterns of Cooperation: Different Market Access Measures (cont.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel B: Robustness							
	$P = 35$							
	$\theta = 6$	$\theta = 7$	$\theta = 8$	$\theta = 9$	$\theta = 10$	$\theta = 11$	$\theta = 12$	$\theta = 13$
Cooperation	0.008***	0.007***	0.006***	0.005***	0.005***	0.005***	0.004***	0.004***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.0010)	(0.0009)	(0.0008)
No. Co-Inventors	0.016***	0.013***	0.012***	0.010***	0.009***	0.009***	0.008***	0.007***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Co-Inventors' Div.	0.015***	0.013***	0.011***	0.010***	0.009***	0.008***	0.008***	0.007***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Multifamily Households	0.012***	0.010***	0.009***	0.007***	0.007***	0.006***	0.005***	0.005***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Local Taxes	0.025***	0.021***	0.019***	0.017***	0.016***	0.015***	0.014***	0.013***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
Civic Engagement	0.001***	0.0009***	0.0008***	0.0007***	0.0006***	0.0006***	0.0006***	0.0005***
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Voters Turnout	0.052***	0.045***	0.039***	0.035***	0.032***	0.029***	0.027***	0.026***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
Family Care	-0.017***	-0.014***	-0.013***	-0.011***	-0.010***	-0.009***	-0.008***	-0.008***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)

Note: This table reports estimates of β from equation (2) when the dependent variables are different measures of historical impersonal or kin-based cooperation and market access is calculated using different average costs P and different trade elasticities θ. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

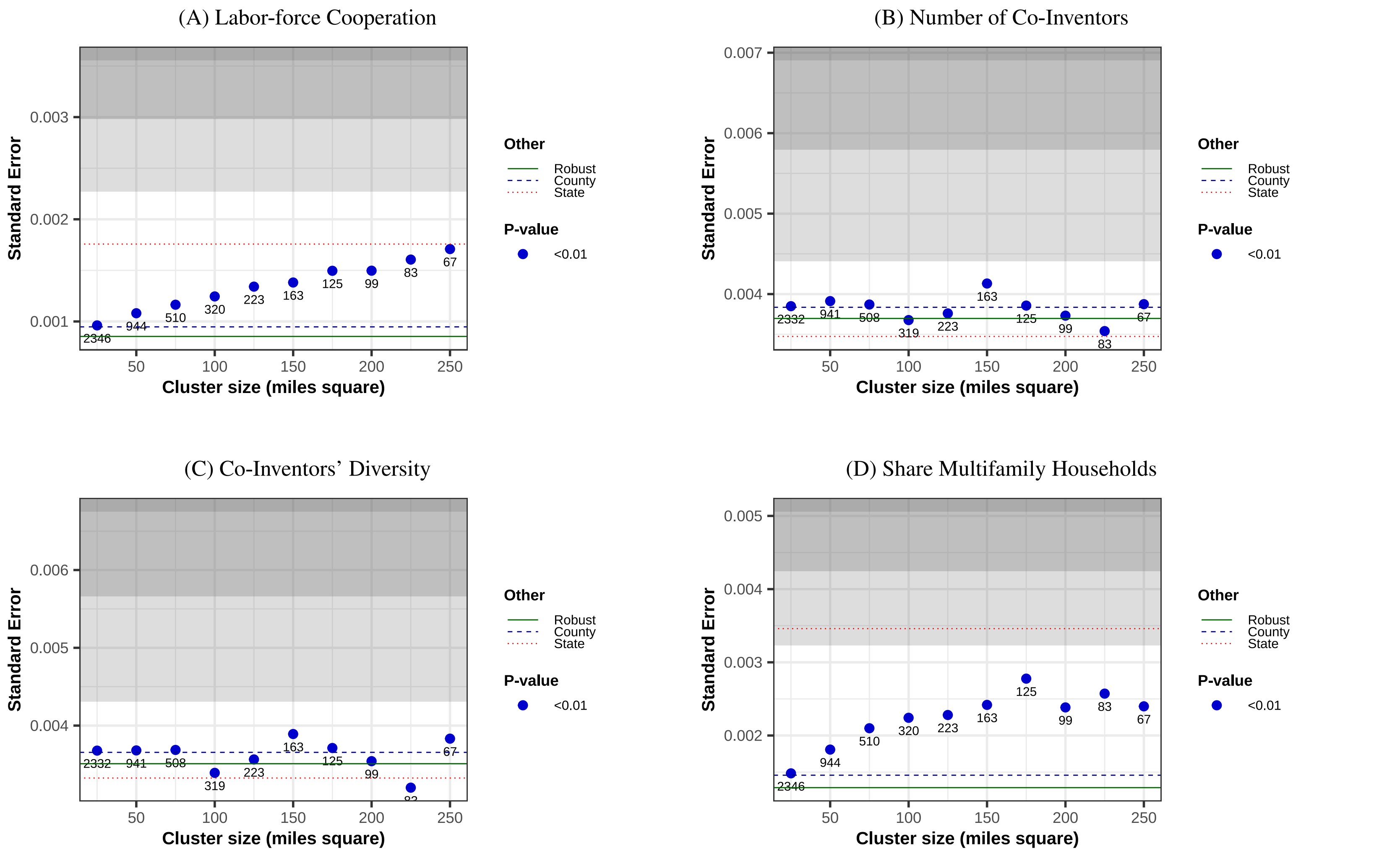


Figure B.2: Patterns of Cooperation: Different Standard Errors

Note: This figure plots the standard errors of β from the preferred specification of equation (2) using different approaches for inference. The blue dots represent the standard errors (on the y-axis) using arbitrary grid-cell of different sizes (on the x-axis), as proposed by Bester et al. (2011). The numeric label under each dot indicates the number of spatial clusters. The dotted dark green horizontal line plots the HC robust standard errors, the dashed dark blue horizontal line plots the standard errors when clustering at the county level, and the dash-dotted red horizontal line plots the standard errors when clustering at the state level. The background color is indicative of the level of statistical significance. The p-value is < 0.01 in the white area, and < 0.05, < 0.1 and > 0.1 in the light to dark shades of gray. The figure continues to the next page.

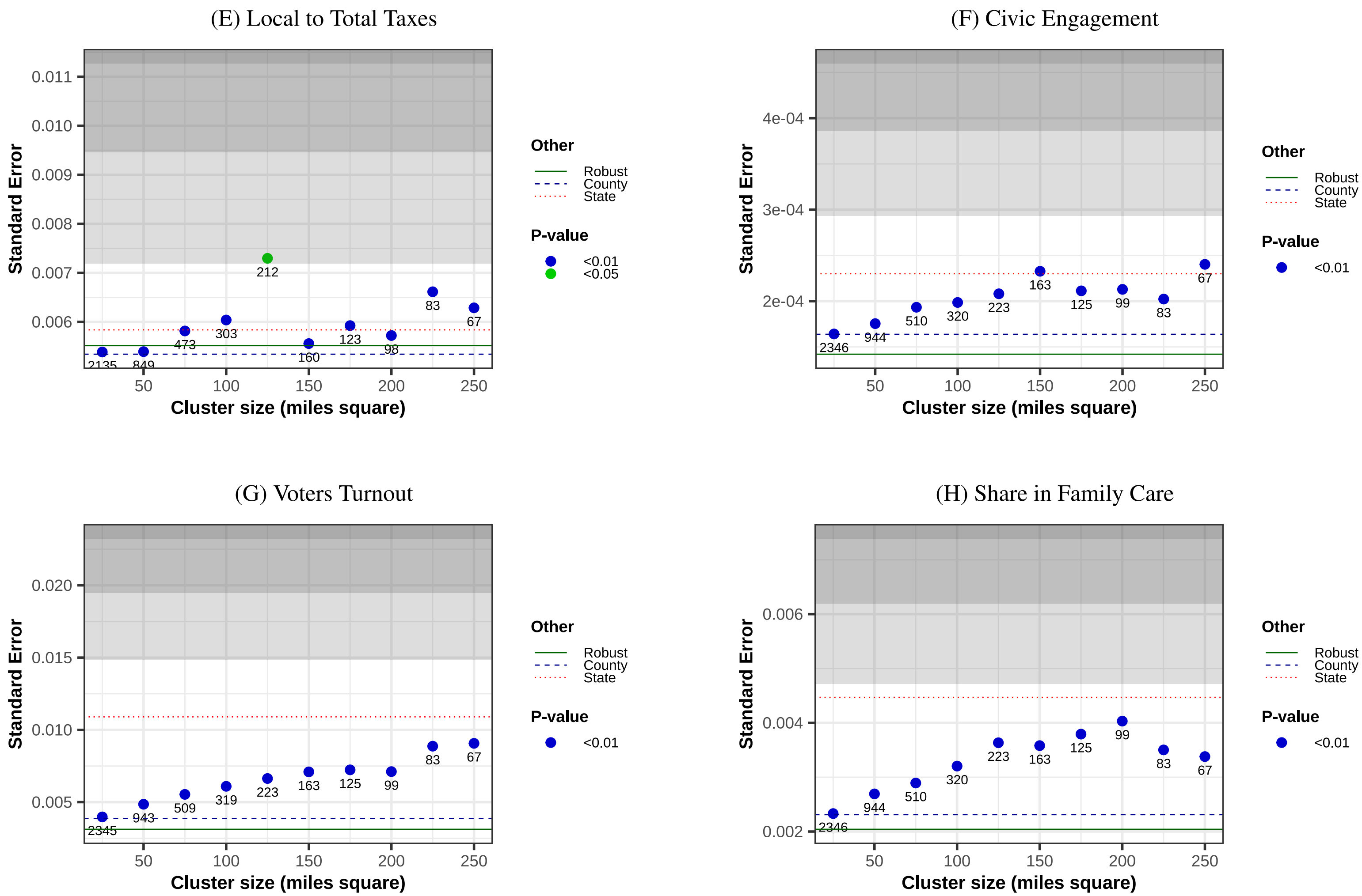


Figure B.2: Patterns of Cooperation: Different Standard Errors (cont.)

Note: This figure plots the standard errors of β from the preferred specification of equation (2) using different approaches for inference. The blue dots represent the standard errors (on the y-axis) using arbitrary grid-cell of different sizes (on the x-axis), as proposed by Bester et al. (2011). The numeric label under each dot indicates the number of spatial clusters. The dotted dark green horizontal line plots the HC robust standard errors, the dashed dark blue horizontal line plots the standard errors when clustering at the county level, and the dash-dotted red horizontal line plots the standard errors when clustering at the state level. The background color is indicative of the level of statistical significance. The p-value is < 0.01 in the white area, and < 0.05, < 0.1 and > 0.1 in the light to dark shades of gray.

Table B.9: Patterns of Cooperation: Winsorize at Different Percentiles

	Dependent variable:					
	p(96)	p(96.5)	p(97)	p(98)	p(98.5)	p(99)
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Number of Co-Inventors					
Log market access	0.0120***	0.0116***	0.0114***	0.0114***	0.0107**	0.0083
	(0.0032)	(0.0035)	(0.0037)	(0.0037)	(0.0042)	(0.0054)
Observations	17,360	17,360	17,360	17,360	17,360	17,360
R^2	0.246	0.242	0.241	0.241	0.241	0.247
DV mean	1.089	1.091	1.092	1.092	1.095	1.100
DV sd	0.1050	0.1130	0.1160	0.1160	0.1290	0.1520
	Panel B: Co-Inventors' Diversity					
Log market access	0.0119***	0.0119***	0.0117***	0.0111***	0.0111***	0.0089*
	(0.0026)	(0.0026)	(0.0029)	(0.0034)	(0.0034)	(0.0049)
Observations	17,360	17,360	17,360	17,360	17,360	17,360
R^2	0.246	0.246	0.243	0.241	0.242	0.249
DV mean	0.0710	0.0710	0.0740	0.0760	0.0760	0.0820
DV sd	0.0890	0.0890	0.0960	0.1060	0.1060	0.1370
	Panel C: Share Multifamily Households					
Log market access	0.0087***	0.0087***	0.0086***	0.0082***	0.0079***	0.0075***
	(0.0019)	(0.0020)	(0.0021)	(0.0023)	(0.0024)	(0.0026)
Observations	18,277	18,277	18,277	18,277	18,277	18,277
R^2	0.787	0.786	0.784	0.780	0.778	0.774
DV mean	0.1490	0.1500	0.1500	0.1520	0.1520	0.1530
DV sd	0.0790	0.0800	0.0820	0.0850	0.0880	0.0920
	Panel D: Civic Engagement					
Log market access	0.0007***	0.0007***	0.0008***	0.0008***	0.0008***	0.0008***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	18,266	18,266	18,266	18,266	18,266	18,266
R^2	0.690	0.689	0.688	0.685	0.682	0.679
DV mean	0.0120	0.0120	0.0120	0.0120	0.0120	0.0120
DV sd	0.0080	0.0090	0.0090	0.0090	0.0090	0.0090
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation (2) when the dependent variables are three different winsorized historical measure of impersonal cooperation: the average number of patents co-inventors (Panel A), the diversity of of patents co-inventors (Panel B), the share of multifamily households (Panel C), and civic engagement (Panel D). In each column that outcome is winsorizied at different percentile at the top, between 4% (column 1) and 1% (column 6). Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.10: Patterns of Cooperation: Alternative Ways to Address Skewed Distributions With Zeros

	Dependent variable:			
	Poisson Regression	asinh(y)	log(1+y)	log(0.0001+y)
	(1)	(2)	(3)	(4)
	Panel A: Number of Co-Inventors (mean = 1.1 , sd = 0.158)			
Log market access	0.0069	0.0062*	0.0043*	0.0089**
	(0.0048)	(0.0032)	(0.0023)	(0.0040)
Observations	17,360	17,360	17,360	17,360
R^2		0.24407	0.24404	0.24452
Pseudo R^2	0.002			
	Panel B: Co-Inventors' Diversity (mean = 0.082 , sd = 0.14)			
Log market access	0.0885*	0.0095**	0.0094**	0.7430***
	(0.0483)	(0.0045)	(0.0037)	(0.0861)
Observations	16,149	17,360	17,360	17,360
R^2		0.24656	0.24613	0.43870
Pseudo R^2	0.077			
	Panel C: Share Multifamily Households (mean = 0.155 , sd = 0.099)			
Log market access	0.0283**	0.0070**	0.0061***	0.0712***
	(0.0134)	(0.0028)	(0.0023)	(0.0204)
Observations	18,277	18,277	18,277	18,277
R^2		0.76390	0.77261	0.69213
Pseudo R^2	0.058			
	Panel D: Civic Engagement (mean = 0.013 , sd = 0.011)			
Log market access	0.0759***	0.0011***	0.0010***	0.2071***
	(0.0190)	(0.0003)	(0.0003)	(0.0364)
Observations	18,258	18,266	18,266	18,266
R^2		0.59370	0.60456	0.56624
Pseudo R^2	0.039			
County Fixed-Effects	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes
Location cubic polynomial × Year Fixed-Effects	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation (2) when the dependent variables are three different historical measure of impersonal cooperation: the average number of patents co-inventors (Panel A), the diversity of of patents co-inventors (Panel B), the share of multifamily households (Panel C), and civic engagement (Panel D). Each columns deals with the skewness of the outcome that contains zeros differently: column 1 uses a Poisson regression, columns 2 uses inverse hyperbolic sine transformation of the dependent variable, and columns 3-4 use log transformations. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.11: Family Care: Winsorize at Different Percentiles

	Dependent variable: Share in Family Care					
Winsorize at:	p(0)	p(1)	p(2)	p(3)	p(4)	p(5)
	(1)	(2)	(3)	(4)	(5)	(6)
Log market access	-0.0103**	-0.0118***	-0.0121***	-0.0120***	-0.0118***	-0.0117***
	(0.0042)	(0.0038)	(0.0033)	(0.0031)	(0.0029)	(0.0028)
Observations	18,173	18,173	18,173	18,173	18,173	18,173
R^2	0.674	0.701	0.717	0.725	0.730	0.732
DV mean	0.7740	0.7750	0.7770	0.7790	0.7800	0.7810
DV sd	0.1270	0.1200	0.1140	0.1090	0.1060	0.1050
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation (2) when the dependent variable is the share of vulnerable individuals in family care. In each column the outcome is winsorizied at different percentile at the bottom, between 0% (i.e., not winsorized, column 1) and 5% (column 6). Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.12: Patterns of Cooperation: Exclusion of Regions

	Dependent variable:				
Sample:	Baseline	Exclude Northeast	Exclude Midwest	Exclude South	Exclude West
	(1)	(2)	(3)	(4)	(5)
	Panel A: Labor-force cooperation				
logMA	0.0058***	0.0059***	0.0090***	0.0055***	0.0035**
	(0.0012)	(0.0013)	(0.0016)	(0.0015)	(0.0014)
Observations	18,267	16,770	11,596	9,943	16,492
R^2	0.680	0.673	0.694	0.601	0.688
	Panel B: Number of co-inventors				
logMA	0.0114***	0.0110***	0.0090*	0.0112**	0.0141***
	(0.0037)	(0.0038)	(0.0046)	(0.0048)	(0.0042)
Observations	17,360	15,666	10,670	10,067	15,677
R^2	0.241	0.242	0.246	0.238	0.238
	Panel C: Diversity of co-inventors				
logMA	0.0111***	0.0108***	0.0080*	0.0133***	0.0126***
	(0.0034)	(0.0035)	(0.0041)	(0.0046)	(0.0038)
Observations	17,360	15,666	10,670	10,067	15,677
R^2	0.241	0.243	0.247	0.240	0.238
	Panel D: Residence with a non-kin				
logMA	0.0083***	0.0083***	0.0096***	0.0079**	0.0086***
	(0.0022)	(0.0023)	(0.0025)	(0.0031)	(0.0024)
Observations	18,277	16,772	11,606	9,951	16,502
R^2	0.782	0.773	0.808	0.791	0.772
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year	Yes	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation (2) when the dependent variables are labor-force cooperation (Panel A), the number of co-inventors (Panel B), co-inventors' diversity (Panel C), the share of multifamily households (Panel D), share of local tax revenues (Panel E), the share employed in civic activities (Panel F), voters turnout in presidential elections (Panel G), and the share of vulnerable individuals in family care (Panel H). Column 1 reports the baseline estimate. Columns 2-5 exclude different regions of the country: the Northeast, the Midwest, the South, and the West. The table continues to the next page.

Table B.12: Patterns of Cooperation: Exclusion of Regions (cont.)

	Dependent variable:				
Sample:	Baseline	Exclude Northeast	Exclude Midwest	Exclude South	Exclude West
	(1)	(2)	(3)	(4)	(5)
	Panel E: Provision of public goods				
logMA	0.0185***	0.0189***	0.0164**	0.0120*	0.0302***
	(0.0060)	(0.0061)	(0.0065)	(0.0072)	(0.0088)
Observations	4,942	4,512	3,237	2,673	4,404
R^2	0.908	0.899	0.893	0.855	0.910
	Panel F: Engagement in civic activities				
logMA	0.0008***	0.0008***	0.0006**	0.0010***	0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Observations	18,266	16,769	11,596	9,943	16,490
R^2	0.688	0.682	0.712	0.677	0.664
	Panel G: Voter turnout				
logMA	0.0382***	0.0402***	0.0434***	0.0187***	0.0388***
	(0.0061)	(0.0062)	(0.0076)	(0.0068)	(0.0065)
Observations	45,308	41,241	28,218	24,534	41,931
R^2	0.800	0.797	0.795	0.740	0.809
	Panel H: Share in Family Care				
logMA	-0.0121***	-0.0122***	-0.0153***	-0.0132***	-0.0081**
	(0.0032)	(0.0032)	(0.0033)	(0.0046)	(0.0035)
Observations	18,173	16,668	11,572	9,873	16,406
R^2	0.721	0.715	0.761	0.715	0.700
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × Year	Yes	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation (2) when the dependent variables are labor-force cooperation (Panel A), the number of co-inventors (Panel B), co-inventors' diversity (Panel C), the share of multifamily households (Panel D), share of local tax revenues (Panel E), the share employed in civic activities (Panel F), voters turnout in presidential elections (Panel G), and the share of vulnerable individuals in family care (Panel H). Column 1 reports the baseline estimate. Columns 2-5 exclude different regions of the country: the Northeast, the Midwest, the South, and the West.

B.2 Adaptation vs. Sorting: Evidence from Domestic Migrants

B.2.1 Cultural Adaptation

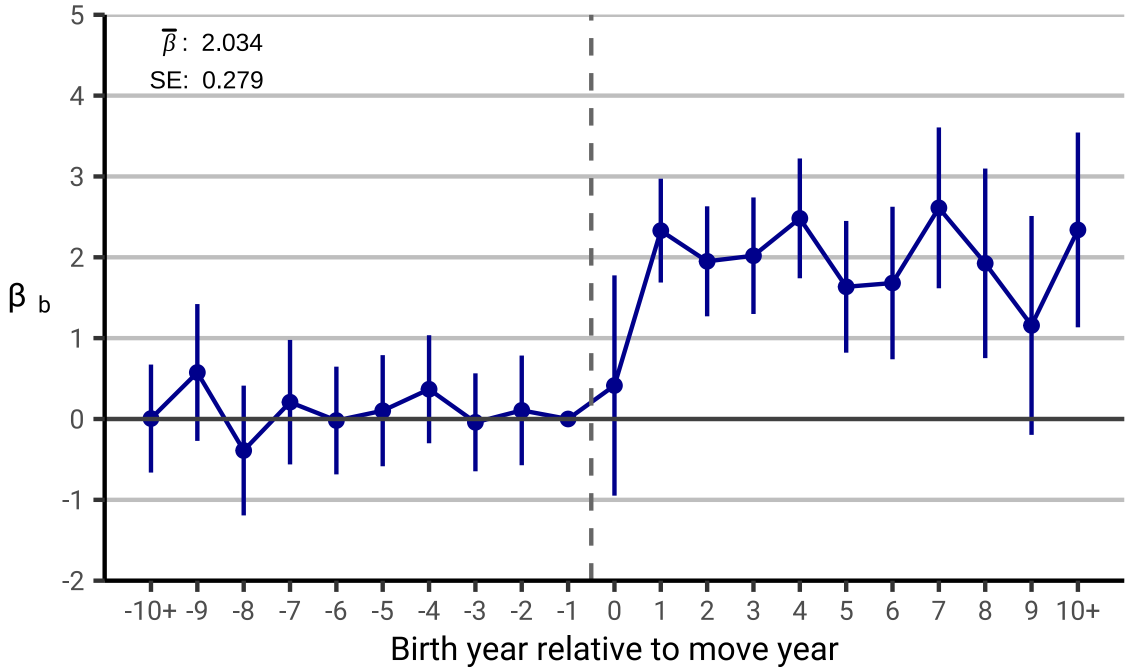


Figure B.3: DID Robustness: Controlling for Children's Characteristics

Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences equation (3), with additional child-level controls: gender, birth order, and a 5-year cohort fixed effects. $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

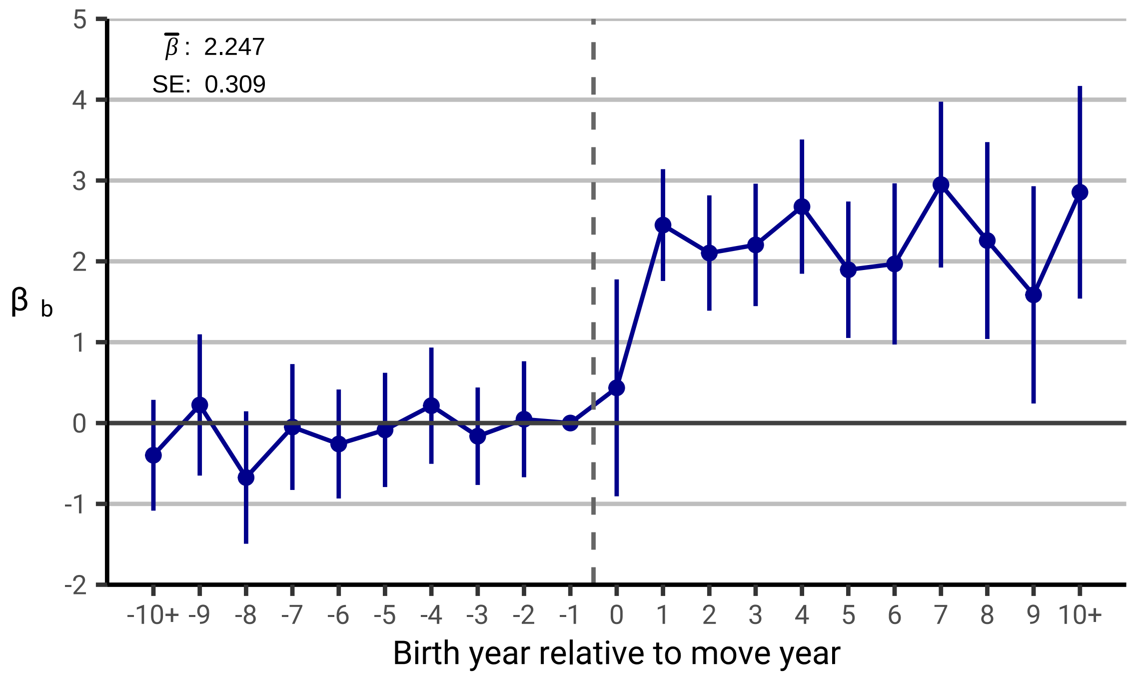


Figure B.4: DID Robustness: Two-way Clustering at Origin and Destination Counties

Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences equation (3) with two-way clustering of standard errors are at the county of destination and the county of origin. $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

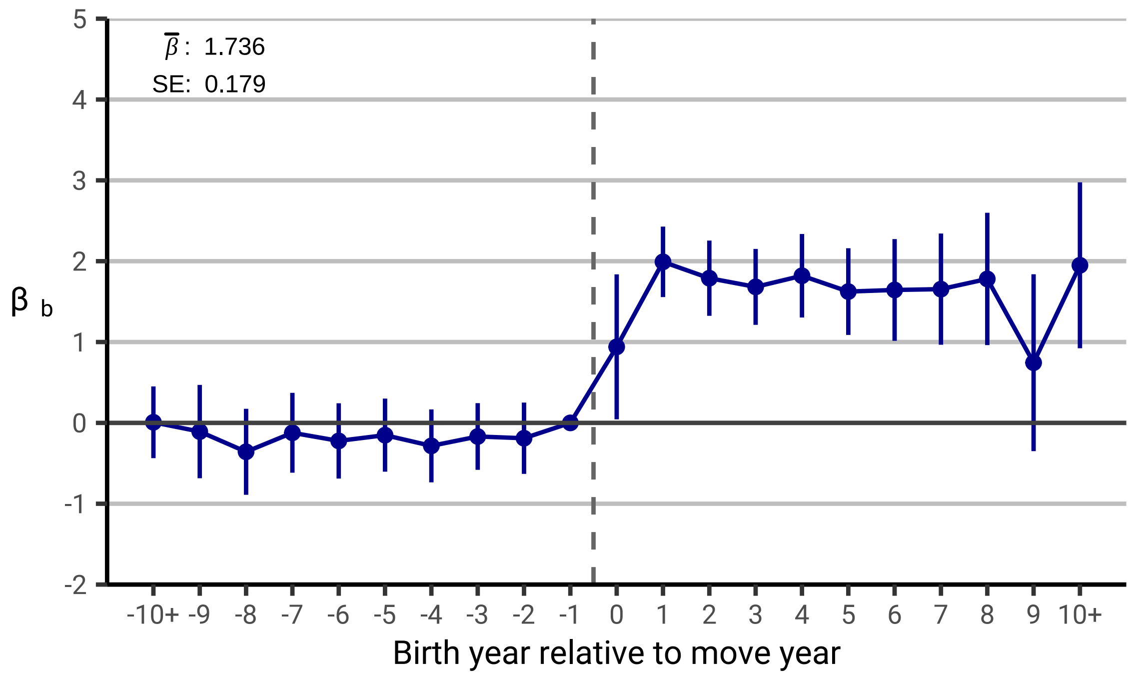


Figure B.5: DID Robustness: Continuous Treatment

Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences estimation when treatment is defined in a continuous way and equals the difference in log market access between the county of destination and the county of origin. $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

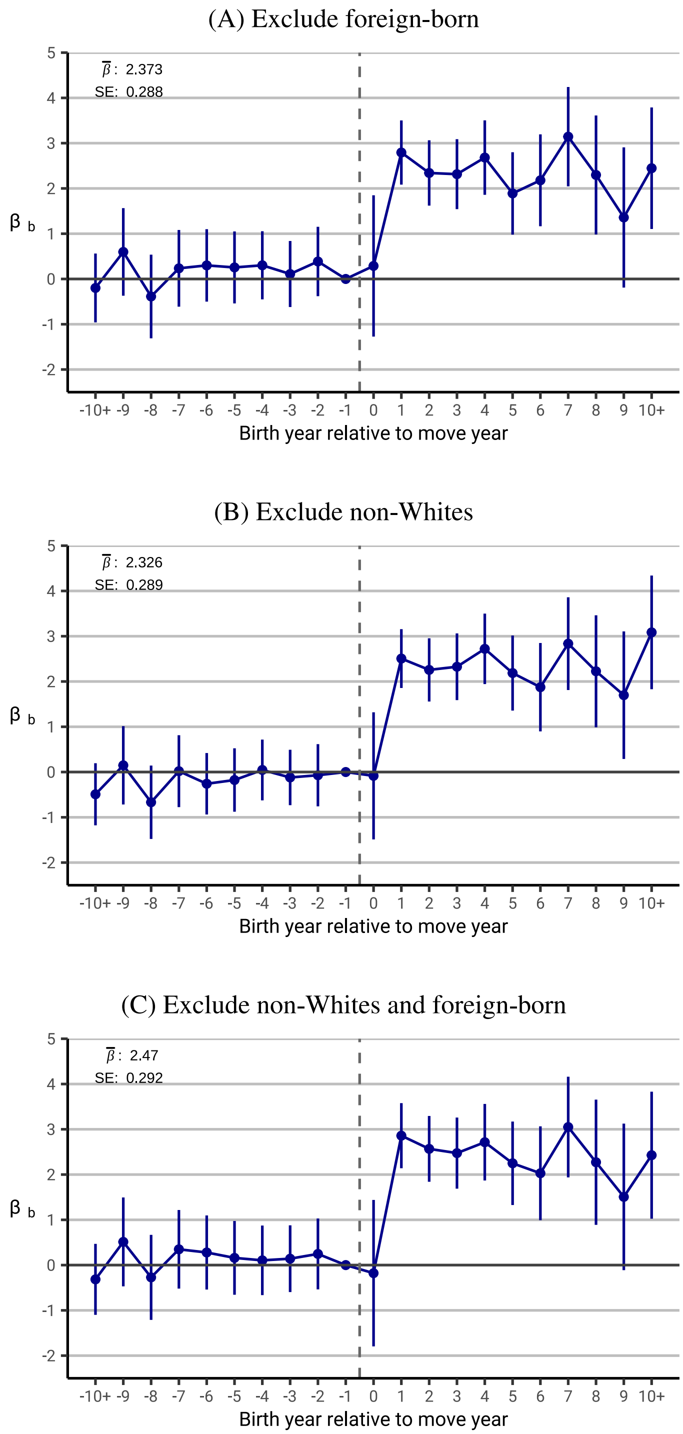


Figure B.6: DID Robustness: Exclusion of Immigrants and Non-Whites

Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences equation (3). $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year. Each panel excludes certain population groups from the sample. Panel A excludes the children of foreign-born domestic migrants, Panel B excludes non-whites, and Panel C excludes both. The UNI is always calculated using the the distribution of names in the relevant demographic group.

B.2.2 Returns to Adaptation

Table B.13: The Returns to Cultural Adaptation

	Dependent variable:					
	Total Property Value (mean = 3461.5 , sd = 4114.0)			Personal Property Value (mean = 838.0 , sd = 1284.2)		
	(1)	(2)	(3)	(4)	(5)	(6)
More Universalistic	-138.0	-133.8	-129.2	-8.660	-8.978	-6.952
	(167.3)	(164.6)	(163.7)	(41.82)	(41.59)	(41.37)
Higher Market Access × More Universalistic	471.1	564.1	547.3	-35.91	-27.83	-30.51
	(356.7)	(345.9)	(342.4)	(92.31)	(90.35)	(90.50)
Observations	23,962	23,962	23,962	33,158	33,158	33,158
R^2	0.886	0.895	0.895	0.865	0.872	0.872
Origin × Destination × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Ctrls. (demographics)	No	Yes	Yes	No	Yes	Yes
Individual Ctrls. (traits)	No	No	Yes	No	No	Yes

Note: This table reports estimates of equation (5) when the dependent variables are different measures of success: total property value (columns 1-3) and personal property value (columns 4-6). Individual demographic controls includes age, race, and birthplace fixed effects. Individual traits controls include fixed effects of ECM and an urban origin. Standard errors clustered at the county of destination in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.14: The Returns to Cultural Adaptation

	Dependent variable:					
	Children Survival Rate (mean = 0.879 , sd = 0.163)			Real Property Value (mean = 2321.0 , sd = 2711.7)		
	(1)	(2)	(3)	(4)	(5)	(6)
More Universalistic	-0.0031	-0.0018	-0.0018	-106.0	-93.20	-93.92
	(0.0059)	(0.0063)	(0.0063)	(125.3)	(122.2)	(122.0)
Higher Market Access × More Universalistic	0.0192**	0.0194**	0.0195**	559.0**	606.2**	599.7**
	(0.0075)	(0.0082)	(0.0082)	(271.9)	(246.4)	(243.8)
Observations	25,432	25,432	25,432	24,835	24,835	24,835
R^2	0.777	0.789	0.789	0.883	0.892	0.892
Origin × Destination × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Ctrls. (demographics)	No	Yes	Yes	No	Yes	Yes
Individual Ctrls. (traits)	No	No	Yes	No	No	Yes

Note: This table reports estimates of equation (5) when the dependent variables are different measures of success: children survival rate (columns 1-3) and real property value (columns 4-6). Individual demographic controls includes age, race, and birthplace fixed effects. Individual traits controls include fixed effects of ECM and an urban origin. Standard errors two-way clustered at the county of destination and the county of origin in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.15: Cultural Adaptation and Real Property: Winsorize at Different Percentiles

	Dependent variable: Real Property Value						
	p(96)	p(96.5)	p(97)	p(98)	p(98.5)	p(99)	p(100)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
More Universalistic	-96.36	-96.36	-95.66	-87.17	-92.29	-89.99	-311.7
	(103.3)	(103.3)	(110.9)	(123.3)	(131.4)	(142.1)	(281.2)
Higher Market Access × More Universalistic	524.9**	524.9**	576.1**	660.1**	704.4**	739.2**	1,174.2**
	(214.6)	(214.6)	(230.0)	(257.7)	(276.4)	(298.6)	(543.8)
Observations	24,835	24,835	24,835	24,835	24,835	24,835	24,835
R^2	0.894	0.894	0.892	0.891	0.890	0.889	0.909
DV mean	2,237.6	2,237.6	2,289.9	2,371.9	2,414.6	2,462.6	2,749.0
DV sd	2,417.5	2,417.5	2,595.7	2,920.0	3,115.4	3,364.3	7,248.5
Origin × Destination × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Ctrls. (demographics)	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation (5) when the dependent variable is the value of real property. In each column the outcome is winsorizied at different percentile at the top, between 4% (column 1) and 0% (i.e., not winsorized, column 7). Standard errors clustered at the county of destination in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.16: Cultural Adaptation and Real Property: Different Transformations

	Dependent variable: Real Property Value (mean = 2748.95, sd = 7248.46)		
	Poisson Regression	asinh(y)	log(y)
	(1)	(2)	(3)
More Universalistic	-0.0647	-0.0793*	-0.0793*
	(0.0619)	(0.0454)	(0.0454)
Higher Market Access × More Universalistic	0.2223**	0.1877**	0.1877**
	(0.0979)	(0.0849)	(0.0849)
Observations	24,835	24,835	24,835
R^2		0.902	0.902
Pseudo R^2	0.979		
Origin × Destination × Year Fixed-Effects	Yes	Yes	Yes
Individual Ctrls. (demographics)	Yes	Yes	Yes

Note: This table reports estimates of variants of equation (5) when the dependent variable is the value of real property. Each columns deals with the skewness of the outcome differently: column 1 uses a Poisson regression, while columns 2-3 use inverse hyperbolic sine and log transformations of the dependent variable, respectively. Standard errors clustered at the county of destination in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$