Doux Commerce: Markets, Culture, and Cooperation in 1850-1920 U.S.

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Abstract

We examine the consequences of market integration for cooperative culture and behavior in the U.S. between 1850 and 1920. Leveraging plausibly exogenous variation in market access due to the expansion of the railroad network and population growth, we study the impact of gaining market access at the county level over seven decades and the short-term cultural and behavioral adaptation after migrating to a higher market access county using difference-in-differences. Both strategies reveal that market access fosters a package of interrelated cultural traits associated with cooperation with anonymous others and broadens the scope of cooperative behavior across diverse spheres of life, even outside the context of markets. These effects appear to stem from increased economic interdependence among diverse individuals and not due to market-induced changes in population diversity, economic development, access to information, or legal institutions.

Keywords: Markets, Trade, Cooperation, Prosociality, Culture, Psychology, Universalism

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

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1 Introduction

Social scientists and philosophers have long debated the social and psychological consequences of markets (Hirschman, 1982). For example, enlightenment thinkers such as Montesquieu (1752) proposed that "Commerce is a cure for the most destructive prejudices [...] wherever manners are gentle there is commerce; and wherever there is commerce, manners are gentle". This *doux commerce* hypothesis is consistent with an influential body of recent theories positing that market interactions—distinct from exchange networks that predominantly involve family and in-group members—promote the internalization of impersonal prosocial norms because anonymous market-based cooperation benefits from fair dealing and honesty with strangers (e.g., Henrich et al., 2001, 2005). Others have argued that markets commodify social relationships and exacerbate inequalities, reducing prosociality, and leading to alienation and exploitation (Marx and Engels, 1848; Polanyi, 1944; Sandel, 2012).

A growing body of evidence from diverse societies suggests a positive link between market exposure and prosocial norms (Henrich et al., 2010; Enke, 2022; Agneman and Chevrot-Bianco, 2023; Rustagi, 2024b). While the existing literature provides important insights, it primarily focuses on experimental behavior in relatively isolated groups or relies on correlational rather than causal evidence. This raises the question: Do markets causally shape culture and cooperation in broader, more complex societies? This paper addresses this question by examining a large-scale historical setting with rich data on both cooperative culture and behavior, leveraging a natural experiment to establish causality.

We investigate the impact of market integration on a package of interrelated cultural traits associated with cooperation with strangers and anonymous others, including moral universalism, norm tolerance, generalized trust and concerns for fairness—which we call *Cooperative Culture*—and cooperative behavior in the United States. We use the expansion of the railroad network and the significant immigration waves from 1850 to 1920 as sources of exogenous variation in market integration across counties. This historical context enables us to establish causal relationships between market integration and both cooperative culture and behavior in a highly market-integrated economy, over both short (years) and long (decades) time spans, and across a broad geographical area. We find a large positive impact of market access on cooperative culture, cooperative behavior, and the scope of cooperation, in various spheres of social life. The effect on culture is concentrated among individuals employed in commerce-intensive industries, while we find no effect in occupations unrelated to commerce. Moreover, we find that the relationship between market access and both cooperative culture and behavior is unlikely to be due to increased intercultural contact, economic development, the inflow of information and ideas from other regions, or the development of local legal institutions. Our findings suggest that greater market integration fostered economic interdependence and interactions among unrelated individuals, contributing to the development of cooperative culture, which supports a broader scope of cooperation even outside the context of markets.

To measure market integration, we build on Donaldson and Hornbeck (2016) and compute a county-

level measure of 'market access', which captures the degree of market integration potential, for each decade from 1850 to 1920. The metric reflects the ease with which residents of a county can access markets in other counties, a factor that evolves with the growth of the railroad network and changes in population sizes across counties.

To measure key aspects of cooperative culture, namely the centrality of the in-group, moral universalism, and tolerance for diverse social and religious norms, we draw on full-count census data and compute county- and individual-level scores, following the methodology in Raz (Forthcoming). In-group centrality and universalism are measured using the Universal Name Index (UNI), which captures the extent to which the local national identity is prevalent in parents' social-identity relative to the communal one, and Extra-Community Marriage (ECM), which captures in-group bias. Norm tolerance is measured using the variability in family related behaviors and religious affiliations. Additionally, we employ county-level measures of social trust and concern for fairness, derived from applying modern Natural Language Processing (NLP) techniques to a comprehensive corpus of U.S. local newspapers by Posch et al. (2025).

To measure cooperative behavior, we employ several county-level indicators that capture cooperation and prosocial behavior across different spheres of life. First, we measure cooperation in the labor force by combining occupation data from the full-count census with work style data from the Occupational Information Network (O*NET) database, which includes ratings of the "cooperative attitude" required for being successful in a given occupation. Second, based on patent data (Berkes, 2018), we measure the frequency of cooperation among inventors and the extent to which such cooperation occurs outside family networks. Third, using full-count census data, we capture non-kin cooperation at home by measuring the proportion of multifamily households. Fourth, we use tax data to construct measures of local public goods provision, a proxy for community cooperation. Fifth, following (Putnam, 1995), we examine civic and social engagement among county residents, focusing on voluntary organizations, local public administration, and recreational activities. Sixth, following established literature (e.g., Alesina and La Ferrara, 2000; Rustagi, 2024a), we investigate voter turnout as a measure of civic behavior.

Before turning to our causal analysis, we document robust positive associations between our measures of cooperative culture and cooperative behavior. Counties with stronger cooperative cultural traits exhibit higher levels and broader scopes of cooperative behavior across all the domains we consider. These initial correlations underscore the potential role of culture in fostering broad-based cooperation.

We conduct two complementary analyses to estimate the causal impact of increased market access on cooperative culture and behavior, each based on a distinct identification assumption. The first analysis is conducted at the county level, following the approach in Donaldson and Hornbeck (2016), and allows us to study effects over seven decades. This specification estimates the effect of greater market access on our measures of cooperative culture and behavior, controlling for county fixed effects, state-by-year fixed effects, and polynomials of longitude and latitude interacted with year fixed effects. The key source of variation for identification comes from the uneven expansion of the railroad network across counties,

leading to varying changes in market access. The identifying assumption is conditional exogeneity of excess changes to counties' market access relative to the rest of the state and broad geographical patterns. That is, that these differential excess changes in the railroad network affecting a county's market access must not be related to unobserved factors that also influence cooperative culture or behavior.

The main threat for causal inference is the potential endogeneity of railroad construction. Specifically, the concern is that the decision to build railroads in or to a particular county might be influenced by unobserved local factors that also affect cooperative culture and behavior. To address this concern, we follow Donaldson and Hornbeck (2016) and leverage the network structure of market access and the fact that it is also affected by changes to the railroad infrastructure in far away destinations, and introduce time-varying control for the presence and mileage of local railroads in and around each county. This isolates the identifying variation to changes in market access that are orthogonal to local expansions of the railroad network.

Using this framework, we first document that market access caused an increase in commerce-related content in local newspapers and the share of residents employed in wholesale and retail. These "zero-stage" results validate the market access measure and demonstrate that the local socioeconomic environment responded to variation in market access. We then proceed to explore the impact of market access on culture and cooperation. Our findings suggest that increased market access led to greater universalism and looser norms. It is associated with a lower emphasis on the local, or particular, identity relative to the universal one, fewer intra-community marriages, more generalized trust and concerns for fairness in newspapers, and greater variability in family-related behaviors and religious affiliations. Additionally, we find robust evidence that market access increases cooperation. A one percent increase in market access results in a 9–14% standard deviation increase in cooperative behavior and its scope (depending on the outcome). We further show that our results are not simply driven by the local expansion of the railroad network in and around the county, lending credibility to a causal interpretation of our findings.

We then implement a second empirical strategy, leveraging individual-level data and within-sibling variation in a sample of domestic migrants (Raz, Forthcoming). This framework enables us to document cultural adaptation and behavioral adjustment in response to higher market integration over the short-run. We use the Census Linking Project (Abramitzky et al., 2022a,b,c,d,e) and information on children's state and year of birth to construct a sample of families that migrated across counties between two decennial censuses and proxy the year in which they migrated. We then compute the difference in market access between the destination county and the county of origin. Finally, using children's UNI to measure parental cooperative cultural traits, and our measures for parents' cooperation at work and at home, we estimate the causal impact of moving to higher versus lower market access county in a dynamic difference-in-differences framework.

Our results show that relocating to a county with higher market access results in higher UNI scores, relative to migrating to a lower market access county, indicating increased parental universalism. Following

a parallel trend in the pre-migration period, the UNI score of children born after their family migrated to a higher market access county increases relative to those born after migration to a lower market access county. The impact is immediate, as the effect becomes apparent after one year in the new county, and it persists for at least a decade. Crucially, this evidence aligns with our county-level analysis findings but is based on a distinct identification assumption. Additionally, we find that moving to a higher market access county leads to greater cooperation at the workplace and more cooperation outside family networks at home. Taken together, these consistent results across different empirical approaches reinforce the conclusion that the observed relationships between market access and both cooperative culture and behavior are not an artifact of local economic development or other unobserved local factors that might simultaneously influence both market access and cooperation.

Having established a positive effect of market access on cooperative culture and behavior, we turn to explore mechanisms. Markets may affect culture and psychology directly by fostering economic interdependence among diverse individuals and indirectly through several pathways. Directly, integration into impersonal markets, characterized by competitive exchanges among strangers, may affect cultural traits because it increases economic interdependence among individuals from diverse backgrounds and promote transactions that go beyond familiar networks of family and friends. In such a market setting, success increasingly hinges on the ability to cultivate a reputation for fairness, honesty, trustworthiness, tolerance, and cooperation with strangers (Smith, 1776; Tabellini, 2008; Buggle and Durante, 2021; Henrich, 2020). Indirectly, market access could enhance population diversity through migration, potentially enhancing inter-group contact, which could lead to greater universalism and normative looseness (e.g., Bursztyn et al., 2024; Gelfand, 2018). Another possibility is that market access induces economic development and modernization, which in turn may induce universalism and normative looseness (e.g., Durkheim, 1984; Inglehart, 2018; Greenfield, 2009). Greater market access might also facilitate the influx of information and ideas from other regions, potentially exposing individuals to universalism and normative looseness. Finally, a higher market integration could support the development of local legal intuitions that are needed to support trade by solving the "fundamental problem of exchange" (Greif, 1993; Cantoni and Yuchtman, 2014). By improving institutional quality, this might contribute to the development of cooperative culture (Gorodnichenko and Roland, 2017; Henrich, 2020; Eruchimovitch et al., 2023).

Our findings align more closely with the direct channel than with the indirect channels. First, using the difference-in-differences framework, we find that the impact of market access on culture is concentrated in individuals employed in commerce-intensive industries, defined as industries engaged in trade with distant markets (e.g., agriculture) or fundamental to market operations (e.g., wholesale and transportation), contrasting with industries focused on local service provision (e.g., utilities and public administration). The differential impact is not driven by the different characteristics of individuals in the two categories, such as urban vs rural origin, family size, or pre-migration cultural attributes. This suggests a direct link between commerce and cooperative culture, rather than through socioeconomic environmental factors.

Second, further analyses of the indirect channels using county-level data indicate that while there is an

initial positive association between market access and the plausible candidates for indirect channels, most of these associations weaken or become insignificant once local railroad connectivity is accounted for. Specifically, measuring population diversity using the immigrant population share or birthplace diversity within counties, we find positive associations with market access in our baseline specification, but when we control for local railroad infrastructure, the coefficients drop in magnitude, and, unlike the case of cooperative culture, become insignificant. Similarly, using urbanization rates, the number of manufacturing establishments per capita, and occupational income scores as proxies of economic development, we find no support for the hypothesis that market integration shaped cooperative culture through its effect on economic growth and modernization. The only potential indirect channels that the evidence from this empirical exercise supports are higher access to information, captured by the per capita number of individuals employed in occupations related to the spread of information in the county (e.g., newspapers, printing, mail, the telegraph), and the development of legal intuitions, measured by the per capita number of judges and lawyers in the county.

Third, we find that including any or all of these proxies for potential indirect channels as "bad controls" in our county and individual-level analyses of market access and cooperative culture has little impact on the results. This provides suggestive evidence that the effect of market access on cooperative culture is not significantly mediated through these indirect channels. In summary, the evidence leans towards a direct impact of market interactions on cooperative culture, rather than through increased population diversity, economic growth, information flow, or the development of legal institutions.

Related Literature. Our findings contribute to several strands of literature. The most closely related studies include Henrich et al. (2010), which finds an association between the proportion of calories purchased from markets and fairness in behavioral games across 15 predominantly small-scale societies; Agneman and Chevrot-Bianco (2023), which identifies a correlation between occupational choice and honesty in experiments across 13 villages in Greenland; and Rustagi (2024b), which provides strong evidence for an effect of market proximity on civic values—measured by cooperative behavior in public goods games—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. Similarly, Enke (2022) shows a correlation between market-related concepts and morality in the folklore of pre-industrial societies.

Leveraging a natural experiment and rich data in the historical United States—when it emerged as the world's largest and most integrated market economy—we add to this earlier work in three main ways. First, we identify the causal impact of market integration using observational data over a long period and broad geography in two district empirical frameworks. Second, we document both cultural adaptation and behavioral responses to market integration, providing evidence for the co-dependency of cooperative culture and cooperative behavior. Third, we shed additional light on the mechanisms through which market integration shapes both cooperative culture and cooperation.

Our paper also relates to the line of research studying the impact of markets and trade on conflict and compromise, ethnic tension, and general trust (Jha, 2013; Jha and Shayo, 2019; Margalit and Shayo, 2021; Buggle and Durante, 2021; Jha et al., 2025). Our results suggest that the impact on these factors may be one aspect of the impact on a broader package of interrelated cultural and psychological traits that we refer to as "cooperative culture".

More generally, our findings tie into the literature on the determinants of prosocial culture and cooperation. The literature has primarily focused on documenting persistence and long-term effects of historical shocks (Nunn and Wantchekon, 2011; 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), while also shorter-run factors can be important in shaping an individual's prosociality (Bauer et al., 2016; Francois et al., 2018; Rao, 2019; Kosse et al., 2020; Lowe, 2021). We highlight the role of market integration in shaping prosocial culture and cooperation over both decades and years.

Finally, our paper ties into the literature on the contribution of the railroads to the development of the American economy (Fogel, 1964; Donaldson and Hornbeck, 2016; Hornbeck and Rotemberg, 2024) and the importance of trade to growth more generally. Our results suggest that trade may have a so far underexplored indirect impact on long-run economic development, by nurturing cultural traits conducive to growth and innovation.

The rest of this paper is organized as follows: Section 2 briefly describes the conceptual framework and historical background. In Section 3, we explain how we measure market access, cooperative culture, and cooperation and prosocial behavior. In Section 4, we document the positive associations between cooperative culture and cooperative behavior. Section 5 presents our results on the impact of market access on cooperative culture and psychology, while Section 6 focuses on the impact on cooperation and prosocial behavior. Section 7 explores potential mechanisms. Section 8 concludes.

2 Concepts and Historical Background

2.1 Conceptual Framework

Cultural evolutionary theory suggests that a package of correlated cultural traits evolve to facilitate cooperation in large-scale societies that extend beyond immediate family and in-group members. This theory posits that the mechanisms which enable cooperation in smaller, kin-based groups are unsuitable for the complex social interactions found in larger, more integrated markets and societies (Henrich et al., 2005; Ensminger and Henrich, eds, 2014; Henrich and Muthukrishna, 2021). Cultural traits such as individualism, universalistic morality, generalized trust, impersonal fairness, and norm tolerance are seen as adaptive responses to the challenges of cooperating in large-scale societies where interactions with strangers are common. Key elements of this perspective have been introduced to the economics literature by Tabellini

(2008).

Market interactions may not only necessitate but also promote the development and reinforcement of cooperative culture (Henrich et al., 2010). This is because markets often involve impersonal transactions with anonymous others, which are facilitated by cooperative cultural traits. The anonymity of market transactions contrasts with the personalized exchanges typical within kinship groups, requiring a cultural adaptation towards more universalistic norms and a greater tolerance for norm diversity. These traits enable individuals to engage effectively in market-based cooperation, which is essential for the functioning of complex economies.

From this perspective, market integration is predicted to act as a catalyst for cultural evolution by directly influencing people's psychology and culture. This direct influence is two-fold: it involves the long-term evolution of "market norms" (Henrich, 2020) —i.e., established standards for judging oneself and others in impersonal transactions and internalization of motivations for trust, fairness, and cooperation with strangers and anonymous others—as societies become increasingly integrated into market economies, and it also involves the shorter-term learning or adaptation of individuals to market norms as they engage in market activities.

Indirectly, market access could affect the development of cooperative culture through four main pathways. First, it could induce migration, increasing population diversity, which in turn may reduce prejudice as diverse groups interact more closely (Allport, 1954). This may also foster cooperative cultural traits, including looser social norms, as people learn to become more tolerant of other groups with different norms (Gelfand, 2018).

Second, greater market access may indirectly influence cooperative culture by spurring the transition from traditional, agrarian societies (where social cohesion and integration come from the homogeneity of individuals) to modern, industrial societies (where cohesion arises from the interdependence of individuals performing specialized tasks), benefiting the cultivation of more cooperative cultural traits, as these traits are adaptive in environments where social and economic interactions extend beyond the immediate community to include a wide range of impersonal and diverse relationships (Durkheim, 1984; Greenfield, 2009; Inglehart, 2018).

The third possibility for how market integration may indirectly affect culture is by facilitating the dissemination of new ideas and information. This process can occur through various channels, including migrants, newspapers, or communication technologies like the telegraph, which expose communities to a broader array of cultural norms, values, and behaviors, which can catalyze changes in local cultures.

Finally, due to the necessity to solve the "fundamental problem of exchange", a higher level of trade and market integration may have induced the local development of legal intuitions (Greif, 1993; Cantoni and Yuchtman, 2014). This may have brought about an increase in the quality of local institutions and public administration, which in turn, could have fostered cooperative cultural traits (Gorodnichenko and Roland, 2017; Henrich, 2020; Eruchimovitch et al., 2023).

2.2 Historical Background

Between 1850-1920, the U.S. experienced a significant expansion of its railroad network, as the total railroad mileage increased from 8,996 miles in 1850 to 237,675 in 1920 (Appendix Figure A.1). This significant expansion brought about a dramatic decrease in the cost of transportation throughout the country. Importantly, the construction of the transcontinental railroads connected the Pacific coast, and more generally the West, to the eastern railroad network, making them more accessible to trade and migrants. But this expansion did not only lower transportation costs across long distances. Some locations, such as the Midwest and Northeast, benefited from a denser railroad network that also significantly lowered the cost of local transportation.

At the same time, the U.S. also experienced a dramatic increase in total population, which rose from about 23 to 106 million. This was the "Age of Mass Migration", during which the "US borders were completely open to European immigrants" (p. 468 Abramitzky et al., 2014) and about 30 million of them arrived in the U.S. Beside Europe, migrants also arrived in large numbers from other counties in North and South America, mainly Argentina, Canada, and Brazil.

The combination of a large domestic market and cheaper means of transporting goods implied a significant increase in market access for both consumers and producers throughout the country, which was conducive to economic development and settlement of rural areas of the country (Donaldson and Hornbeck, 2016; Chan, 2022), and to manufacturing activity and aggregate productivity (Hornbeck and Rotemberg, 2024).

3 Data

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.2 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 Figure 1 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, focusing on commerce-related content in historical U.S. 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 U.S. newspapers. To construct this metric, we draw on text data from *newspapers.com*, the largest online archive of historical U.S. 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.

Given this data access limitation, 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.[1] 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,

[1] 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.*

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 Cooperative Culture

Our hypothesis is that market integration affects the development of a package of correlated cultural traits that support cooperation with anonymous others—that we refer to as a cooperative culture, or cooperative cultural traits. Because cooperative culture is a multidimensional construct, no single measure captures all its aspects. Instead, we operationalize cooperative culture using multiple indicators at both the county and individual levels. Specifically, we use four measures from Raz (Forthcoming), 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 two measures from Posch et al. (2025) obtained by applying NLP techniques to a corpus of U.S. local newspapers.[2] 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.[3] 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 Figure 2 plot the spatial distribution of the UNI in 1850 and 1920, and Panel A in

[2]For more details on these measures and their validation, see Raz (Forthcoming) and Posch et al. (2025).
[3]The UNI is the reverse of the LNI originally used in Raz (Forthcoming): $UNI = 100 - LNI$.

Appendix Figure A.3 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.[4] 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 Figure 2 plot the spatial distribution of the ECM in 1850 and 1920, and Panel B in Appendix Figure A.3 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 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.[5] 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 Figure 2 and Panel C in Appendix Figure A.3 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 to a lower extent, 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 Taxes, 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 toward 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

[4]The ECM is the reverse of the ICM originally used in Raz (Forthcoming): $ECM = 1 - ICM$.
[5]The NTI is the reverse of the TNI originally used in Raz (Forthcoming): $NTI = -1 \times TNI$.

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.[6]

Panels G and H in Figure 2 and Panel D in Appendix Figure A.3 plot the spatial variation in the data.

Social Trust and Concern for Fairness. These measures are derived using recent Natural Language Processing (NLP) techniques applied to a large full-text corpus provided by *newspaperarchive.com*. U.S. newspapers were historically highly local in their readership and often catered to their readers' preferences (Gentzkow and Shapiro, 2010), providing a lens through which we can trace what individuals' cultural and psychological traits. The corpus consists of digitized texts from approximately 241 million historical newspaper scans, covering all U.S. states and spanning the years 1736 to 2023.

In essence, the method embeds each newspaper page along with (1) the generalized social trust items from the General Social Survey and World Values Survey (e.g., "Most people can be trusted") and (2) the equality and proportionality items from the most recent version of the Moral Foundations Questionnaire (MFQ, Atari et al., 2023b), which together approximate fairness concerns. These embeddings are generated using the transformer-based language model Sentence-BERT (SBERT, Reimers and Gurevych, 2019). The semantic similarity between each newspaper page and the survey items is then computed, where higher similarity scores indicate a stronger association with the construct of interest (i.e., trust and fairness). Finally, we aggregate the data at the county-decade level by first computing the average across all pages published in a given county-year and then rounding arithmetically (e.g., data from 1855 to 1864 are aggregated to 1860).

This method has been shown to outperform dictionary-based and static word embedding approaches (e.g., word2vec) by a wide margin across various cultural and psychological traits (Atari et al., 2023a). Appendix Figure A.4 plots the spatial variation in the data in 1850 and 1920. Due to the limited coverage, it is difficult to eyeball strong spatial patterns.

3.4 Cooperation and Prosocial Behavior

We employ several county-level measures to capture historical cooperation and prosociality across different spheres of social life, such as cooperation in the labor force, in innovation, at home, and within the community. The variables are constructed by maintaining 1890 county boundaries.

Cooperation in the labor force. We use data from the Occupational Information Network (O*NET)

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

and the 1850-1920 full count censuses (Ruggles et al., 2020) to construct a county-level measure of the extent of historical labor-force cooperation. 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.[7] 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 year, using the number of individuals in each occupation as weights. Panels A and B of Appendix Figure A.9 plot the spatial distribution of labor-force cooperation in 1850 and 1920, respectively.

Cooperation among inventors. Following Posch et al. (2024), 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.[8] 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,

[7] 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.

[8] 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.

especially during the early years of our study period. Panels C-F of Appendix Figure A.9 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.9 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.9 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 administration, and recreational activities based on IPUMS's *IND1950* variable.[9] 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.9 plot the spatial distribution of civic engagement in 1850 and 1920, respectively.

Voter turnout in presidential elections. Finally, 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 election returns in presidential elections (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

[9] 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).

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, in our baseline analysis 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. The results are similar when we use alternative cutoffs. Note that our empirical analysis below (Section 6) includes state-by-year fixed effects, which controls for differences in disenfranchise policies across states. Panels M and N of Appendix Figure A.9 plot the spatial distribution of voters turnout in presidential elections in 1852 and 1920, respectively.

4 Cooperative Culture and Cooperative Behavior

Before documenting the causal impact of market integration on cooperative cultural traits and cooperative behavior, we present evidence on the association between cooperative culture, cooperation, and prosociality. To do so, we compute a composite cooperative culture index at the county-year level defined as the mean of four cooperative cultural traits: the UNI, the ECM, the NTI, and the RDI.[10] Appendix Figure A.5 plots the spatial distribution of cooperative culture in 1850 and 1920. We then document a robust positive relationship between our measures of cooperation and prosociality and the composite cooperative culture index, using regressions of the following form:

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

Where c and t denote county and year, respectively. $\delta_{s(c)t}$ represents state-by-year fixed effects, which remove the temporal variation that is shared by all counties in the same state, thereby exploiting only variation within-state in the same year; δ_c denotes county fixed effects, thereby shifting the focus from levels to within-county temporal changes in cooperation and cooperative culture; and $f(x_c, y_c)\delta_t$ is a cubic polynomial in longitude and latitude interacted with year fixed effects, which further removes all time-varying smooth broad geographical variation in the data. β is the coefficient of interest, representing the relationship between the composite cooperative culture index and cooperation. Standard errors are clustered at arbitrary spatial grids of 100 miles square Bester et al. (2011) to account for spatial autocorrelation.

Figure 3 presents the results for four different specifications: one without any controls, and three sequentially adding controls. To ease comparison across the seven different measures of cooperation, we

[10] The traits are standardized into z-scores within each year. Not all four measures are available in all years. In 1880, the RDI is missing and the composite index is calculated using only the UNI, ECM and NTI. In 1890, only the RDI is available while the UNI, ECM, and NTI are missing and the composite index is calculated using only the RDI. We do not include social trust and concern for fairness in the composite index due to their limited geographic coverage (see Appendix Figure A.4).

standardize each measure of cooperation into z-scores. We find a strong and robust positive association between cooperative culture and cooperative behavior. The coefficients are always positive, and the relationships are statistically significant in all cases except for cooperation among inventors once county fixed effects are included. Appendix Table A.5 reports the results in tabular form using the original, non-standardized measures of cooperation.

These findings indicate that counties characterized by stronger cooperative cultural traits exhibit higher levels of cooperative behavior and display a broader scope of cooperation and prosociality across all domains considered. These initial correlations lend support to our diverse—and in some cases, novel—measures of cooperation, while underscoring the potential role of cooperative culture in fostering widespread cooperative practices.

5 The Impact of Markets on Cooperative Culture

In this section, we explore the impact of market access on cooperative cultural and psychological traits using two different empirical frameworks. First, we use a county-level analysis that exploits excess changes in counties' market access that are orthogonal to local variation in railroad network (Section 5.1). Second, we exploit individual-level data on domestic migrants in a difference-in-differences framework (Section 5.2). Using both strategies, we find that market access had a positive impact on cooperative culture.

5.1 County-Level Analysis

5.1.1 Estimation framework

We start by following the baseline specification in Donaldson and Hornbeck (2016) and estimate regressions of the following form:[11]

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

Where o and t denote county and year, respectively, δ_o is a county fixed effect, $\delta_{s(o)t}$ is a state-by-year fixed effect, $f(x_o, y_o)\delta_t$ is a cubic polynomial in longitude and latitude interacted with year fixed effects, and X_{ot} is a vector of additional potential time-varying controls. β is the coefficient of interest, representing the relationship between log market access and the outcome of interest. We cluster standard errors at arbitrary spatial grids to account for spatial auto-correlation, as proposed by Bester et al. (2011). Our baseline specification uses a grid size of 100 miles square, but results are robust to using cells of different sizes.

The identifying assumption in this framework is conditional exogeneity. County fixed-effects imply that the impact is identified from counties' temporal variation in market access, after all the variation resulting

[11] The same specification was more recently employed in this historical setting by Hornbeck and Rotemberg (2024).

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.

While those controls deal with the most obvious threats to identification given the historical context, a remaining identifying concern is that even those excess conditional changes in counties' market access might also be endogenous. There are two general concerns. The first is a reverse causality concern. Specifically, it may be the case that counties that experienced an excess increase in cooperative traits became more favorable to trade, which generated endogenous expansions of the local railroad network. The second is an omitted variable concern. For example, it might be the case that a positive shock to counties' economic development would positively impact both local railroad connectivity and local cooperative culture.

Following Donaldson and Hornbeck (2016), we address this concern by exploiting the network structure of market access, which implies that counties' market access is affected not just by trade infrastructure in the county itself or close-by, but also from changes in far away destinations. Therefore, by controlling for local railroads, the impact of market access can be estimated using only the variation in excess changes in market access that are orthogonal to the expansion of the railroad network in and around the county.

5.1.2 Results

The Prevalence of Commerce. First, we use Equation 2 to explore the impact of market access on the local prevalence of commerce, focusing on the commerce-related content in local newspapers and the share of residence working in the wholesale and retail trade industries. Table 1 presents the results.

We find a robust and stable relationship between market access and market language (Panel A). The baseline specification (column 2) suggest that a 1 percent increase in market access increases the mean share of commerce-related content in local newspapers by 0.0158 (p-value < 0.01) points. This is a substantial effect relative to a mean and standard deviation of 0.466 and 0.116.6, respectively. The impact remains remarkably stable when time-varying controls for local railroad access in and around the county are introduced (columns 3-6). Following the specification in Donaldson and Hornbeck (2016), in column 3, we add a time-varying dummy variable that equals one of the county has any railroad track, and zero otherwise. 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. These controls have a negligible impact on the coefficient of interest. Appendix Table B.1 documents that this

finding is robust to using different thresholds for the words most related to commerce-related content. Specifically, the result hold when a threshold of 20, 50, or 100 top words are used.

In Panel B, we focus on the wholesale and retail trade industries share and find a positive and robust relationship. The baseline specification suggest that a 1 percent increase in market access increases the share residence working in the wholesale and retail trade industries by 0.005 (p-value < 0.01) points, which amounts to about 10% and 14% of the mean and standard deviation, respectively. The coefficient attenuates when we introduce time-varying controls for local railroad access in and around the county (columns 3-6). In the most demanding specification in column 6, the estimate is marginally insignificant with a p-value of 0.102. Appendix Table B.2 documents that the result is robust to using different winsorizing cutoffs. Similarly, Appendix Table B.3 documents that the finding is robust to using alternative ways to address skewed distributions that contains zeros: Poisson regression and different transformations of the outcome. Finally, Appendix Table B.4 suggests that this result is not driven by demographics by documenting that the finding is robust to the inclusion or exclusion of immigrants and non-whites in the sample when calculating industries employment shares.

We view these empirical exercises as "sanity checks" or a "zero-stage" results. First, they validate the measure of market access. Second, they show that the local socioeconomic 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.

Cooperative Culture. Next, we turn to explore the impact of market access on cooperative culture, using all six measures of cooperative cultural and psychological traits. Table 2 reports the results for six different specifications.

Panel A focuses on the UNI and finds that market access resulted in a higher tendency of parents to identify with the national identity relative to the local one. The results of the baseline specification in column 2 suggest that a 1 percent increase in market access results in a 0.93 (p-value < 0.01) points increase in the average UNI, corresponding to a 2.9% and 14.1% increase relative to a mean value of 32.19 and a standard deviation of 6.6, respectively. Figure 4 plots graphical representations of the baseline specification results. Panel A shows that the relationship between market access and the UNI is quite linear on average, and that it is not driven by a small number of outliers. Columns 2-6 suggest that roughly two third of this impact is driven by the expansion of railroads in and around the county. Yet even when the existence of railroads and a cubic polynomial in railroad length in the county, and in 10, 20, 30, and 40-mile buffers around it are controlled for, the association between market access and the UNI remains positive and economically and statistically significant (p-value = 0.033).

In Panel B we examine the impact of market access on a preference for an in-group spouse. We find a robust positive association, however statistical power is low. The results of our baseline specification in column 2 suggest that a 1 percent increase in market access is associated with a 0.69 (p-value = 0.062) percentage point increase in the tendency to marry a different-birthplace spouse, equal to a 1.8 percent in-

crease relative to the sample mean. This finding is also not driven by a small number of outliers (Figure 4, Panel B). However, when controls for local railroad connectedness beyond a dummy variable for railroad in the county are included in the model (columns 4-6), the coefficients attenuate and become statistically insignificant.

Panels C-D focus on norm tolerance and find strong and highly robust positive effects. That is, that markets contribute to a looser culture. In our baseline specification, the impact of a 1 percent increase in market access is a 0.17 and 0.272 (p-values < 0.01) standard deviation increase in the NTI and the RDI, respectively. These are substantial effect sizes. Here too, the relationships are close to linear and not driven by outliers (Figure 4, Panels C-D). Controlling for local railroads and identifying an impact using only variation in excess market access that is orthogonal to the expansion of railroads in and around the county (columns 3-6) results in some attenuation of the coefficients, yet they remain highly economically and statistically significant.

Panel E reports the estimates of the impact on social trust. Our baseline specification suggests that a 1 percent increase in market access increases social trust by 0.1201 (p-value = 0.014) points. The coefficient remains remarkably stable when local railroad connectivity in and around the county is controlled for (columns 3-6), strongly supporting a causal interpretation of the finding. Finally, Panel F reports our estimates when the dependent variable is concern for fairness. We find that a 1 percent increase in market access increases concern for fairness by 0.106 (p-value = 0.024) points, and that this relationship is also not driven by local railroads connectivity.

Robustness. Appendix Table B.5 documents that the finding is not driven by demographics or population diversity by showing that the baseline results are not sensitive to the inclusion or exclusion of immigrants and non-whites in the sample from which the county-level measures of cooperative cultural traits are calculated. Appendix Figure B.1 documents robustness to alternative ways to account for spatial auto-correlation. In calculating market access, we follow the baseline specification in Donaldson and Hornbeck (2016) and set the trade elasticity to $\theta = 8.22$ and the average value of transported goods per ton to $P = 35$. However, Appendix Table B.6 documents that our results are robust to using the alternative parameter values in Hornbeck and Rotemberg (2024)—($P = 38.7$ and $\theta = 3.05$)—and all values of θ between 1 and 13. While the point estimates naturally vary with the parameters, in all cases we find a positive and significant effect.

Finally, Appendix A.3 reports the results of the same analysis and robustness checks when the depended variable is the composite cooperative culture index, documenting a robust positive impact of market integration on cooperative culture. Overall, our finding from the county-level analysis suggest that market integration had a robust positive causal impact on cooperative cultural and psychological traits.

5.2 Individual-Level Analysis

We follow Raz (Forthcoming) and leverage individual-level data on children of domestic migrants and their UNI scores to estimate the causal treatment effect of moving to a location with a higher market access in a difference-in-differences framework. To construct the sample of domestic migrants, we first use the Census Linking Project (Abramitzky et al., 2022a,b,c,d,e) to link heads of household to their record in the previous decennial census. Focusing on individuals that migrated across states, we then use information on their children's year and state of birth to proxy for the year of migration as the midpoint between the year of birth of the last child born in the state of origin and the first child born in the destination state. We fuzzy match households' counties of residence in both periods to 1890 counties to match the market access data based on the geographical overlap of counties' boundaries. In this probabilistic match, individuals can be matched to multiple 1890 counties of origin and destination, with varying probability weights. Finally, we compute the difference in market access between the destination county and the county of origin at the time of the later census.

Estimation framework. To identify the causal impact of market access on universalism, we use a fully dynamic *Difference-in-Differences* framework, comparing the UNI score of children born in families that migrated to a higher versus lower market access county, before and after the migration. Regressions take the form:

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

where UNI_i is the UNI score of child i, who currently resides in county $d(i)$, and was born $b(i)$ years relative to the year the family $f(i)$ migrated from county $o(i)$ to county d. $\delta_{b(i)}$ is a relative-year-of-birth fixed effect, which controls for the dynamics in universal identification relative to the year of migration in families that migrated into a lower market access county. $\theta_{f(i)}$ is a family fixed effect, which removes all the variation that is common among siblings, including the family's migration path from county of origin o to destination d, as well as its fixed cultural and economic characteristics. X_i is a vector of child i characteristics, which includes gender, birth order, and a 5-year cohort fixed effects, that we include as a robustness check. We cluster standard errors ϵ_i at the county of destination d (Bertrand et al., 2004), but results are robust to two-way clustering. Whenever families are fuzzy-matched into multiple 1890 counties, we treat duplicated families as separate, and weigh observations by the probability that an individual i is matched to 1890 counties o and d, such that the total weight of each individual is one. β_b are the coefficients of interest, which identify the impact of moving to a higher versus lower market access county on universal identification. We normalize β_{-1} to zero so that β_b is interpreted as the effect relative to the year just before the migration. Note that this specification uses "event-time" rather than "calendar-time", implying that all families are first treated between $b = 0$ and $b = 1$. Therefore, concerns relating to negative weights in TWFE regressions with staggered treatment timing, or more generally in designs in

which groups experience different evolution of their exposure to treatment over time, as highlighted in the recent literature (e.g. Borusyak et al., 2024; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021), do not arise.

Results. We find that migrating to a location with higher market access increases universalism. Figure 5 plots the estimates of and 95% confidence intervals β_b from our baseline specification. Before the migration, we find no differential trends in universalism, as captured by children's UNI, across families that moved to a higher market access county, relative to families that moved to a lower market access county. This validates the empirical design, suggesting that there was no selective in-migration on prior trends of universal identification. However, in the first year after the migration the trends diverge. The UNI score of a child born one year after her family moved to a higher market access county increases by 2.45 ($p-value < 0.01$) points relative to a child born one year after migration to a lower market access county. The impact remains roughly stable in the following years, as the UNI score of a child born 10 year after the family migrated to a higher market access county is 2.85 ($p-value < 0.01$) points higher from that of a child born to a family that experienced a decline in market access. Table 3 reports the estimates from "static" DID and designs that aggregate the effect over all post-migration periods. The findings are consistent with those of the dynamic specifications. The estimate in column 1 suggests that the UNI of children born to families that experienced an increase in market access due to migration was about 2.35 ($p-value < 0.01$) points higher relative to children born to families that experienced a decrease in market access.

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 an 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 3 and Appendix Figure A.8 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 in smaller.

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

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.5 documents that the finding is not driven by demography, as the finding is robust to the exclusion of immigrants and non-white.

6 The Impact of Markets on Cooperation and Prosocial Behavior

Having established a causal effect of market access on cooperative culture, we proceed to study its impact on cooperative behavior and prosociality.

6.1 County-Level Analysis

We use the county-level estimation framework (Equation 2) and our seven measures of cooperation described in Section 3.4. Table 4 presents the results.

We find positive and significant estimates of the impact of market access on cooperation and prosociality across all seven measures. In column 1 the dependent variable is the average labor-force cooperation rating, based on O*NET rating and the distribution of occupations in each county-year. Our finding suggest that a 1 percent increase in market access results in a 0.0058-points (p-value < 0.01) increase in the average labor-force cooperation rating, which amounts to about 10% of the standard deviation. Columns 2-3 focus on cooperation in innovation. We find that a 1 percent increase in market access results in 0.0115-point (p-value < 0.01) and 0.0112-point (p-value < 0.01) increase in the number of co-inventors and the diversity of co-inventors, respectively. Here too the impact amounts to about 10% of the standard deviation. Columns 4-6 focus on the share of multifamily households, public funding of local collective action, and civic engagement, respectively, and find highly significant effects (p-value < 0.01) of a similar magnitude of about 9-11% of the standard deviation. Finally, in column 7 we focus on voter turnout in presidential elections. Our finding suggests that a 1 percent increase in market access results in a 0.0338-points (p-value < 0.01) increase in the turnout rate, amounting to about 14% of the standard deviation. Appendix Figure A.10 plots graphical representations of the results. In all outcomes, the relationship is quite linear on average and is not driven by outliers. Overall, our findings provide strong support for the hypothesis that market integration increases the extent of cooperation outside kinship lines and induces prosocial behavior.

To support a causal interpretation of these findings, we again leverage the network structure of market access and identify effects using only changes in market access that are orthogonal to local expansions of the railroad network. Appendix Table A.4 reports the results. All coefficients remain positive, and for all outcomes except civic engagement (Panel F), they are statistically significant when we flexibly control for the expansion of railroads in and around the county (columns 3-6). In addition, for all outcomes except civic engagement the coefficients remain fairly stable and the baseline estimates in column 2 are not statistically different from those in column 6, which includes the full controls for local railroads. These

results suggest that the impact is not merely driven by local railroad expansion.

Robustness. Appendix Figure B.6 documents robustness to alternative ways to account for spatial autocorrelation. Appendix Table B.7 documents that our findings are robust to using alternative parameter values for the trade elasticity θ and average value of transported goods per ton P when calculating counties' market access. Because the empirical distributions of four of the outcomes—the number of co-inventors, co-inventors' diversity, the share of multifamily households, and civic engagement—are very skewed with a long right tail, we winsorize those outcomes at the top 2.5% in our baseline estimation. Appendix Table B.8 documents that the results are robust to using different cutoffs. Similarly, Appendix Table B.9 documents that the findings are robust to using alternative ways to address skewed distributions that contains zeros: Poisson regression and different transformations of the outcome.

6.2 Individual-Level Analysis

We provide additional evidence on the positive impact of market access on cooperation using our sample of domestic migrants. We focus on two of our measures of cooperation that are calculated at the family-level: the father's labor-force cooperation score and multifamily residence.

Estimation framework. We use a simple two-period *Difference-in-Differences* framework to identify the causal impact of market access on cooperation:

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

where $cooperation_{ft}$ is the degree of cooperation for family f, that migrated from county $o(f)$ to county $d(f)$, measured at period t, which can be pre- or post-migration. $Post_t$ is an indicator for the post-migration period and θ_f is a family fixed effect. Standard errors ϵ_{ft} are clustered at the county of destination d (Bertrand et al., 2004) or two-ways at $d \times o$. As before, we use weights to account for the fuzzy-matching of families into multiple 1890 counties. β is the coefficient of interest that identifies the impact of moving to a higher versus lower market access county on cooperation.

Results. We present the findings in Table 5. The result in column 1 suggests that domestic migrants moving to a higher market-access county had a higher tendency to switch to occupations that require a higher degree of on-the-job cooperation, relative to those migrating to a lower market-access county. The O*NET cooperation score increased by 0.005 points (p-value < 0.01) after migration in relative terms, which is approximately 0.03 of the standard deviation. Column 4 documents a similar finding focusing on residence with a non-kin instead. We find that after moving to a higher market-access county the probability of residing with a non-kin increases by 0.0138 points (p-value < 0.01), or 0.04 of the standard deviation, relative to moving to a lower market-access county. Columns 2 and 5 document that the findings are robust to two-way clustering at the counties of destination and origin. Columns 3 and 6 document that

the finding is robust to using a continuous definition of treatment. These results join the findings of the county-level analysis in documenting the positive impact of market integration on cooperation outside kinship lines.

7 Channels

This section explores the mechanisms that may underlie our effects. Market access may influence cooperative culture through both direct and indirect channels. Directly, economic interdependence with anonymous others may induce humans to learn a sense of impersonal prosociality, universalism and tolerance of other norms, for example, as they experience the benefits of economic interactions with them. Indirectly, market access could affect cooperative cultural traits via four pathways: increased migration enhancing population diversity and thereby fostering a more universalist and less tightly-knit local culture (Allport, 1954; Gelfand, 2018); economic development prompted by markets leading to more universalist culture, as suggested by (Greenfield, 2009); the dissemination of new ideas and information through migrants, newspapers, or technologies such as the telegraph, which could change local cultures (e.g., Beach and Hanlon, 2023); and the development of local legal institutions (Greif, 1993; Cantoni and Yuchtman, 2014), which can improve institutional quality and induce cooperative culture (Gorodnichenko and Roland, 2017; Henrich, 2020; Eruchimovitch et al., 2023).

We present evidence suggesting that, first, market integration has a direct impact on cooperative cultural traits, as its impact is concentrated among individuals working in commerce-intensive industries. And, second, that the relationship between market access and cooperative culture and psychology is unlikely to be attributable solely to the indirect channels considered.

7.1 The Direct Impact of Commerce

We present evidence suggesting that the impact of market access on cooperative cultural traits stem from a direct and inherent effect of commerce. To do so, we use information on the industries migrants worked in. Intuitively, if indeed the impact relates to the fact that commerce generates a dependence on, or requires the cooperation of, anonymous out-group members, then, as some industries are more commerce-intensive than others, the extent to which migrants are expected to be impacted by a change in market access depends on the industry they work in.

We divide industries into two broad categories. The first category, which we refer to as *commerce-intensive*, includes industries that tend to sell to far-away markets (e.g., manufacturing and agriculture), or those that form an essential part of commerce and the functioning of markets (e.g., wholesale, retail, and transportation).[12] The second, which we refer to as *commerce-moderate*, includes industries that

[12] Specifically, this category includes the following IPUMS *IND1950* codes: 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

mostly service the local economy (e.g., construction, utilities, real estate, entertainment and recreation, personal and professional services, and public administration).[13] We then limit the sample of domestic migrants to households in which the father remained in the same category before and after the migration, and estimate the causal impact of moving to a higher market access county separately for each category.

Figure 6 presents the results. Panel A plots the dynamic impact of moving to a higher market access county, relative to moving to a lower market access county, when the sample only includes individuals working in commerce-intensive industries. The dynamic effect is similar to that estimated using the whole sample, suggesting a positive impact on cooperative cultural traits. Panel B plots the dynamic impact when the sample only includes individuals working in commerce-moderate industries. It suggests that moving to a higher vs lower market access county has no impact on cooperative traits in this group. This pattern of heterogeneous response to changes in market access supports the hypothesis that market integration has an inherent and direct impact on cooperative culture. Furthermore, the finding of a null impact among individuals working in commerce-moderate industries suggests that it is unlikely that the relationship between market access and cooperative traits is driven by the indirect channel, since those can be expected to affect all residence in the county, at least to some extent.

There are several concerns regarding this results. The first two related concerns stem from the fact that about 53% of domestic migrants' households in which the father remained in the same category were farmers. Since farmers belong to the commerce-intensive category, one might be concerned that the finding is unique to, or driven by, farmers, or that it is driven by the significant differences in sample size across the two broad categories.[14] To address those concerns, in Appendix Figure A.11 we splits the commerce-intensive group into two sub-groups: those who were farmers in both periods, and those who where non-farmers in both periods,[15] and estimate the impact of moving to a higher market access county separately in each subgroup. The figure documents that the impact on both subgroups is similar, suggesting that the finding is not driven by farming. Specifically, a significant impact is found also in the commerce-intensive non-farmers group, in which the number of observations is much smaller. In Appendix Figure A.12, we provide further evidence that the null impact in the commerce-moderate group is unlikely to be driven by the smaller number of observation. We take 1,000 random draws of 5,985 families—the number of families in the commerce-moderate group—from the commerce-intensive group and estimate the impact of moving to a higher market access county in each of these random samples. In

commodity brokerage and investment companies (726), Insurance (736), Advertising (806), Accounting, auditing, and book-keeping services (807), and Miscellaneous business services (808).

[13] Specifically, this category includes the following IPUMS *IND1950* codes: 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).

[14] Specifically, the DID analysis in the commerce-intensive category has 266,001 observations, compared to 25,390 in the commerce-moderate category.

[15] Note that since some individuals change their occupation after the migration, the union of the two sub-groups is smaller than the commerce-intensive group. The DID analysis of farmers includes 152,319 observations, and of the commerce-intensive non-farms 50,430.

96.2% of the draws we find a stronger impact than the impact we find in the commerce-moderate group.

A more general concern is that families in the two categories may differ along other dimensions and these differences might explain the heterogeneous treatment effects. Indeed, A.6 documents that families in the commerce-intensive group had weaker cooperative cultural traits to begin with. They had more children, were less likely to originate from an urban location, to be in an extra-community marriage, and gave their children born before the migration universal names. However, our analyses suggest that none of these differences explain the heterogeneous impact across the two categories and the null impact on families in the commerce-moderate group. Specifically, Appendix Figures A.13-A.16 document similar impacts across smaller and larger families, families originating from urban and rural locations, or families in extra-community or intra-community marriages, and a relatively smaller, yet significant, impact on families with low average prior UNI scores. Appendix Figure A.16 further documents that individuals working in commerce-moderate industries were not affected even if their children's average prior UNI scores were high (Panel D), unlike individuals working in commerce-intensive industries (Panel C). These results support the hypothesis that the heterogeneous response to changes in market access between the two groups is driven by differences in exposure to commerce.

7.2 Indirect Channels

In this section we provide a few indirect tests to evaluate the potential role of indirect channels in generating the positive impact of market access on cooperative culture, and find that they are unlikely to be central. While informative, the test we present below only provide suggestive evidence that can not rule out the possibility that indirect channels played an important role.

Population diversity. Before discussing the additional analysis exploring the potential role of population diversity, it is useful to recall that our results from both the county-level and the individual-level analysis are robust to the inclusion or exclusion of immigrants and non-whites in the sample (Appendix Table B.5 and Appendix Figure B.5), suggesting that diversity is unlikely to be a central mediating factor. Nevertheless, we proceed to test the possibility that market access affected cooperative culture through its impact on population diversity more formally. To do so, we calculate for each county-decade the population share of immigrants and a birthplace diversity index, defined as one minus the Herfindahl-Hirschman Index over birthplaces.

We then use those measures to conduct three tests. First, we estimate the effect of market access on these two outcomes using Equation 2. Panel A and B of Table 6 presents the results. We find a positive and significant association between market access and both measures of population diversity in columns 1 and 2, which drop in magnitude and become insignificant once local connectivity to railroads is controlled for (columns 3-6). This suggests that population diversity is not affected by market access per se, but by local connectivity to railroads. It also suggests that population diversity is unlikely to account for the associations between cooperative culture and the variation in market access that is not driven by local

expansions of the railroad network.

Second, we include both variables separately as additional "bad controls" in Equation 2 to examine their potential role as mediators. The results are presented in columns 2 and 3 of Table 7. Column 1 repeats our baseline estimate without the additional controls. We find that the estimated impact of market access on cooperative culture is virtually unchanged by the inclusion of both measures of population diversity.[16] This suggests that the relationship between market access and cooperative cultural traits does not operate through an increase in local population diversity.

Third, we follow the same logic and augment the difference-in-differences framework (Equation 3) to also control for the dynamic impact of potential mediators. That is, we include in the estimation dynamic controls for the differences in the levels of the potential mediator between origin county o and destination county d, and examine the change in the estimated impact of moving to a higher versus lower market access county on universal identification.[17] Appendix Figure A.17 presents the dynamic and average impact of market access when the dynamic impact of the different potential mediators are controlled for. Panels A-B control for the dynamic impact of differences in the share of immigrants and birthplace diversity, respectively. In both cases, the estimated impact of market access with the mediators controls is not statistically different from the baseline estimation in Figure 5.

Taken together, these findings suggest that the relationship between market access and cooperative culture is unlikely to be driven by population diversity.

Economic development. To test for the role of economic development as a channel, we would ideally have a measure of economic development such as GDP or income at the county-decade level. Unfortunately, such data is not available for the time period we study. Instead, we use three common proxies for local economic development in the period of our study: the share of the urban population, the number of manufacturing establishments per captia, and the mean occupational income score. We then estimate the effect of market access on these three outcomes using Equation 2. Panel C-E of Table 6 present the results. We find *negative* effects of market access for the first two measures of economics development, which are statistically significant for the urban population share. This is consistent with the evidence in Chan (2022), who finds that market access increased total agricultural output but not in per capita terms, as the increase was offset by a rise in rural population. Somewhat contrary to that, we find a positive relationship with the mean occupational income score, but it becomes statistically insignificant when local connectivity to railroads above having any railroad in the county is controlled for (columns 4-6).

Next, we include the three proxies for economic development separately as additional controls in Equa-

[16] The estimates for fairness lose some statistical significance due to a reduction in the sample size but remain stable compared to our baseline.

[17] The additional dynamic controls take the following form:

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

tion 2. The results are presented in columns 4-6 of Table 7. We find that the estimated impact of market access on cooperative culture changes little when proxies for economic development are included as a controls.[18]

Finally, Panels C-E in Appendix Figure A.17 present the dynamic DID estimation when also controlling for the dynamic impact of differences in the urban population, mean occupational income scores, and manufacturing establishments per capita, respectively. A significant negative impact of moving to a higher market access county is maintained in all cases. The impact remains stable when the the change in the mean occupational income scores and manufacturing establishments are accounted for (Panels D-E), while a marginally insignificant attenuation of about 27.9% ($p-value = 0.11$) in the average treatment effect is found when the change in the urban population is controlled for (Panel C).

In sum, these findings are inconsistent with the possibility that the effect of market access on cooperative culture can be explained through its effect on economic development.

Access to Information. We also explore the role of access to information as a channel. Although we do not have direct measures of access to information, we use as a proxy the number of workers in occupations relating to the spread of information per 1,000 workers in the county, winsorized at the top 2.5%. We focus on occupations related to newspapers, printing, mail and the telegraph.[19] We then estimate the effect of market access on this outcome using Equation 2. Panel F of Table 6 presents the results. We find a positive and significant association between market access and the population share of informational works in columns 1 to 3, which drops in magnitude and the level of statistical significance once local connectivity is further controlled for (columns 4-6), although the association remains significant at the 10%. This suggests that market access may have increase access to information. Next, we include the information measure as an additional "bad control" in Equation 2. As reported in column 7 of Table 7, the estimated impact of market access on cooperative culture is virtually unchanged by this inclusion. Panel F of Appendix Figure A.17 presents the parallel exercise for the individual-level analysis and find similar stability of the estimated impact of market access on universal identification. Hence, these results lead us to conclude that access to information is unlikely to be a major channel through which market access affected cooperative culture.

Legal Institutions. Finally, it is also possible that the increase in trade following a higher market access induced the development of local legal institutions, due to the need to solve the "fundamental problem of exchange" (Greif, 1993; Cantoni and Yuchtman, 2014). The increase in institutional quality might have, in turn, strengthened cooperative cultural traits (Gorodnichenko and Roland, 2017; Henrich, 2020;

[18] If anything, the impact tends to become *stronger* when the share of urban population and manufacturing establishments per capita are included, although the change in coefficient size is mostly statistically insignificant and likely driven by the change in sample due to data availability.

[19] 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).

Eruchimovitch et al., 2023). To assess this possibility, we use data on the number of lawyers and judges per 1,000 workers in the county, winsorized at the top 2.5%, to proxy for the development of legal institutions. Panel G in Table 6 documents a positive and significant association between market access and the degree of development of local legal institutions, that is robust to local railroads connectivity. This provides further empirical support for the centrality of legal institutions for trade. However, the findings presented in column 8 of Table 7 suggest that legal institutions were unlikely to be a central part of the story, as the estimated impact of market access on cooperative culture remains stable when the time-varying proxy for legal institutions is included as a "bad control" in the estimation of Equation 2. Panel G of Appendix Figure A.17 supports the same conclusion by presenting the results of the parallel exercise for the individual-level analysis.

8 Conclusions

Focusing on the United States, during the period when it rose to become the world's largest and most integrated economy (1850-1920), we study the impact of market integration on cooperative culture and psychology and cooperation and prosocial behavior. A large body of theories and scholars going back to enlightenment thinkers posit that market interactions benefit from fair dealing and honesty with strangers, giving rise to a demand for impersonal prosocial norms. We measure counties' market integration by their market access, as developed by Donaldson and Hornbeck (2016), which evolved as a function of the growth of the railway network and mass immigration from 1850 to 1920. To measure the centrality of the in-group, moral universalism and norm looseness, key aspects of cooperative psychology and culture, we use a variety of measures from census and newspaper data, including the Universal Name Index (UNI) and the looseness of family norms and religious affiliations. To measure cooperation and prosociality, we rely on census, work style, patent, and voting data to develop novel indicators of cooperation at work, in innovation, at home, and within the community. Our results document that cooperative culture goes hand in hand with cooperative behavior.

In our analysis, we first identify the causal effect of market access on cooperative cultural traits and cooperation in a county-level framework that leverages excess changes in market access that are orthogonal to local changes in railroad infrastructure. We find that increased market access led to greater universalism, looser norms, more generalized trust and concerns for fairness, and more cooperative behavior. We then move to an individual-level difference-in-differences analysis, estimating the impact of migrating to a higher versus lower market access location. We find that, following a parallel trend in the pre-migration period, universal identification strengthened in families after they migrated to a higher market access county, relative to those migrating to a lower market access county. Building on distinct identification assumption, these analysis suggest a consistent conclusion: market integration foster cooperative traits, which support broader cooperation. Our analysis closes by presenting results documenting that the impact is limited to individuals working in commerce-intensive industries, and suggesting that the impact is not

explained by an indirect effect operating through markets' impact on population diversity, economic development, access to information, or the development of local legal institutions. This leads us to conclude that market integration directly influence culture and psychology.

The findings indicate that current debates on the potential negative impacts of markets on prosocial behavior should also take into account the medium and long-term effects of markets on prosocial tendencies. For example, distrust of strangers, xenophobia, and racism are typically more evident in remote regions and among their populations. If markets and globalization integrate these remote areas into wider networks of economic exchange, promoting mutual benefits, it is possible that a growing number of people will adopt impersonal prosocial norms.

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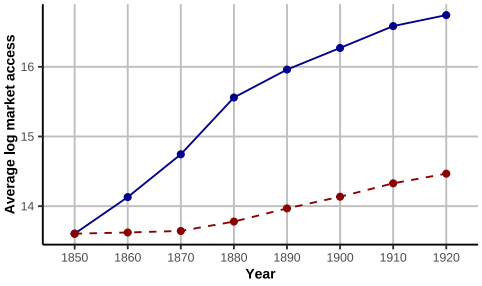
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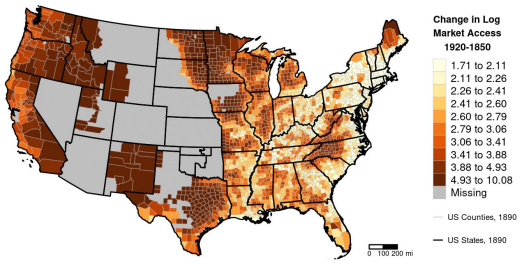
Figures

Figure 1: The Change in log Market Access, 1850-1920

(a) Average log market access by year



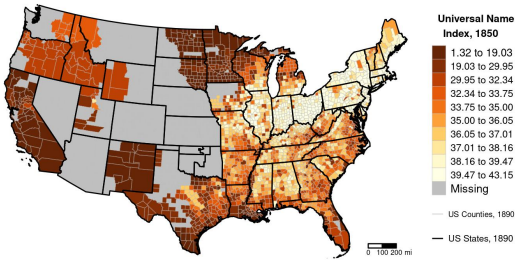
(b) Differences in log market access, 1850-1920



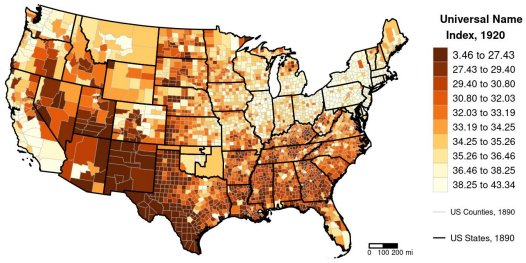
Note: This figure plots the changes in log market access over time. Panel A plots the average log market access by decade. The blue curve represents market access calculated using the contemporaneous transportation costs and population, and the dashed dark red curve fixes transportation costs to 1850.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

Figure 2: Cooperative Cultural Traits, 1850 and 1920

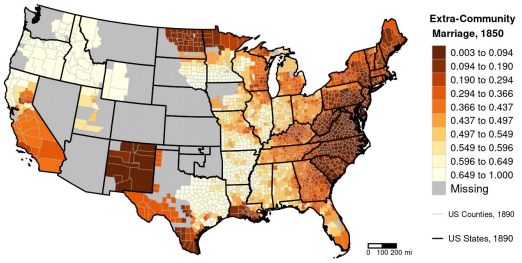
(a) Universal Name Index, 1850



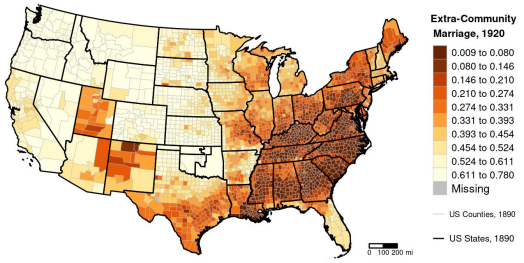
(b) Universal Name Index, 1920



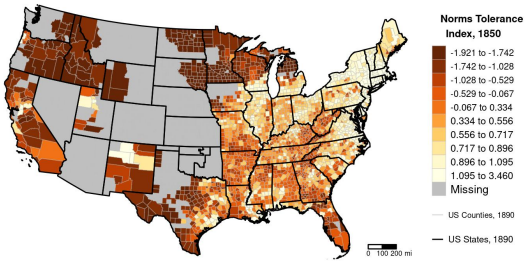
(c) Extra-Community Marriage, 1850



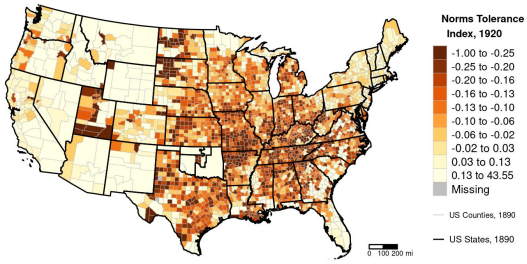
(d) Extra-Community Marriage, 1920



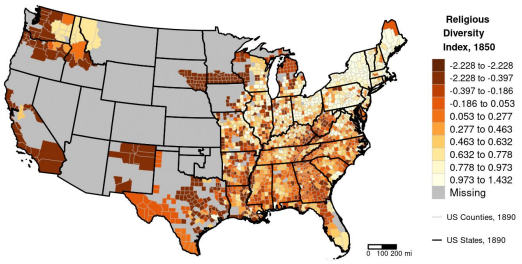
(e) Norms Tolerance Index, 1850



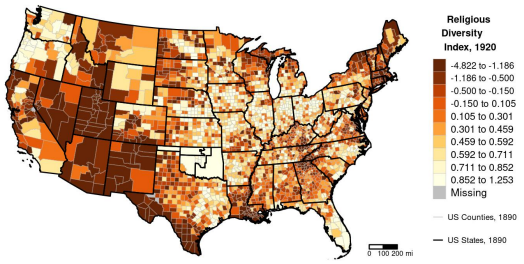
(f) Norms Tolerance Index, 1920



(g) Religious Diversity Index, 1850

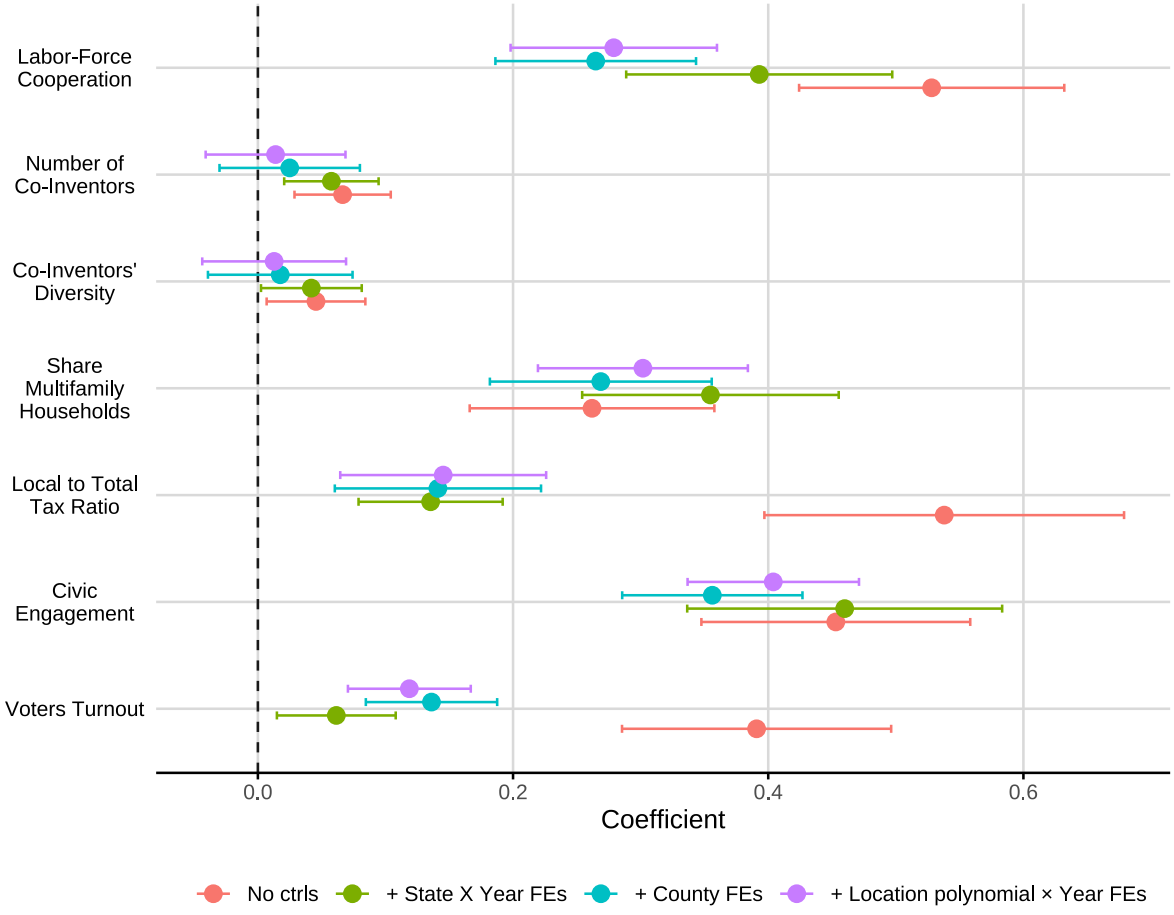


(h) Religious Diversity Index, 1920



Note: This figure plots the spatial distributions of four measures of cooperative cultural traits: the UNI, the ECM, the NTI, and the RDI, in 1850 (left column) and in 1920 (right column). A lighter color implies a higher prevalence of cooperative traits. See Appendix Figure A.4 for the spatial distributions of the newspapers-based measures.

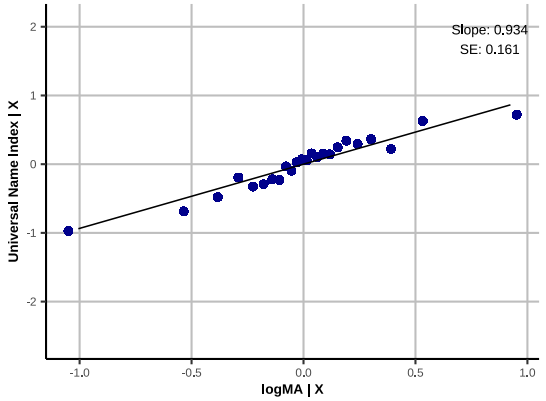
Figure 3: The Relationship Between Cooperative Culture and Cooperative Behavior



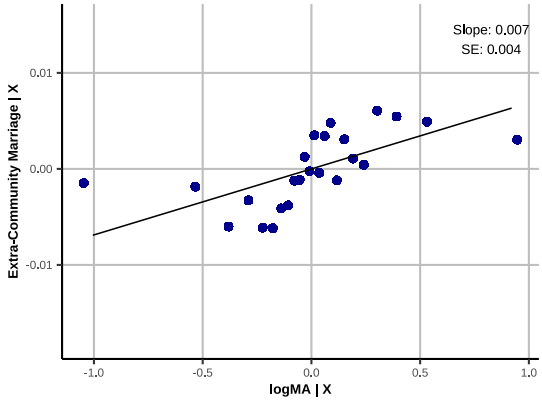
Note: This figure plots the estimates of β and 95% confidence intervals from equation 1 for all seven historical measure of cooperation, standardize into z-scores, and prosocial behavior and four different specification, sequentially adding the controls in the regression: without any controls, with state-by-year 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).

Figure 4: Market Access and Cooperative Traits: County-level Bin Scatter Plots

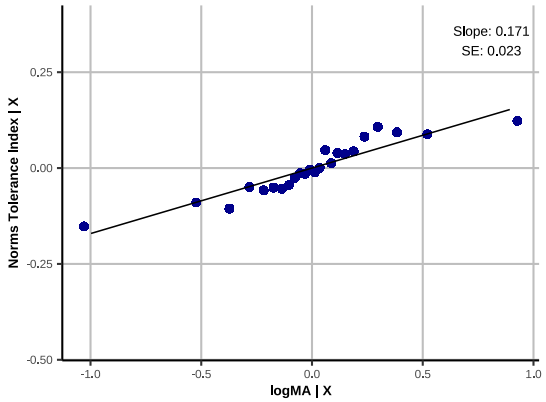
(a) Universal Name Index



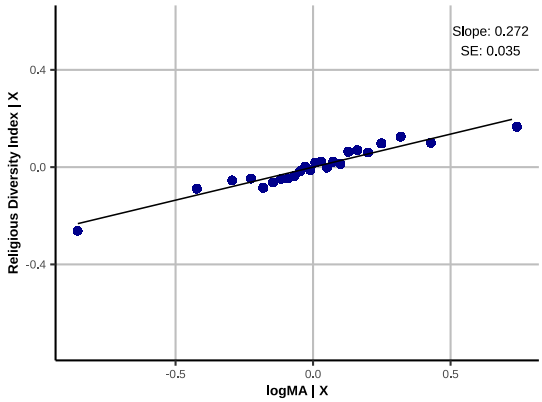
(b) Extra-Community Marriage



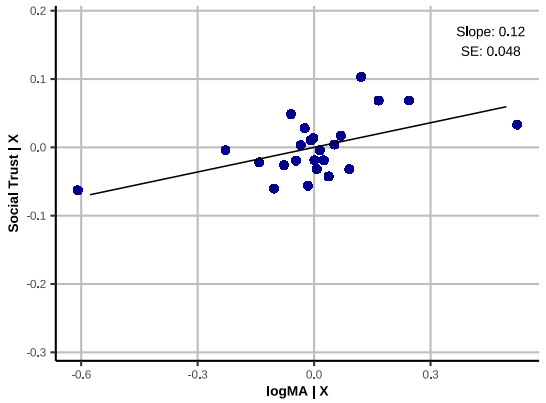
(c) Norms Tolerance Index



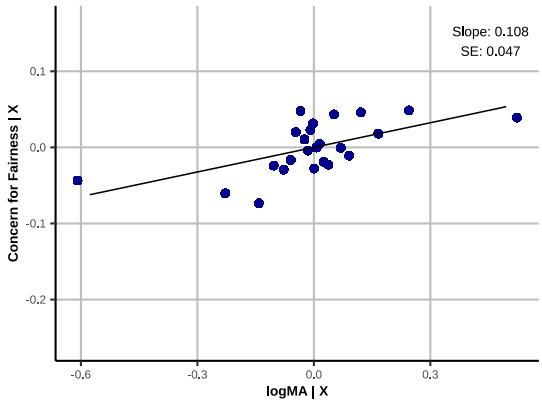
(d) Religious Diversity Index



(e) Social Trust

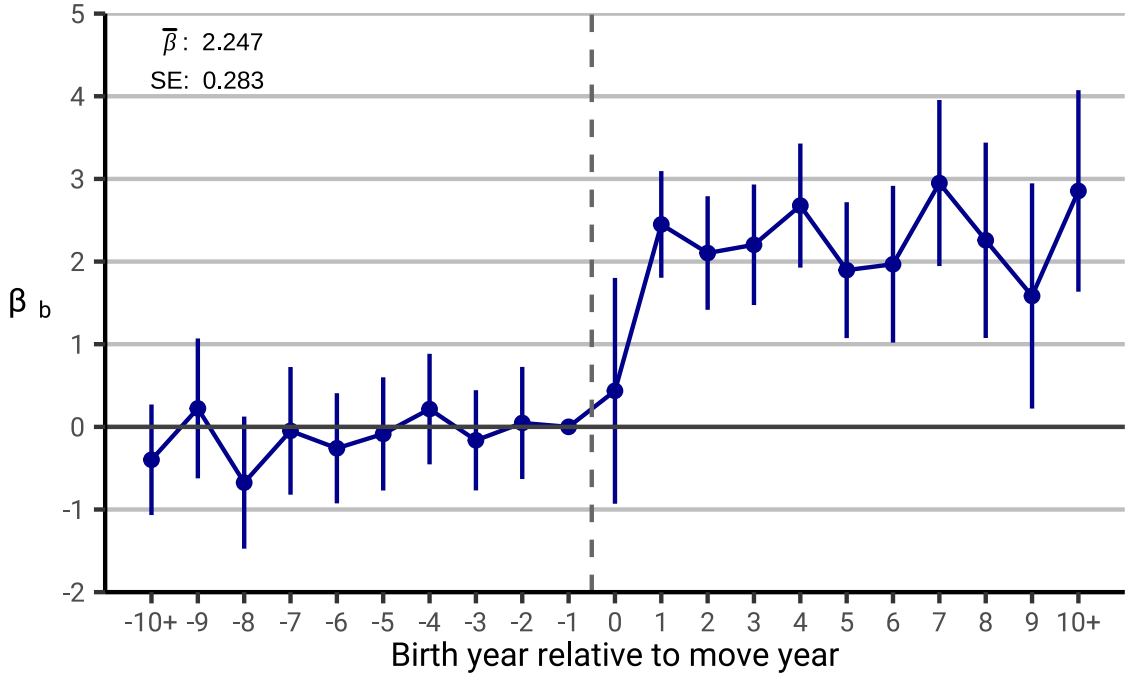


(f) Concern for Fairness



Note: This figure presents bin scatter plots of the relationship between log market access and 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.

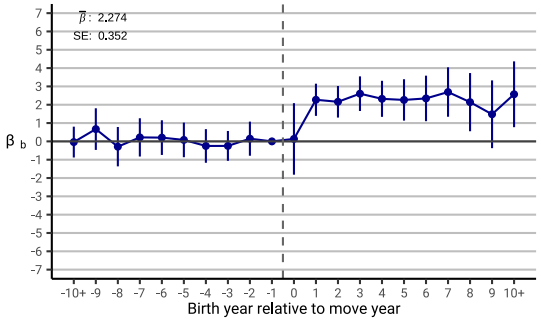
Figure 5: The Impact of Moving to a Higher Market Access County on Universal Identification



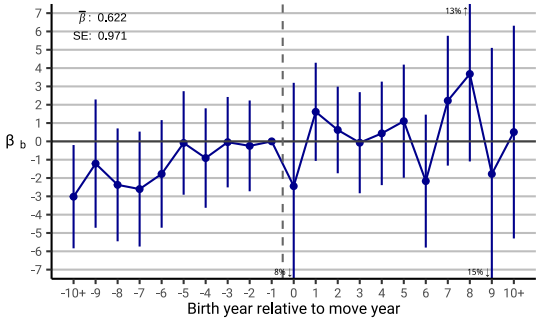
Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences estimation (equation 3). $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

Figure 6: Market Access Affects Individuals Working in Commerce-Intensive Industries

(a) Commerce-intensive



(b) Commerce-moderate



Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences estimation (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.

Tables

Table 1: Market Access and the Local Prevalence of Commerce

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Mean top 10 market terms share (mean = 0.466 , sd = 0.116)					
Log market access	0.0181***	0.0158***	0.0122**	0.0177***	0.0174***	0.0170***
	(0.0043)	(0.0044)	(0.0050)	(0.0053)	(0.0056)	(0.0059)
Observations	8,610	8,610	8,610	8,610	8,610	8,610
R^2	0.628	0.629	0.629	0.631	0.632	0.634
	Panel B: Wholesale and Retail Share (mean = 0.055 , sd = 0.036)					
Log market access	0.0043***	0.0050***	0.0037***	0.0024***	0.0019**	0.0015
	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Observations	18,262	18,262	18,262	18,262	18,262	18,262
R^2	0.770	0.772	0.773	0.781	0.781	0.782
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × State		Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes
Railroads within further buffers						Yes

Note: This table reports estimates of equation 2 with additional controls for local railroad infrastructure when the dependent variables are measures of the local prevalence of commerce. In Panel A, the dependent variable is the mean share of the 10 semantically most related keywords to "buy", "sell", "money", "price", "trade" in 19th century US newspapers, according to chatGPT. 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. 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 2: Market Access and Cooperative Cultural Traits

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Universal Name Index (mean = 32.19 , sd = 6.6)					
Log market access	1.147***	0.9342***	0.7131***	0.5650***	0.4772***	0.3669**
	(0.1608)	(0.1614)	(0.1685)	(0.1699)	(0.1741)	(0.1716)
Observations	18,178	18,178	18,178	18,178	18,178	18,178
R^2	0.796	0.806	0.807	0.810	0.811	0.813
	Panel B: Extra-Community Marriage (mean = 0.382 , sd = 0.2)					
Log market access	0.0061*	0.0069*	0.0072*	0.0044	0.0056	0.0055
	(0.0037)	(0.0037)	(0.0039)	(0.0040)	(0.0041)	(0.0041)
Observations	18,175	18,175	18,175	18,175	18,175	18,175
R^2	0.904	0.908	0.908	0.909	0.910	0.910
	Panel C: Norms Tolerance Index (mean = 0 , sd = 1)					
Log market access	0.2224***	0.1709***	0.1538***	0.1636***	0.1417***	0.1225***
	(0.0220)	(0.0226)	(0.0228)	(0.0233)	(0.0231)	(0.0230)
Observations	18,094	18,094	18,094	18,094	18,094	18,094
R^2	0.620	0.642	0.643	0.645	0.647	0.651
	Panel D: Religious Diversity Index (mean = 0 , sd = 1)					
Log market access	0.2927***	0.2717***	0.2346***	0.2218***	0.2072***	0.1951***
	(0.0374)	(0.0346)	(0.0363)	(0.0383)	(0.0383)	(0.0384)
Observations	17,295	17,295	17,295	17,295	17,295	17,295
R^2	0.673	0.681	0.682	0.683	0.683	0.687
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × State		Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes
Railroads within further buffers						Yes

Note: This table reports estimates of equation 2 with additional controls for local railroad infrastructure when the dependent variables are different historical cooperative cultural traits: the UNI (Panel A), the ECM (Panel B), the NTI (Panel C), the RDI (Panel D), Social Trust (Panel E), and Concern for Fairness (Panel F). 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. 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 2: Market Access and Cooperative Cultural Traits (cont.)

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel E: Social Trust (mean = 0.002 , sd = 0.998)					
Log market access	0.1307***	0.1201**	0.1257**	0.1229**	0.1372**	0.1290**
	(0.0449)	(0.0485)	(0.0534)	(0.0586)	(0.0615)	(0.0631)
Observations	6,821	6,821	6,821	6,821	6,821	6,821
R^2	0.678	0.681	0.681	0.681	0.681	0.683
	Panel F: Concerns for Fairness (mean = 0.002 , sd = 0.998)					
Log market access	0.0897*	0.1078**	0.1323**	0.1188**	0.1233**	0.1203**
	(0.0462)	(0.0466)	(0.0520)	(0.0539)	(0.0555)	(0.0583)
Observations	6,821	6,821	6,821	6,821	6,821	6,821
R^2	0.685	0.689	0.689	0.689	0.689	0.691
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × State		Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes
Railroads within further buffers						Yes

Note: This table reports estimates of equation 2 with additional controls for local railroad infrastructure when the dependent variables are different historical cooperative cultural traits: the UNI (Panel A), the ECM (Panel B), the NTI (Panel C), the RDI (Panel D), Social Trust (Panel E), and Concern for Fairness (Panel F). 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. 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: The Impact of Moving to a Higher Market Access County on Universal Identification

	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	2.348***	1.995***	0.5194***	0.3782***
	(0.2250)	(0.2130)	(0.1284)	(0.1301)
Observations	470,929	470,929	431,709	431,709
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 when the dependent variable is domestic migrants' children's UNI. In columns 1-2, "local" is defined 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Market Access, Cooperation, and Prosocial Behavior

	Dependent variable:						
	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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log market access	0.0058***	0.0115***	0.0112***	0.0083***	0.0216***	0.0008***	0.0376***
	(0.0012)	(0.0037)	(0.0034)	(0.0022)	(0.0064)	(0.0002)	(0.0062)
DV mean	3.996	1.092	0.0760	0.1510	0.6700	0.0120	0.6300
DV sd	0.0590	0.1160	0.1060	0.0840	0.1980	0.0090	0.2400
Observations	18,263	17,355	17,355	18,273	4,879	18,262	45,308
R^2	0.680	0.241	0.241	0.782	0.908	0.687	0.782
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × State Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation 2 when the dependent variables are different historical measure of cooperation and prosocial behavior: labor-force cooperation (column 1), the average number of patents co-inventors (column 2), the diversity of 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). 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 5: The Impact of Moving to a Higher Market Access County on Cooperation

	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***	0.0051**	0.0034***	0.0138***	0.0138***	0.0050*
	(0.0018)	(0.0020)	(0.0013)	(0.0039)	(0.0042)	(0.0028)
Observations	189,562	189,562	189,562	189,562	189,562	189,562
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 when the dependent variables are labor-force cooperation (columns 1-3) and residence with a non-kin (columns 4-6). In columns 1-2, "local" is defined the county of origin for children born before the migration and the county of destination for children born after it. 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 × county of origin in columns 2 and 5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Possible Indirect Channels and Mediators

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Share Immigrants (mean = 0.166 , sd = 0.193)					
Log market access	0.0074**	0.0075***	0.0040	0.0021	0.0009	-0.0002
	(0.0035)	(0.0028)	(0.0031)	(0.0032)	(0.0032)	(0.0033)
Observations	18,278	18,278	18,278	18,278	18,278	18,278
R^2	0.899	0.903	0.904	0.904	0.905	0.906
	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
	(0.0039)	(0.0033)	(0.0035)	(0.0036)	(0.0037)	(0.0037)
Observations	18,278	18,278	18,278	18,278	18,278	18,278
R^2	0.923	0.925	0.926	0.926	0.927	0.928
	Panel C: Share Urban (mean = 0.106 , sd = 0.199)					
Log market access	-0.0104***	-0.0085***	-0.0065*	-0.0168***	-0.0174***	-0.0187***
	(0.0034)	(0.0033)	(0.0036)	(0.0035)	(0.0036)	(0.0037)
Observations	21,183	21,183	21,183	21,183	21,183	21,183
R^2	0.801	0.804	0.804	0.821	0.821	0.821
	Panel D: Manufacturing Est. PC (mean = 0.354 , sd = 0.312)					
Log market access	-0.0013	-0.0035	-0.0137	-0.0196*	-0.0237*	-0.0139
	(0.0100)	(0.0101)	(0.0114)	(0.0117)	(0.0125)	(0.0141)
Observations	15,371	15,371	15,371	15,371	15,371	15,371
R^2	0.612	0.618	0.619	0.620	0.620	0.622
	Panel E: Mean Occupational Income Score (mean = 17.38 , sd = 3.265)					
Log market access	0.2477***	0.3125***	0.2359***	0.1246	0.0971	0.0384
	(0.0785)	(0.0762)	(0.0796)	(0.0817)	(0.0815)	(0.0802)
Observations	18,264	18,264	18,264	18,264	18,264	18,264
R^2	0.745	0.750	0.751	0.758	0.759	0.761
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × State		Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes
Railroads within further buffers						Yes

Note: This table reports estimates of equation 2 with additional controls for local railroad infrastructure when the dependent variables are measures of potential indirect channels: population diversity (Panels A-B), economic development (Panels C-E), information (Panel F), and legal institutions (Panel G). 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. 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 6: Possible Indirect Channels and Mediators (cont.)

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel F: Information Workers per 1,000 (mean = 3.154 , sd = 2.918)					
Log market access	0.1739***	0.1754***	0.1664***	0.0981*	0.1066*	0.1041*
	(0.0549)	(0.0578)	(0.0581)	(0.0593)	(0.0586)	(0.0560)
Observations	18,264	18,264	18,264	18,264	18,264	18,264
R^2	0.750	0.756	0.756	0.759	0.759	0.762
	Panel G: Lawyers and Judges per 1,000 (mean = 3.094 , sd = 2.414)					
Log market access	0.4630***	0.3852***	0.3660***	0.3965***	0.3557***	0.3324***
	(0.0728)	(0.0789)	(0.0839)	(0.0851)	(0.0841)	(0.0847)
Observations	18,264	18,264	18,264	18,264	18,264	18,264
R^2	0.544	0.552	0.551	0.553	0.557	0.561
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × State		Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes
Railroads within further buffers						Yes

Note: This table reports estimates of equation 2 with additional controls for local railroad infrastructure when the dependent variables are measures of potential indirect channels: population diversity (Panels A-B), economic development (Panels C-E), information (Panel F), and legal institutions (Panel G). 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. 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 7: Market Access and Cooperative Traits: Controlling for Possible Channels

	Dependent variable:								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Universal Name Index								
logMA	0.9342***	0.8867***	0.8122***	1.001***	1.493***	0.8723***	0.9259***	0.8466***	1.350***
	(0.1614)	(0.1586)	(0.1550)	(0.1601)	(0.1984)	(0.1590)	(0.1611)	(0.1601)	(0.1868)
Observations	18,178	18,178	18,178	18,159	12,435	18,164	18,164	18,164	12,418
R^2	0.806	0.808	0.813	0.811	0.830	0.808	0.806	0.809	0.840
	Panel B: Extra-Community Marriage								
logMA	0.0069*	0.0080**	0.0064*	0.0077**	0.0135***	0.0051	0.0059	0.0059	0.0105**
	(0.0037)	(0.0037)	(0.0036)	(0.0037)	(0.0048)	(0.0036)	(0.0036)	(0.0037)	(0.0046)
Observations	18,175	18,175	18,175	18,156	12,427	18,161	18,161	18,161	12,410
R^2	0.908	0.910	0.908	0.910	0.925	0.911	0.910	0.909	0.934
	Panel C: Norms Tolerance Index								
logMA	0.1709***	0.1717***	0.1716***	0.1736***	0.2227***	0.1670***	0.1716***	0.1597***	0.2091***
	(0.0226)	(0.0227)	(0.0226)	(0.0225)	(0.0339)	(0.0226)	(0.0226)	(0.0220)	(0.0331)
Observations	18,094	18,094	18,094	18,075	12,387	18,080	18,080	18,080	12,370
R^2	0.642	0.642	0.642	0.644	0.678	0.643	0.643	0.648	0.681
	Panel D: Religious Diversity Index								
logMA	0.2717***	0.2473***	0.2378***	0.2732***	0.2345***	0.2268***	0.2460***	0.2414***	0.1737***
	(0.0346)	(0.0358)	(0.0357)	(0.0346)	(0.0388)	(0.0365)	(0.0363)	(0.0367)	(0.0410)
Observations	17,295	14,618	14,618	17,280	12,026	14,604	14,604	14,604	9,348
R^2	0.681	0.708	0.709	0.682	0.709	0.709	0.706	0.706	0.747
	Panel E: Social Trust								
logMA	0.1201**	0.1014*	0.1041*	0.1307***	0.1012*	0.0988*	0.0962*	0.0891*	0.0793
	(0.0485)	(0.0538)	(0.0538)	(0.0490)	(0.0599)	(0.0536)	(0.0529)	(0.0532)	(0.0684)
Observations	6,821	5,861	5,861	6,815	5,209	5,853	5,853	5,853	4,242
R^2	0.681	0.683	0.684	0.681	0.706	0.684	0.684	0.684	0.711
	Panel F: Concern for Fairness								
logMA	0.1078**	0.0797	0.0831	0.1104**	0.1721***	0.0954*	0.0777	0.0697	0.1469**
	(0.0466)	(0.0516)	(0.0516)	(0.0478)	(0.0534)	(0.0524)	(0.0509)	(0.0516)	(0.0625)
Observations	6,821	5,861	5,861	6,815	5,209	5,853	5,853	5,853	4,242
R^2	0.689	0.696	0.696	0.689	0.714	0.697	0.696	0.696	0.723
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × State	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
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 cooperative cultural traits: the UNI (Panel A), the ECM (Panel B), the NTI (Panel C), the RDI (Panel D), Social Trust (Panel E), and Concern for Fairness (Panel F). Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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B.2 Robustness of Cooperative Culture Results: County-Level 80

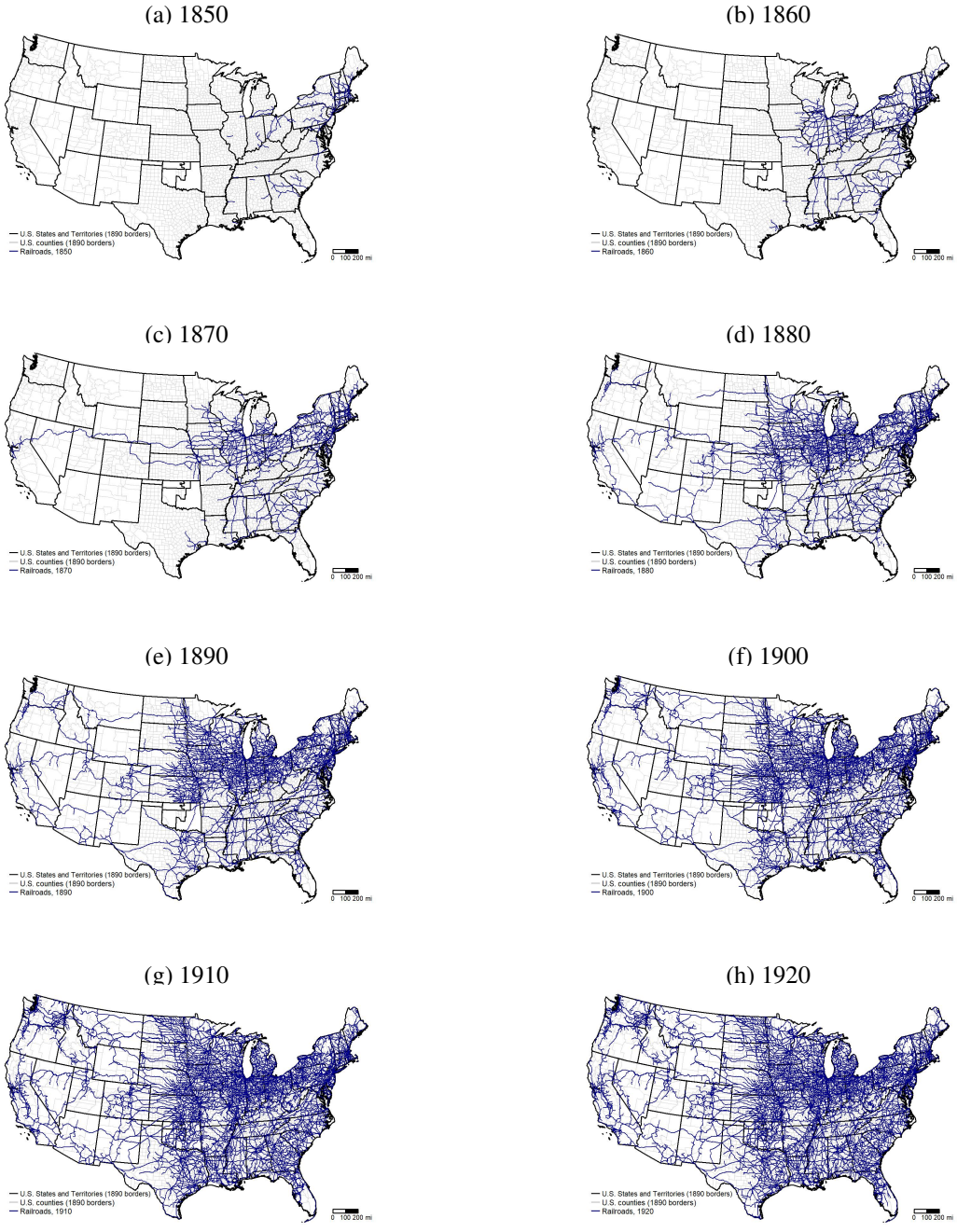
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A Further Figures, Analysis and Results

A.1 The Development of the Railroad Network and Market Access

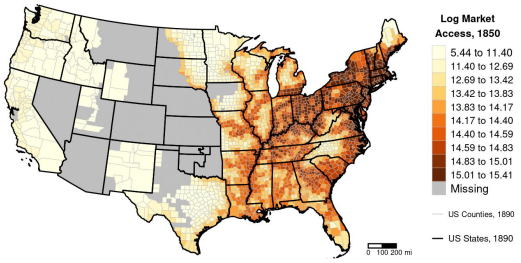
Figure A.1: The Railroad Network, 1850-1920



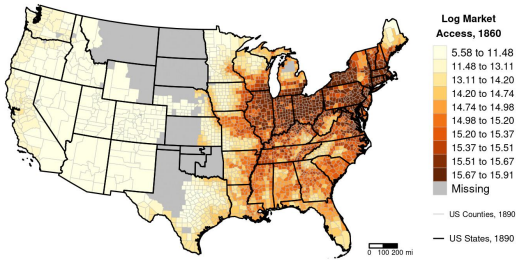
Note: This figure plots the railroad network for each decade between 1850-1920.

Figure A.2: Log Market Access, 1850-1920

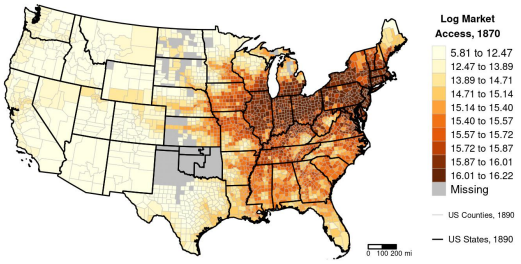
(a) 1850



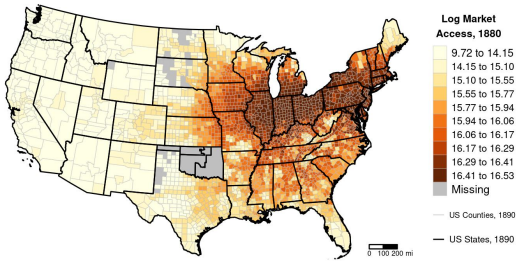
(b) 1860



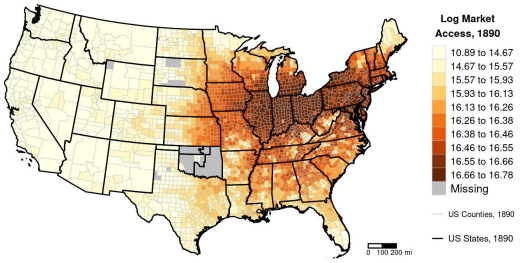
(c) 1870



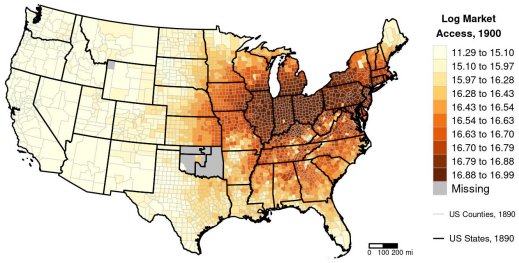
(d) 1880



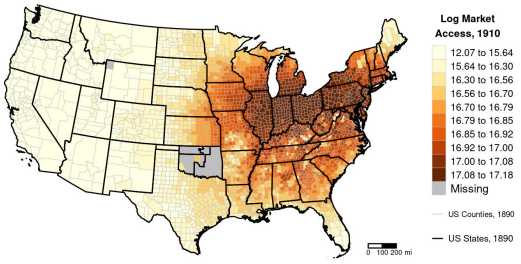
(e) 1890



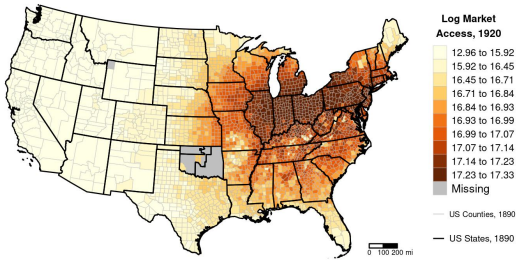
(f) 1900



(g) 1910



(h) 1920

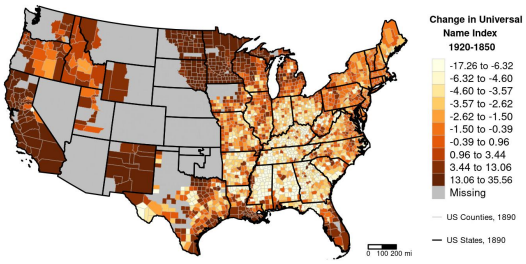


Note: This figure plots the spatial distributions of log market access for each decade between 1850-1920. Within each decade, a darker color implies a higher market access.

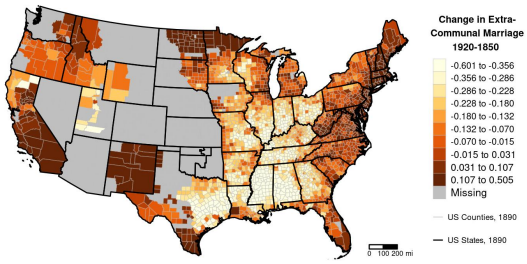
A.2 Cooperative Cultural Traits

Figure A.3: The Change in Cooperative Cultural Traits Between 1850-1920

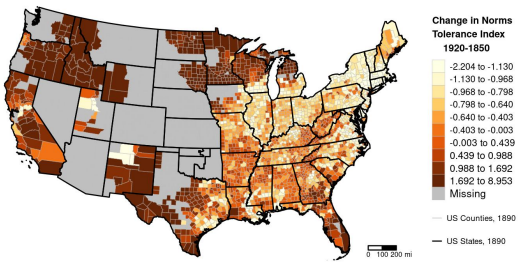
(a) Universal Name Index



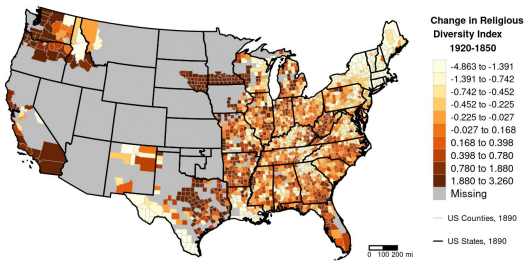
(b) Extra-Communal Marriage



(c) Norms Tolerance Index



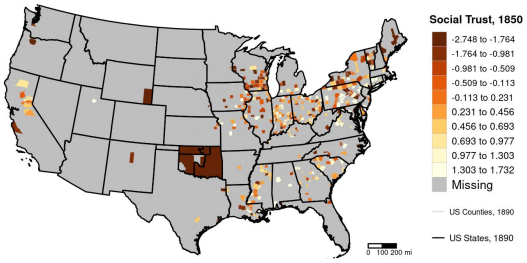
(d) Religious Diversity Index



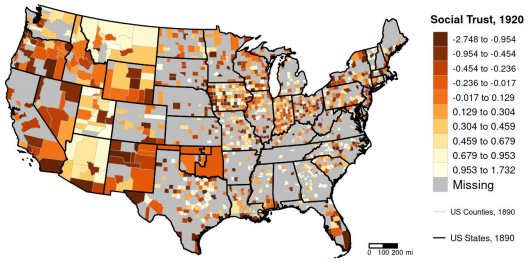
Note: This figure plots the difference in four cooperative cultural traits between 1920 and 1850: the UNI, the ECM, the NTI, and the RDI.

Figure A.4: Cooperative Cultural Traits, 1850 and 1920: Newspapers-based Measures

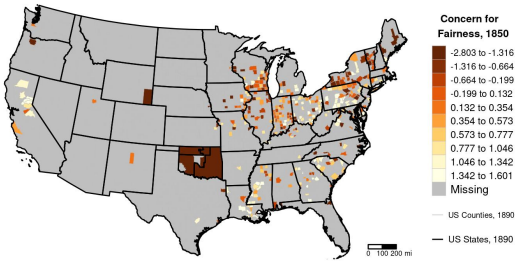
(a) Social Trust, 1850



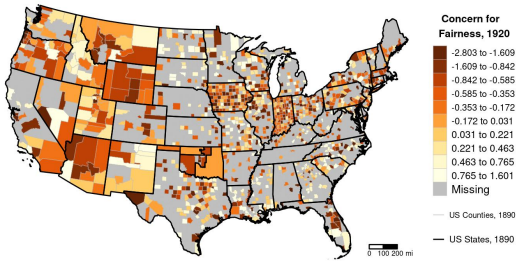
(b) Social Trust, 1920



(c) Concern for Fairness, 1850



(d) Concern for Fairness, 1920

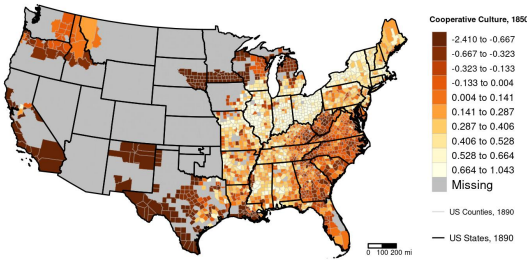


Note: This figure plots the spatial distributions of two newspaper-based measures of cooperative cultural traits: social trust and concern for fairness, in 1850 (left column) and in 1920 (right column). A lighter color implies a higher prevalence of cooperative traits.

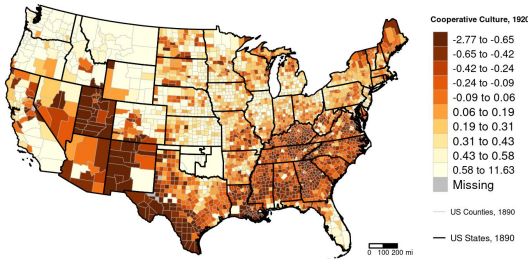
A.3 Cooperative Culture

Figure A.5: Cooperative Culture, 1850 and 1920

(a) Cooperative Culture, 1850



(b) Cooperative Culture, 1920



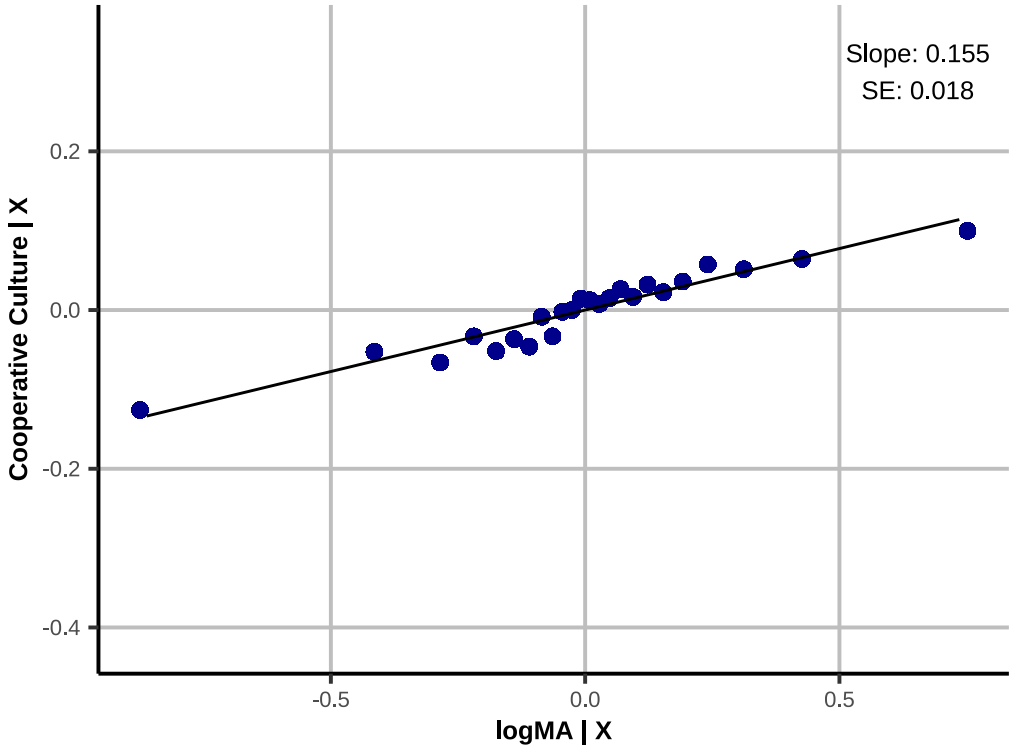
Note: This figure plots the spatial distributions of the composite cooperative culture index, in 1850 (left column) and in 1920 (right column). A lighter color implies a higher prevalence of cooperative culture.

Table A.1: Market Access and Cooperative Culture

	Dependent variable: Cooperative Culture (mean = 0.024, sd = 0.64)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log market access	0.1747***	0.1550***	0.1291***	0.1111***	0.1002***	0.0887***
	(0.0162)	(0.0179)	(0.0162)	(0.0263)	(0.0168)	(0.0169)
Observations	19,903	19,903	19,903	19,903	19,903	19,903
R^2	0.731	0.695	0.740	-0.143	0.744	0.746
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × State		Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes
Railroads within further buffers						Yes

Note: This table reports estimates of equation 2 with additional controls for local railroad infrastructure when the dependent variable is the composite 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. 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.6: Market Access and Cooperative Culture: County-level Bin Scatter Plots



Note: This figure presents bin scatter plots of the relationship between log market access and cooperative culture 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: Cooperative Culture: Exclusion of Immigrants and Non-Whites

	Dependent variable: Cooperative Culture			
Sample:	Baseline	Exclude foreign-born	Exclude non-whites	Exclude non-whites and foreign-born
	(1)	(2)	(3)	(4)
logMA	0.1550***	0.1560***	0.1516***	0.1543***
	(0.0179)	(0.0167)	(0.0186)	(0.0168)
Observations	19,903	19,890	19,903	19,887
R^2	0.695	0.730	0.677	0.736
County Fixed-Effects	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes
Location cubic polynomial × State	Yes	Yes	Yes	Yes

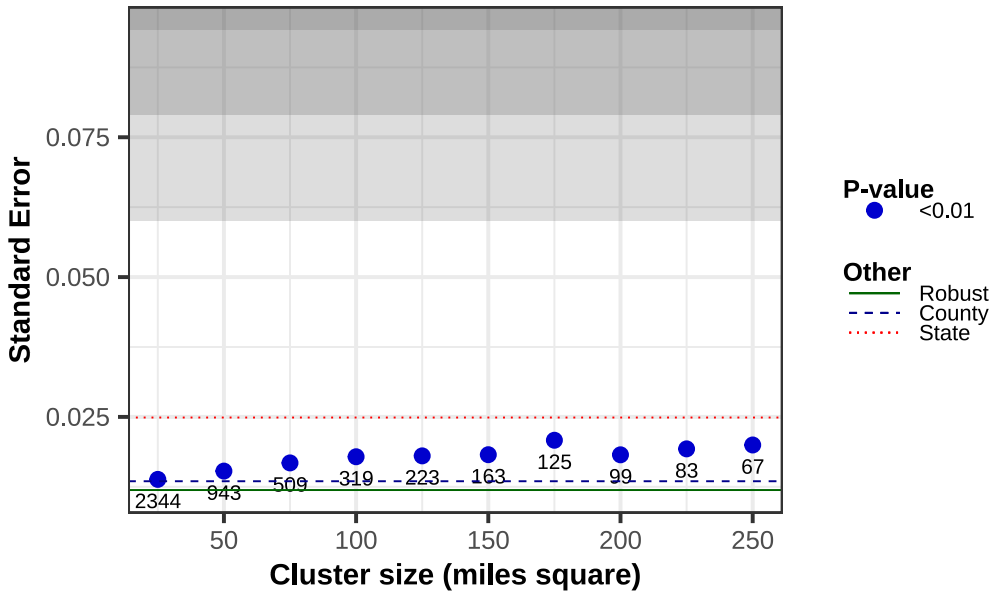
Note: This table reports estimates of equation 2 when the dependent variable is the composite cooperative culture index. The base sample used to calculate the county-level measures in column 1 includes all of the population not residing in group quarters. In column 2 the sample excludes foreign-born,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

Table A.3: 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	0.155***	0.414***	0.163***	1.20***	0.598***	0.399***	0.300***	0.241***
	(0.018)	(0.046)	(0.017)	(0.132)	(0.066)	(0.044)	(0.033)	(0.029)
	Panel B: Robustness							
	$P = 35$							
	$\theta = 6$	$\theta = 7$	$\theta = 8$	$\theta = 9$	$\theta = 10$	$\theta = 11$	$\theta = 12$	$\theta = 13$
Cooperative Culture	0.204***	0.178***	0.159**	0.144***	0.132***	0.123***	0.115***	0.109***
	(0.022)	(0.019)	(0.066)	(0.015)	(0.013)	(0.012)	(0.011)	(0.011)

Note: This table reports estimates of β from equation 2 when the dependent variable is the composite 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

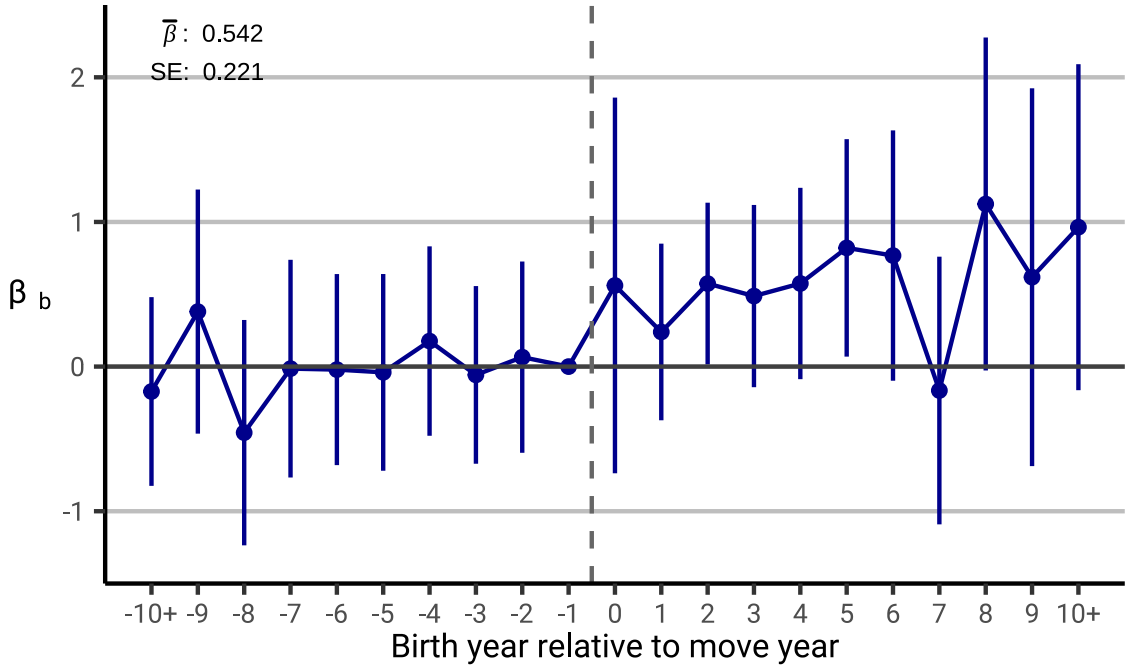
Figure A.7: Cooperative Culture: Different Standard Errors



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.4 Cooperative Cultural Traits: Individual-Level Analysis

Figure A.8: The impact of moving to a higher market access county on universal identification

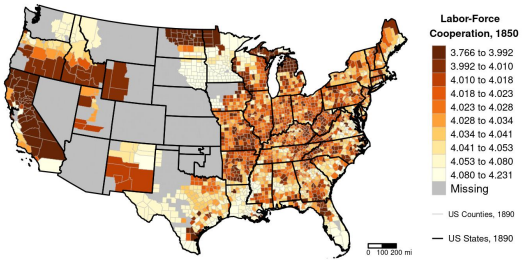


Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences estimation (equation 3), with an UNI measure in which "local" is always the county of origin. $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number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

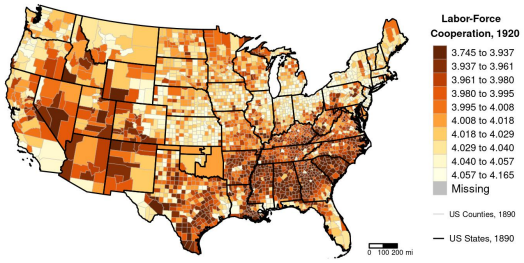
A.5 Market Access, Cooperation, and Prosocial Behavior

Figure A.9: Measures of Cooperation and Prosocial Behavior, 1850 and 1920

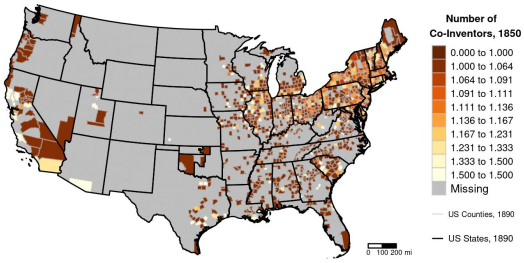
(a) Labor-force Cooperation, 1850



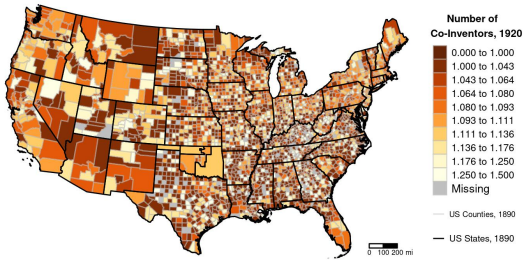
(b) Labor-force Cooperation, 1920



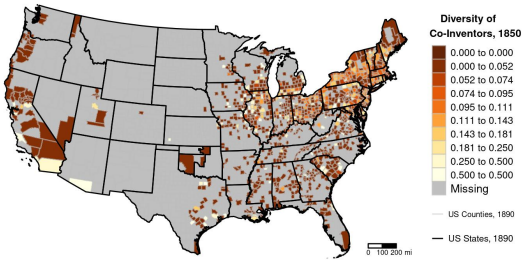
(c) Number of Co-Inventors, 1850



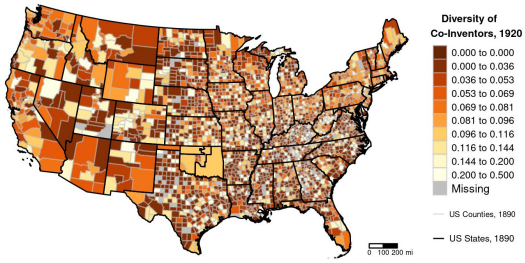
(d) Number of Co-Inventors, 1920



(e) Co-Inventors' Diversity, 1850



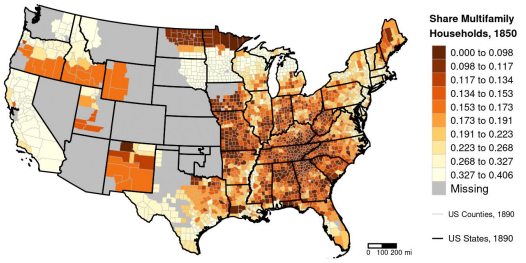
(f) Co-Inventors' Diversity, 1920



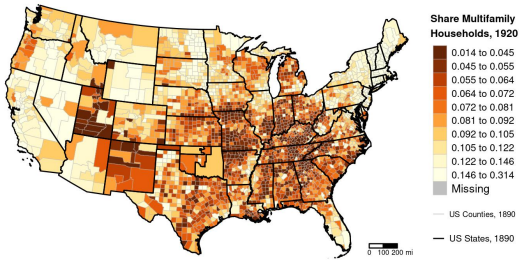
Note: This figure plots the spatial distributions of six measures of cooperation and prosocial behavior in the earlier period (left column) and the later period (left column). Exact periods vary my outcome. A darker color implies a higher degree of cooperation and prosociality.

Figure A.9: Measures of Cooperation and Prosocial Behavior, 1850 and 1920 (cont.)

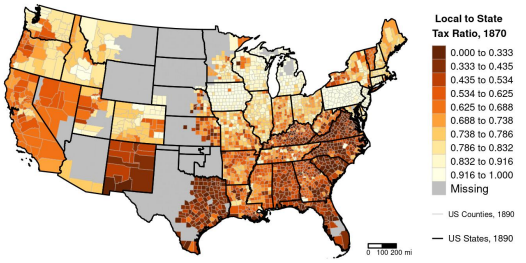
(g) Share Multifamily Households, 1850



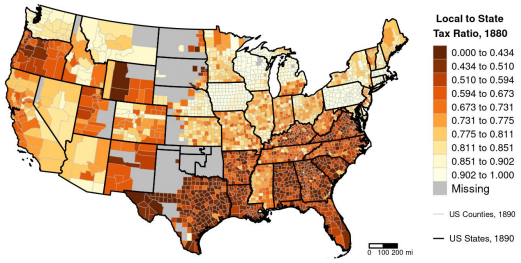
(h) Share Multifamily Households, 1920



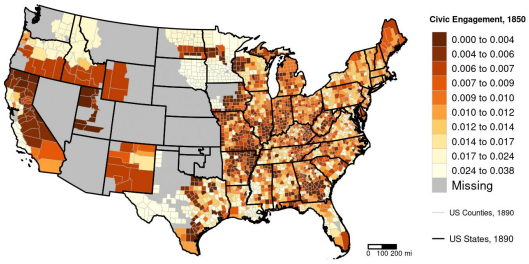
(i) Local to Total Taxes Ratio, 1870



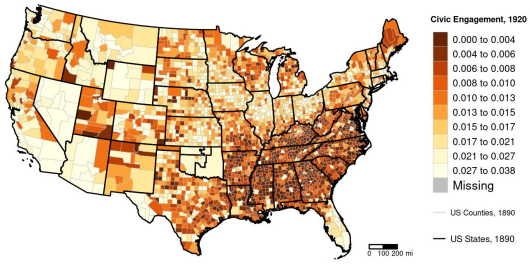
(j) Local to Total Taxes Ratio, 1880



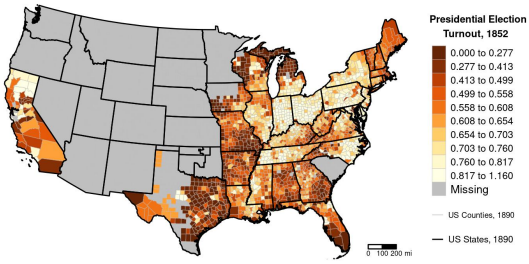
(k) Civic Engagement, 1850



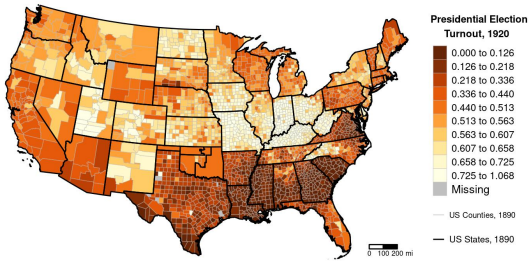
(l) Civic Engagement, 1920



(m) Voters Turnout, 1852

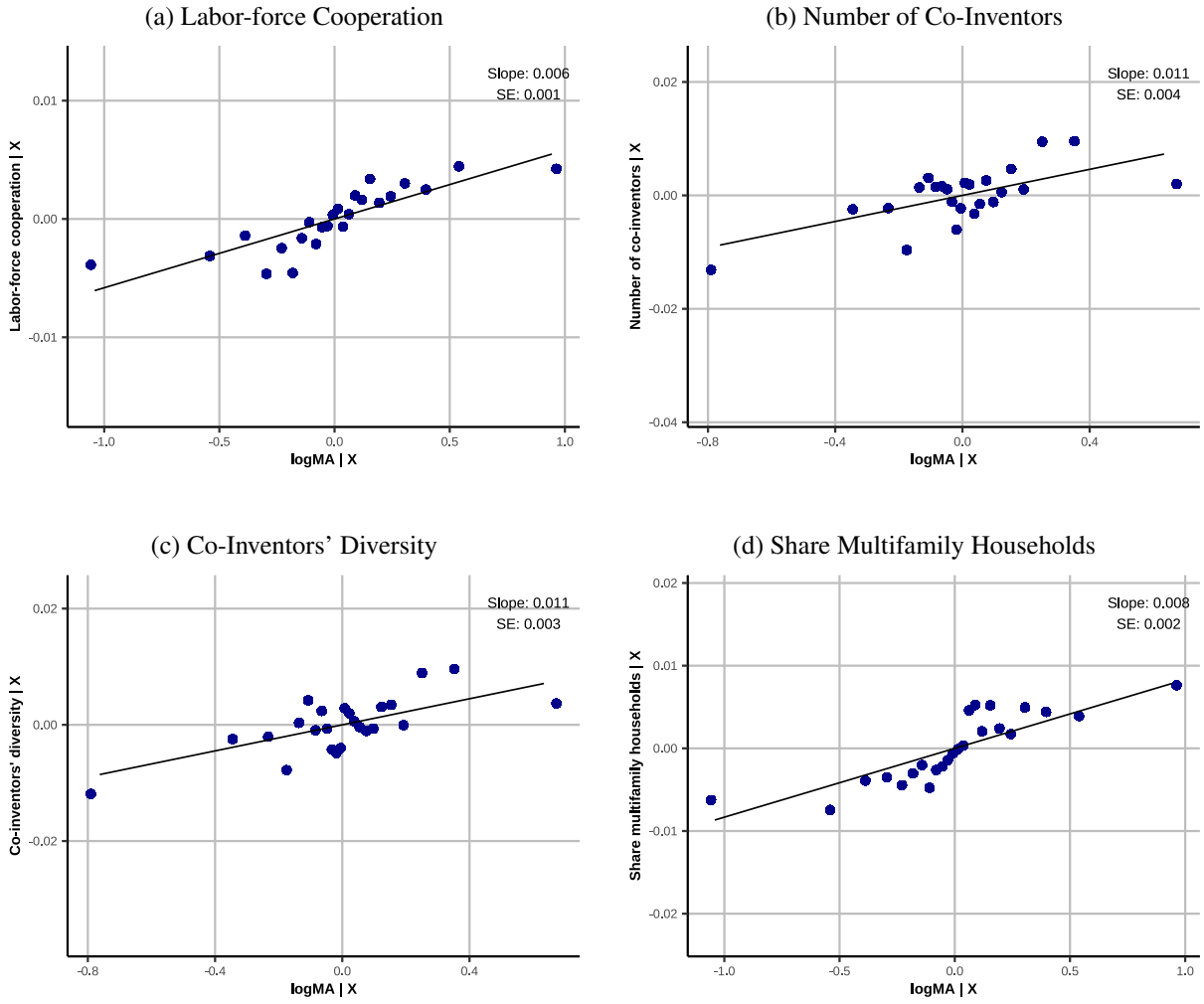


(n) Voters Turnout, 1920



Note: This figure plots the spatial distributions of six measures of cooperation and prosocial behavior in the earlier period (left column) and the later period (left column). Exact periods vary my outcome. A darker color implies a higher degree of cooperation and prosociality.

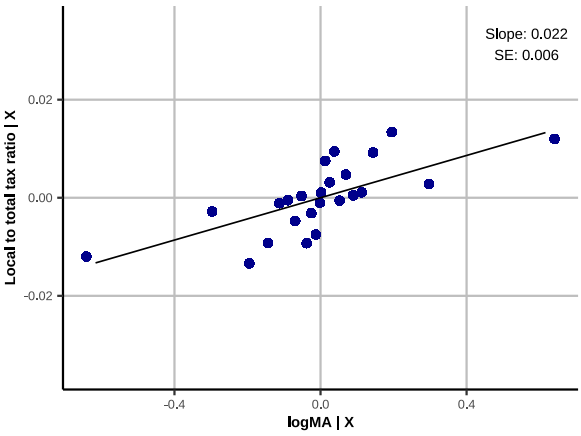
Figure A.10: Market Access, Cooperation, and Prosocial Behavior: County-level Bin Scatter Plots



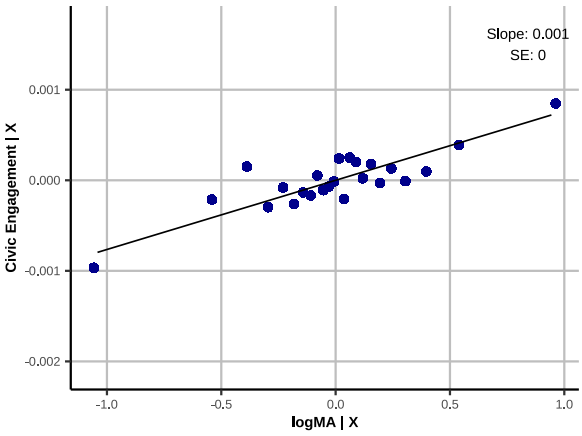
Note: This figure presents bin scatter plots of the relationship between log market access and cooperation and prosocial behavior, using equation 2. The plots present the conditional relationship after partialling out the baseline controls, corresponding to column 2 in Table 4. The size of the points is representative of the number of observations within each bin.

Figure A.10: Market Access, Cooperation, and Prosocial Behavior: County-level Bin Scatter Plots (cont.)

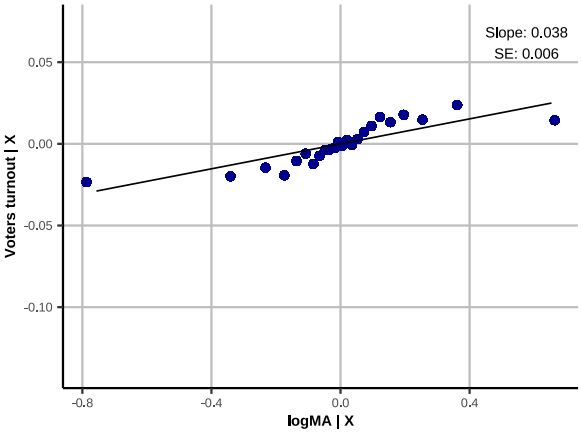
(e) Local to Total Tax Ratio



(f) Civic Engagement



(g) Voters Turnout



Note: This figure presents bin scatter plots of the relationship between log market access and cooperation and prosocial behavior, using equation 2. The plots present the conditional relationship after partialling out the baseline controls, corresponding to column 2 in Table 4. All bins have the same number of observations.

Table A.4: Market Access, Cooperation, and Prosocial Behavior: Railroad controls

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Labor-Force Cooperation (mean = 3.996 , sd = 0.059)					
Log market access	0.0055***	0.0058***	0.0047***	0.0036***	0.0033***	0.0024*
	(0.0013)	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Observations	18,263	18,263	18,263	18,263	18,263	18,263
R^2	0.670	0.680	0.680	0.683	0.683	0.684
	Panel B: Number of Co-Inventors (mean = 1.092 , sd = 0.116)					
Log market access	0.0119***	0.0115***	0.0083**	0.0100**	0.0100**	0.0092**
	(0.0035)	(0.0037)	(0.0041)	(0.0042)	(0.0045)	(0.0045)
Observations	17,355	17,355	17,355	17,355	17,355	17,355
R^2	0.237	0.241	0.241	0.242	0.239	0.242
	Panel C: Co-Inventors' Diversity (mean = 0.076 , sd = 0.106)					
Log market access	0.0100***	0.0112***	0.0080**	0.0090**	0.0090**	0.0085**
	(0.0032)	(0.0034)	(0.0038)	(0.0039)	(0.0041)	(0.0043)
Observations	17,355	17,355	17,355	17,355	17,355	17,355
R^2	0.238	0.241	0.242	0.242	0.239	0.243
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × State		Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes
Railroads within further buffers						Yes

Note: This table reports estimates of equation 2 with additional controls for local railroad infrastructure when the dependent variables are different historical measure of cooperation and prosocial behavior. 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. 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.4: Market Access, Cooperation, and Prosocial Behavior: Railroad controls (cont.)

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel D: Share Multifamily Households (mean = 0.151 , sd = 0.084)					
Log market access	0.0050**	0.0083***	0.0062**	0.0050**	0.0048*	0.0051**
	(0.0025)	(0.0022)	(0.0024)	(0.0025)	(0.0025)	(0.0025)
Observations	18,273	18,273	18,273	18,273	18,273	18,273
R^2	0.769	0.782	0.783	0.784	0.784	0.786
	Panel E: Local to Total Tax Ratio (mean = 0.67 , sd = 0.198)					
Log market access	0.0204***	0.0216***	0.0172**	0.0182**	0.0158**	0.0129*
	(0.0061)	(0.0064)	(0.0069)	(0.0071)	(0.0073)	(0.0072)
Observations	4,879	4,879	4,879	4,879	4,879	4,879
R^2	0.908	0.908	0.908	0.908	0.909	0.909
	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
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	18,262	18,262	18,262	18,262	18,262	18,262
R^2	0.680	0.687	0.687	0.697	0.697	0.698
	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***
	(0.0061)	(0.0061)	(0.0064)	(0.0068)	(0.0065)	(0.0064)
Observations	45,308	45,308	45,308	45,308	45,308	45,308
R^2	0.792	0.800	0.801	0.802	0.803	0.806
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × State		Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes
Railroads within further buffers						Yes

Note: This table reports estimates of equation 2 with additional controls for local railroad infrastructure when the dependent variables are different historical measure of cooperation and prosocial behavior. 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. 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: Cooperative Culture and Cooperative Behavior

	Dependent variable:			
	(1)	(2)	(3)	(4)
	Panel A: Labor-Force Cooperation (mean = 3.996 , sd = 0.059)			
Cooperative Culture	0.0285***	0.0204***	0.0131***	0.0135***
	(0.0030)	(0.0028)	(0.0020)	(0.0021)
Observations	17,248	17,248	17,248	17,248
R^2	0.080	0.499	0.703	0.711
	Panel B: Number of Co-Inventors (mean = 1.092 , sd = 0.116)			
Cooperative Culture	0.0069***	0.0063***	0.0028	0.0013
	(0.0022)	(0.0022)	(0.0033)	(0.0033)
Observations	16,988	16,988	16,988	16,988
R^2	0.001	0.048	0.241	0.244
	Panel C: Co-Inventors' Diversity (mean = 0.076 , sd = 0.106)			
Cooperative Culture	0.0046**	0.0041*	0.0016	0.0010
	(0.0021)	(0.0021)	(0.0031)	(0.0031)
Observations	16,988	16,988	16,988	16,988
R^2	0.0007	0.048	0.242	0.244
State × Year Fixed-Effects		Yes	Yes	Yes
County Fixed-Effects			Yes	Yes
Location cubic polynomial × State				Yes

Note: This table reports estimates of equation 1 when the dependent variables are different historical measure of cooperation and prosocial behavior: 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). 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: 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	0.0155***	0.0212***	0.0150***	0.0173***
	(0.0036)	(0.0032)	(0.0028)	(0.0026)
Observations	17,262	17,262	17,262	17,262
R^2	0.013	0.638	0.814	0.824
	Panel E: Local to Total Tax Ratio (mean = 0.67 , sd = 0.198)			
Cooperative Culture	0.1035***	0.0261***	0.0257***	0.0269***
	(0.0136)	(0.0055)	(0.0083)	(0.0082)
Observations	4,751	4,751	4,751	4,751
R^2	0.078	0.752	0.918	0.919
	Panel F: Civic Engagement (mean = 0.012 , sd = 0.009)			
Cooperative Culture	0.0038***	0.0040***	0.0031***	0.0035***
	(0.0005)	(0.0005)	(0.0003)	(0.0003)
Observations	17,248	17,248	17,248	17,248
R^2	0.065	0.423	0.735	0.742
	Panel G: Voters Turnout (mean = 0.63 , sd = 0.24)			
Cooperative Culture	0.0954***	0.0122**	0.0291***	0.0256***
	(0.0132)	(0.0052)	(0.0056)	(0.0053)
Observations	44,409	44,409	44,409	44,409
R^2	0.053	0.728	0.805	0.816
State × Year Fixed-Effects		Yes	Yes	Yes
County Fixed-Effects			Yes	Yes
Location cubic polynomial × State				Yes

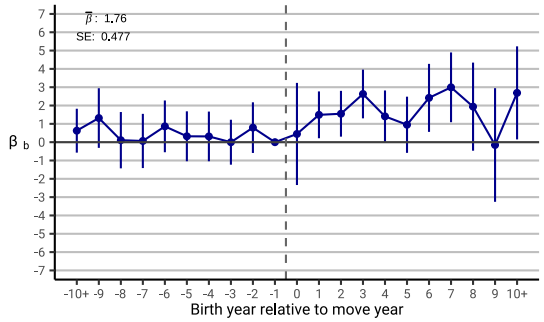
Note: This table reports estimates of equation 1 when the dependent variables are different historical measure of cooperation and prosocial behavior: labor-force cooperation (Panel A), the average number of patents co-inventors (Panel B), the diversity of of patents co-inventors (Panel C), the share 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). 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.6 Channels

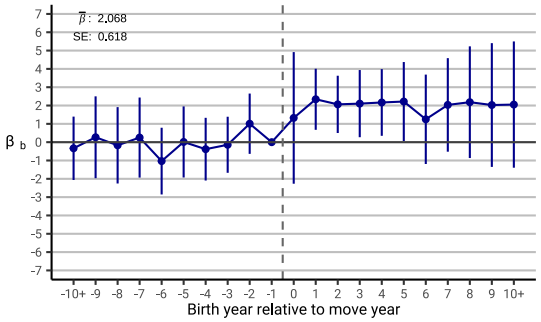
A.6.1 The Direct Impact of Commerce

Figure A.11: DID: The impact on farmers and migrants working in other commerce-intensive industries

(a) Commerce-intensive: farmers

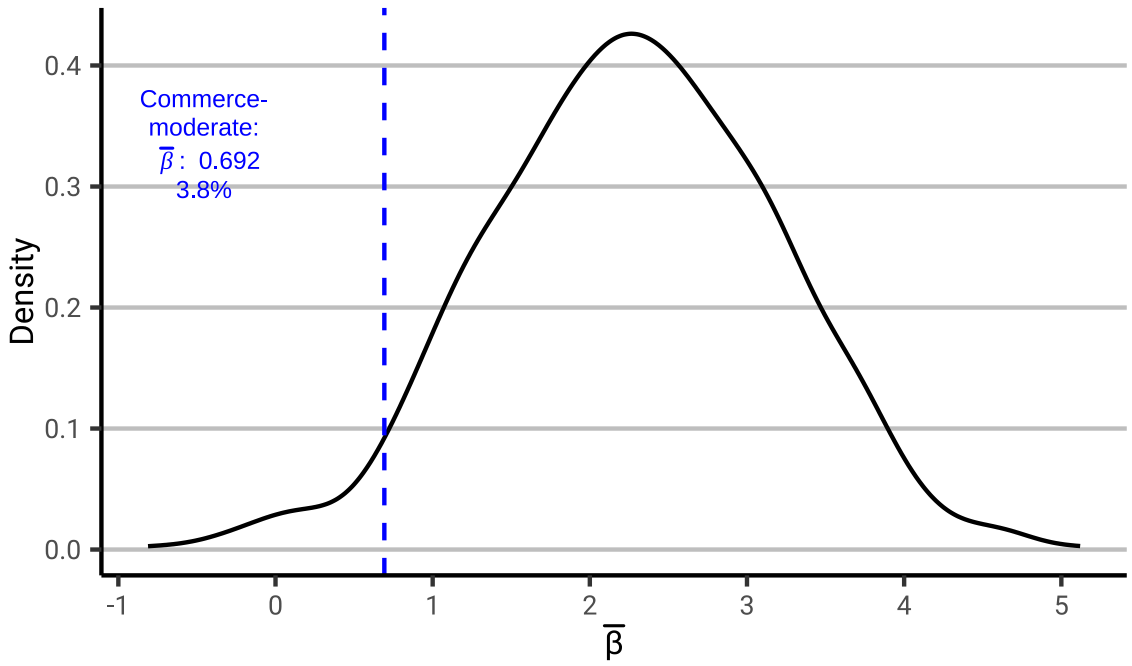


(b) Commerce-intensive: non-farmers



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. $\tilde{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

Figure A.12: Heterogeneous Impact is Not Driven by Sample Size



Note: This figure plots the distribution of estimates of $\tilde{\beta}$, the average treatment effects from the difference-in-differences framework (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 $\tilde{\beta}$ for the commerce-moderate group (Figure 6, Panel B).

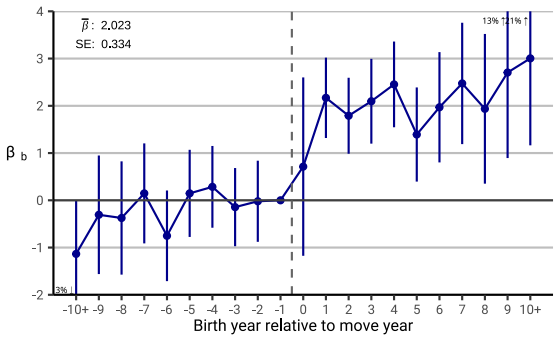
Table A.6: Characteristics of Families in Commerce-Intensive and Commerce-Moderate Categories

	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

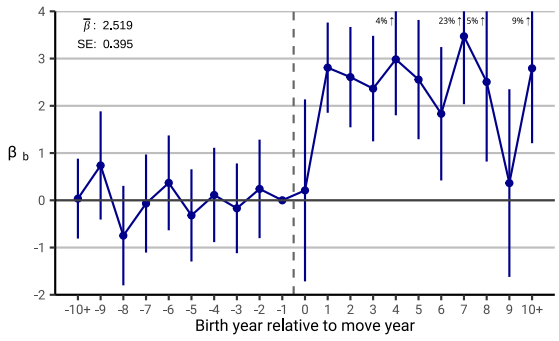
Note: This table reports the mean characteristics of domestic out-of-state migrant households in the commerce-intensive and commerce-moderate categories. Standard errors in parenthesis.

Figure A.13: Heterogeneous Impact is Not Driven by Family Size

(a) Small Families (No. Children ≤ median)



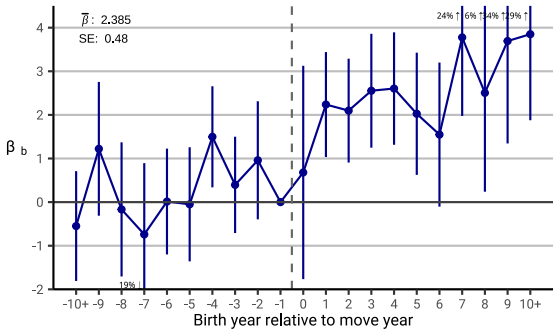
(b) Large Families (No. Children > median)



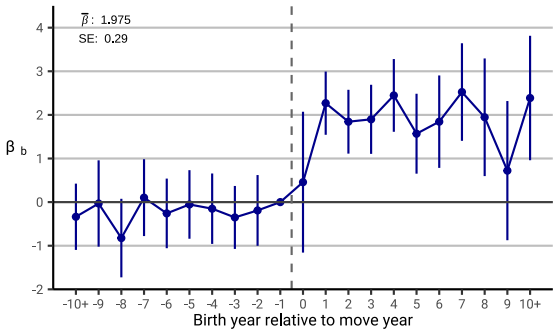
Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences estimation (equation 3). In Panel A, the sample is restricted to households in which the number of children is below or equal to the median. In Panel B, the sample is restricted to households 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.14: Heterogeneous Impact is Not Driven by Urban vs. Rural Origins

(a) Urban Origin



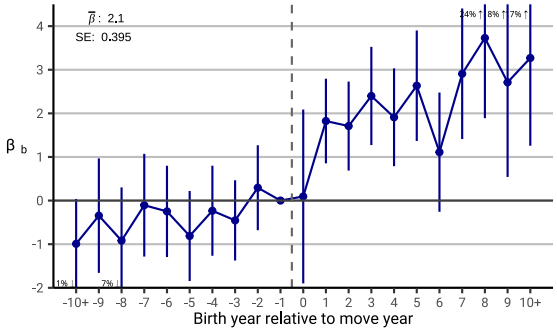
(b) Rural Origin



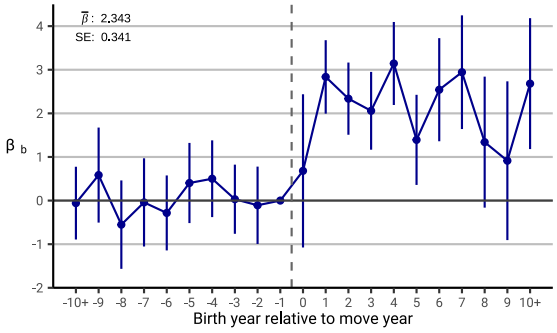
Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences estimation (equation 3). In Panel A, the sample is restricted to households that originated from urban location. In Panel B, the sample is restricted to households that originated from rural locations.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

Figure A.15: Heterogeneous Impact is Not Driven by Intra- vs. Extra-Community Marriage

(a) Extra-Community Marriage



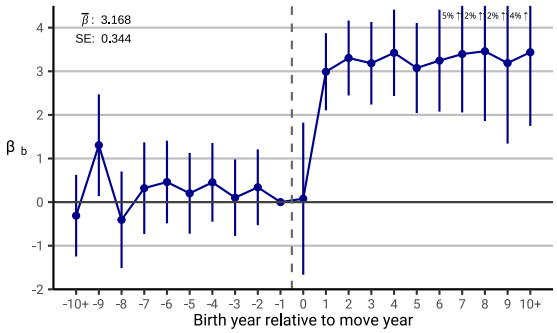
(b) Intra-Community Marriage



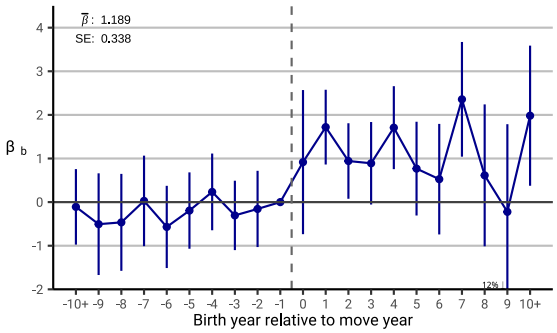
Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences estimation (equation 3). In Panel A, the sample is restricted to households in extra-community marriage. In Panel B, the sample is restricted to households in intra-community marriage. $\bar{\beta}$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

Figure A.16: Heterogeneous Impact is Not Driven by High vs. Low Prior Universal Identification

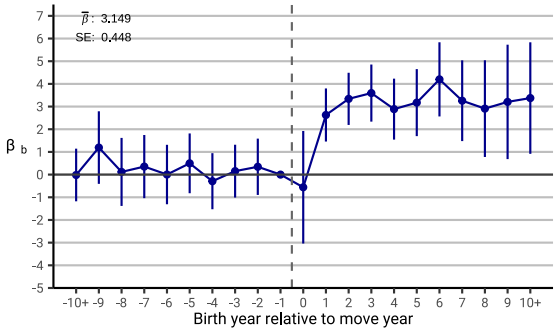
(a) High Prior UNI



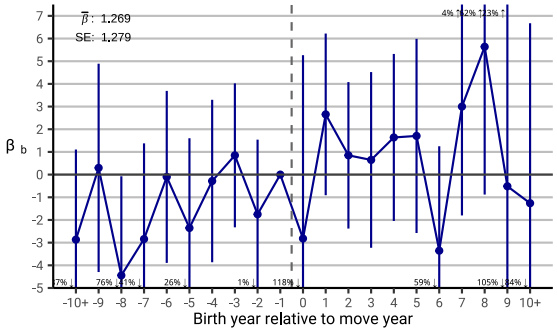
(b) Low Prior UNI



(c) Commerce Intensive, High Prior UNI



(d) Commerce Moderate, High Prior UNI

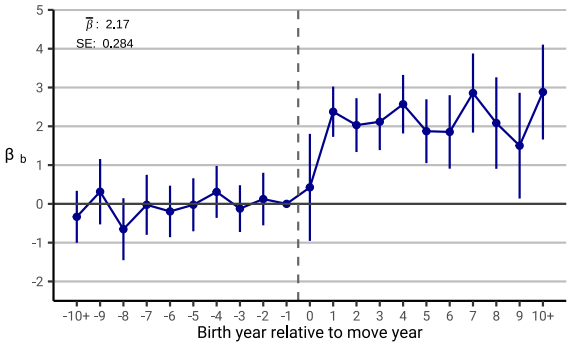


Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences estimation (equation 3). In Panel A, the sample is restricted to households in which the average UNI of children born before the migration is above the median. In Panel B, the sample is restricted 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. 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.

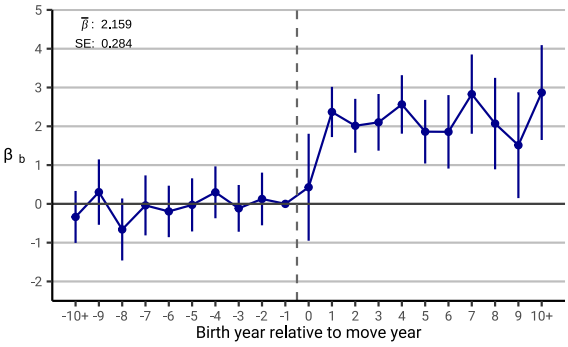
A.6.2 Indirect Channels

Figure A.17: The Impact is Not Driven by Indirect Channels

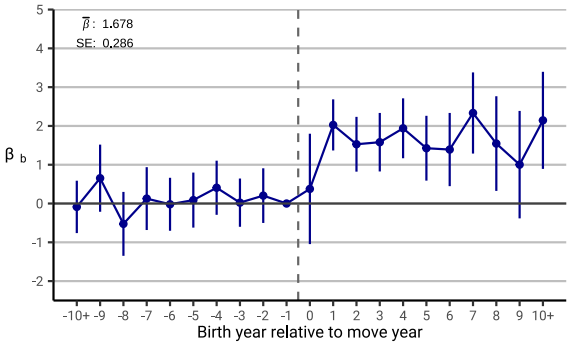
(a) Add. ctrl: Share Immigrants



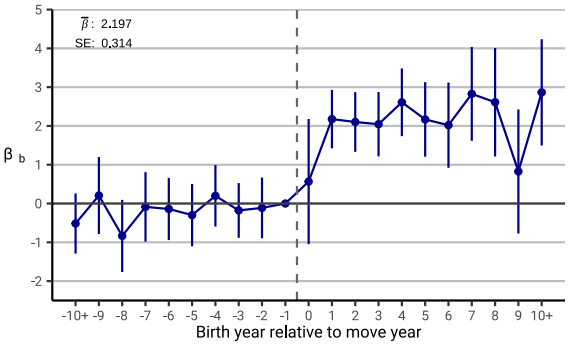
(b) Add. ctrl: Birthplace Diversity



(c) Add. ctrl: Share Urban



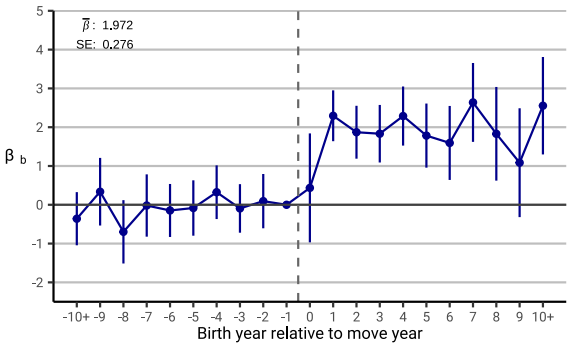
(d) Add. ctrl: Manufacturing Est. PC



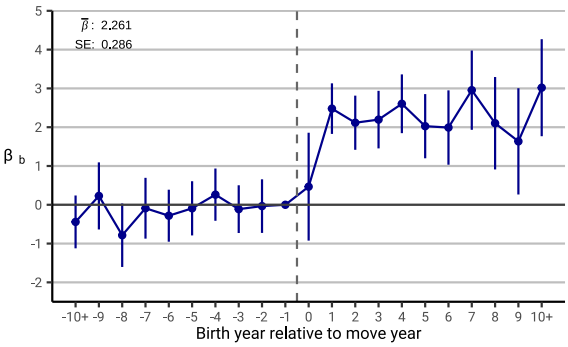
Note: This figure plots the estimates of β_b and 95% confidence intervals from an augmented version of the difference-in-differences estimation (equation 3) that also controls for the dynamic impact of potential mediators, defined as the differences in the levels of the potential mediator between origin 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), the number of information workers per 1,000 (Panel F), the number of lawyers and judges per 1,000 (Panel G), and all potential mediators (Panel H). $\tilde{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

Figure A.17: The Impact is Not Driven by Indirect Channels

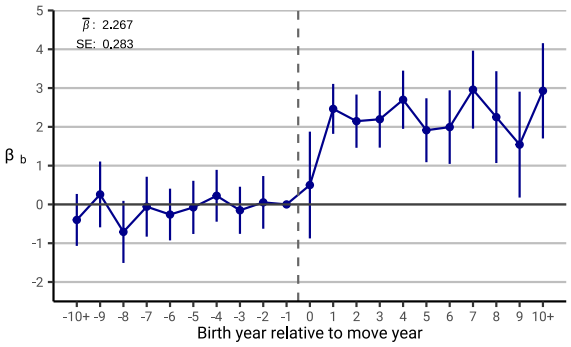
(e) Add. ctrl: Occupational Income Score



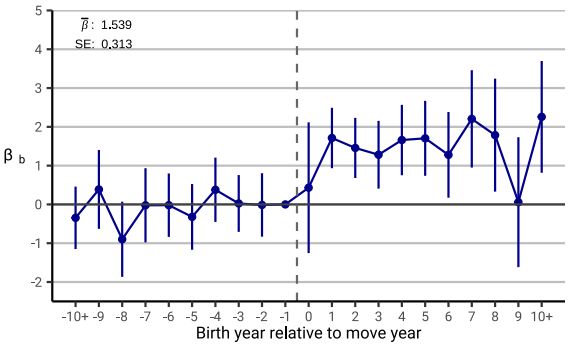
(f) Add. ctrl: Information Workers per 1,000



(g) Add. ctrl: Lawyers and Judges per 1,000



(h) Add. ctrl: All



Note: This figure plots the estimates of β_b and 95% confidence intervals from an augmented version of the difference-in-differences estimation (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), the number of information workers per 1,000 (Panel F), the number of lawyers and judges per 1,000 (Panel G), and all potential mediators (Panel H). $\bar{\beta}$ 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 Robustness of Prevalence of Commerce Results

Table B.1: Market Access and Market Language: More market terms

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Mean top 20 market terms share (mean = 0.365 , sd = 0.097)					
Log market access	0.0141***	0.0129***	0.0098**	0.0140***	0.0136***	0.0132***
	(0.0036)	(0.0038)	(0.0042)	(0.0045)	(0.0047)	(0.0050)
Observations	8,610	8,610	8,610	8,610	8,610	8,610
R^2	0.642	0.642	0.642	0.644	0.645	0.647
	Panel B: Mean top 50 market terms share (mean = 0.227 , sd = 0.062)					
Log market access	0.0098***	0.0088***	0.0069***	0.0093***	0.0088***	0.0084***
	(0.0023)	(0.0024)	(0.0026)	(0.0028)	(0.0029)	(0.0031)
Observations	8,610	8,610	8,610	8,610	8,610	8,610
R^2	0.642	0.643	0.643	0.645	0.646	0.647
	Panel C: Mean top 100 market terms share (mean = 0.169 , sd = 0.047)					
Log market access	0.0073***	0.0065***	0.0050**	0.0067***	0.0063***	0.0060**
	(0.0018)	(0.0019)	(0.0020)	(0.0022)	(0.0023)	(0.0023)
Observations	8,610	8,610	8,610	8,610	8,610	8,610
R^2	0.642	0.643	0.643	0.644	0.645	0.647
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location cubic polynomial × State		Yes	Yes	Yes	Yes	Yes
Any railroad			Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes
Railroads within further buffers						Yes

Note: This table reports estimates of equation 2 with additional controls for local railroad infrastructure 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. 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***	0.0050***	0.0050***	0.0050***	0.0050***	0.0050***
	(0.0007)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0010)
Observations	18,262	18,262	18,262	18,262	18,262	18,262
R^2	0.773	0.773	0.773	0.770	0.767	0.763
DV mean	0.0540	0.0540	0.0540	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 × State 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	0.0805***	0.0042***	0.0042***	0.2263***
	(0.0224)	(0.0013)	(0.0012)	(0.0326)
Observations	18,256	18,262	18,262	18,262
R^2		0.726	0.736	0.605
Pseudo R^2	0.053			
County Fixed-Effects	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes
Location cubic polynomial × State 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. 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	0.0050***	0.0046***	0.0040***	0.0036***
	(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	18,262	18,208	18,253	18,193
R^2	0.772	0.782	0.772	0.775
County Fixed-Effects	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes
Location cubic polynomial × State	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.2 Robustness of Cooperative Culture Results: County-Level

Table B.5: 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	0.9342***	0.8147***	1.014***	0.9070***
	(0.1614)	(0.1683)	(0.1655)	(0.1745)
Observations	18,178	18,178	18,178	18,178
R^2	0.806	0.812	0.811	0.816
	Panel B: Extra-Community Marriage			
logMA	0.0069*	0.0145***	0.0011	0.0082*
	(0.0037)	(0.0044)	(0.0035)	(0.0042)
Observations	18,175	18,166	18,174	18,158
R^2	0.908	0.911	0.909	0.917
	Panel C: Norms Tolerance Index			
logMA	0.1709***	0.1854***	0.1762***	0.1889***
	(0.0226)	(0.0241)	(0.0232)	(0.0247)
Observations	18,094	17,994	18,072	17,966
R^2	0.642	0.635	0.642	0.633
County Fixed-Effects	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes
Location cubic polynomial × State	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation 2 when the dependent variables are the UNI (Panel A), the share of EICM (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: 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	0.934***	2.46***	0.973***	7.15***	3.58***	2.39***	1.80***	1.45***
	(0.161)	(0.451)	(0.171)	(1.30)	(0.648)	(0.431)	(0.323)	(0.259)
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	0.171***	0.432***	0.179***	1.25***	0.625***	0.417***	0.314***	0.255***
	(0.023)	(0.066)	(0.024)	(0.191)	(0.095)	(0.063)	(0.047)	(0.038)
RDI	0.272***	0.748***	0.286***	2.17***	1.08***	0.720***	0.540***	0.433***
	(0.035)	(0.097)	(0.037)	(0.281)	(0.141)	(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)	(0.399)	(0.199)	(0.132)	(0.099)	(0.079)
Fairness	0.108**	0.306**	0.115**	0.898**	0.441**	0.292**	0.218**	0.174**
	(0.047)	(0.134)	(0.050)	(0.384)	(0.191)	(0.127)	(0.095)	(0.076)

Note: This table reports estimates of β from equation 2 when the dependent variables are different historical cooperative cultural traits: the UNI, the ECM, the NTI, the RDI, social trust, and concern for fairness, 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

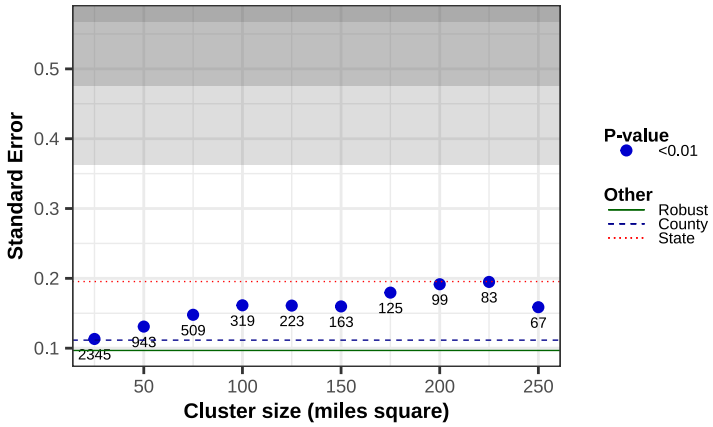
Table B.6: Cooperative Cultural Traits: Different Market Access Measures (cont.)

	(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	1.23***	1.07***	0.956***	0.867***	0.797***	0.744***	0.705***	0.679***
	(0.217)	(0.188)	(0.166)	(0.148)	(0.135)	(0.124)	(0.115)	(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	0.218***	0.193***	0.174***	0.159***	0.147***	0.137***	0.129***	0.122***
	(0.031)	(0.027)	(0.023)	(0.021)	(0.019)	(0.017)	(0.016)	(0.015)
RDI	0.363***	0.314***	0.278***	0.251***	0.230***	0.214***	0.201***	0.191***
	(0.047)	(0.040)	(0.036)	(0.032)	(0.029)	(0.027)	(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)
Fairness	0.146**	0.125**	0.111**	0.099**	0.090**	0.082**	0.076**	0.071**
	(0.064)	(0.054)	(0.048)	(0.043)	(0.038)	(0.035)	(0.033)	(0.030)

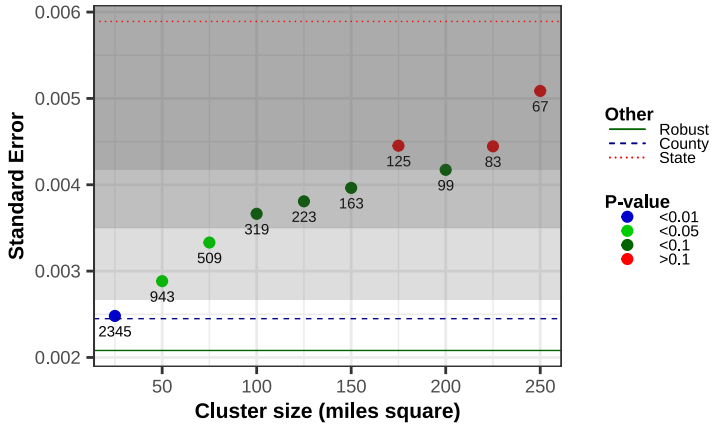
Note: This table reports estimates of β from equation 2 when the dependent variables are different historical cooperative cultural traits: the UNI, the ECM, the NTI, the RDI, social trust, and concern for fairness, and market access is calculated using different average costs P and different trade elasticities 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: Cooperative Cultural Traits: Different Standard Errors

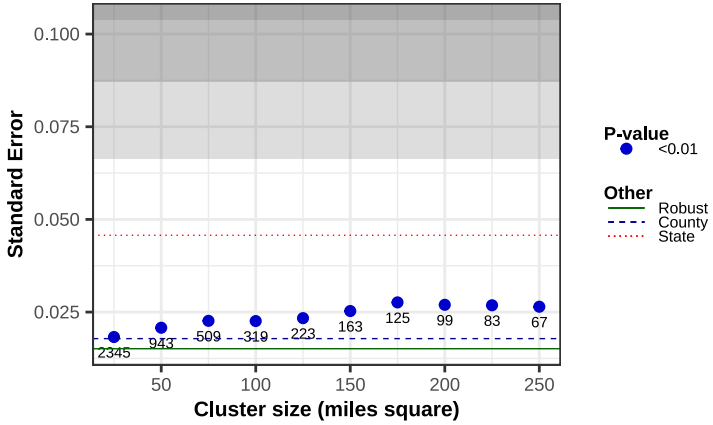
(a) Universal Name Index



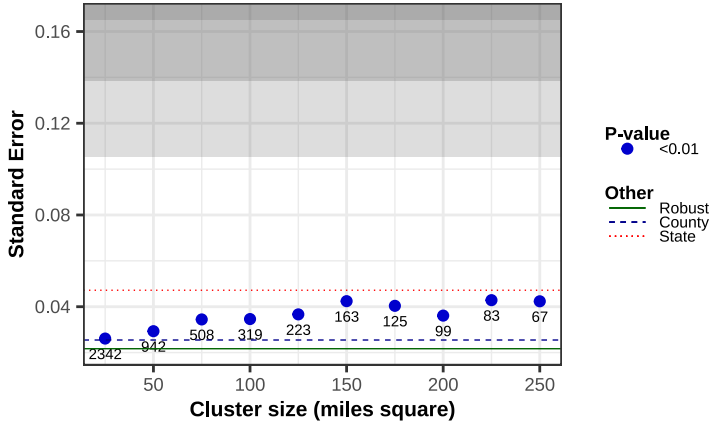
(b) Extra-Community Marriage



(c) Norms Tolerance Index



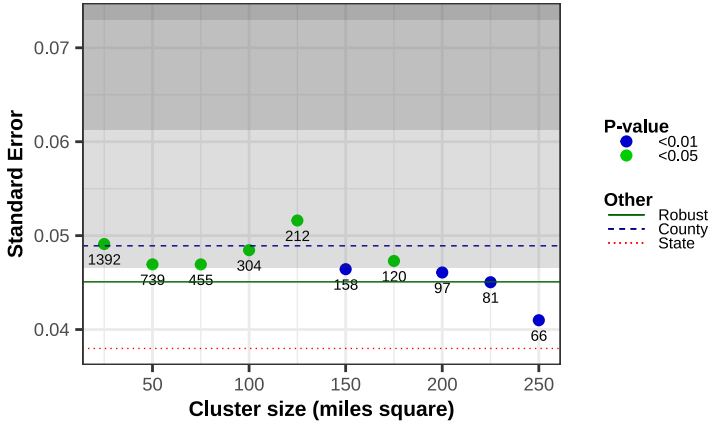
(d) Religious Diversity Index



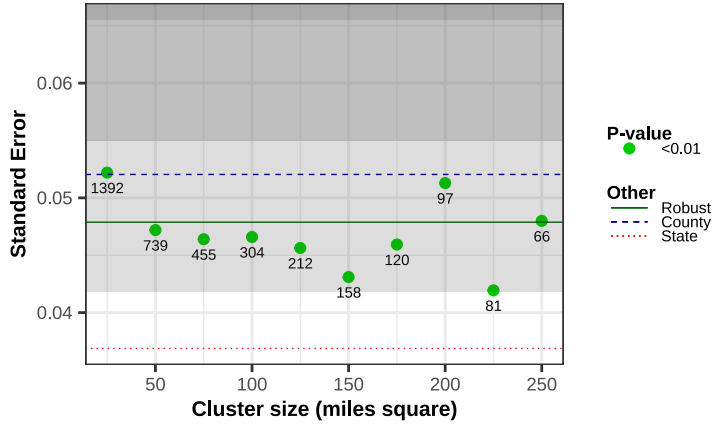
Note: This figure plots the standard errors of β from the preferred specification of equation 2 using different approaches for inference. The blue dots represent the standard errors (on the y-axis) using arbitrary grid-cell of different sizes (on the x-axis), as proposed by Bester et al. (2011). The 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.

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

(e) Social Trust



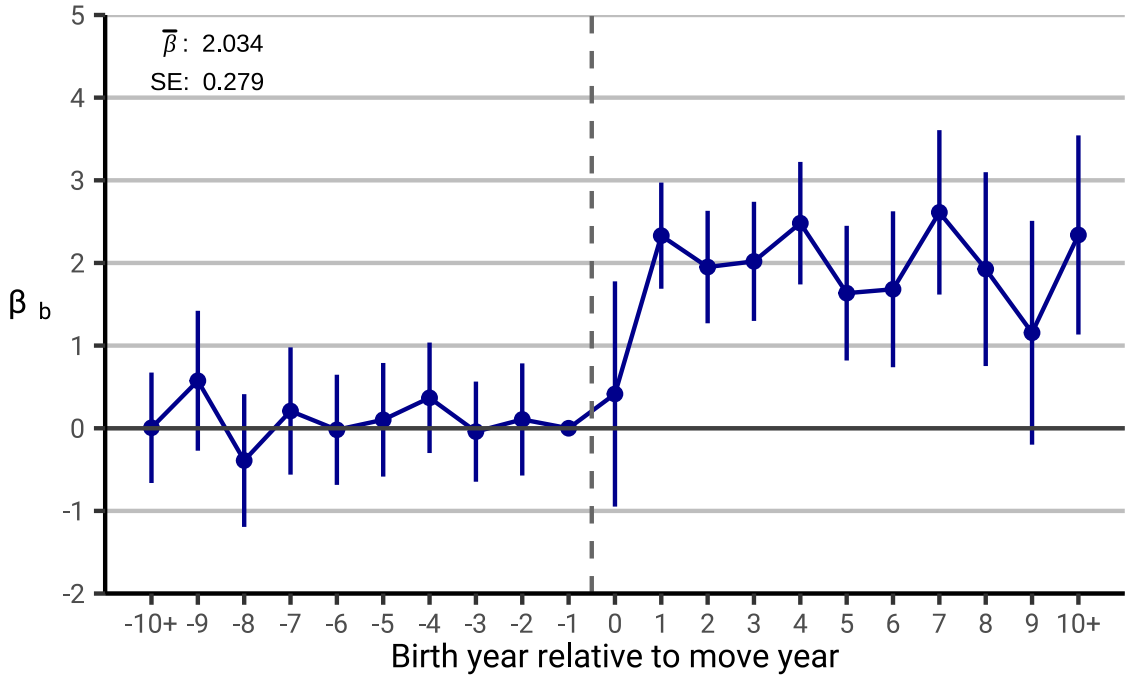
(f) Concern for Fairness



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.

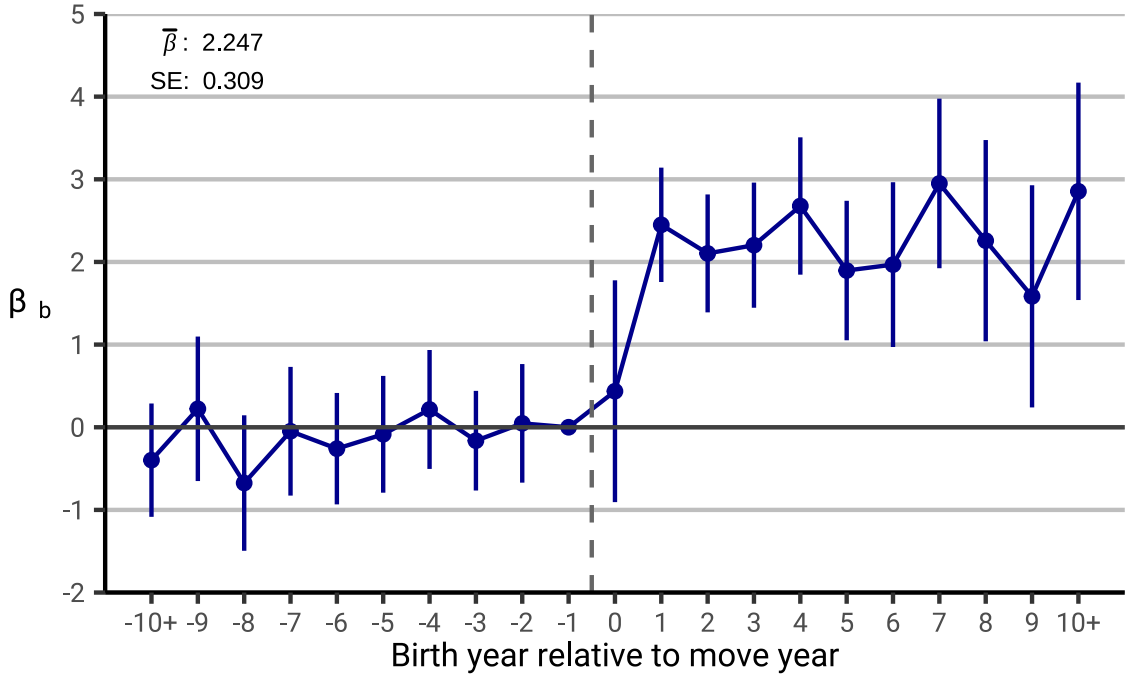
B.3 Robustness of Cooperative Cultural Traits Results: DID

Figure B.2: DID robustness: controlling for children's characteristics



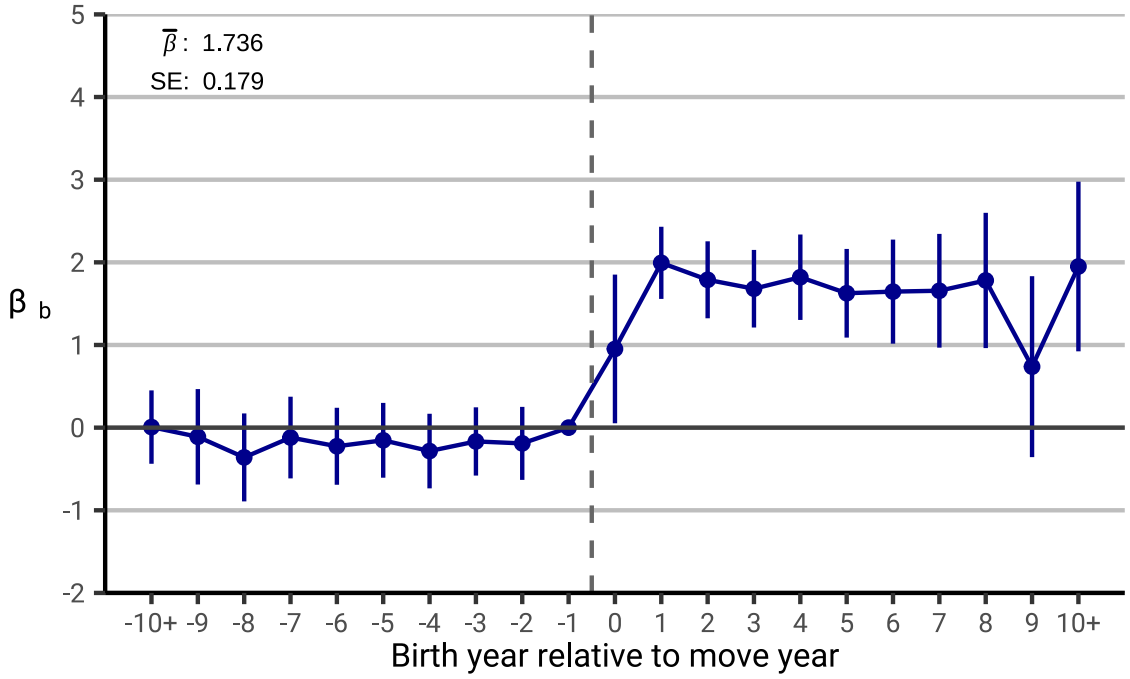
Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences estimation (equation 3), with additional child-level controls: gender, birth order, and a 5-year cohort fixed effects. $\bar{\beta}$ is the average treatment effect across post-migration periods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

Figure B.3: 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 estimation (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.

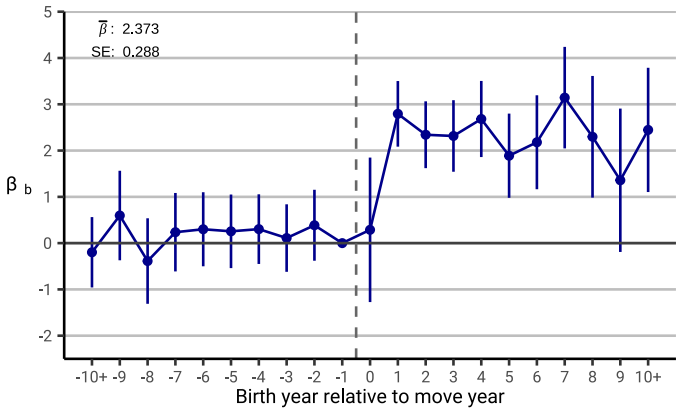
Figure B.4: DID robustness: continuous treatment



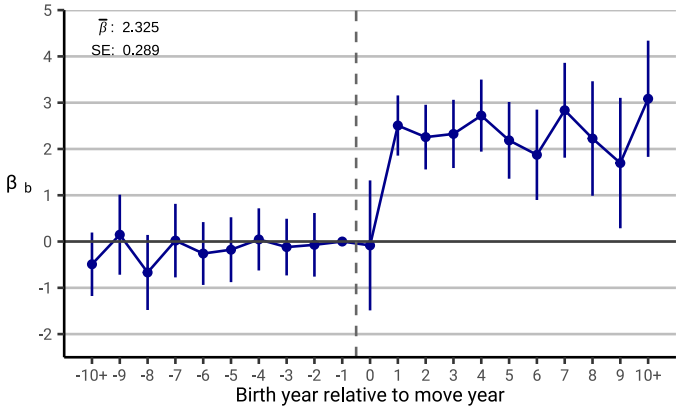
Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences estimation when treatment is defined in a continuous way and equals the difference in log market access between the county of destination and the county of origin. $\bar{\beta}$ is the average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

Figure B.5: DID robustness: Exclusion of Immigrants and Non-Whites

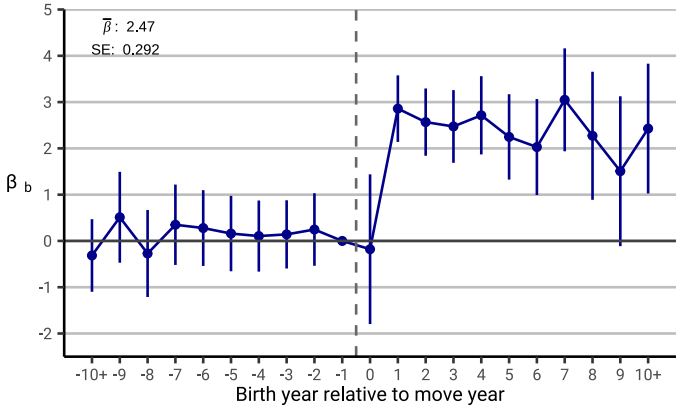
(a) Exclude foreign-born



(b) Exclude non-whites



(c) Exclude non-whites and foreign-born



Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences estimation (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.4 Robustness of Cooperation Results

Table B.7: 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***	0.023***	0.016***	0.012***	0.009***
	(0.001)	(0.004)	(0.001)	(0.010)	(0.005)	(0.003)	(0.003)	(0.002)
No. Co-Inventors	0.011***	0.033***	0.012***	0.096***	0.048***	0.032***	0.024***	0.019***
	(0.004)	(0.011)	(0.004)	(0.032)	(0.016)	(0.010)	(0.008)	(0.006)
Co-Inventors' Div.	0.011***	0.033***	0.012***	0.096***	0.048***	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	0.022***	0.060***	0.023***	0.175***	0.087***	0.058***	0.043***	0.035***
	(0.006)	(0.018)	(0.007)	(0.052)	(0.026)	(0.017)	(0.013)	(0.010)
Civic Engagement	0.0008***	0.002***	0.0008***	0.006***	0.003***	0.002***	0.002***	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)

Note: This table reports estimates of β from equation 2 when the dependent variables are different measures of historical 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

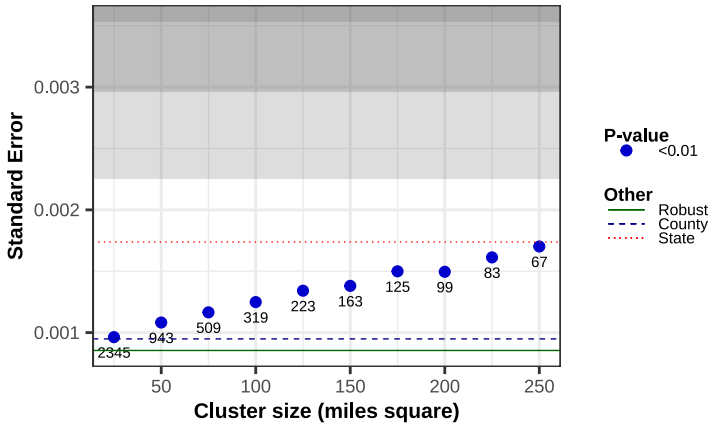
Table B.7: Cooperation: Different Market Access Measures (cont.)

	(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***	0.004***	0.004***	0.004***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0010)	(0.0009)	(0.0008)
No. Co-Inventors	0.016***	0.014***	0.012***	0.011***	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.	0.016***	0.013***	0.011***	0.010***	0.009***	0.008***	0.008***	0.007***
	(0.005)	(0.004)	(0.004)	(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	0.029***	0.025***	0.022***	0.020***	0.018***	0.017***	0.016***	0.015***
	(0.009)	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(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)

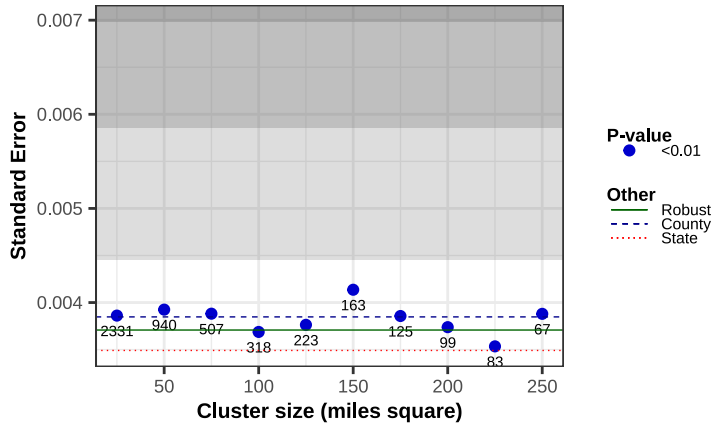
Note: This table reports estimates of β from equation 2 when the dependent variables are different measures of historical cooperation and market access is calculated using different average costs P and different trade elasticities θ. Standard errors clustered at arbitrary grid cells of 100 miles square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

Figure B.6: Cooperation: Different Standard Errors

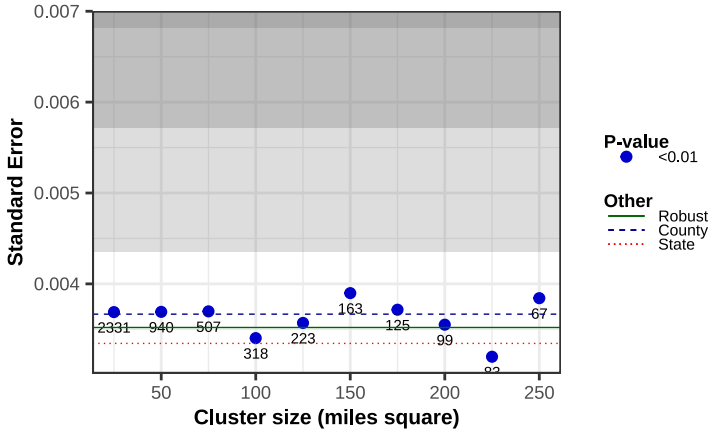
(a) Labor-force Cooperation



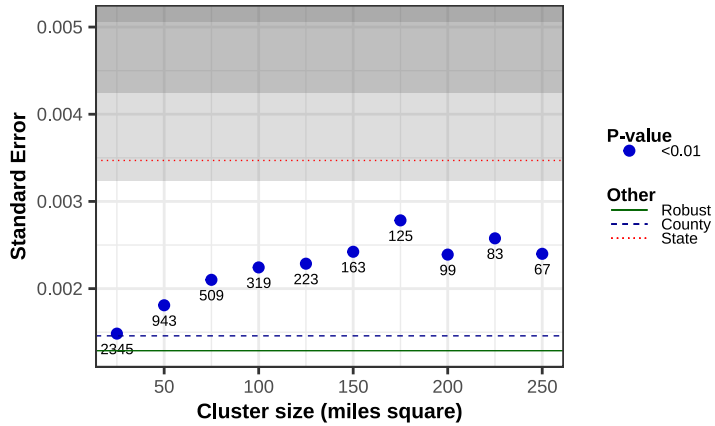
(b) Number of Co-Inventors



(c) Co-Inventors' Diversity



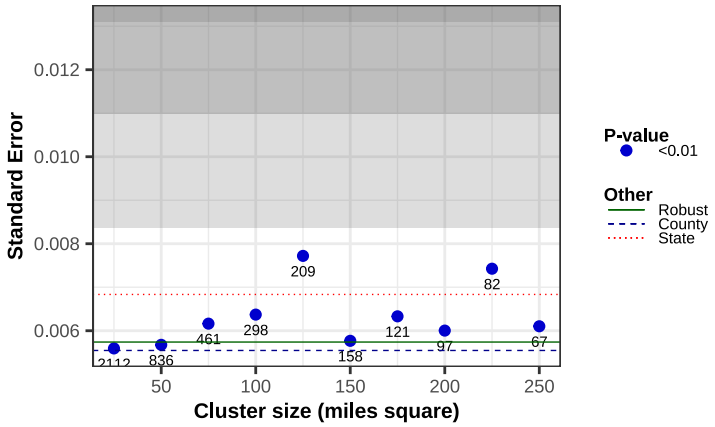
(d) Share Multifamily Households



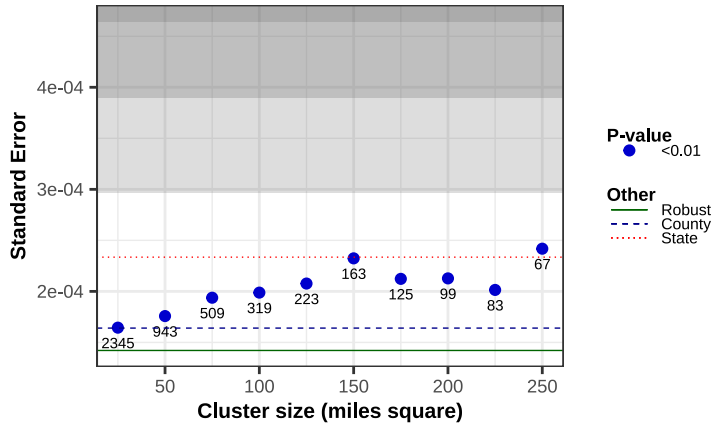
Note: This figure plots the standard errors of β from the preferred specification of equation 2 using different approaches for inference. The blue dots represent the standard errors (on the y-axis) using arbitrary grid-cell of different sizes (on the x-axis), as proposed by Bester et al. (2011). The 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.

Figure B.6: Cooperation: Different Standard Errors (cont.)

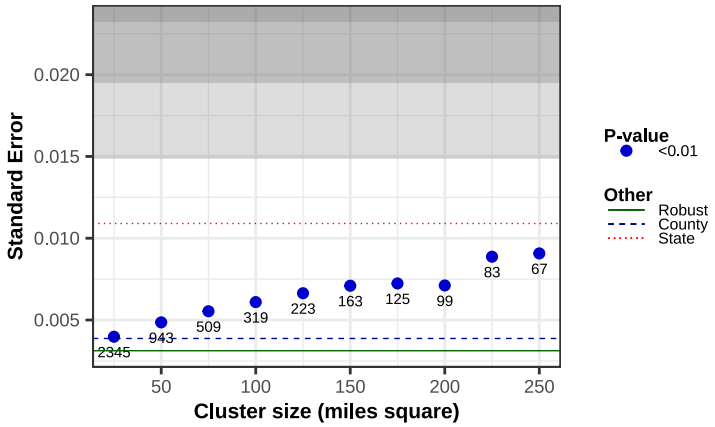
(e) Local to Total Taxes



(f) Civic Engagement



(g) Voters Turnout



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.8: 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	0.0121***	0.0117***	0.0115***	0.0115***	0.0108**	0.0084
	(0.0032)	(0.0035)	(0.0037)	(0.0037)	(0.0042)	(0.0054)
Observations	17,355	17,355	17,355	17,355	17,355	17,355
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	0.0120***	0.0120***	0.0118***	0.0112***	0.0112***	0.0090*
	(0.0026)	(0.0026)	(0.0029)	(0.0034)	(0.0034)	(0.0049)
Observations	17,355	17,355	17,355	17,355	17,355	17,355
R^2	0.246	0.246	0.243	0.241	0.241	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)	(0.0027)
Observations	18,273	18,273	18,273	18,273	18,273	18,273
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	0.0860	0.0880	0.0920
	Panel D: Civic Engagement					
Log market access	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	18,262	18,262	18,262	18,262	18,262	18,262
R^2	0.690	0.689	0.688	0.685	0.682	0.678
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 × State 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 cooperation and prosocial behavior: 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.9: 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	0.0070	0.0063*	0.0044*	0.0090**
	(0.0049)	(0.0032)	(0.0023)	(0.0040)
Observations	17,355	17,355	17,355	17,355
R^2		0.244	0.244	0.244
Pseudo R^2	0.002			
	Panel B: Co-Inventors' Diversity (mean = 0.082 , sd = 0.14)			
Log market access	0.0884*	0.0096**	0.0095***	0.7488***
	(0.0483)	(0.0045)	(0.0037)	(0.0863)
Observations	16,144	17,355	17,355	17,355
R^2		0.247	0.246	0.439
Pseudo R^2	0.077			
	Panel C: Share Multifamily Households (mean = 0.155 , sd = 0.099)			
Log market access	0.0284**	0.0070**	0.0061***	0.0715***
	(0.0135)	(0.0028)	(0.0023)	(0.0204)
Observations	18,273	18,273	18,273	18,273
R^2		0.764	0.773	0.692
Pseudo R^2	0.058			
	Panel D: Civic Engagement (mean = 0.013 , sd = 0.011)			
Log market access	0.0765***	0.0011***	0.0010***	0.2085***
	(0.0191)	(0.0003)	(0.0003)	(0.0365)
Observations	18,254	18,262	18,262	18,262
R^2		0.593	0.604	0.567
Pseudo R^2	0.039			
County Fixed-Effects	Yes	Yes	Yes	Yes
State × Year Fixed-Effects	Yes	Yes	Yes	Yes
Location cubic polynomial × State Fixed-Effects	Yes	Yes	Yes	Yes

Note: This table reports estimates of equation 2 when the dependent variables are three different historical measure of cooperation and prosocial behavior: 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). Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$