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

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Abstract

We study how rising market integration shaped cooperative culture and behavior in the United States between 1850 and 1920. This period marked a major episode of domestic market integration, when rapid railroad expansion and mass migration created an unprecedented, highly integrated national economy. We combine county-level market access with full-count censuses, newspapers, election returns, tax records, and patent data to construct measures of universalism, tolerance, and generalized trust—cultural traits that support cooperation with strangers—as well as indicators of cooperative behavior and the prevalence of impersonal, mutually beneficial interactions. We find that increased market access fostered impersonal cooperative cultural traits, increased impersonal cooperation, and reduced kin-based support. Using linked census records to track domestic migrants, we find no systematic evidence of selection: counties gaining market access did not attract migrants with stronger pre-migration universalism or related characteristics. Instead, migrants who moved to these counties adapted rapidly, becoming more universalistic and increasingly engaged in impersonal interactions. Adaptation was concentrated among individuals working in commerce-intensive industries and was associated with improved economic outcomes. Our analysis of mechanisms suggests that exposure to impersonal, mutually beneficial exchange was central to how market integration reshaped cooperative culture and broadened the scope of cooperation. These findings help reconcile competing views on markets' social consequences: market integration fostered impersonal cooperation while eroding kin-based support.

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

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

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

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

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

— Adam Smith, The Wealth of Nations, Chapter I

1 Introduction

How markets shape the social fabric remains a contested question. Enlightenment thinkers such as Montesquieu (1748) argued that commerce softens manners and reduces prejudice, a view echoed by Smith (1776) and Hume (1758). This *doux commerce* hypothesis is consistent with modern work claiming that market interactions—unlike those within families or in-groups—foster *impersonal* prosocial norms that support cooperation beyond kin and local networks (e.g., Henrich et al., 2010; Tabellini, 2008), and it aligns with recent evidence stemming primarily from small-scale or pre-industrial societies (Henrich et al., eds, 2004; Henrich et al., 2010; Enke, 2022; Agneman and Chevrot-Bianco, 2023; Rustagi, 2024b). In these frameworks, cooperation is sustained by internalized values and norms: individuals derive non-monetary benefits from acting fairly and trustworthily. Morality can be parochial, sustaining cooperation within a narrow in-group, or impersonal, extending values and norms of fairness and trust to strangers and anonymous others. As economies become more integrated and people gain more opportunities for mutually beneficial exchanges beyond their in-group networks, the returns to impersonal cooperative cultural traits rise, making them more adaptive and expanding the scope of cooperation. In contrast, critics—from Marx (1867), Veblen (1899) and Polanyi (1944) to more recent commentators (Sandel, 2012; Stiglitz, 2024) and laboratory work debating whether markets erode moral concerns (Falk and Szech, 2013; Bartling et al., 2023)—have argued that expanding markets can commodify social relationships, crowd out intrinsic moral motivations, and foster alienation.

In this paper, we provide new evidence on this question by focusing on one of history’s most significant episodes of market integration: the United States between 1850 and 1920, when the country became the world’s largest economy and a highly integrated national market. During this period, the U.S. underwent a “great transformation” into what Polanyi (1944) called a “market society”, in which expanding market integration fundamentally altered social and economic life. This transition was facilitated by a vast expansion of the railroad network, which grew from about 9,000 miles in 1850 to 238,000 by 1920, and the rapid growth in population driven by mass immigration from Europe and internal migration. We combine a county-level measure of market integration potential with a wide range of measures of impersonal cooperative culture, cooperative behavior directed at both kin and non-kin, and impersonal mutually beneficial social interactions constructed from full-count census data, historical newspapers, patents, and other sources. We make three main findings. First, rising market integration fostered a package of interrelated impersonal cultural traits: universalism, tolerance, and generalized trust. Second, it increased impersonal forms of cooperative behavior. Third, it decreased kin-based support. Consistent with this reorientation of cooperation away from kin-based networks, we also find that greater market integration increased local commerce and the prevalence of impersonal, mutually beneficial interactions in workplaces, households, and civic life. Using linked individual census data on domestic migrants, we further find that these changes arose primarily through cultural adaptation rather than selective migration. This cultural response is concentrated among migrants working in commerce-intensive industries, appears to have brought material benefits to those who adapted, and is not easily accounted for by concurrent changes in factors such as income or contact with more diverse populations. Taken together, these findings support a mechanism in which market integration reshapes culture and forms of cooperation through increased exposure to impersonal, mutually beneficial exchange, and they help reconcile the competing views on the social consequences of markets.

Guided by a simple conceptual framework adapted from Tabellini (2008), we map the core concepts to empirical measures. We operationalize market integration using a county-level measure of "market access" (Donaldson and Hornbeck, 2016). This measure combines transportation costs to all other counties with their population sizes, capturing each county's potential for trade. Counties' market access grew unevenly over time, driven by the expansion of the railroad network and by population growth—largely due to mass immigration and internal migration.

We capture what we refer to as *impersonal cooperative culture* by focusing on cultural traits that support cooperation with strangers—universalism, tolerance, and social trust. We measure universalism and tolerance using measures developed and validated in Raz (2025). Drawing on full-count census data, universalism is measured with the Universal Name Index (UNI), which reflects parental identification with the broader nation relative to their local community, and the rate of Extra-Community Marriage (ECM), which indicates openness to relationships beyond the in-group. Higher UNI and ECM scores reflect greater orientation toward out-group cooperation. Tolerance of different family-related behaviors (such as mothers' ages at first birth) is measured with the Norms Tolerance Index (NTI), and tolerance of religious practices and identities with the Religious Diversity Index (RDI). Finally, we construct and validate a new county-level measure of social trust by applying modern natural language processing techniques to a large historical corpus of U.S. local newspapers, capturing generalized trust in others, including out-group members.

To measure *cooperative behavior*—defined as individually costly but socially beneficial actions—we construct county-level indicators of both impersonal and kin-based cooperation. For impersonal cooperation, we use voter turnout in presidential elections as a standard proxy for civicness (e.g., Putnam, 1995; Alesina and La Ferrara, 2000; Rustagi, 2024a), and we use the share of tax revenues raised at the town and county level rather than the state level to capture willingness to incur private costs to finance local public goods that benefit broad, non-kin populations (Putnam et al., 1993). For kin-based cooperation, we follow Ghosh et al. (2023) and focus on vulnerable individuals—orphans, people with disabilities, and the elderly—measuring the share cared for by relatives at home, using the full-count censuses.

In addition, we measure the prevalence of commerce and impersonal, mutually beneficial social interactions in labor markets, innovation, households, and civic life. These outcomes capture beneficial interactions that may not always involve individually costly behavior and are therefore conceptually distinct from cooperation. We measure the local prevalence of commerce with the share of newspaper pages with commerce-related content, calculated using historical local U.S. newspapers from *newspapers.com*, and the share of residents employed in wholesale and retail, calculated using census data. Additionally, we combine census data with modern O*NET work-style ratings matched to historical occupations to construct a county-level index of employment in occupations that require cooperation in the workplace. Using patent data (Berkes, 2018), we track collaborative invention and whether co-invention extends beyond family networks. We use census data on multifamily households to proxy for day-to-day interaction among non-kin within homes, and census-based employment in civic, public administration, and recreational sectors to capture opportunities for impersonal social and civic engagement (Putnam, 1995).

Before turning to our main analysis, we first show that our measures of impersonal cooperative culture are strongly associated with observed cooperative behavior and social interactions. Counties with higher levels of impersonal cooperative culture exhibit more impersonal cooperation, a higher prevalence of impersonal, mutually beneficial interactions across domains, and a lower reliance on kin-based networks to support vulnerable individuals. These relationships hold both across counties within states and within counties over time, and remain robust to controlling for local economic development. Taken together, this evidence supports the construct validity of our measures and underscores the tight empirical relationship between impersonal cooperative culture and behavior.

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

Our estimates suggest sizable effects: a one percent increase in a county's market access raises universalism by 0.14 standard deviations (Universal Name Index) and 0.03 SD (Extra-Community Marriage). Tolerance increases by 0.18 SD (NTI, family-related norms) and 0.27 SD (RDI, religious norms), while social trust rises by 0.12 SD. The same increase in market access also increases impersonal cooperation by 0.09–0.16 SD across measures, while kin-based cooperation falls by 0.11 SD.

To further strengthen the causal interpretation of these findings, we use three strategies developed in the market access literature (Donaldson and Hornbeck, 2016; Hornbeck and Rotemberg, 2024). First, we show that our estimates are very similar when we recenter market access around its "expected" value following Borusyak and Hull (2023), based on potential extensions to the canal network in the absence of the railroad network (Fogel, 1964). Second, we leverage the fact that county market access depends on the entire transportation network and population sizes in other counties, and not only local changes in railroads and population. By flexibly controlling for own- and nearby-county railroad expansion and population, we demonstrate that our findings are robust to using only distant changes in the railroad network and population to identify the effect of market access. Third, we employ two instrumental variable strategies to instrument for changes in market access—a recentered-IV using the expected market access in the absence of railroads and a measure of market access based on the 1850 canal and river network.

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

To explore sorting, we test whether counties with increasing market access attracted a selected set of migrants who were already more universalistic or differed in other important ways. We consider a range of pre-migration characteristics, including universalism (average UNI of children born pre-migration, ECM), social interactions (father's labor-force cooperation score, prior residence with non-kin, kinship geographic proximity), demographic attributes (number of children, urban vs. rural origin, nativity), and economic measures (occupational income scores, sector of employment). We find no systematic relationship between changes in market access and these pre-migration characteristics. While we cannot entirely rule out selection, this finding suggests that sorting plays at most a limited role in explaining the positive link between market access and impersonal cooperative culture and behavior.

To study cultural adaptation, we use an event-study difference-in-differences design. We compare siblings born before and after migration in families who gained or lost market access due to the move and track changes in parental universalism, measured by their children's UNI scores. We find that moving to a county with greater market access (relative to origin) increased parents' universalism by 0.13 SD, relative to moves that reduced market access, with the effect appearing within a year of migration and persisting for at least a decade. This result is robust to alternative definitions of the UNI, including computing UNI scores using the origin county as the reference population rather than the destination county. These results indicate that migrants who gain market access adapt their cooperative cultural traits in ways consistent with responding rapidly to the economic incentives and opportunities for impersonal exchange in more market-integrated environments, and are consistent with recent findings documenting rapid cultural adaptation to environmental changes (e.g., Rao, 2019; Bau, 2021; Lowe, 2021; Raz, 2025; Ghosh et al., 2025).

We close by shedding light on *why* market access shaped impersonal cooperative culture and behavior. Because market integration fundamentally transformed many aspects of economic and social life, several channels may be at play, and, absent exogenous variation in each, we cannot fully disentangle their individual roles. Nevertheless, we perform an array of empirical tests to assess the plausibility of multiple potential channels.

We provide evidence consistent with a mechanism in which increased market access led to cultural adaptation primarily through greater exposure to beneficial exchanges with strangers and increased economic interdependence beyond family and local networks. First, using both the county-level and migrant-level frameworks, we show that increases in market access raised the local prevalence of commerce and broadened the extent of impersonal, mutually beneficial interactions—at work, at home, and in civic life. Second, we use our difference-in-differences framework to provide direct evidence supporting our hypothesis that cultural adaptation was a response to increased economic interdependence. Specifically, we show that the increase in universalism is concentrated among migrants employed in commerce-intensive industries—those whose livelihoods depended most on interactions with strangers and market-based exchange—including manufacturing, agriculture, wholesale, retail, and transportation, with no effect among workers in locally oriented sectors like construction, utilities, entertainment and recreation, and public administration.[1] This suggests that adaptation is related to greater exposure to impersonal, commerce-driven interactions. Importantly, this heterogeneous treatment effect cannot be readily explained by observed pre-existing differences between individuals across these groups (e.g., rural versus urban origin, family size, or prior cultural traits). Third, we provide evidence suggesting that this cultural adaptation brought economic benefits. Comparing families who moved from the same origin to the same destination county in the same decade, we find that those who became more universalistic after moving to a higher market access county experienced larger gains: their children's survival rates are 0.12 SD higher and their parents' real property holdings 0.21 SD higher, than those of migrants who became less universalistic. While these correlations do not identify causal returns to adaptation, they show that migrants who adapted culturally to a higher market access environment experienced substantially better economic and demographic outcomes. Taken together, these findings suggest that market integration shaped impersonal cooperative culture directly by increasing exposure to impersonal, commerce-based interactions, rather than solely through broader shifts in the local socioeconomic environment.

We then turn to explore plausible alternative channels highlighted in the literature. First, market in-

[1] Results are very similar when we use a modern classification of industries into tradable and non-tradable (Barkai and Karger, 2020).

tegration may promote income growth, urbanization, and industrialization, which have been linked to universalistic and tolerant values (e.g., Inglehart, 1997; Inglehart and Welzel, 2005; Fouka and Serlin, 2024). Second, it may increase intergroup contact and diversity, as improved transport can attract more migrants. This may foster broader social ties and shift social relationships away from tightly knit social networks toward looser and more diverse ones, which, in turn, may shift norms toward greater universalism and tolerance (e.g., Allport, 1954; Lowe, 2021; Bursztyn et al., 2024; Ghosh et al., 2025). We empirically assess both of these alternative channels. Using the migrant data, we show that cultural adaptation to higher market access is similar for migrants who moved up versus down the occupational ladder, and for those who transitioned out of agriculture versus those who remained farmers. Likewise, migrants who continued to have strong contact with a narrow in-group after migration, as measured by living near kin, adapted as much as those who did not. These patterns suggest that neither higher income nor a simple shift away from kin-centered networks are sufficient to account for our results.

More generally, higher market access might have affected multiple socioeconomic features, such as inducing industrialization and the transition out of agriculture, promoting urbanization, and improving the flow of information, which, in turn, could shape culture and behavior. Moreover, our cultural measures might partially reflect changes in economic conditions rather than, or in addition to, genuine cultural change. To explore these possibilities, we construct historical proxy measures that together capture changes in income, structural change, industrialization, urbanization, population diversity, access to information, and the development of legal institutions, and demonstrate that all of our results remain highly robust when we control for them.

Thus, while we cannot rule out the possibility that these alternative channels played some role, our evidence points to increased exposure to impersonal, mutually beneficial exchange with strangers, including out-group members and anonymous others, as a central mechanism through which market integration reshaped impersonal cooperative culture and the scope of cooperation.

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

Related Literature. Our findings contribute to several strands of literature. First, we advance the centuries-long debate about the social consequences of markets (see Hirschman, 1982). Cross-cultural and local contemporary studies often find a positive relationship between market integration and prosocial cultural traits and behaviors (Henrich et al., eds, 2004; Henrich et al., 2010; Baldassarri, 2020; Enke, 2022; Agneman and Chevrot-Bianco, 2023; Rustagi, 2024b). In contrast, laboratory experiments suggest that market interaction can erode moral concerns (Falk and Szech, 2013), although this interpretation is debated (Bartling et al., 2023). A third line of work studies exposure to financial markets and trade in large-scale societies, documenting associations with trust, social and political cohesion (Guiso et al., 2009; Jha, 2013; Jha and Shayo, 2019; Grosfeld et al., 2020; Buggle and Durante, 2021; Margalit and Shayo, 2021; Jha et al., 2025), but also with nationalism and backlash (Shayo, 2009, 2020; Montenegro Helfer, 2025).

Leveraging the expansion of the railroads and rich historical U.S. data, we contribute to this literature in four main ways. First, we study a transformative period when market integration became a central organizing principle in what became the world's leading market economy, leveraging rich historical U.S. data. Second, we provide comprehensive evidence that market integration simultaneously increased impersonal cooperation and decreased kin-based cooperation, documenting a fundamental cultural impact and a reorientation in the scope of cooperative behavior. Third, we establish that these effects operate mainly through individual cultural adaptation rather than selective migration. Fourth, we provide extensive evidence on the underlying mechanism, documenting an important role for exposure to impersonal, mutually beneficial exchange. Our results support the *doux commerce* hypothesis (Montesquieu, 1748; Smith, 1776) by documenting a positive effect of market integration on impersonal cooperation and the traits that sustain it, and by providing empirical support for mechanisms emphasized in Tabellini (2008) and Henrich (2020). At the same time, we find that market integration weakened kin-based social insurance, consistent with concerns raised by critics of markets (Marx, 1867; Polanyi, 1944). Our findings thus support the reconciliation of these competing views proposed by Henrich (2020): market integration fosters impersonal cooperation while weakening kin-based ties.

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

Finally, our paper complements the literature on the economic impact of railroads in the U.S. (Fogel, 1964; Atack et al., 2010, 2011; Donaldson and Hornbeck, 2016; Chan, 2022; Hornbeck and Rotemberg, 2024) and elsewhere (e.g., Metzer, 1974; Donaldson, 2018). We focus on the cultural impact of market integration driven by the expansion of the railroad network. Our results suggest that market integration and trade may also promote development indirectly, by fostering cultural traits that are conducive to growth and innovation (Gorodnichenko and Roland, 2011, 2017; Posch et al., 2025).

Outline. The rest of this paper is organized as follows: Section 2 lays out the conceptual framework, deriving five testable predictions and guiding our empirical measures. Section 3 briefly describes the historical background. In Section 4, we explain how we measure market access, impersonal cooperative culture, cooperative behavior, impersonal mutually beneficial social interactions, and local prevalence of commerce. In Section 5, we document the correlations between impersonal cooperative culture, behavior, and mutually beneficial interactions. Section 6 presents our results from the county-level analysis, while Section 7 examines selection and adaptation using the design based on domestic migrants. Section 8 explores mechanisms. Section 9 concludes.

2 Conceptual Framework

A central hypothesis in both economics and cultural evolution is that integration into markets shapes people's psychology and norms. This idea traces back to Enlightenment thinkers such as Montesquieu (1748) and Smith (1776), and features prominently in modern theories of cultural evolution (e.g., Henrich et al., eds, 2004; Henrich et al., 2010; Henrich, 2020). As previously isolated economies become more interconnected, individuals become increasingly economically interdependent and engage more frequently in mutually beneficial exchanges with people beyond their kin and local networks. Such interactions create stronger incentives to internalize universalistic values, generalized trust, and tolerance for diverse norms. These traits, in turn, facilitate cooperation with distant others—individuals separated along kinship, social, cultural, economic, or geographic lines—and are viewed as adaptive in large-scale, integrated societies (e.g., Henrich et al., 2005; Ensminger and Henrich, eds, 2014; Fehr and Schurtenberger, 2018; Henrich and Muthukrishna, 2021).

This idea has been formalized by the seminal work of Tabellini (2008), which conceptualizes social exchange as a one-shot prisoner's dilemma game between two individuals separated by some social distance. Given the one-shot nature of the interaction, cooperation is socially optimal, but defecting is individually rational based on material payoffs alone. Cooperation is therefore sustained not by the prospect of future reward, but by a culturally acquired psychological utility derived from the act of cooperating itself. Individuals are endowed with one of two ideal types of morality that determine the scope of this psychological utility: a parochial-morality type, who emphasizes loyalty and obligation to a narrow in-group (e.g., family) and derives utility primarily from cooperating with close individuals, and an impersonal-morality type, characterized by impersonal prosocial cultural traits—trust, fairness, and tolerance toward anonymous others and strangers—who also derives utility from cooperating with more distant individuals.

A key insight of the model is that the prevalence of these traits is endogenous to the prevailing socioeconomic environment. In particular, changes in the "matching technology" that governs social interactions can drive cultural evolution. Specifically, as the likelihood of interacting with more distant individuals rises, the economic return to investing in cultural traits that facilitate such interactions increases.[2] As

[2]In the model, the effect occurs up to a threshold distance beyond which the psychological utility from cooperating is too low to

a result, impersonal morality becomes more adaptive. This dynamic is further strengthened through a strategic complementarity: as the share of the impersonal-morality type in society increases, the probability of a cooperative and beneficial interaction when matched with a distant partner also increases, which incentivizes further investment in impersonal morality. At the new equilibrium, society will have a higher share of the impersonal-morality type, a broader scope of cooperation, and more mutually beneficial social interactions with members of other groups.

We use this theoretical framework to guide our empirical investigation. First, we conceptualize the increase in domestic market integration, driven by the expansion of the railroad network, as the shock to the matching technology described above, increasing the probability that an individual's economic opportunities will involve interacting with strangers and anonymous others rather than with members of their own close-knit group. Second, we map the model's core concepts to empirical measures: impersonal morality is measured via universalism, tolerance, and generalized trust; cooperation, defined as socially beneficial but individually costly actions, is measured for both impersonal and kin-based domains; market exchange and social interactions with members of other groups are measured across different social contexts, from local labor markets to team production and within households. Third, our empirical analysis focuses on the following set of sharp, testable predictions:

Prediction 1 (Impersonal cooperative culture)
Greater market integration will foster cultural traits that support cooperation with distant individuals: universalism, tolerance, and generalized trust.

Prediction 2 (Impersonal cooperative behavior)
Greater market integration will increase the scope of impersonal cooperative behavior.

The same mechanism that incentivizes investment in impersonal cooperative culture also implies a substitution away from traditional forms of cooperation. As market-based interactions and a culture defined by generalized trust, tolerance, and universalism expand, they begin to provide opportunities and risk-mitigation channels that were once the exclusive domain of the family. This functional substitution diminishes the economic necessity of relying on traditional, kin-based networks for social insurance and support (Henrich, 2020). Consequently, our third main prediction is:[3]

Prediction 3 (Kin-based cooperative behavior)
Greater market integration will weaken kin-based cooperative behavior.

The theoretical framework posits that these outcomes are driven, at least in part, by a process of cultural adaptation. Our fourth prediction focuses on this mechanism.[4] Following the model's core logic of

compensate for the material incentive to deviate.

[3]We note that this prediction does not directly stem from the model in Tabellini (2008).

[4]The theory does not require that individual adaptation be the sole driver of the empirical association between market integration and impersonal cooperative culture and behavior. Other forces, such as geographic selective sorting, may also contribute.

forward-looking adaptation to changing environments, but focusing on a shorter time horizon, we test for individual-level adaptation rather than slower intergenerational transmission.[5] This focus is consistent with a growing body of recent evidence showing that cultural traits can respond dynamically to new socioeconomic incentives and institutional shocks over relatively short time horizons (e.g., Rao, 2019; Bau, 2021; Lowe, 2021; Ghosh et al., 2025; Raz, 2025).

Prediction 4 (Cultural adaptation)
Exposure to a more integrated market environment induces individuals to adapt culturally, shifting toward stronger impersonal cooperative culture.

Our final prediction focuses on the *conceptual* mechanism. We hypothesize that market integration fosters cultural adaptation by increasing economic interdependence and mutually beneficial exchanges beyond kinship lines and local networks.

Prediction 5 (Mechanism: economic interdependence and impersonal mutually beneficial interactions)
The process of cultural adaptation induced by greater market integration operates through increased economic interdependence and more frequent mutually beneficial exchanges with socially distant individuals.

Alternative mechanisms. Our main hypothesis must be distinguished from two other prominent theoretical channels through which the railroad-driven expansion of market integration could foster impersonal cooperative culture.

First, market integration might foster prosociality primarily by raising incomes. In this view, the railroad expansion spurred economic growth, which in turn is seen as a key driver of cultural change (e.g., Inglehart, 1997; Inglehart and Welzel, 2005). As societies become wealthier, existential pressures on survival diminish. This rising material security reduces dependence on kin-based support networks and may thereby foster a more universalistic outlook and greater tolerance for diversity.

Second, a broad literature in the social sciences, rooted in the classic work of Allport (1954), posits that intergroup contact can reduce prejudice and promote impersonal cooperative norms. The expansion of the railroad network could facilitate this channel by increasing population diversity within counties. The key distinction, however, lies in the nature of interactions: while the contact hypothesis focuses on the effects of building personal relationships with out-group members, our mechanism emphasizes impersonal, anonymous, mutually beneficial market exchanges and economic interdependence.

More generally, as we discuss in Section 8.2, market integration likely shaped multiple features of the socioeconomic environment, such as inducing industrialization and the transition out of agriculture, promoting urbanization, and improving access to information. It is plausible that these features, in turn, affected culture and social relationships. Therefore, these features might be competing channels and mediators. It is also possible that our measures for impersonal cooperative culture, behavior, and mutually

[5] This can be seen as a reinterpretation of the model, in which parents and children are replaced with the present self and the future self.

beneficial interactions partially capture changes in these features rather than, or in addition to, cultural change.

Given the presence of multiple competing hypotheses, empirically identifying the precise mechanisms is particularly challenging. However, based on the results of multiple empirical tests (Section 8.1), we argue that dependence on and exposure to impersonal market exchange played a central role in this historical context. In Section 8.2, we explore the potential role of multiple competing mechanisms and mediators and present suggestive evidence consistent with this interpretation.

3 Historical Background

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

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

The nature of manufacturing activity was also fundamentally transformed. At the beginning of the nineteenth century, manufacturing in the U.S. was organized primarily around small artisan workshops centered on highly skilled craftsmen, sometimes employing a few assistants. The division of labor was limited, and production largely served local markets. From the mid-nineteenth century onward, large-scale factories employing substantial workforces, and characterized by extensive division of labor began to emerge. Falling transport costs and rising market integration enabled these factories to sell their output and source raw materials from increasingly distant markets (Atack et al., 2011).

Similar shifts occurred in household consumption. Over the course of the nineteenth and early twentieth centuries, U.S. households transitioned from reliance on home production to purchasing a growing share of goods through markets (Gordon, 2017). The period saw a dramatic rise in the production and consumption of processed and manufactured foods—such as canned and dried fruits and vegetables, butter, cheese, and meats. By 1900, a quarter of all bread consumed in the country was baked by commercial bakeries;

by 1910, Americans were consuming an average 33 cans of food per person each year. The transformation extended to clothing: whereas, at mid-century, most women made not only their own garments but also many of their children's and husbands' clothes, by the early twentieth century, mass-produced, ready-made clothing had become commonplace for urban and rural Americans alike (Gordon, 2017, p. 85–87). The growth of department stores in cities and, crucially, the spread of mail-order catalogs such as Montgomery Ward and Sears Roebuck (e.g., Appendix Figures B.1-B.2)—facilitated by the introduction of Rural Free Delivery—brought market goods to even the most remote households.

Two key developments drove this integration. First, the period from 1850 to 1920 witnessed the explosive expansion of the U.S. railroad network: total track mileage grew from just under 9,000 miles in 1850 to nearly 238,000 by 1920 (Appendix Figure A.1). Railroads dramatically reduced the cost of transportation nationwide. The construction of transcontinental lines integrated the Pacific Coast and the West with eastern markets, while denser rail networks in the Midwest and Northeast made local and regional transportation far more efficient. Second, the U.S. experienced a massive population boom, rising from about 23 million in 1850 to 106 million by 1920. This "Age of Mass Migration" saw the arrival of roughly 30 million immigrants, primarily from Europe but also from Canada, Argentina, Brazil, and elsewhere (Abramitzky et al., 2014, p. 468).

The combination of a large and rapidly growing domestic market with increasingly cheap and efficient transportation greatly expanded market access for both producers and consumers throughout the country. This expansion facilitated economic development, the settlement and growth of rural areas (Donaldson and Hornbeck, 2016; Chan, 2022), a surge in manufacturing activity and aggregate productivity (Atack et al., 2011; Hornbeck and Rotemberg, 2024), and urbanization (Atack et al., 2010).

4 Data

We assemble a panel of U.S. counties from 1850 to 1920 that combines census data (Ruggles et al., 2020; Manson et al., 2020), historical election and tax data (ICPSR, 1999; Manson et al., 2020), patent records (Berkes, 2018), and large-scale newspaper corpora. We provide a concise presentation of the measures used throughout the paper, focusing on their construction and interpretation. Appendix A provides additional details on data sources, variable construction, descriptive and spatial patterns, and measurement limitations, and presents evidence that our measures pass a battery of construct-validity checks.

Measurement of cultural traits and their behavioral counterparts in historical data is particularly challenging. Our approach is to rely on multiple complementary measures capturing different dimensions of the same underlying constructs—impersonal cooperative culture—and demonstrate that our findings are robust across these distinct measures. We construct all variables at the county-census year level and harmonize them to 1890 county boundaries following Hornbeck (2010).

4.1 Market Access

Our measure of market integration follows Donaldson and Hornbeck (2016). Building on a model of trade among counties, they define an empirical first-order approximation to county o's market access in year t as:

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

where τ_{odt} is a bilateral trade cost between counties o and d in year t relative to the average value of the transported goods P, N_{dt} is county d's population in year t, which proxies for its market size, and θ is the trade elasticity. Intuitively, MA_{ot} increases when nearby or easily reached counties become more populous, so it captures the size and accessibility of o's potential trading partners.

We use the county-to-county cost matrices from Donaldson and Hornbeck (2016), which hold the cost parameters and county borders fixed at their 1890 values and allow costs to vary over time as the railroad and canal network expands. County-level population comes from Manson et al., 2020. Following Donaldson and Hornbeck (2016), our baseline sets $\theta = 8.22$ and $P = 35$; we show that our results are robust to alternative calibrations of θ and P, including those in Hornbeck and Rotemberg (2024), and to a broad range of θ between 1 and 13.

4.2 Impersonal Cooperative Culture

Our main cultural outcomes are county-level measures of what we refer to as *impersonal cooperative culture*—a bundle of interrelated traits that support cooperation with socially distant others. Because this construct is multidimensional, we use several complementary indicators: four validated measures from Raz (2025)—two for universalism and two for norm tolerance—and a novel measure of social trust. The indicators are constructed using the 1850-1920 full-count censuses (Ruggles et al., 2020), the Censuses of Religious Bodies (Manson et al., 2020), and a newspaper corpus from *newspaperarchive.com*.

Universal Name Index (UNI). The UNI focuses on universalism and uses children's first names to measure the importance of the national identity in parents' social identity, relative to the local, communal, identity. Following Raz (2025) and Fryer and Levitt (2004), the index ranges from 0-100, and captures the probability that parents give their children names that are common among same-gender children aged 0-10 nationally, rather than locally. The index is first computed for all children aged 0-10, and the county-level UNI is defined as the mean UNI score of children aged 0-10 in the county. Intuitively, higher UNI reflects stronger parental universal identification.

Extra-Community Marriage (ECM). The ECM focuses on universalism and captures the tendency to marry outside one's local community. For each married couple, we compare spouses' birthplaces (state for US-born, country for foreign-born) and define ECM as having a spouse with a different birthplace. The indicator is calculated for all married couples and the county-level ECM is the share of married couples with different birthplaces. Higher ECM indicates a weaker preference for marrying within the birthplace-defined in-group.

Norms Tolerance Index (NTI). The NTI captures tolerance, or cultural looseness, with respect to family norms (e.g., Gelfand et al., 2006, 2011). At the county-census-year level and focusing on married mothers aged 35-44, we compute the coefficient of variation of (i) mothers' age at first birth, (ii) the total number of children, and (iii) the number of distinct families within a household. We then extract the first principal component of these three measures, coded such that higher values indicate greater within-county dispersion. Finally, we standardize the measure into z-scores within each census year. Following Posch (2021) and Dimant et al. (2025), we interpret this dispersion as reflecting looser norms—i.e., greater tolerance of diverse actions—while the mean or mode of the distributions reflects the behavior prescribed by a norm.

Religious Diversity Index (RDI). The RDI captures tolerance of different religious identities and practices. Using data from the Censuses of Religious Bodies, we compute, for each county-census year, a Herfindahl-Hirschman Index of the diversity of religious membership across denominations. We standardize the RDI to z-scores within each census year. We interpret higher values as reflecting greater openness to denominational diversity.

Newspaper-based social trust. Finally, we construct a new measure of generalized trust using full-text local newspaper data from *newspaperarchive.com*. We apply the contextualized-construct approach of Atari et al. (2023): we embed newspaper pages and standard survey items about trust (e.g., "Most people can be trusted") using Sentence-BERT. To improve precision, we also embed negatively worded trust items (e.g., "You can't be too careful in dealing with people") and subtract this negative embedding from the positive embedding. We then measure the cosine similarity between the embeddings of newspaper pages and the anchored trust embedding. We average the similarity scores across pages in each county-year and assign them to the nearest census decade. We validate this measure against General Social Survey trust data in the post-1970 period and against our other cultural measures in 1850-1920 (see Appendix A.2).

Composite index. For some analyses, we construct a composite index of impersonal cooperative culture by averaging the standardized UNI, ECM, NTI, and RDI in each county-decade. We exclude the newspaper-based trust measure from the composite because of its more limited geographic coverage.

4.3 Impersonal and Kin-based Cooperative Behavior

To capture the prevalence of both impersonal and kin-based cooperative behavior—defined as individually costly but socially beneficial actions (Fehr and Fischbacher, 2003; Bowles and Gintis, 2011)—we construct county-level measures of voter turnout, local public goods provision, and family care.

Voter turnout in presidential elections. Following established work (Putnam, 1995; Alesina and La Ferrara, 2000; Rupasingha et al., 2006; Rustagi, 2024a), we use voter turnout as a measure of civicness and impersonal cooperative behavior. We combine historical presidential election returns (ICPSR, 1999) with full-count census-based estimates of the eligible voting population, accounting for constitutional amendments and legislative changes affecting women's and Black suffrage, to compute turnout rates in each county-election. Because population estimates are interpolated between censuses, our constructed turnout can occasionally exceed 100%; we drop a small number of observations with implausibly high rates that likely reflect coding error in the data.

Local public goods provision. Using county-level tax data from 1870 and 1880 from Manson et al., 2020, we measure the share of total tax revenues raised at the town and county level rather than at higher (state) levels. Holding overall tax revenues constant, a higher local share indicates a greater willingness to contribute to broad, non-kin beneficiaries through local public goods provision (Putnam et al., 1993).

Family care. To capture kin-based cooperation, we follow Ghosh et al. (2023) and focus on the provision of care for vulnerable individuals, using the 1850-1920 full-count censuses. Vulnerable individuals include orphans (children under 16 without co-resident parents), people with disabilities (deaf, blind, "idiotic," "insane," sick, or temporarily disabled on the day of enumeration), and the elderly (65+). Using IPUMS household variables, we determine whether each vulnerable person is cared for by a relative at home. We then measure the share of vulnerable individuals cared for by relatives at home.

4.4 Impersonal Mutually Beneficial Social Interactions

We also measure the prevalence of impersonal, mutually beneficial social interactions in labor markets, innovation, households, and civic life. These outcomes capture beneficial interactions that may not always involve individually costly behavior and are therefore conceptually distinct from cooperation.

Labor-force cooperation. This measure captures the degree to which success in the local labor market regularly required interacting with others in a cooperative, pleasant manner. We rely on contemporary O*NET work-style "cooperation" rating, which measures the extent to which the job requires being pleasant with others and displaying a cooperative attitude. We map O*NET's SOC codes to historical IPUMS `OCC1950` codes, assuming that the relative differences in cooperation requirements across occupations are stable over time. This allows us to assign a labor-force cooperation score for every working individual in the full count censuses 1850-1920. We then compute an employment-weighted average at the county-decade level.

Inventor collaboration. We construct two measures of the scale and diversity of collaboration among inventors. Using U.S. patent data (Berkes, 2018), we compute the average number of inventors per patent and the entropy of co-inventors' surnames. The former captures the degree of collaboration, and the latter proxies the extent to which collaboration extends beyond family networks, given surname-based kinship (Posch et al., 2025).

Residence with non-kin. This measure focuses on day-to-day mutually beneficial interactions outside family lines. Using the full-count censuses 1850-1920 and IPUMS's family identifiers, we calculate the share of households containing multiple families (i.e., co-resident groups unrelated by blood, marriage, or adoption) in every county-decade. Intuitively, co-residence involves a high degree of interaction.

Civic engagement. Finally, we construct a measure of broad impersonal social engagement at the communal level. Using the full-count censuses 1850-1920 and IPUMS's industry codes, we compute the share of county residents employed in sectors related to civic organizations, public administration, and recreational activities (e.g., religious and membership organizations, local government, restaurants, theaters, and other entertainment services). This share proxies for the local prevalence of settings in which residents can beneficially engage in social and civic interactions with distant others (Putnam, 1995).

4.5 Prevalence of Commerce

To study how market access affected exposure to commerce, we construct two county-level measures: commerce-related newspaper content and employment in wholesale and retail trade.

Market language in newspapers. We develop a metric for commerce-related content in historical local US newspapers using keyword-count data from *newspapers.com*, which provides OCR-based page-level counts (in contrast to the full-text *newspaperarchive.com* corpus used for our trust measure). Starting from five seed words (e.g., "buy," "sell," "trade"), we use a language model to expand the dictionary to 100 terms reflecting nineteenth-century U.S. usage. For each keyword, we compute the share of pages in a county-year that contain the word; our baseline measure averages the shares for the ten most central terms (e.g., "buy," "sell," "money," "price," "trade," "market"). We show that measures based on the top 20, 50, and 100 keywords are highly correlated and that our results are robust across them.

Wholesale and retail employment. Using industry codes in the 1850-1920 full-count censuses, we compute the share of county residents employed in wholesale and retail trade.

4.6 Other Demographic and Economic Measures

Finally, we use a set of more standard demographic and economic outcomes to explore mechanisms and robustness (e.g., occupational income scores, urbanization, the share employed in manufacturing, and a Herfindahl-Hirschman birthplace diversity index). These variables are constructed using the 1850-1920 full-count and county-level census data (Ruggles et al., 2020; Manson et al., 2020). Appendix A.6 provides the details.

5 The Relationship Between Impersonal Cooperative Culture, the Scope of Cooperation, and Impersonal Social Interactions

Before examining the impact of market integration, we first explore the relationships between our composite index of impersonal cooperative culture, patterns of cooperation, and the extent of mutually beneficial social interactions outside kinship lines. Guided by the literature on kinship and universalism, we expect impersonal cooperative culture to be positively related to impersonal forms of cooperation and broad social interactions, and negatively related to kinship-based cooperation (Schulz et al., 2019; Enke, 2019).

We estimate an equation of the following form, using the same baseline county-level empirical approach that we later employ to study the impact of market access:

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

where c and t denote county and year, respectively. The outcome $Behavior_{ct}$ encompasses impersonal cooperative behaviors (voter turnout and local public-goods provision), kin-based cooperation (family-based care), as well as a range of impersonal mutually beneficial social interactions (labor-force cooperation, the scale and diversity of collaboration, co-residence with non-kin, and civic engagement). The coefficient β captures the association between impersonal cooperative culture and both impersonal and kin-based cooperation, as well as impersonal beneficial social interactions. We sequentially add the following controls: $\delta_{s(c)t}$ are state-by-year fixed effects, controlling for time-varying factors shared by counties within a state; δ_c are county fixed effects, absorbing persistent county-level differences and shifting the focus from levels to within-county temporal changes; and $f(x_c, y_c)\delta_t$ is a cubic polynomial in longitude and latitude interacted with year, controlling for broad, time-varying smooth spatial patterns. To verify that the relationships are not trivially explained by local economic development, we also include time-varying log GDP per capita in X_{ct} (Fulford et al., 2020). Standard errors are clustered using arbitrary 100-mile square spatial grids to account for potential spatial autocorrelation, following the method proposed by Bester et al. (2011).

Figure 1 presents results for five specifications: the first includes no controls, followed by four specifications that sequentially add the fixed effects, spatial polynomials, and log GDP per capita. For comparability, we standardize all left-hand-side measures to z-scores.[6] We find robust positive associations between impersonal cooperative culture and our two measures of impersonal cooperative behavior. In contrast, we find a robust negative association with kin-based cooperation. In addition, impersonal cooperative culture is positively and significantly associated with broader, impersonal, mutually beneficial social interactions. The exception is inventor collaboration, where coefficients lose significance in some specifications, possibly due to lower statistical power stemming from more limited spatial coverage.

[6] Appendix Table B.1 reports the estimates using the original, non-standardized measures.

Taken together, these findings indicate that counties with stronger impersonal cooperative cultural traits display higher levels of impersonal social behavior across multiple domains and rely less on kin-based social insurance. These initial correlations support the construct validity of our diverse—and, in some cases, novel—measures of cooperation and social interactions and underscore their relationship with impersonal cooperative culture.

At the same time, these correlations should not be interpreted as causal. Impersonal cooperative culture, cooperative behavior, and the scope of social interactions are likely to co-evolve, with causality running in both directions. Our empirical strategy in this section cannot disentangle these dynamic relationships. Instead, our focus in the remainder of the paper is on identifying the causal impact of market integration on both culture and behavior. The results above suggest that impersonal cooperative culture and behavior move together, making it meaningful to study how market integration shapes this joint evolution.

6 The Impact of Market Access on Impersonal Cooperative Culture and the Scope of Cooperation

We now turn to our main county-level analysis. We leverage variation in county-level market access over time and bring to bear four complementary empirical designs: we (i) estimate a baseline specification that relates changes in market access to changes in impersonal cooperative culture and cooperative behavior conditional on a rich set of fixed effects and controls; (ii) implement a recentering approach following Borusyak and Hull (2023); (iii) isolate variation in market access driven solely by distant changes in the railroad network and population; and (iv) use two instrumental-variable strategies employed in previous work (Donaldson and Hornbeck, 2016; Hornbeck and Rotemberg, 2024).[7]

6.1 Empirical Strategy

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

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

where o indexes counties and t indexes years. Our key explanatory variable is the log of market access, $\ln(MA_{ot})$, and the coefficient of interest is β. The specification includes county fixed effects (δ_o) to absorb all time-invariant differences across counties and state-by-year fixed effects ($\delta_{s(o)t}$) to capture common state-level trends and shocks over time. It also flexibly accounts for smooth geographic trends by including cubic polynomials in longitude and latitude interacted with year fixed effects ($f(x_o, y_o) \times \delta_t$). Finally, X_{ot} denotes additional time-varying controls that we introduce below to strengthen a causal interpretation and

[7] In Section 7, we complement this analysis with an individual-level difference-in-differences design based on domestic migrants. The results are consistent across levels of analysis and identification strategies.

to probe competing mechanisms and mediators. Because the treatment is spatially assigned, we cluster standard errors using arbitrary 100-mile square spatial grids to account for spatial autocorrelation (Bester et al., 2011). Our results are highly robust to using grid sizes between 50 and 250 miles and to clustering at the state level.

The identifying assumption is conditional exogeneity: conditional on the controls in (2), changes in market access are as good as random with respect to other unobserved determinants of the outcomes we study. County fixed effects imply that identification comes from within-county changes in market access over time, after netting out all average cross-sectional differences. The state-by-year fixed effects remove all time variation common to counties within the same state, including state-level policies and shocks related to both geography and institutions, so that identification comes from *excess* changes in counties' market access relative to other counties in the same state. The cubic spatial polynomial interacted with year fixed effects further removes time-varying smooth spatial patterns, so that the remaining variation in market access reflects county-specific deviations from both their state and broad national spatial trends.

Even with this rich set of controls, two main concerns remain. First, reverse causality: counties that became more cooperative might have been more successful in lobbying for, or attracting, local railroad construction, which in turn increased their market access. Second, omitted variable bias: unobserved factors—such as income growth or prospective economic development—might have simultaneously influenced both railroad construction and our outcomes of interest.

We address these concerns in three ways. First, we implement the recentering approach recommended by Borusyak and Hull (2023) and purge remaining omitted-variable bias by recentering the treatment, $\ln(MA_{ot})$, around its "expected" value. Following Hornbeck and Rotemberg (2024), we define the expected treatment as a measure of market access that excludes railroads but includes the network of canals that might have been built instead, as proposed by Fogel (1964).[8] We then recenter the treatment by adding log expected market access as a control.

Second, we follow Donaldson and Hornbeck (2016) and Hornbeck and Rotemberg (2024) and leverage the fact that a county's market access depends not only on railroad construction within or near that county, but also on developments in distant counties throughout the broader transportation network, which are more plausibly exogenous to local conditions. By including flexible time-varying controls for the presence and extent of local railroads in and around each county, we isolate variation in market access that is orthogonal to changes in local infrastructure.[9] Following the same logic, we also include flexible controls for local population in and around each county. This further mitigates concerns that local population

[8]This expected treatment measures market access in a counterfactual scenario in which railroad technology did not exist, but extensive investment in network canals occurred instead to facilitate low-cost transportation and efficient trade flows, given the counterfactual technology. We share the view of Hornbeck and Rotemberg (2024) that effectively random placement and timing of railroads is not plausible in this setting.

[9]Specifically, we add a dummy for railroad presence in the county, a cubic polynomial in total railroad mileage in the county, and controls for railroad presence and a cubic polynomial in railroad mileage within a 10, 20, 30, and 40-mile buffer around each county.

shifts—which might respond endogenously to local culture or behavior—could bias our estimates.[10] With these controls in place, identification relies on plausibly exogenous changes in the broader rail and population network.[11] In addition, we combine both approaches by jointly controlling for expected market access and for local railroad connectivity and population.

Third, for completeness, we implement two instrumental-variable strategies used in the literature. The first applies the alternative recentering IV suggested by Borusyak and Hull (2023), instrumenting market access with $\widetilde{ln(MA_{ot})} = \ln(MA_{ot}) - \ln(\mu_{ot})$, where $\ln(\mu_{ot})$ is log expected market access. The second follows Donaldson and Hornbeck (2016) and Hornbeck and Rotemberg (2024) and uses preexisting low-cost waterway transportation to instrument for growth in market access.[12] We report these IV results in Appendix Table B.2; they are consistent with the main estimates.

6.2 The Impact on Impersonal Cooperative Culture

We begin by testing Prediction 1. We examine the impact of market access on impersonal cooperative culture using both our composite index and all five individual measures of cultural traits that support cooperation with strangers: universalism, tolerance, and social trust. The results are reported in Table 1.

Panel A focuses on the composite impersonal cooperative culture index. In our baseline specification (column 1), a 1 percent increase in market access strengthens impersonal cooperative culture by 0.146 points (p-value < 0.001), which corresponds to about 22 percent of a standard deviation. Appendix Figure B.3, Panel A, shows that this relationship is approximately linear and not driven by outliers. Recentering market access has little impact on the estimate (column 2). When we focus only on variation arising from far-away changes in infrastructure and population—by controlling for the presence and extent of local railroads and local population growth (columns 3–7)—the coefficients attenuate somewhat but remain economically meaningful (about 14 percent of a standard deviation) and highly statistically significant (p-value < 0.001) even with the most comprehensive railroad and population controls. Combining the two methods in column 8 yields a very similar estimate (about 13 percent of a standard deviation). We obtain comparable coefficients when we use the two instrumental-variables strategies described above (Appendix Table B.2).

Panels B–F present results for the individual cooperative cultural traits. Panel B focuses on the Universal Name Index (UNI), which reflects parental orientation toward national rather than local identity. In our baseline specification (column 1), a 1 percent increase in market access raises the average UNI

[10] Note that a county's own population size does not enter the market access measure; see Section 4.1.

[11] In this framework, local railroad connectivity and population growth are not omitted confounders in the usual sense, but components of the treatment itself—market access. We include them only to strip out the potentially endogenous local component of market access and focus on variation driven by distant parts of the network. Consequently, the attenuation of the market access coefficient when these controls are added reflects a change in which part of the treatment is used for identification, rather than evidence of omitted-variable bias, as in Oster (2019).

[12] Specifically, we use log water market access in 1850 interacted with year fixed effects to predict changes in log market access in subsequent decades.

by 0.925 points (p-value < 0.001), or about 14 percent of a standard deviation. The relationship is linear and not driven by outliers (Appendix Figure B.3, Panel B). A similar effect is estimated when market access is recentered (column 2). With the most comprehensive railroad and population controls (column 7), the effect remains sizable at about 6 percent of a standard deviation (p-value = 0.019). Combining both recentering and local controls yields very similar findings (column 8).

Panel C reports results for Extra-Community Marriage (ECM), which captures openness to out-group relationships. The estimated effect is smaller and less precise. A 1 percent increase in market access increases the likelihood of marrying someone born outside the community by 0.69 percentage points (p-value = 0.081), about 3 percent of a standard deviation (column 1). The relationship is not driven by outliers (Appendix Figure B.3, Panel C), and recentering has little impact. When we add more detailed controls for local railroad connectivity beyond a simple dummy for a railroad in the county (columns 4–6), the coefficients attenuate and become statistically insignificant. When we also control for local population, the point estimate increases and is only marginally insignificant (p-value = 0.11). Combining both methods (column 8) yields similar conclusions.

Panels D and E show strong effects on cultural tolerance. A 1 percent increase in market access raises the Norm Tolerance Index (NTI) and the Religious Diversity Index (RDI) by 0.18 and 0.27 standard deviations, respectively (p-value < 0.001 in both cases, column 1). These are sizable effects. The relationships are linear (Appendix Figure B.3, Panels D–E) and robust to recentering (column 2), to the inclusion of local railroad and population controls (columns 3–7), and to combining both approaches (column 8).

Panel F reports the effects on social trust. We find that a 1 percent increase in market access increases social trust by 0.12 standard deviations (p-value = 0.014). The estimate is stable across specifications. Appendix Figure B.3, Panel F, visualizes the relationship, which again appears linear and not driven by outliers.

Robustness. We conduct a range of robustness checks. Appendix Table C.1 shows that the results are not sensitive to including or excluding immigrants and non-whites when constructing county-level cultural indicators, suggesting that they are not mechanically driven by changing demographics or population diversity. Appendix Figure C.1 documents robustness to alternative methods for clustering standard errors to account for spatial autocorrelation, including clustering at the state level. Appendix Table C.2 shows that our results are robust to alternative values of the trade elasticity (θ) and the value of transported goods (P) when calculating market access, including those used by Hornbeck and Rotemberg (2024).[13] Finally, Appendix Table C.3 confirms that no single region of the country drives the results.

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

6.3 The Impact on Impersonal and Kin-based Cooperative Behavior

Having established a positive impact of market access on impersonal cooperative culture, we next examine how market access affected cooperative behavior—specifically, whether it increased impersonal cooperation and reduced kin-based support (Predictions 2–3). We focus on two indicators of impersonal cooperation and one measure of kin-based social insurance. The results are presented in Table 2.

We find that market access increased impersonal cooperative behavior and reduced kin-based cooperation. Panel A, column 1, shows that a 1 percent increase in market access increases turnout by 0.038 points, or 16 percent of a standard deviation (p-value < 0.001). This effect remains economically and statistically significant when the treatment is recentered and when we restrict attention to variation driven by distant changes in railroad connectivity and population growth (columns 2–8). Similarly, Panel B, column 1, shows that a 1 percent increase in market access raises the share of local taxes by 0.019 percentage points, about 9 percent of a standard deviation (p-value $= 0.002$). Recentering market access again has little impact (column 2). Because data on this outcome are available only for 1870 and 1880, statistical power declines once we add the richest set of local railroad controls (columns 6–8). With both recentering and the most comprehensive railroad and population controls (column 8), the estimated effect is about 5 percent of a standard deviation and only marginally insignificant (p-value $= 0.148$).

By contrast, Panel C, column 1, shows that provision of kin-based social insurance falls. A 1 percent increase in market access reduces the share of vulnerable individuals cared for by relatives by 0.012 points (p-value < 0.001), an effect size of about 11 percent of a standard deviation. Recentering and focusing on distant variation leave the estimates largely unchanged. For all three outcomes, Appendix Figure B.4 shows that the relationships between market access and the outcomes are approximately linear and not driven by a few outliers.

Robustness. These findings are also robust to a wide range of checks. The results are not sensitive to alternative ways of accounting for spatial autocorrelation or to clustering at the state level (Appendix Figure C.2), to alternative values of the parameters used to calculate market access (Appendix Table C.4), or to different ways of handling skewed outcome distributions (Appendix Table C.5). The results also hold when we drop any one census region at a time (Appendix Table C.6).

Overall, our county-level analysis supports Predictions 1–3. Market integration had a broad and robust impact on both culture and behavior: it increased the prevalence of impersonal cooperative culture and impersonal forms of cooperation, while reducing reliance on kin-based social insurance.

7 Adaptation vs. Sorting: Evidence from Domestic Migrants

In this section, we use individual-level data on domestic migrants to explore *how* market access strengthened impersonal cooperative culture and behavior. Consistent with the model in Tabellini (2008), our theory emphasizes cultural adaptation: people adjust their culture and behavior in response to greater market integration (Prediction 4). An alternative explanation is spatial selective sorting, whereby people with stronger impersonal cooperative cultural traits and related characteristics move to areas experiencing larger increases in market access. Both forces could operate simultaneously. Here, we empirically assess the importance of selective sorting and cultural adaptation.

To construct the sample of domestic migrants, we use the Census Linking Project (Abramitzky et al., 2022a,b,c,d,e), which enables us to link male heads of household across decennial censuses. To proxy the timing of migration, we focus on families who migrated across states and had at least one child born in the origin state and one in the destination state. We proxy the year of migration by the midpoint between the birth year of the last child born in the origin state and the birth year of the first child born in the destination.[14] We then link each household to the level of market access in both its origin and destination counties at the time of the later census, harmonizing county borders to 1890 (Hornbeck, 2010) to match the market access data.[15]

7.1 Selective Sorting

One possibility is that people with stronger impersonal cooperative cultural traits and related characteristics were more likely to move to areas that were becoming more market-integrated. If so, the positive relationship between market access and impersonal cooperative culture might simply reflect selective sorting with respect to where people chose to move, rather than cultural adaptation.

We explore this possibility using over 100,000 observations on migrating families. Specifically, using family-level data on incoming domestic migrants and a family-level version of Equation (2), we test whether counties that experienced excess increases in market access attracted migrants with higher pre-migration universalism, as measured by the average Universal Name Index (UNI) of children born before migration and Extra-Community Marriage (ECM).[16] We also explore selection more broadly using multiple relevant pre-migration attributes: the tendency to engage in broad, beneficial social interactions, as measured by a labor-force cooperation score and residence with non-kin; kinship propinquity;[17] the

[14] For example, consider a family living in Massachusetts in 1860 with two children: the first was born in 1854 in New York, and the second in 1856 in Massachusetts. In 1850, the father was living in New York. The proxy for this family's year of migration from New York to Massachusetts is 1855.

[15] Specifically, households can be fuzzy-matched to multiple (1890-borders) origin and destination counties, with probability weights determined by the geographical overlap between historical counties and the harmonized county units.

[16] Our estimation equation takes the following form:

$$trait_{f,t-1} = \beta \ln(MA_{dt}) + \delta_d + \delta_{s(d)t} + f(x_d, y_d) \times \delta_t + \epsilon_{ft},$$

where f denotes a family that migrated into destination county d between period $t-1$ and period t. As in Equation (2), δ_d are destination-county fixed effects, $\delta_{s(d)t}$ are state-by-year fixed effects, and $f(x_d, y_d) \times \delta_t$ are cubic polynomials in longitude and latitude interacted with year fixed effects. This specification, therefore, relates pre-migration traits to the same notion of excess changes in market access as in the county-level analysis.

[17] We measure kinship propinquity using data from Nelson (2020). The measure exploits the fact that the distance between households on the census enumeration form correlates with geographical distance. When a same-race same-surname house-

number of children; urban versus rural origin; nativity; occupational income score; and working in the agricultural, manufacturing, and trade sectors. For comparability, we standardize all outcomes to z-scores.

Figure 2 plots the results.[18] We find little evidence for selective sorting of migrating families based on differential market access trends. Specifically, there is no relationship between excess changes in market access and prior levels of universalism among incoming migrants. Migrants to counties experiencing higher growth in market access are also no more or less likely to work in occupations that rely on impersonal interactions, although they are somewhat more likely to have previously lived with a non-kin. In addition, they do not differ systematically in kinship propinquity, number of children, urban versus rural origin, nativity, occupational income scores, or the sectors in which they worked.

Thus, although we cannot rule out that selection played some role, these null findings suggest selection on observables played at most a limited role. This points to a central role for cultural adaptation, which we examine next.

7.2 Cultural Adaptation

To test our theory that people adapt to an increase in market integration by strengthening impersonal cooperative cultural traits (Prediction 4), we examine changes in parental universalism using a dynamic difference-in-differences framework, following Raz (2025). We compare UNI scores among siblings born before and after migration in families that moved to higher versus lower market access counties.[19]

Empirical strategy. We estimate the following equation:

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

where UNI_i is the Universal Name Index score for child i, currently residing in county $d(i)$ and born $b(i)$ years relative to the year the family $f(i)$ migrated from origin county $o(i)$ to destination county $d(i)$. The term $\delta_{b(i)}$ is a set of relative-year-of-birth fixed effects, absorbing any changes in universal identification relative to the year of migration among families that moved to a lower market access county. Crucially, $\theta_{f(i)}$ is a family fixed effect, removing any unobserved factor common to siblings, including the family's

hold exists within the same enumeration district, the probability that the match is not random and reflects kinship is computed as follows:

$$P(K_{rie}) = \left(1 - \frac{N_{rie} - 1}{N_{re} - 1}\right)^{D_i}$$

where N_{rie} is the number of same-race (r) same-surname (i) households in the same enumeration district (e), N_{re} is the total number of same-race households in the enumeration district, and D_i is the number of different-surname households that are as close as the nearest same-surname household. We define kinship propinquity when the probability that the match reflects kinship exceeds 50%.

[18] Appendix Table B.3 presents these results using non-standardized pre-migration characteristics of incoming domestic migrants.

[19] This empirical exercise can also be viewed as an alternative method of estimating the causal impact of market integration on impersonal cooperative culture. The findings of this exercise align closely with the county-level estimates.

migration path and permanent cultural and economic characteristics, so that identification comes from within-family changes over time. The vector X_i contains child characteristics—gender, birth order, and a set of 5-year cohort fixed effects—which we include when we assess robustness. The coefficients of interest, β_b, capture the impact of moving to a higher versus a lower market access county on universal identification over time.[20] We normalize β_{-1} to zero, so that β_b can be interpreted as the effect relative to the year just before migration.[21] We cluster standard errors ϵ_i at the county-of-destination level (Bertrand et al., 2004), but results are robust to two-way clustering by origin and destination. When families are matched to multiple 1890-borders counties in the process of county-border harmonization, we weight observations by the matching probabilities, so that the total weight per child sums to one.[22]

The identifying assumption is that, absent differences in the change in market access, within-family UNI scores in families migrating to higher versus lower market access counties would have evolved similarly. We assess the plausibility of this assumption by examining the pre-trends ($\beta_{b<0}$).[23]

Results. We find that migration to a higher market access county rapidly increases universalism. Figure 3 shows that there are no differential trends in UNI prior to migration between families who moved to counties with higher versus lower market access, supporting the identifying assumption. In the first year after migration, the UNI of a child born to a family that moved to a higher market access county jumps by 2.45 points (p-value < 0.001) relative to a child born to a family whose move reduced market access, and this effect persists for at least ten years.

This finding joins a growing body of evidence documenting rapid cultural responses to environmental changes (e.g., Rao, 2019; Bau, 2021; Lowe, 2021; Raz, 2025; Ghosh et al., 2025). In interpreting the result, two points are important. First, the estimated impact corresponds to the *difference* in adaptation between migrants moving to higher versus lower market access environments, not to absolute adaptation. Second, our sample consists of migrants who relocated to new economic environments after separating from existing social networks. In this setting, adaptation to new economic incentives is likely to be rapid, potentially facilitated by horizontal learning about which cooperative norms are prevalent and economically rewarded in more market-integrated localities.

Estimating a static version of Equation (3) yields similar results: Appendix Table B.4, column 1, shows

[20] In our data, 41,828 families moved to a higher market access county while 74,456 moved to a lower market access county. Due to the process of harmonizing county borders to 1890, our data also contains 55 families that, although they migrated, are matched to the same county of origin and destination. Dropping these observations has a negligible impact on the results.

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

[22] Our results are robust to restricting the sample to families that are matched to a single county or to the highest-probability match only.

[23] In Section 8.2, we show that our findings are also robust to dynamically controlling for differences in multiple, potentially confounding socioeconomic characteristics between the origin and destination counties. This further strengthens the plausibility of our identification assumption.

that the UNI of children born to families that gained market access through migration was about 2.35 points higher (p-value < 0.001) than that of children whose families lost market access after moving.

A concern with interpreting these results as indicating a positive impact of market access on universalism is that the UNI measures national relative to local identity; however, migration changes the definition of "local." If a migrant to a higher market access county increases their identification with the origin community after migration relative to migrants to a lower market access county, this would lead to a relative increase in their children's UNI (measured relative to the destination community). But such an increase in UNI should be interpreted as lower universalism—that is, stronger identification with the (former) local community.

To address this concern, we also construct a version of UNI in which we fix the definition of "local" at the county of origin. For children born after migration, this origin-based UNI is computed not for their county of birth, but for their family's previous county of residence. We then use this measure in 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 Appendix Table B.4 and Appendix Figure B.5 present the results. The findings are qualitatively similar: we again document a positive and highly significant causal impact of market access on universal identification, reinforcing the conclusion that migrants adapted to the higher market access environment by becoming more universalistic. Quantitatively, the effect is smaller, as expected when holding the reference community fixed.

Robustness. The finding that migration to higher market access areas increases universalism is robust to variation in specification, treatment definition, sample, and inference. Appendix Figure C.3 and columns 2 and 4 of Appendix Table B.4 show that the results are robust to controlling for gender, birth order, and 5-year cohort fixed effects. Appendix Figure C.4 shows that the results are robust to two-way clustering by counties of destination and origin. Appendix Figure C.5 shows robustness to using a continuous treatment definition—the difference in log market access—instead of a binary indicator. Our baseline specification aggregates the dynamic effects 10 or more years before and after migration, because the number of observations declines with distance from the year of migration, resulting in highly imprecise estimates. However, the results are similar when we use the maximal possible horizons (Appendix Figure C.6).[24] Finally, Appendix Figure C.7 documents that the results are not driven by demography: they are robust to excluding immigrants and non-Whites.

These findings reinforce the county-level evidence that market integration increases impersonal cooperative culture (Prediction 1), and they suggest that this effect is driven primarily by cultural adaptation rather than by selective migration (Prediction 4).

[24] Following the literature, we focus on children's names and compute UNI only for children aged 0–10 in each decade (Bazzi et al., 2020; Raz, 2025). As such, we can estimate the impact for at most 19 years before and after the year of migration.

8 Conceptual Mechanisms: Why Did Market Access Transform Impersonal Cooperative Culture?

In this section, we explore *why* greater market access transformed impersonal cooperative culture and patterns of cooperation. First, we present evidence that is consistent with our mechanism that cultural adaptation resulted from increased economic interdependence and more frequent mutually beneficial exchanges with distant individuals (Prediction 5, Section 8.1). We then examine multiple competing mechanisms and potential mediators and find that their explanatory power is limited (Section 8.2).

8.1 Commerce and Beneficial Impersonal Interactions

We begin by documenting that the impact of market access on impersonal cooperative culture appears to operate through greater exposure to commerce, which increased economic interdependence and facilitated frequent mutually beneficial impersonal exchanges and social interactions.

First, using our county-level framework, we show that counties with greater market access became more commercially oriented. Second, using both county- and individual-level frameworks, we show that residents of these counties were more likely to engage in broad, impersonal, beneficial social interactions. We then provide evidence that these market-based interactions are central to cultural adaptation by leveraging heterogeneity across industries in their dependence on commerce. The key intuition is that, if market integration shapes culture through direct exposure to commerce, individuals whose livelihoods depend more heavily on commerce should be more strongly affected. Conversely, individuals working in industries that mostly serve the local community should be less affected. Finally, we provide suggestive evidence that adapting to a more market-integrated environment was beneficial for migrants and their families.

8.1.1 Market Access Increases the Prevalence of Commerce

We use our county-level framework (Eq. 2) to estimate the impact of market integration on the local prevalence of commerce. In line with Prediction 5, we find that market access increases the prevalence of commerce-related activities, as measured by commerce-related content in local newspapers and the share of residents working in the wholesale and retail trade sectors (Table 3, columns 1–2). Our results indicate that a 1 percent increase in market access raises the share of commerce-related content by 1.5 percentage points (p-value < 0.01) and employment in the wholesale and retail trade sectors by 0.51 percentage points (p-value < 0.001). These effects correspond to about 13 and 14 percent of the standard deviation of the two outcomes, respectively. Appendix Table B.5 supports a causal interpretation by documenting that these findings are robust to recentering market access (Borusyak and Hull, 2023) and to controlling for railroad connectivity and population growth in and around each county. Appendix Figure B.6 shows that these relationships are approximately linear and not driven by outliers. Together, these findings suggest that counties experiencing larger increases in market access saw stronger growth in economic interdependence and more frequent mutually beneficial market-based exchanges with distant others.

In Appendix Figure B.7, we also show that the prevalence of commerce is positively associated with impersonal cooperative traits and impersonal cooperative behavior, and negatively associated with kin-based cooperation. These associations hold in the raw data, with state-by-year fixed effects, and when further including county fixed effects, spatial polynomials interacted with year fixed effects, and time-varying controls for log real GDP per capita. While these correlations are not causally identified, they are consistent with a central role for increased economic interdependence and market-based exchanges in driving our main results.

Robustness. These results are robust to a range of variations in specification and sample, including alternative methods for clustering standard errors (Appendix Figure C.8), different price and elasticity parameters when calculating market access (Appendix Table C.11), using different thresholds (20, 50, or 100 words) when identifying commerce-related content in local newspapers (Appendix Table C.12), alternative ways of handling outliers and skewness in the share of county residents working in trade (Appendix Tables C.13 and C.14), including or excluding immigrants and non-whites when constructing employment shares (Appendix Table C.15), and dropping any one census region at a time (Appendix Table C.16).

8.1.2 Market Access Increases Beneficial Impersonal Social Interactions

County-level evidence. Next, we document that market access increases the frequency of impersonal social interactions in the community across several social domains (Prediction 5). Using our county-level framework (Eq. 2), we find that market access increases labor-force cooperation, diverse inventors' collaborations, the share of multifamily households, and residents' civic engagement (Table 3, columns 3–7). Column 3 shows that a 1 percent increase in market access raises impersonal cooperation in the labor force by 0.0058 points (p-value < 0.001), or about 10 percent of a standard deviation. Columns 4 and 5 document similar effects for collaborative invention: market access increases both the number and diversity of co-inventors by 0.011 points (p-value < 0.01 for both), corresponding to approximately 10 percent of a standard deviation in each outcome. Market access also increases the share of multifamily households and civic engagement by about 8 to 10 percent of a standard deviation (p-value < 0.01 for both, columns 6–7). Appendix Table B.6 provides further evidence consistent with a causal interpretation, and Appendix Figure B.8 plots the relationships.

These results are robust to alternative clustering of standard errors (Appendix Figure C.9), to different parameters used in calculating market access (Appendix Table C.17), to various ways of handling skewness in the data (Appendix Tables C.18 and C.19), and to dropping any one census region (Appendix Table C.20).

As above, we also provide supporting evidence for the potential role of broad, impersonal, mutually beneficial interactions in driving our main results. We construct a composite index of impersonal interactions, defined as the mean of five standardized measures: labor-force cooperation, the number of co-inventors, the diversity of co-inventors, the share of multifamily households, and residents' civic engagement. Appendix Figure B.9 shows that this composite measure of impersonal interactions is positively associated with impersonal cooperative traits and impersonal cooperative behavior, and negatively associated with kin-based cooperation.

Evidence from migrants' adaptation. Using our sample of domestic migrants and a simple two-period difference-in-differences framework, we further document that families moving to higher market access counties quickly adapted their behavior by broadening impersonal beneficial social interactions. We focus on two indicators that can be measured at the family level before and after migration: the father's labor-force cooperation score and residence with non-kin. Specifically, we estimate:

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

where $interactions_{ft}$ is our measure of impersonal beneficial social interactions for family f at time t, measured either before or after the move from origin county $o(f)$ to destination county $d(f)$. $Post_t$ is an indicator for the post-migration period, and θ_f is a family fixed effect. The coefficient β captures the effect of moving to a county with higher (versus lower) market access on impersonal beneficial interactions. Standard errors ϵ_{ft} are clustered at the county of destination d (Bertrand et al., 2004); results are robust to two-way clustering by origin and destination. As before, we weight observations by matching probabilities to account for families that are matched to multiple 1890-borders counties when harmonizing county borders (Hornbeck, 2010).

We find that families moving to higher market access counties were more likely to engage in broad, beneficial day-to-day social interactions. Table 4 shows that the labor-force cooperation score increased by 0.005 points (p-value < 0.01), about 3 percent of a standard deviation, and the probability of living with a non-kin rose by 0.0138 percentage points (p-value < 0.001), about 4 percent of a standard deviation, relative to families moving to lower market access counties. These results are robust to two-way clustering at the destination- and origin-county level (columns 2 and 5) and to using a continuous definition of treatment (columns 3 and 6).

Interpretation. Taken together, these findings suggest that market integration changed everyday life not only by increasing the volume of economic activity, but also by altering the structure of social interactions. Our measures capture shifts in how people work, live, and participate in civic life that are closely aligned with the mechanism in our conceptual framework: more frequent, beneficial interactions with socially distant others.

One way to see this is through the transformation of manufacturing. Market integration shifted production from small artisan shops staffed by a few highly skilled workers to large establishments with many workers and a pronounced division of labor (Atack et al., 2011). In such settings, employment opportunities, job retention, and productivity increasingly depended on coordinating tasks with non-kin co-workers, supervisors, customers, and suppliers who were geographically and socially distant. Our labor-force cooperation measure is designed to capture this relational aspect of work. In Section 8.2, we show that the impact on labor-force cooperation is robust to extensive controls for the rise of manufacturing and the transition out of agriculture, suggesting that we are not merely detecting structural change in sectoral composition, but a deeper shift in the nature of workplace interactions.

Similar dynamics arise outside the workplace. As market integration and the division of labor intensify, opportunities for mutually beneficial exchanges with distant others expand across many spheres of social life. Recreation and leisure activities increasingly take place in market-mediated settings and in the company of socially distant others. The costs and benefits of collective action in civic associations—from fraternal organizations to local political clubs—change in ways that make broader participation more attractive. These forms of impersonal, mutually beneficial interaction are captured by our civic engagement measure. As we document below (Section 8.2), the effects we find are not simply artifacts of income growth, urbanization, or sectoral shifts. Instead, they reflect a more general reorganization of social life around exchanges and joint activities with strangers and out-group members.

Finally, our evidence is consistent with a two-way relationship between interactions and culture. Our migrant analysis suggests that increased exposure to commerce and impersonal interactions prompted people to adopt more impersonal cooperative cultural traits, which in turn made such interactions more profitable and sustainable. At the same time, once people became more universalistic and trusting, they may have sought out environments with more impersonal interactions. The patterns in Figure 1 and Appendix Figure B.9 are consistent with this mutually reinforcing process.

8.1.3 Cultural Adaptation is Limited to Commerce-Intensive Industries

We next provide more direct evidence that cultural adaptation was a response to increased economic interdependence, which raised the returns to impersonal cooperative cultural traits (Prediction 5). Using the sample of domestic migrants and our dynamic difference-in-differences framework, we show that cultural adaptation is concentrated among individuals whose livelihoods are highly dependent on commerce.

We classify migrants' industries into two broad groups. *Commerce-intensive* industries are sectors that either sell primarily to distant markets—such as manufacturing and agriculture—or are essential to the functioning of markets, such as wholesale, retail, and transportation. *Commerce-moderate* industries mostly serve local markets and community needs, such as construction, utilities, entertainment and recreation, and public administration.[25] We then restrict the sample to households where the father remained

[25] Specifically, we classify the following IPUMS `IND1950` codes as commerce-intensive: Agriculture, Forestry, and Fishing (105–126), Mining (206–239), Manufacturing (306–499), Transportation (506–568), Telecommunications (578–579), Wholesale Trade (606–627), Retail Trade (636–699, except 679 — Eating and drinking places), Banking and credit agencies (716), Security and commodity brokerage and investment companies (726), Insurance (736), Advertising (806), Accounting, au-

in the same broad industry category before and after migration and estimate our dynamic difference-in-differences specification separately for each category.

Figure 4 presents the results. For individuals in commerce-intensive industries, moving to a county with higher market access leads to an immediate and persistent increase in universalistic traits, relative to moving to a lower market access county (Panel A). This pattern closely mirrors the findings from the full sample of migrants. By contrast, for individuals working in commerce-moderate industries, there is no discernible impact: moving to a county with greater market access has essentially no effect on universalism (Panel B).

This heterogeneity supports the hypothesis that direct exposure to economic interdependence and mutually beneficial exchanges with distant individuals—as opposed to simply living in a more market-oriented place—shapes impersonal cooperative cultural traits. The fact that the effect is concentrated among migrants in commerce-intensive industries also makes it unlikely that the association is driven by county-level changes that affect all residents alike.

We conduct several additional analyses to address possible concerns. One might worry that the effect is driven primarily by farmers, who account for about 58% of the commerce-intensive sample, or by the larger sample size in this category (266,028 observations, compared to 25,402 in the commerce-moderate group). To address this, we split the commerce-intensive category into farmers and non-farmers and repeat the analysis (Appendix Figure B.10).[26] The positive effect of market access on universalism is present in both subgroups. Even among non-farmers, where the sample is much smaller, the effect remains highly statistically significant, showing that the result is not simply driven by farming.

Differences in sample size are also unlikely to explain the null effect for commerce-moderate jobs. In Appendix Figure B.11, we take 1,000 random draws of 5,985 families (the same number of families as in the commerce-moderate group) from the commerce-intensive group and re-estimate the impact in each draw. We find a stronger effect in 96.1% of these draws than in the commerce-moderate group.

A more general concern is that families in the two industrial categories might differ in other important ways that could explain the results. In particular, we find that families in commerce-intensive industries tend to have weaker impersonal cooperative cultural traits ex ante: they have more children, are less likely to originate from urban areas, are less likely to be in extra-community marriages, and are less likely to have given their children universal names before migrating (Appendix Table B.7). However, our analyses suggest that these differences do not drive the pattern of heterogeneous effects. Appendix

diting, and bookkeeping services (807), and Miscellaneous business services (808); and the following codes as commerce-moderate: Construction (246), Utilities and Sanitary Services (586–598), Eating and drinking places (679), Real estate (746), Real estate-insurance-law offices (756), Auto repair services and garages (816), Miscellaneous repair services (817), Personal services (826–849), Entertainment and Recreation Services (856–859), Professional and Related Services (868–899), and Public Administration (906–946).

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

Figures B.12–B.14 show similar impacts across small and large families, rural and urban origins, and different types of marriage. Appendix Figure B.15, Panels A and B, shows that both families with high and low average prior UNI scores respond, with somewhat stronger effects among those with high prior UNI. Since UNI scores are lower in the commerce-intensive group, this pattern, if anything, works against finding an effect only in that group. Moreover, even individuals in commerce-moderate industries with high initial universalism show no response to market access, while those in commerce-intensive industries do (Appendix Figure B.15, Panels C and D).

Finally, we also show that this finding is robust to using an alternative classification of industries. Using Barkai and Karger (2020)'s modern-day classification of industries as tradable and non-tradable, which is based on the geographic radius served by each industry, we map `NAICS` codes to historical IPUMS `IND1950` codes, assuming that industries' classifications are stable over time. We then examine heterogeneous adaptation to a higher market access environment across migrants working in tradable industries or the trade sector (wholesale and retail, except eating and drinking places) and migrants working in non-tradable industries. We find similar results using this categorization instead of our own commerce-intensive vs commerce-moderate categorization (Appendix Figure B.16).

Taken together, these results indicate that an important driver of the effect of market access on culture is the nature of everyday economic interaction and interdependence. The effect appears to be linked to the direct and repeated experience of engaging in impersonal, market-based exchange with strangers and out-group members, or being dependent on them, rather than to broad county-level changes alone.

8.1.4 The Positive Returns to Adaptation

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

Empirical strategy. We estimate:

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

where $success_i$ denotes two measures of success available in the historical censuses: the survival rate of children (available for 1900–1910),[27] and the value of real property owned (available for 1850–1870).[28] $Adapted_i$ is a dummy equal to one if the mean UNI score of children born to migrant i after the move was higher than the mean UNI of children born before migration—that is, if the migrant became more universalistic. δ_{dot} is an origin-by-destination-by-year fixed effect, which also captures the main effect

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

[28] We rely on IPUMS variable `REALPROP` (available for 1850–1870).

of moving to a county with higher versus lower market access. X_i is a vector of migrant characteristics, including fixed effects for age, race, birthplace, ECM, and urban origin. The coefficient of interest is β, which captures the differential association between becoming more universalistic and success for migrants who gained versus lost market access.[29] We cluster standard errors ϵ_i at the county of destination d.

Results. We find that families that became more universalistic after moving to a higher market access county had better outcomes. Table 5 shows a strong and statistically significant association between cultural adaptation and both measures of economic success. Column 1 suggests that children of migrants who gained market access and became more universalistic had a 1.9 percentage points higher survival rate (p-value = 0.032) than children of migrants who became less universalistic, corresponding to about 12% of a standard deviation. This result remains stable when we add fixed effects for age, race, and birthplace (column 2) and when we further control for preexisting cooperative traits (ECM) and urban versus rural origin (column 3). Column 4 shows a similar pattern for real property value: migrants who culturally adapted to a higher market access environment owned $559 more in real property (p-value = 0.026) than those who did not adapt, roughly 21% of a standard deviation. This finding also holds when we include individual-level controls (columns 5 and 6).[30]

These patterns are consistent with Prediction 5 and the idea that people adapt their cultural traits to reduce costly mismatch between their values and their changing economic environment (Nunn, 2021). Market integration increased economic interdependence and created more opportunities for beneficial exchanges with socially distant individuals. Those who adapted appear to have been better positioned to exploit these opportunities.

Robustness. Appendix Table C.8 shows that the results are robust to two-way clustering at the counties of destination and origin. In our baseline, we winsorize real property values at the top 2.5%; Appendix Table C.9 shows that the finding also holds when we winsorize at different top percentiles, or do not winsorize at all. Appendix Table C.10 demonstrates that the results for real property values are robust to different methods of addressing the long right tail of the distribution.

8.2 Alternative Channels and Potential Mediators

We close our analysis by examining the potential role of competing channels and mediating factors. We focus on two central alternative hypotheses—income growth and increased social contact with diverse, distant individuals—and then consider several additional potential mediators. Across a range of empirical tests, we find that these factors have limited capacity to explain our results.

A prominent alternative hypothesis is that market integration raised incomes, and that income growth,

[29] In this framework, β is identified from several thousand cases in which there are multiple migrants within the same origin-destination-decade cell.

[30] We find no comparable effect on personal property. When we use total property value (real plus personal property) as the dependent variable, the effect is only marginally significant; see Appendix Table C.7.

in turn, fostered cultural adaptation (e.g., Inglehart, 1997; Inglehart and Welzel, 2005). Using the sample of domestic migrants and the difference-in-differences framework (Eq. 3), we provide direct evidence suggesting that this is unlikely to be central. Using the father's occupational income score, we split the sample into three groups: those who moved up the occupational ladder between the pre- and post-migration periods, those who did not switch occupation, and those who moved down the ladder. We find similar cultural adaptation to an increase in market access across all three groups (Appendix Figure B.17). This suggests that adaptation was not driven by economic changes that allowed migrants to switch to higher-paying occupations. More generally, it suggests that our findings are unlikely to be driven by income gains: even if market integration raised incomes across the occupational distribution, income would be expected to rise more among those moving up the ladder than among those moving down. If a rise in income were the key driver of cultural adaptation, we would expect larger effects in the upwardly mobile sub-sample, which we do not observe.

In a related exercise, we show that the impact is not driven by the transition out of agriculture. We have already shown that the effects on farmers and on non-farmers in commerce-intensive industries are similar (Appendix Figure B.10). Focusing on migrants who previously worked in agriculture, we also find similar paths of cultural adaptation among those who transitioned out of agriculture after migration and those who remained farmers (Appendix Figure B.18).

Another central alternative hypothesis is that market integration induced migration and increased population diversity, thereby reducing individuals' day-to-day social contact with a narrow in-group (e.g., family) and increasing their contact with socially distant, diverse populations, which in turn shaped culture (Allport, 1954).[31] To investigate this possibility, we again use data on kinship propinquity from Nelson (2020). We find similar responses to migrating to a higher market access environment among the subpopulation living close to kin after migration and among those who did not (Appendix Figure B.19, Panels A–B). Likewise, we find similar effects for migrants who moved away from kin—those who lived close to kin before migrating but not after—and for those who did not (Appendix Figure B.19, Panels C–D). If substituting relationships within a narrow in-group for relationships with socially distant others were a key channel, we would expect stronger adaptation among migrants who moved away from kin. The data suggest otherwise.

Because market integration may shape multiple features of the socioeconomic environment, other pathways are possible. For example, railroad connectivity and market integration might have facilitated the spread of new ideas and information.[32] Places with better access to information might have been more likely to encounter diverse cultural norms, making them more open-minded to different ways of life. Market integration may also have contributed to the emergence and strengthening of local legal institutions

[31]Recall that our results are not sensitive to including or excluding immigrants and non-whites from the sample (Appendix Table C.1 and Appendix Figure C.7), suggesting that diversity is not a key driver.

[32]In our historical context, railroad connectivity was related to communication technologies such as mail, the telegraph, and newspaper circulation.

that address the "fundamental problem of [impersonal] exchange" (Greif, 1993, 2000; Cantoni and Yuchtman, 2014). External enforcement by public-order institutions may foster impersonal cooperative cultural traits and broaden the scope of cooperation (Tabellini, 2008; Gorodnichenko and Roland, 2017; Henrich, 2020; Eruchimovitch et al., 2023).

Beyond these conceptual alternatives, there are also empirical concerns about competing channels and mediators. For example, market integration may have enabled urbanization, and urbanization may in turn have brought income growth, economic interdependence, and more social contact with distant others. In that case, market integration could affect culture and behavior only through urbanization, rather than directly. A related concern is that some of our measures of impersonal cooperative culture, behavior, and mutually beneficial interactions might be picking up factors such as urbanization, economic growth, or the transition out of agriculture.

To address these concerns, we examine the robustness of our results to accounting for the potential effects of several competing channels and possible mediators. We construct measures that together flexibly capture changes in income, the transition out of agriculture, industrialization, urbanization, population diversity, access to information, and the development of legal institutions: the share of urban population, the share of immigrants, birthplace diversity, the number of manufacturing establishments, the share working in manufacturing, the share working in agriculture, the mean occupational income score, log real GDP per capita, the number of information workers per 1,000 residents, and the number of lawyers and judges per 1,000 residents.[33]

We then augment the difference-in-differences framework (Eq. 3) to account for the dynamic impact of moving to a county with higher versus lower levels of these alternative channels and mediators. Specifically, we include dynamic controls for the difference in each measure between the origin county (o) and the destination county (d) and then examine how controlling for these differences affects the estimated impact of moving to a higher market access county on universal identification.[34]

We find that, even after controlling for the dynamic effects of all the considered factors, the estimated impact of moving to a higher market access county on universalism remains fairly stable (Appendix Figure B.20). This is true when each factor is included separately (Panels A–J) and when all factors are included jointly (Panel K). Moreover, we show that the differential impact across commerce-intensive and commerce-moderate industries is also not driven by differential responses to these factors between the pre- and post-migration environments (Appendix Figure B.21).

In addition, we follow a parallel strategy in our county-level analysis (Eq. 2), including all measures of competing channels and potential mediators as "bad controls" to assess their potential role in delivering our findings. Figure 5 and Appendix Table B.8 demonstrate that the estimated impact on impersonal cooperative culture is remarkably robust to flexibly controlling for all possible combinations of these

[33]For more information on these measures, see Appendix B.6.2.3.

[34]The additional controls take the following form: $\sum_{b\neq 0} \gamma_b \cdot \mathbb{1}\left[b(i)=b\right] \cdot \mathbb{1}\left[Mediator_{d(i)} > Mediator_{o(i)}\right]$.

factors. The same is true for the impacts on cooperative behavior, the prevalence of commerce, and impersonal beneficial social interactions (Appendix Figures B.22–B.24 and Appendix Tables B.9–B.11).

In summary, across all these tests, none of the competing channels or potential mediators we consider appears to drive cultural adaptation or to account for the robust link between market access and impersonal cooperative culture and behavior. Although we cannot rule out some role for these factors, our findings point to direct exposure to impersonal, beneficial exchange with distant others as the central driver.

9 Conclusions

We provide new evidence that rising market integration in the United States between 1850 and 1920 fundamentally transformed key aspects of social life. Using county-level market access—driven by the expansion of the railroad network and population growth, including mass immigration—as a measure of integration into broader markets, we show that increased market integration fostered a package of interrelated cultural traits—universalism, tolerance, and generalized trust—that support cooperation with socially distant others. Hand in hand with this cultural shift, higher market access reoriented the scope of cooperation away from kin-based networks and toward more impersonal, generalized forms, enabling greater cooperation with strangers and out-group members.

Guided by a conceptual framework in which market integration changes the "matching technology" of social interactions, we assemble rich historical data from the full-count U.S. censuses, newspapers, and other sources to construct a broad set of measures of impersonal cooperative culture, impersonal cooperation, kin-based cooperation, and mutually beneficial interactions across social domains. We validate that counties with higher levels of impersonal cooperative culture display more impersonal cooperation and a broader range of impersonal, mutually beneficial interactions, and are less reliant on kin-based support systems.

To support a causal interpretation, we exploit county-level variation in market access using several distinct identification strategies. We recenter treatment around expected market access (Borusyak and Hull, 2023) based on the network of proposed canals in Fogel (1964); we leverage uneven, network-driven changes in market access across space and time in a design that flexibly accounts for local railroad construction and population shifts; and we use recentered and waterways-based instrumental variables following Hornbeck and Rotemberg (2024) and Donaldson and Hornbeck (2016). Across all these approaches, increases in market access lead to substantial and persistent increases in universalism, tolerance, social trust, and impersonal cooperation, alongside a decline in kin-based cooperation.

We then turn to linked individual-level census data to study domestic migrants who moved between counties with differing market access. These analyses rule out selective sorting as the main explanation for our findings: migrants to higher-access counties were not already more universalistic before moving, nor were they more likely to engage in impersonal beneficial interactions, live near kin, have more children, originate from an urban location, be native-born, or work in higher-paying occupations or particular industries. Instead, we find evidence of rapid cultural adaptation: families who moved to places with greater market access quickly adopted more universalistic names for their children, relative to observably similar families who moved to lower market-access environments.

We shed light on the mechanisms linking market integration to changes in culture and cooperation. We show that residents of counties experiencing increases in market access became more economically interdependent and engaged in more mutually beneficial, market-based exchanges with distant others, as higher market access raised the local prevalence of commerce. We also document a broad increase in the extent of impersonal beneficial interactions—at work, at home, and in civic life—and show that families who moved to higher-access counties became more likely to engage in such interactions both at work and within the household. Cultural adaptation is concentrated among individuals employed in commerce-intensive industries, such as manufacturing, agriculture, wholesale, and transportation—those whose livelihoods depended most on interactions with strangers and market-based exchange—with no significant effect among workers in more locally oriented sectors. We also show that migrants who adapted culturally to a higher market-access environment achieved better outcomes, with higher property values and child survival rates than comparable migrants who became less universalistic.

Our analysis also tests, and largely rules out, two of the most plausible competing channels: higher income and a shift to more diverse social relationships. We find similar patterns of cultural adaptation among migrants who moved up versus down the occupational ladder and among those who transitioned out of agriculture versus those who remained farmers. Likewise, migrants who continued to live near kin after migration adapted as much as those who did not. More broadly, a series of empirical tests suggests that other potential mediators—including rising incomes, industrialization, urbanization, increased population diversity, improved access to information, and the expansion of local legal institutions—do not appear to be primary drivers.

Taken together, our findings provide new support for the *doux commerce* hypothesis—that expanding market integration can foster impersonal prosocial norms, generalized trust, and broader patterns of cooperation. At the same time, we show that this shift toward impersonal cooperation comes with a decline in traditional kin-based social insurance, echoing concerns articulated by critics of markets such as Polanyi (1944) and Marx (1867). The historical experience of the United States demonstrates that markets can transform not only patterns of production and consumption, but also the psychological and cultural boundaries of cooperation. As debates about markets and globalization continue, our findings highlight the potential of market integration to expand prosocial norms and to foster cooperation beyond immediate in-groups.

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Figures

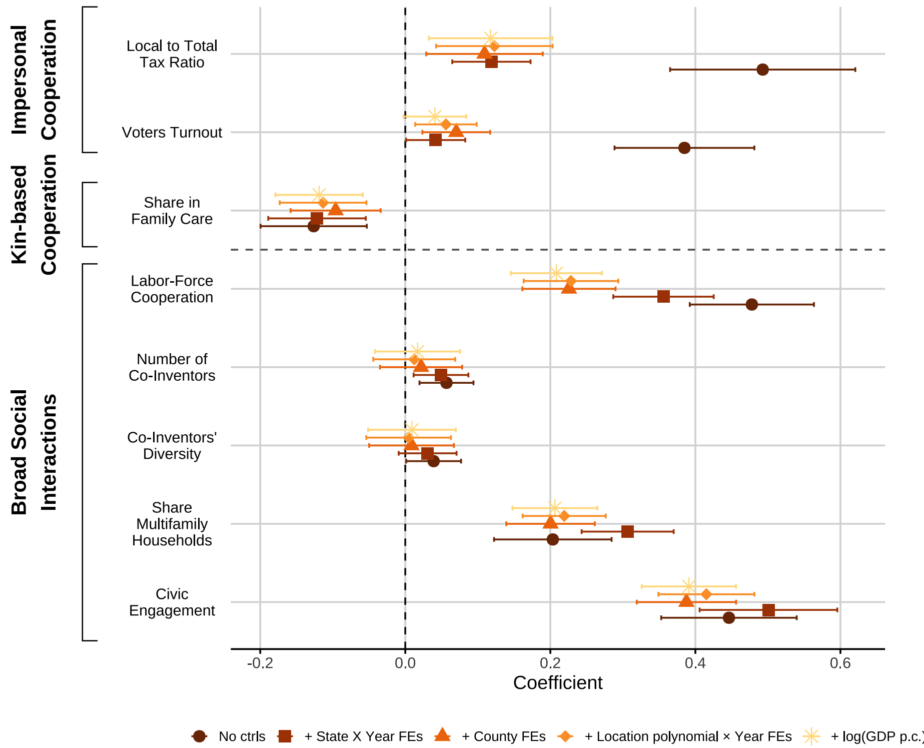


Figure 1: Impersonal Cooperative Culture, Cooperative Behavior, and Broad Social Interactions

Note: This figure plots the estimates of β and 95% confidence intervals from Equation (1) for all three historical measures of cooperation and five measures of broad social interactions, standardized into z-scores, and five different specifications, sequentially adding controls to the estimation equation: without any controls, with state-by-year fixed effect $\delta_{s(c)t}$, with additional county fixed effect δ_c, with additional cubic spatial polynomial interacted with year fixed effects $f(x_c, y_c)\delta_t$, and with additional time-varying control for log real GDP per capita (Fulford et al., 2020). Standard errors are clustered at arbitrary grid cells of 100 miles square (Bester et al., 2011).

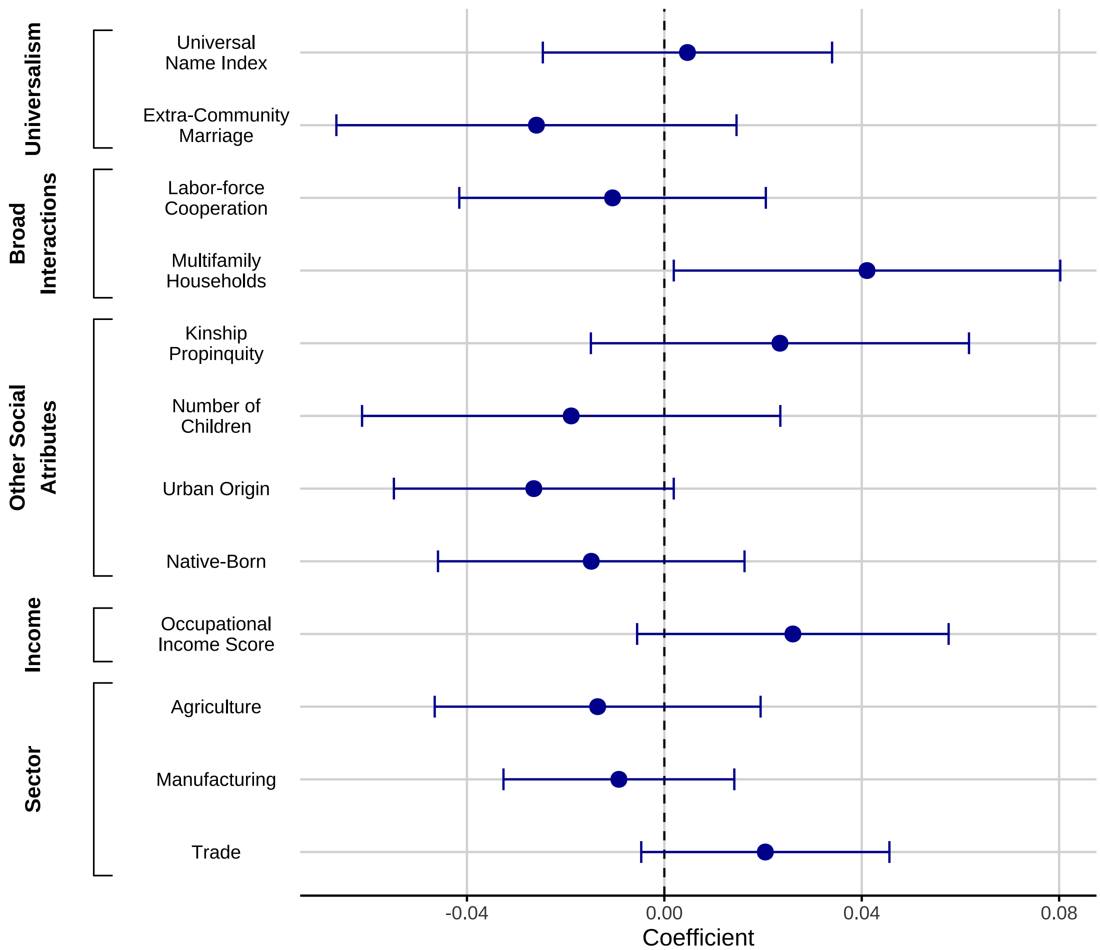


Figure 2: The Relationship is Not Driven by Selective Sorting of Domestic Migrants

Note: This figure plots the estimates of β and 95% confidence intervals from a family-level version of Equation (2), estimated on a dataset of incoming domestic migrants into counties. The dependent variables are two measures of migrants pre-migration universalism: mean UNI of children born before migration and ECM; two measures of pre-migration broad beneficial social interactions: labor-force cooperation and residing with a non-kin; four social attributes measured before migration: kinship propinquity, the number of children, urban vs rural origin, and nativity; pre-migration occupational income score; and dummy variables for working in three different sectors before migration: agriculture, manufacturing, and trade. All outcomes are standardized into z-scores. Standard errors are clustered at arbitrary grid cells of 100 miles square (Bester et al., 2011).

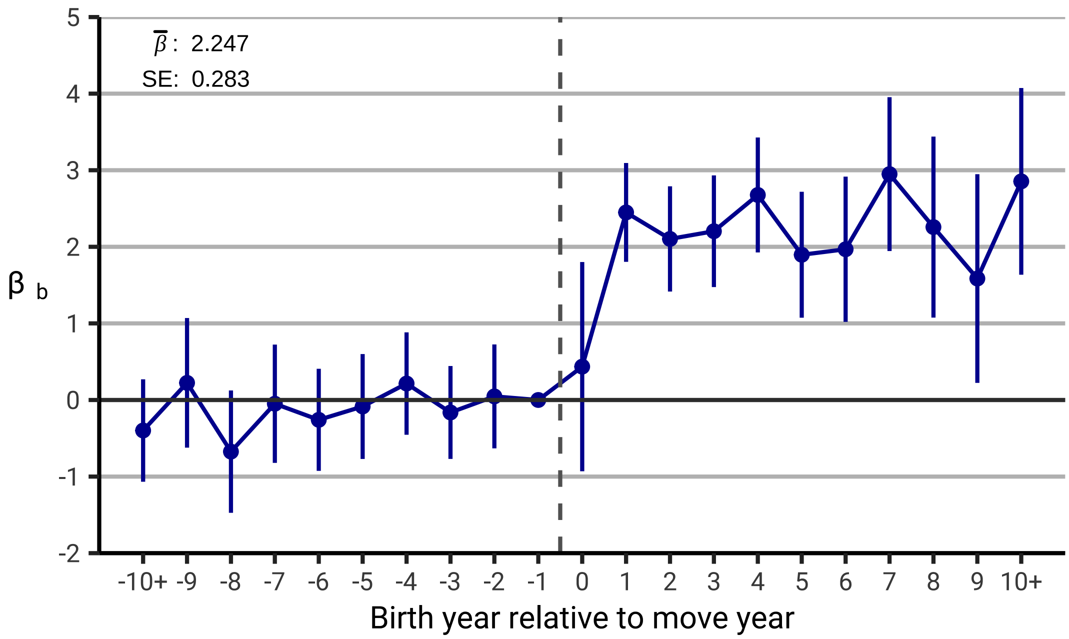


Figure 3: Migrants Become More Universalistic After Moving to a Higher Market Access County

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

(A) Commerce-intensive (B) Commerce-moderate

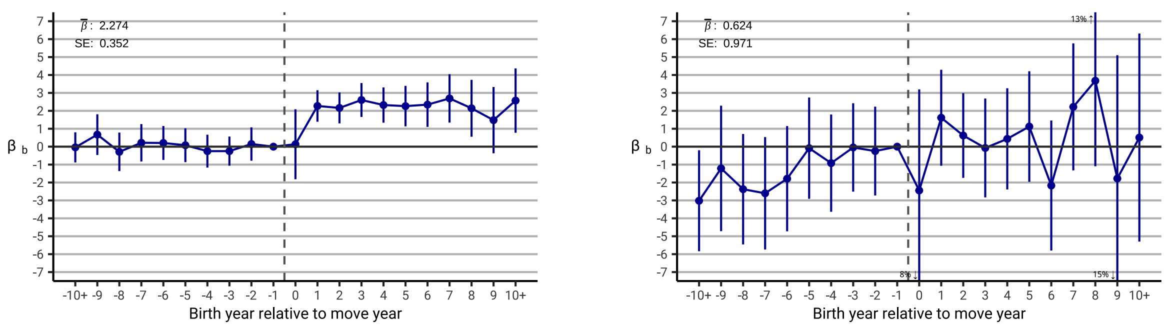


Figure 4: Market Access Only Affects Individuals Working in Commerce-Intensive Industries

Note: This figure plots the estimates of β_b and 95% confidence intervals from the dynamic difference-in-differences equation (3). The dependent variable is children's UNI. 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.

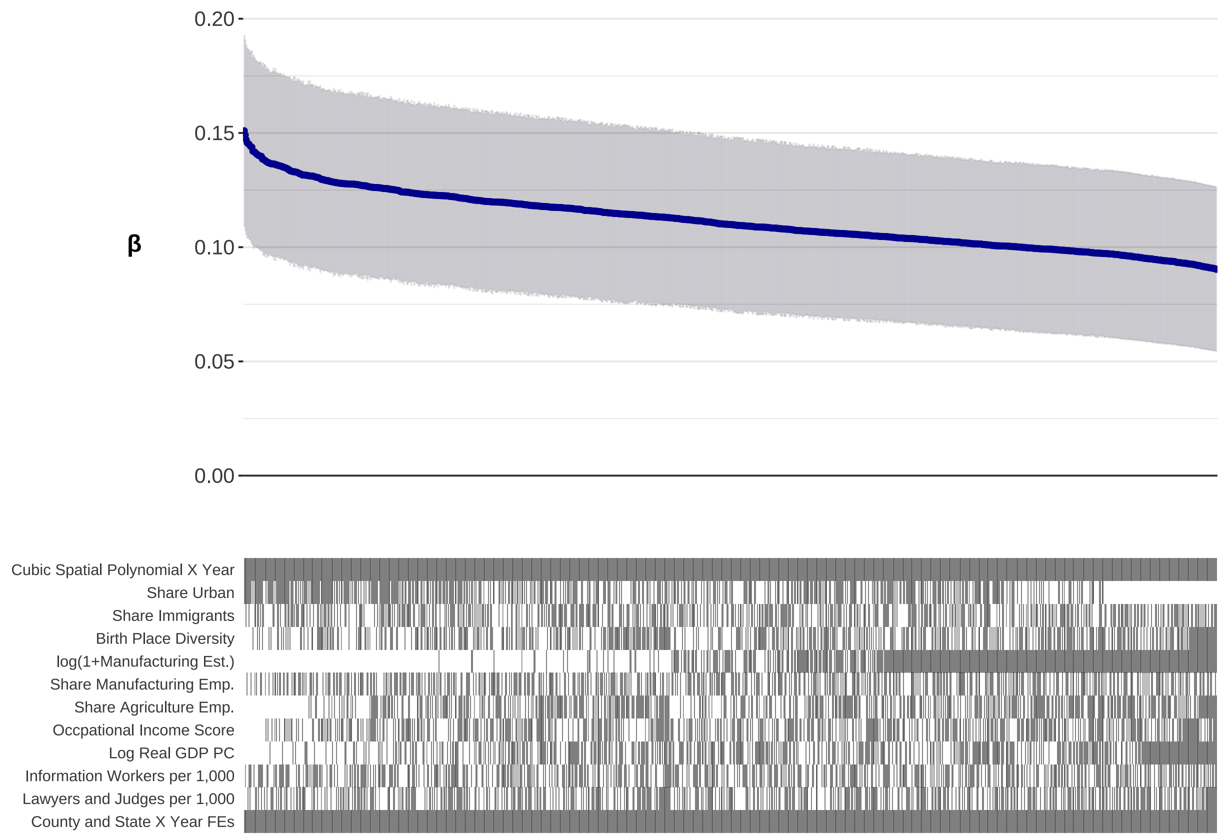


Figure 5: The Impact on Culture is Robust to Controlling for Competing and Mediating Factors

Note: This figure plots estimates of β and 95% confidence intervals from Equation (2) when the dependent variable is the composite impersonal cooperative culture index. In addition to the baseline controls, the regressions control for all possible combination of the considered competing and mediating factors: the share of urban population, the share of immigrants, birth-place diversity, log of one plus the number of manufacturing establishments, the share working in manufacturing, the share working in agriculture, the mean occupational income score, log real GDP per capita, the number of information workers per 1,000, and the number of lawyers and judges per 1,000. Standard errors are clustered at arbitrary grid cells of 100 miles square (Bester et al., 2011).

Tables

Table 1: Market Access Fosters Impersonal Cooperative Culture

	Dependent variable:							
	Baseline	Recentering	Controlling for local railroads and population					Both
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Impersonal Cooperative Culture (mean = 0.023 , sd = 0.655)							
Log market access	0.1461***	0.1377***	0.1265***	0.1059***	0.0971***	0.0868***	0.0917***	0.0839***
	(0.0178)	(0.0170)	(0.0173)	(0.0175)	(0.0173)	(0.0175)	(0.0174)	(0.0176)
Observations	19,912	19,891	19,912	19,912	19,912	19,912	19,912	19,891
R^2	0.726	0.756	0.748	0.758	0.758	0.759	0.762	0.763
	Panel B: Universal Name Index (mean = 32.18 , sd = 6.6)							
Log market access	0.9250***	0.8959***	0.7035***	0.5531***	0.4657***	0.3572**	0.4051**	0.3838**
	(0.1610)	(0.1617)	(0.1681)	(0.1690)	(0.1735)	(0.1713)	(0.1724)	(0.1750)
Observations	18,182	18,154	18,182	18,182	18,182	18,182	18,182	18,154
R^2	0.805	0.799	0.806	0.809	0.810	0.813	0.816	0.816
	Panel C: Extra-Community Marriage (mean = 0.382 , sd = 0.2)							
Log market access	0.0069*	0.0070*	0.0072*	0.0044	0.0056	0.0056	0.0065	0.0068
	(0.0037)	(0.0038)	(0.0039)	(0.0040)	(0.0040)	(0.0041)	(0.0041)	(0.0043)
Observations	18,179	18,151	18,179	18,179	18,179	18,179	18,179	18,151
R^2	0.908	0.908	0.908	0.909	0.910	0.910	0.911	0.911
	Panel D: Norms Tolerance Index (mean = 0 , sd = 1)							
Log market access	0.1785***	0.1701***	0.1753***	0.1753***	0.1610***	0.1465***	0.1496***	0.1397***
	(0.0321)	(0.0322)	(0.0334)	(0.0333)	(0.0340)	(0.0347)	(0.0346)	(0.0349)
Observations	18,098	18,070	18,098	18,098	18,098	18,098	18,098	18,070
R^2	0.698	0.695	0.698	0.698	0.699	0.700	0.701	0.698
	Panel E: Religious Diversity Index (mean = 0 , sd = 1)							
Log market access	0.2681***	0.2541***	0.2306***	0.2180***	0.2031***	0.1909***	0.1893***	0.1751***
	(0.0347)	(0.0345)	(0.0362)	(0.0383)	(0.0382)	(0.0383)	(0.0384)	(0.0379)
Observations	17,303	17,283	17,303	17,303	17,303	17,303	17,303	17,283
R^2	0.681	0.681	0.682	0.683	0.684	0.687	0.689	0.689
	Panel F: Social Trust (mean = 0.002 , sd = 0.998)							
Log market access	0.1201**	0.1194**	0.1258**	0.1229**	0.1373**	0.1291**	0.1291**	0.1274**
	(0.0485)	(0.0482)	(0.0532)	(0.0592)	(0.0616)	(0.0631)	(0.0632)	(0.0632)
Observations	6,821	6,812	6,821	6,821	6,821	6,821	6,821	6,812
R^2	0.680	0.680	0.680	0.679	0.681	0.683	0.685	0.685
Expected log market access		Yes						Yes
Any railroad			Yes	Yes	Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes	Yes	Yes
Railroads within further buffers						Yes	Yes	Yes
Population within further buffers							Yes	Yes

Note: This table reports estimates of equation (2). The dependent variables are: the composite impersonal cooperative culture index (Panel A), the UNI (Panel B), the ECM (Panel C), the NTI (Panel D), the RDI (Panel E), and Social Trust (Panel F). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Column 1 is our baseline estimation. Column 2 implements the approach recommended by Borusyak and Hull (2023) using Fogel (1964)'s proposed canal to control for the expected log market access. Columns 3-7 add additional controls for local railroad infrastructure and population. Column 8 controls for both the expected log market access and local railroads and population. Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Market Access Strengthens Impersonal and Weakens Kin-based Cooperative Behavior

	Dependent variable:							
	Baseline	Recentering	Controlling for local railroads and population					Both
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Voters Turnout in Presidential Elections (mean = 0.63 , sd = 0.24)							
Log market access	0.0375***	0.0371***	0.0286***	0.0367***	0.0290***	0.0211***	0.0205***	0.0202***
	(0.0061)	(0.0062)	(0.0064)	(0.0068)	(0.0066)	(0.0066)	(0.0065)	(0.0065)
Observations	45,308	45,268	45,308	45,308	45,308	45,308	45,308	45,268
R^2	0.804	0.804	0.804	0.806	0.806	0.734	0.809	0.809
	Panel B: Share of Local Tax Revenues (mean = 0.67 , sd = 0.198)							
Log market access	0.0185***	0.0175***	0.0144**	0.0153**	0.0131*	0.0106	0.0105	0.0096
	(0.0060)	(0.0058)	(0.0065)	(0.0067)	(0.0069)	(0.0067)	(0.0067)	(0.0066)
Observations	4,942	4,940	4,942	4,942	4,942	4,942	4,942	4,940
R^2	0.908	0.908	0.908	0.908	0.908	0.909	0.910	0.910
	Panel C: Share in Family Care (mean = 0.778 , sd = 0.111)							
Log market access	-0.0121***	-0.0112***	-0.0113***	-0.0107***	-0.0103***	-0.0104**	-0.0104**	-0.0094**
	(0.0032)	(0.0032)	(0.0036)	(0.0037)	(0.0039)	(0.0040)	(0.0040)	(0.0040)
Observations	18,173	18,145	18,173	18,173	18,173	18,173	18,173	18,145
R^2	0.721	0.721	0.721	0.722	0.722	0.722	0.722	0.722
Expected log market access		Yes						Yes
Any railroad			Yes	Yes	Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes	Yes	Yes
Railroads within further buffers						Yes	Yes	Yes
Population within further buffers							Yes	Yes

Note: This table reports estimates of equation (2). The dependent variables are two historical measures of impersonal cooperation: voter turnout in presidential elections (Panel A), and the share of local tax revenues (Panel B); and one measure of historical kin-based cooperation: the share of vulnerable individuals in family care (Panel C). Column 1 is our baseline estimation. Column 2 implements the approach recommended by Borusyak and Hull (2023) using Fogel (1964)'s proposed canal to control for the expected log market access. Columns 3-7 add additional controls for local railroad infrastructure and population. Column 8 controls for both the expected log market access and local railroads and population. Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Market Access Increases Commerce and Impersonal Beneficial Social Interactions

	Dependent variable:						
	The Prevalence of Commerce		Impersonal Beneficial Interactions				
	Market Language in Newspapers	Share in Trade	Labor-force cooperation	Number of co-inventors	Diversity of co-inventors	Residence with a non-kin	Engagement in civic activities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log market access	0.0146***	0.0051***	0.0058***	0.0114***	0.0111***	0.0083***	0.0008***
	(0.0045)	(0.0008)	(0.0012)	(0.0037)	(0.0034)	(0.0022)	(0.0002)
DV mean	0.4660	0.0550	3.996	1.092	0.0760	0.1510	0.0120
DV sd	0.1160	0.0360	0.0590	0.1160	0.1060	0.0840	0.0090
Observations	8,625	18,266	18,267	17,360	17,360	18,277	18,266
R^2	0.633	0.780	0.680	0.241	0.241	0.782	0.688

Note: This table reports estimates of equation (2). The dependent variables are two measures for the prevalence of commerce: the share of market language in local newspapers (column 1), the share of residents working in the wholesale and retail trade industries (column 2); and five historical measure of impersonal beneficial social interactions: labor-force cooperation (column 3), the average number of patent co-inventors (column 4), the diversity of patents co-inventors (column 5), the share of multifamily households (column 6), and the share employed in civic activities (column 7). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. 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 4: The Impact of Moving to a Higher Market Access County on Impersonal Beneficial Interactions

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

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

Table 5: The Positive Returns to Cultural Adaptation

	Dependent variable:					
	Children Survival Rate (mean = 0.879 , sd = 0.163)			Real Property Value (mean = 2321.0 , sd = 2711.7)		
	(1)	(2)	(3)	(4)	(5)	(6)
More Universalistic	-0.0031	-0.0018	-0.0018	-106.0	-93.20	-93.92
	(0.0064)	(0.0066)	(0.0066)	(117.5)	(115.4)	(114.6)
Higher Market Access × More Universalistic	0.0192**	0.0194**	0.0195**	559.0**	606.2**	599.7**
	(0.0090)	(0.0095)	(0.0095)	(250.9)	(240.2)	(238.6)
Observations	25,432	25,432	25,432	24,835	24,835	24,835
R^2	0.777	0.789	0.789	0.883	0.892	0.892
Origin × Destination × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Ctrls. (demographics)		Yes	Yes		Yes	Yes
Individual Ctrls. (traits)			Yes			Yes

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

Online Appendices

A Data and Measurement

This appendix provides additional details on data sources, variable construction, and spatial patterns for all measures used in the paper. It also provides a discussion of the limitations and validations of selected measures. Throughout, we harmonize county-level variables to 1890 county boundaries using the procedure in Hornbeck (2010). For outcomes with highly skewed distributions and long upper tails (e.g., inventor collaboration, multifamily households, civic and recreational employment, wholesale and retail employment), we winsorize the top 2.5% in our baseline specifications and verify robustness to alternative treatments of skewness (Appendix C).

A.1 Market Access

Transport cost matrices and parameterization. Our market access measure follows Donaldson and Hornbeck (2016), who construct bilateral trade-cost matrices τ_{odt} between counties o and d for each decade t between 1850 and 1920 (expressed relative to the average value of shipments P). County borders and cost parameters are fixed at their 1890 values; changes in τ_{odt} over time are driven solely by changes in the transport network—the construction of additional water canals and railroads.

We use the cost matrices to compute a market access measure defined as:

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

where N_{dt} is county d's population from Manson et al., 2020 and θ is a trade elasticity parameter. Following Donaldson and Hornbeck (2016), we set $\theta = 8.22$ and $P = 35$ in the baseline. We also re-estimate all main specifications using the parameter values in Hornbeck and Rotemberg (2024) and for $\theta \in \{1, 2, \ldots, 13\}$; the results are similar across the full range.

Appendix Figure A.2 plots the spatial distribution of log market access for each census year between 1850 and 1920. Substantial differences in market access across regions are evident: market access is generally highest in the Northeast and Midwest and lowest in the West. Panel A of Appendix Figure A.3 documents the significant increase in average log market access over our sample period. The solid blue curve represents market access calculated using contemporaneous transportation costs and population, while the dashed dark red curve fixes transportation costs to 1850 levels. The comparison shows that the main driver of the increase in market access was the decline in transportation costs due to the expansion of the railroad network. Panel B shows that this average increase masks substantial spatial heterogeneity: counties with low initial market access in 1850—typically less settled and less developed areas—tended to experience larger absolute increases in market access between 1850 and 1920.

Discussion of limitations. Market access is a model-based measure of *potential* integration into national markets rather than realized trade flows. It abstracts from within-county transport frictions, assumes population is a sufficient statistic for market size, and holds cost parameters fixed at 1890 levels. These assumptions entail three main limitations:

1. *Potential vs. realized trade:* Changes in MA_{ot} may not map one-for-one into realized trade flows, especially if local institutions or credit constraints hinder trade.

2. *Homogeneous demand and income:* The measure does not incorporate differences in income, demand composition, or preferences across counties.

3. *Technological and pricing changes:* Fixing cost parameters ignores changes in railroad technology, pricing strategies, and competition that may have affected costs over time.

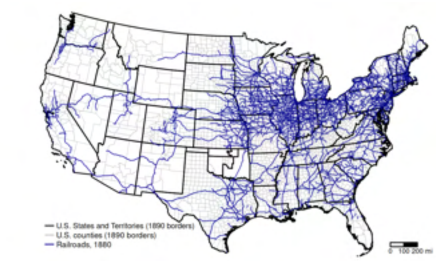
These limitations likely introduce measurement error, which could attenuate our estimates. Several features of our empirical design mitigate concerns: (i) we focus on within-county changes, absorbing time-invariant mismatches between potential and realized trade; (ii) we show robustness to alternative parameterizations of θ and P; and (iii) we validate MA_{ot} by showing that counties with larger increases in MA_{ot} also see larger increases in commerce-related outcomes (Section 8.1).

(A) 1850

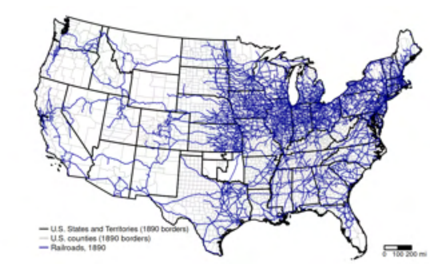
(B) 1860

(C) 1870

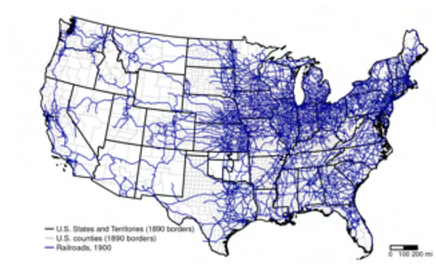
(D) 1880



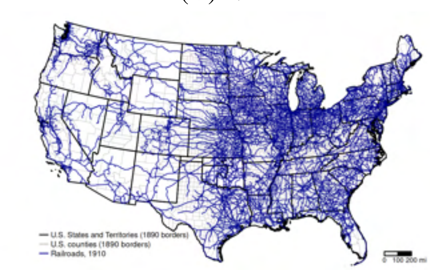
(E) 1890



(F) 1900



(G) 1910



(H) 1920

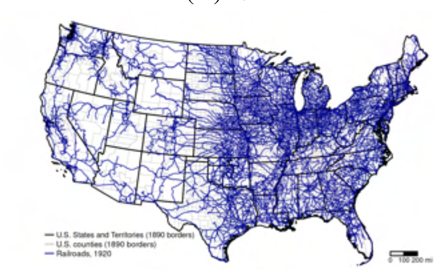
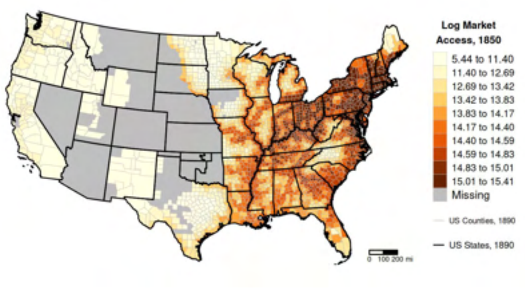


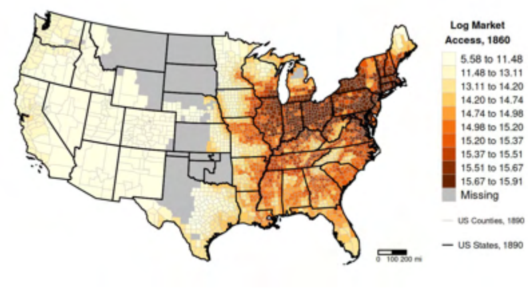
Figure A.1: The Railroad Network, 1850-1920

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

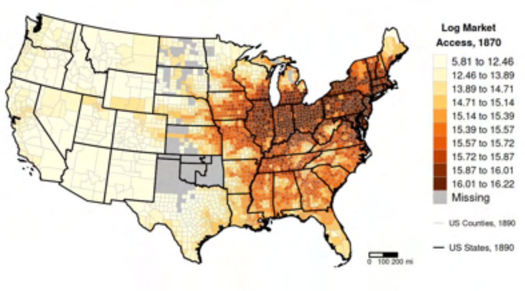
(A) 1850



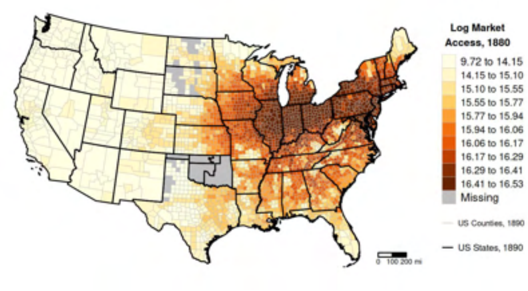
(B) 1860



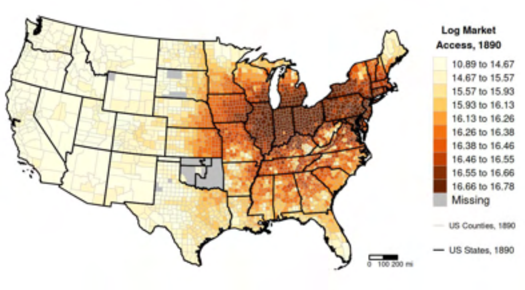
(C) 1870



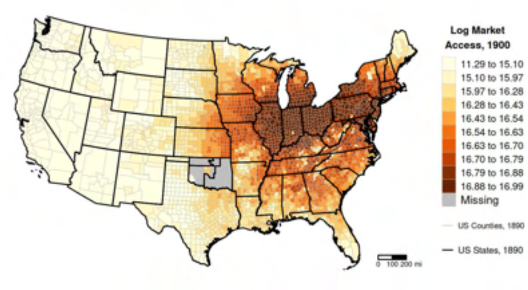
(D) 1880



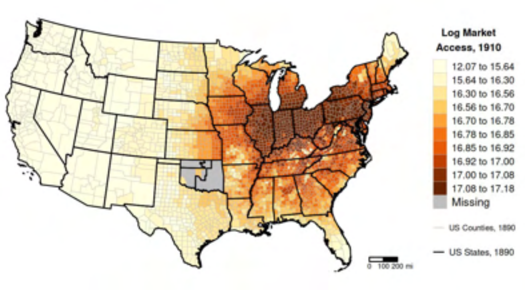
(E) 1890



(F) 1900



(G) 1910



(H) 1920

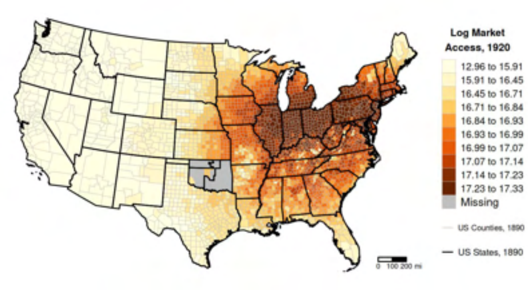
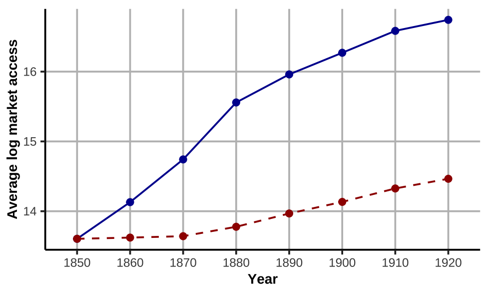


Figure A.2: Log Market Access, 1850-1920

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

(A) Average log market access by year



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

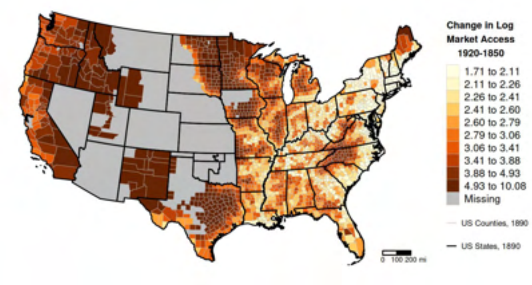


Figure A.3: The Change in log Market Access, 1850-1920

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

A.2 Impersonal Cooperative Culture

This section provides details on the construction and validation of the four census-based culture measures (UNI, ECM, NTI, RDI) and the newspaper-based trust measure. The census-based measures are taken from Raz (2025), but we invert them so that higher values consistently indicate more impersonal, universalistic, tolerant traits.[35]

Universal Name Index (UNI). The UNI is based on the relative frequency of first names among children aged 0-10 in the full-count U.S. censuses. Let $Pr(n\,|\,l,g,t)$ denote the probability that name n is given to a child of gender g in county l in census year t, and $Pr(n\,|\,-l,g,t)$ the corresponding probability in all other counties. Following Fryer and Levitt (2004) and Raz (2025), we define

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

The index ranges from 0 (name used only locally) to 100 (name used only outside the county), with 50 indicating equal local and non-local use. For each county-census-year, we aggregate the name-specific UNI into a county measure by taking the average UNI across children in the county. Raz (2025) demonstrates robustness to alternative samples, phonetic standardization, and trimming rare names.

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, or nationality.

Panels C and D in Appendix Figure A.4 plot the spatial distribution of the UNI in 1850 and 1920, and Panel B in Appendix Figure A.5 plots the change in the UNI between those years. The spatial patterns are intuitive. In 1850, frontier counties exhibit more "local" names, indicating lower universalism. By 1920, the West Coast, the Northeast, and large metropolitan areas tend to be more universalist, whereas the South, the wheat belt, and Utah display more local naming patterns. Counties that were in early stages of development in 1850 experienced the largest increases in the tendency to give children universal names.

Extra-Community Marriage (ECM). The ECM uses birthplaces to define communities. For each married couple in the census not living in group quarters with birthplace information for both partners, we record spouses' birthplaces (state for US-born, country for foreign-born) and define an indicator that equals one if the couple does *not* have a common birthplace. The county-level ECM is the share of couples with different birthplaces.

Panels E and F in Appendix Figure A.4 plot the spatial distribution of the ECM in 1850 and 1920, and Panel C in Appendix Figure A.5 plots the change. Some of the spatial patterns described above for the UNI are also evident for the ECM. In addition, the ECM displays a clear East-West division: in the more recently settled West, the share of same-birthplace spouses tended to be much lower.

[35] The corresponding measures in Raz (2025) are: LNI, ICM, TNI, and RHI.

The Norms Tolerance Index (NTI). We focus on households with married mothers aged 35-44 to avoid capturing variation originating from demographics rather than culture and psychology. For each county-census-year, we compute the coefficient of variation of (i) mothers' age at first birth, (ii) the total number of children, and (iii) the number of distinct families residing in the same dwelling. We extract the first principal component (PC1) of these three standardized variables and multiply it by -1, so that higher values indicate more dispersion, which we interpret as looser family norms. The index is standardized to z-scores within each census year.

Panels G and H in Appendix Figure A.4 and Panel D in Appendix Figure A.5 plot the spatial distributions of the NTI in 1850, 1920, and the change between those years, respectively. Again, development seems to matter: counties in early stages of settlement in 1850 tend to be very "tight." By 1920, the West and Northeast appear relatively loose, whereas Utah and much of the South and Midwest appear tighter. Large metropolitan counties (e.g., Dallas County in Texas, Jefferson County in Alabama, and Shelby and Davidson Counties in Tennessee) tend to be looser than their neighbors.

Religious Diversity Index (RDI). Using county-level data on membership in religious denominations from the Census of Religious Bodies, we compute a Herfindahl-Hirschman Index, and define $RDI_{ot} = 1 - \sum_j s_{ojt}^2$, where s_{ojt} is the share of members in denomination j in county o and year t. We standardize the RDI into z-scores within each census wave. Panels I and J in Appendix Figure A.4 and Panel E in Appendix Figure A.5 plot its spatial variation.

Newspaper-based social trust. U.S. newspapers historically had very local readership and often reflected their readers' values and attitudes (Gentzkow and Shapiro, 2010). This makes newspapers a useful source for studying cultural and psychological traits.

We use full-text local newspapers from *newspaperarchive.com*, covering about 241 million pages across U.S. states from 1736 to 2023. We assign each page to a county based on the newspaper's place of publication and to a year based on the publication date.

We employ the contextualized-construct method developed by Atari et al. (2023). This approach measures how closely newspaper texts match psychometric questionnaire items commonly used to quantify psychological and cultural constructs in surveys. For example, the General Social Survey (GSS) has asked respondents whether "most people can be trusted" since 1972. We embed text using Sentence-BERT (SBERT), a transformer-based language model (Reimers and Gurevych, 2019) designed to create sentence-level embeddings, and compute cosine similarity between embeddings of questionnaire items and newspaper texts.[36]

[36] SBERT outperforms other transformer-based models on sentence-related tasks and greatly reduces computation time. It creates embeddings that effectively capture the semantic content of sentences, placing semantically similar sentences close together in vector space. This method performs substantially better than dictionary-based or simpler word-embedding approaches (such as word2vec) and matches the performance of advanced large language models across a variety of cultural and psychological traits (Atari et al., 2023; Abdurahman et al., 2024). A further advantage of SBERT is its transparency and computational efficiency, making it well suited to large textual datasets.

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

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

Finally, we calculate the cosine similarity between the embeddings of newspaper pages and the anchored trust embedding. Higher scores indicate greater social trust. For our analysis of market access, we aggregate these scores at the county-decade level by averaging across all newspaper pages published in each county-year and then rounding to the nearest decade (e.g., 1855-1864 is assigned to 1860). Panels K and L in Appendix Figure A.4 show the spatial distribution of this measure for 1850 and 1920.

We validate our trust measure in two ways. First, we compare it with trust data from the GSS between 1972 and 2014. We find that (i) when aggregated by year, our newspaper-based measure closely tracks the well-documented decline in social trust since the 1970s (correlation $\rho = 0.77$; Appendix Figure A.6, Panel B); and (ii) when aggregated by state, it is positively and significantly correlated with GSS-based trust (Appendix Figure A.6, Panel C), suggesting that it captures meaningful variation across time and space. Second, to assess performance in our historical period (1850-1920), we correlate our trust measure with impersonal cooperative culture at the county level and find a strong positive association (Appendix Figure A.6, Panel D).

Composite Index of Impersonal Cooperative Culture. To simplify some of our analyses, we construct a county-year composite index of impersonal cooperative culture, defined as the mean of four standardized traits: the UNI, the ECM, the NTI, and the RDI. All traits are standardized to z-scores within each year. Not all measures are available in all years: in 1880, RDI is missing and the index is constructed using UNI, ECM, and NTI; in 1890, only RDI is available. Social trust is excluded from the composite due to its more limited geographic coverage (see Panels K and L in Appendix Figure A.4). Panels A and B in Appendix Figure A.4 plot the spatial distribution of the composite index in 1850 and 1920.

Discussion of limitations. We acknowledge several limitations of our census-based cultural measures:

- **UNI:** Naming choices may reflect religious traditions, commemoration of relatives, imitation of local celebrities, fashion trends, or tight local norms (including pressure to assimilate) rather than universalism per se. Moreover, the index depends on census enumeration and transcription quality and only captures parents with surviving children recorded in the census.

- **ECM:** Birthplace is an imperfect proxy for social group membership. Couples from the same state or country may belong to different ethnic, religious, or class groups, and cross-birthplace marriages may still occur within relatively homogeneous subgroups. Moreover, the measure considers only formal marriages recorded in the census and may confound preferences with market constraints: for example, in sparsely populated frontier counties, extra-community marriages may be driven by necessity rather than openness to out-groups.

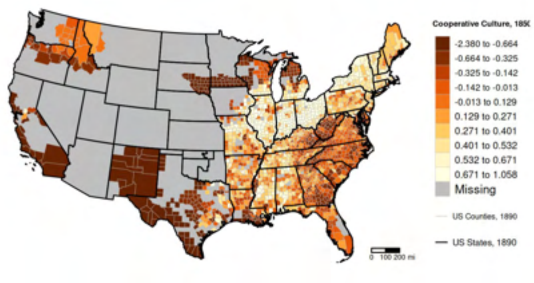
- **NTI:** Dispersion in family outcomes may reflect economic shocks, mortality, migration, or institutional changes rather than cultural tolerance alone. Restricting to married mothers aged 35-44 reduces demographic confounding but omits norms among younger, older, or unmarried individuals.

- **RDI:** The RDI captures the dispersion of formal religious membership and ignores non-affiliated individuals and informal practice. It treats all denominations as equally distinct, ignoring doctrinal and historical proximity. High RDI may reflect ethnic diversity or fragmentation within a broader tradition rather than openness to diverse practices, and membership patterns are influenced by both demand- and supply-side factors (e.g., church planting, denominational competition).

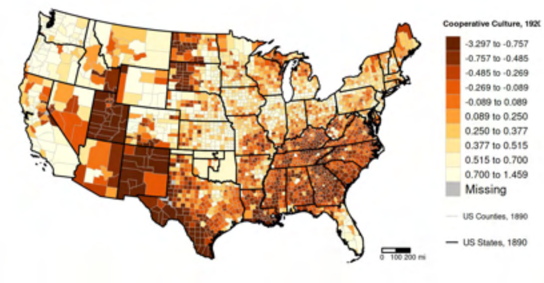
While these limitations are potentially important, Raz (2025) shows that the underlying measures of UNI, ECM, NTI, and RDI are strongly correlated among each other and with independent indicators of close-knit communities (e.g., kin propinquity) and contemporary social network density (e.g., social clustering among Facebook users) and cultural outcomes (e.g., universalistic moral values), supporting their validity as proxies for in-group versus out-group orientation or cultural tolerance. Moreover, in our data, our cultural and behavioral measures are intercorrelated in theoretically consistent ways (Figure 1, Appendix Figures B.7 and B.9), and results are robust across measures and for the composite index. We therefore interpret each variable as a noisy but informative proxy for one aspect of impersonal cooperative culture.

We also acknowledge the limitations of our newspaper-based trust measure. The measure reflects the content of newspapers, which are shaped by readers (demand) as well as by editors, owners, and advertisers (supply). While extensive, coverage is uneven across time and space, and some communities are underrepresented. We partially address these concerns by probing the correlations with GSS-based trust and our composite index of impersonal cooperative culture (see above) and by including county fixed effects in our regression analysis, leveraging within-county variation over time.

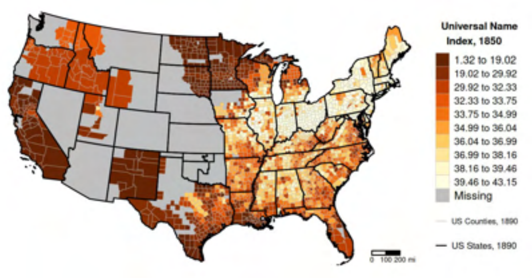
(A) Impersonal Cooperative Culture, 1850



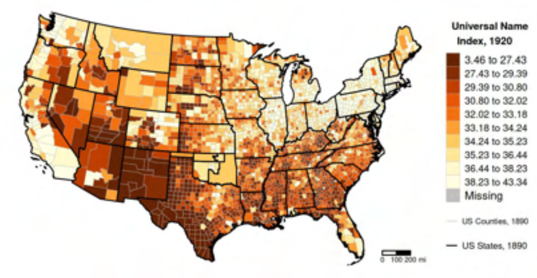
(B) Impersonal Cooperative Culture, 1920



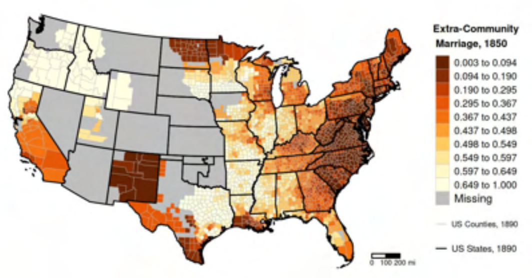
(C) Universal Name Index, 1850



(D) Universal Name Index, 1920



(E) Extra-Community Marriage, 1850



(F) Extra-Community Marriage, 1920

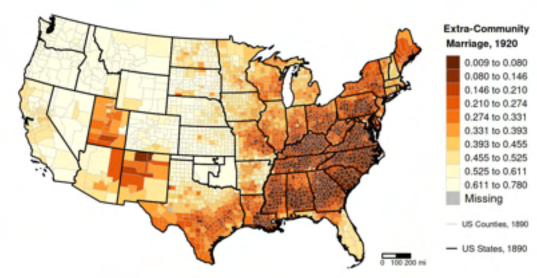
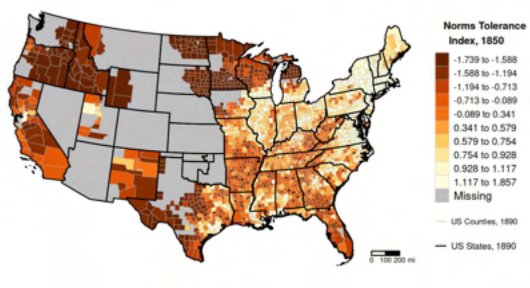


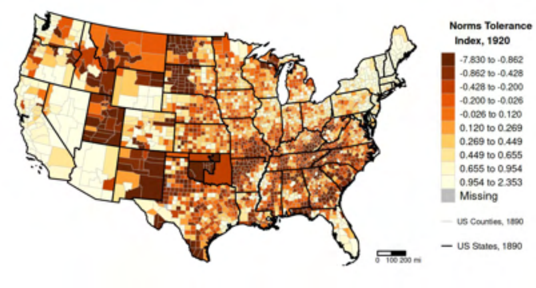
Figure A.4: Impersonal Cooperative Culture, 1850 and 1920

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

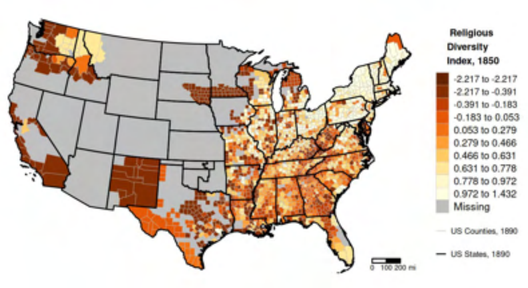
(G) Norms Tolerance Index, 1850



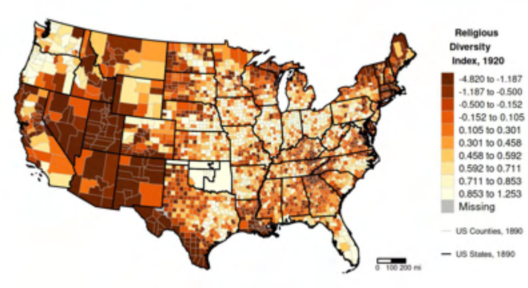
(H) Norms Tolerance Index, 1920



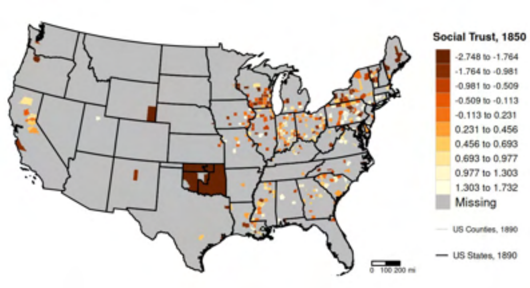
(I) Religious Diversity Index, 1850



(J) Religious Diversity Index, 1920



(K) Social Trust, 1850



(L) Social Trust, 1920

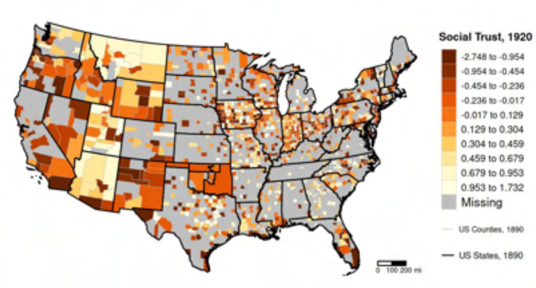
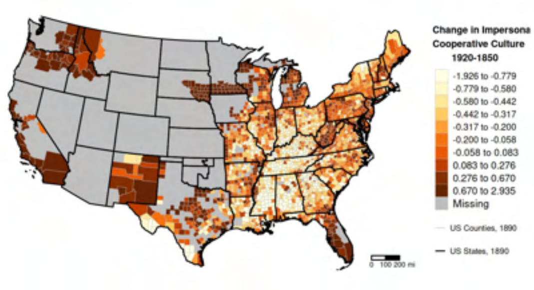


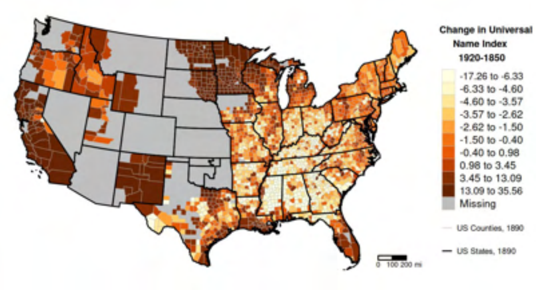
Figure A.4: Impersonal Cooperative Cultural Traits, 1850 and 1920 (cont.)

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

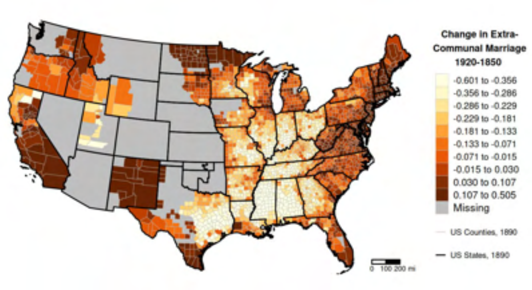
(A) Impersonal Cooperative Culture



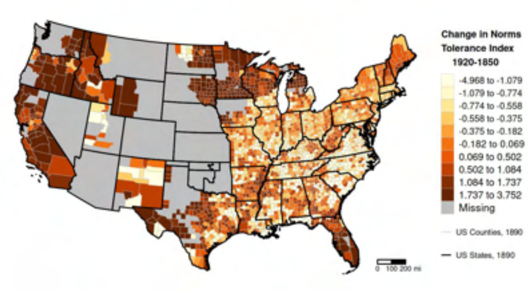
(B) Universal Name Index



(C) Extra-Communal Marriage



(D) Norms Tolerance Index



(E) Religious Diversity Index

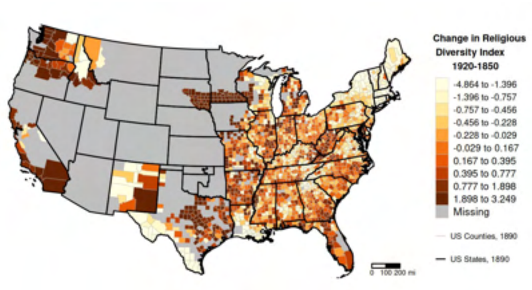


Figure A.5: The Change in Impersonal Cooperative Cultural Traits Between 1850-1920

Note: This figure plots the difference in impersonal cooperative culture between 1920 and 1850: the UNI, the ECM, the NTI, and the RDI.

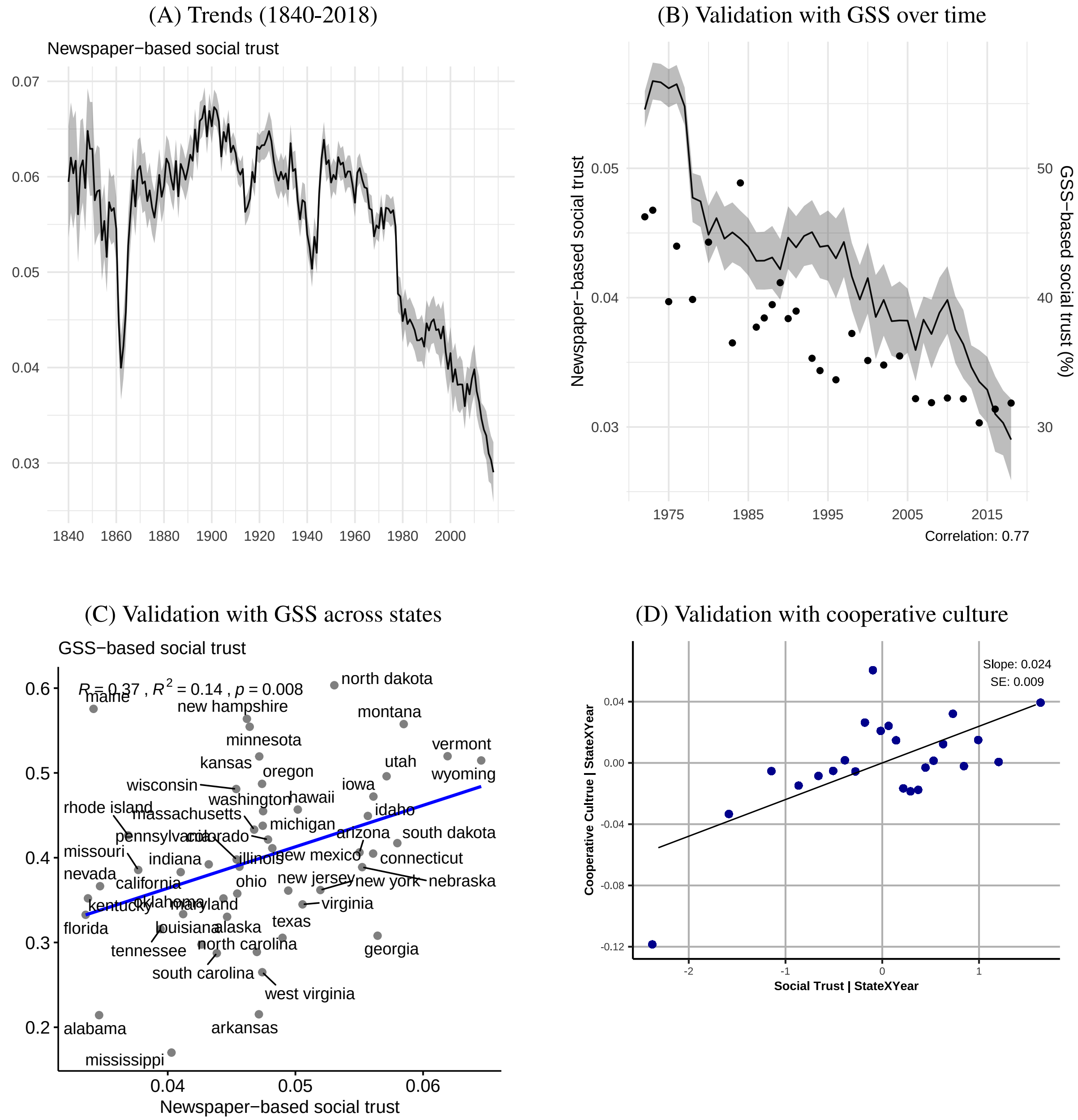


Figure A.6: Newspaper-based Social Trust: Trends and Validation

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

A.3 Impersonal and Kin-based Cooperative Behavior

Voter turnout in presidential elections. We compute county-level turnout rates for all presidential elections between 1850 to 1920 using historical presidential election returns (ICPSR, 1999) and estimates of the eligible voting population. For the latter, we use the 1850-1920 full-count censuses (Ruggles et al., 2020) and 1890 county-level data on the male population aged 21 and over (Manson et al., 2020) to estimate the eligible voter stock in census years (round decades), taking into account historical changes in women's and Black suffrage. We then linearly interpolate 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 exceed 100%. In some cases, estimated turnout rates are unreasonably high (e.g., 500%), suggesting data or coding errors. To improve precision, we drop 338 county-election observations (0.7% of the sample) with turnout rates greater than 125%, which are highly likely to reflect such errors. Panels A and B of Appendix Figure A.7 plot the spatial distribution of voter turnout in 1852 and 1920.

Local public goods provision. We use county-level data on total tax revenues in 1870 and 1880 (Manson et al., 2020) to construct a proxy for the provision of local public goods and services. To account for potential confounding by overall economic development, we focus on the share of local (town and county) tax revenues in total tax revenues (town, county, and state). While total tax revenues reflect both economic capacity and higher-level policy, the share of revenues raised and allocated locally likely captures local political decisions about public goods provision. Panels C and D of Appendix Figure A.7 plot the spatial distribution of the local-to-total tax revenue ratio in 1870 and 1880.

Family care. We define vulnerable individuals using the full-count censuses as:

- *Orphans:* Children under 16 whose mother and father are not present in the household, as identified using IPUMS variables `MOMLOC` and `POPLOC`.
- *People with disabilities:* Individuals coded as deaf, blind, "idiotic," "insane," sick or temporarily disabled on the day of enumeration, using IPUMS variables `DEAF`, `BLIND`, `IDIOTIC`, `INSANE`, and `SICKNESS`, where available.
- *Elderly:* Individuals aged 65 or older.

Using IPUMS variables `FAMSIZE` and `GQ` (group quarters), we classify a vulnerable individual as being cared for by relatives at home if they reside in a family household (not in group quarters) and share a household with at least one relative. For orphan children, we do not count co-residence with a sibling orphan as family care. For each county-year, we compute the share of vulnerable individuals in this category. Panels E and F of Appendix Figure A.7 show the spatial distribution of family care in 1850 and 1920.

Discussion of limitations. We acknowledge several limitations of our measures of cooperative behavior:

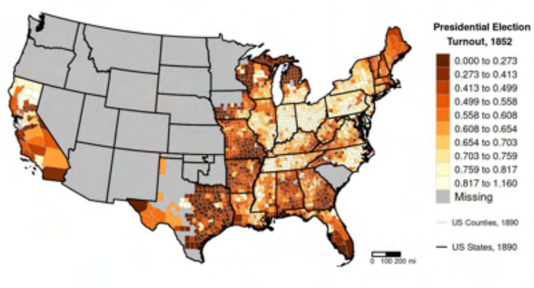
- **Voter turnout:** Turnout reflects civicness but also the intensity of political competition, mobilization, and sometimes conflict. Legal barriers, coercion, and fraud also influence turnout, particularly in the nineteenth-century U.S. (e.g., poll taxes, literacy tests, and violence against Black voters in the South).

- **Local public goods provision:** The local share of tax revenues reflects citizens' willingness to contribute to broad, non-kin beneficiaries, but may also be shaped by local economic growth, fiscal institutions, and political arrangements (e.g., constitutional rules, tax-base composition, or elite preferences). Moreover, these data are available only for a narrow time window (1870-1880), so they provide a partial snapshot rather than a full picture of long-run changes in impersonal cooperation.

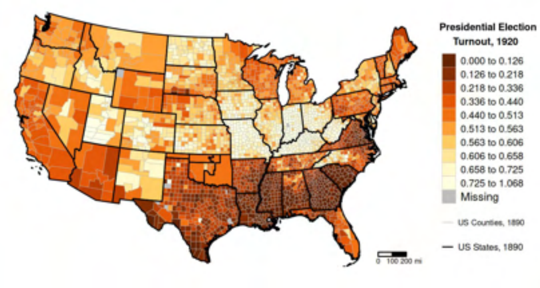
- **Family care:** While the measure captures co-residence with relatives and thus one important form of kin-based support, it does not capture financial transfers or support from non-resident kin. Co-residence is also influenced by economic constraints, housing availability, and institutional care options, which varied over time and across space.

To mitigate these concerns, our analysis includes county and state-by-year fixed effects in all regressions to account for time-invariant local characteristics and state-level differences in electoral rules and practices. Moreover, the three measures co-move with our cultural indices and impersonal-interaction outcomes in the directions implied by our framework (Figure 1, Appendix Figures B.7 and B.9). These associations are virtually unchanged when we control for local GDP per capita, which is inconsistent with economic development driving the measures. We therefore interpret each variable as a noisy but informative proxy for cooperative behavior.

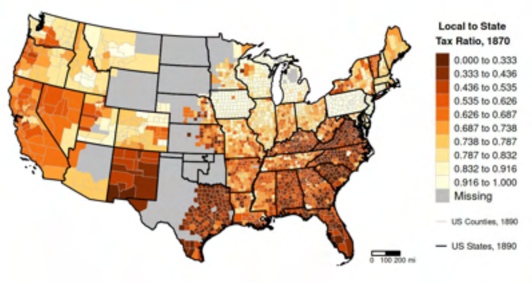
(A) Voters Turnout, 1852



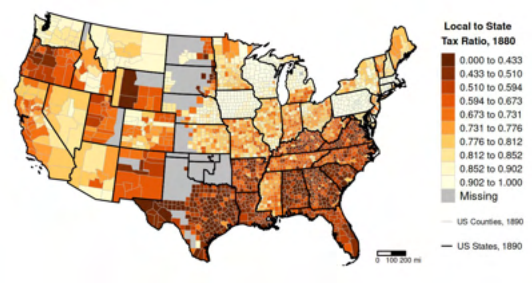
(B) Voters Turnout, 1920



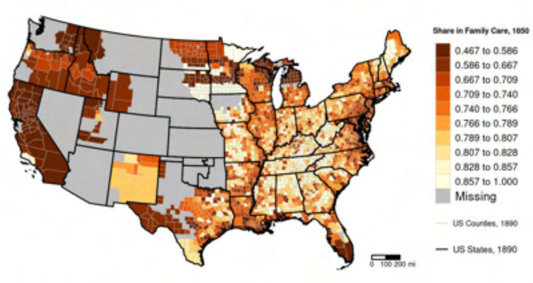
(C) Local to Total Taxes Ratio, 1870



(D) Local to Total Taxes Ratio, 1880



(E) Family Care, 1850



(F) Family Care, 1920

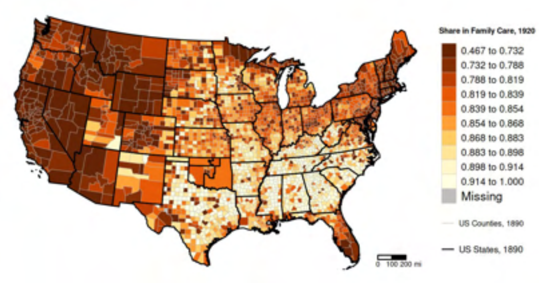


Figure A.7: Measures of Impersonal and Kin-based Cooperation

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

A.4 Impersonal Mutually Beneficial Social Interactions

Labor-force cooperation. We use the Occupational Information Network (O*NET) work-style database to obtain occupation-level ratings of "cooperation" in local labor markets. O*NET is a comprehensive database, widely used by researchers (e.g., Acemoglu and Autor, 2011), developed by the U.S. Department of Labor to provide detailed information on job characteristics and worker attributes. The O*NET work-style data focus on personal characteristics and soft skills essential for successful job performance across occupations. We focus on occupations' cooperation rating, which reflects the extent to which the "job requires being pleasant with others on the job and displaying a good-natured, cooperative attitude." Intuitively, this captures the extent of required interaction and coordination with others while working.

We map O*NET SOC codes to historical IPUMS `OCC1950` codes using an OCC1950-OCCSOC crosswalk and additional hand-coding. For the 1850-1920 full-count censuses records (Ruggles et al., 2020) with valid `OCC1950` codes, we assign the corresponding cooperation rating. Depending on the census year, we successfully match between 95.4% and 99.3% of individuals with a valid occupational response. For example, `OCC1950` codes "Members of the armed services" (585) and "Taxicab drivers and chauffeurs" (682) are missing.

The cooperation rating ranges from 1 to 5; the mean across `OCC1950` occupations is about 4.04. The occupations with low 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 ratings are "Actors and actresses" (001)—4.72, "Ticket, station, and express agents" (380)—4.70, "Clergymen" (009)—4.66, "Officials and administrators (n.e.c.), public administration" (250)—4.61, and "Teachers (n.e.c.)" (093)—4.58. Farmers ("Farmers (owners and tenants)" (100) and "Farm managers" (123)) have a cooperation rating of 4.01, close to the mean (4.04) and median (4.03). We aggregate to the county-year level by taking an employment-weighted average. Panels A and B of Appendix Figure A.8 plot the spatial distribution of labor-force cooperation in 1850 and 1920.

The key assumption is that the relative differences in cooperation requirements across occupations in O*NET reflect similar differences in the historical period—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.

Inventor collaboration. From the U.S. patent database assembled by Berkes (2018), we extract all patents with at least one inventor residing in the contiguous United States, assign inventors to counties based on residence, and construct two county-year outcomes:

1. The average number of inventors listed on a patent;

2. The average entropy of co-inventors' surnames, defined as $-\sum_k p_k \log p_k$ over surnames k and shares p_k among co-inventors on the patent.

Surname entropy is zero when all co-inventors share a surname and increases with the number and balance of distinct surnames. For example, US patent 821,393, for a "Flying Machine," granted to Orville and Wilbur Wright on May 22, 1906 has a surname entropy of zero, whereas US 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. It captures the likelihood that collaboration extends beyond the kin group. Panels C-F of Appendix Figure A.8 plot the spatial distribution of collaboration among inventors, as measured by the number of co-inventors and co-inventors' surname diversity, in 1850 and 1920.

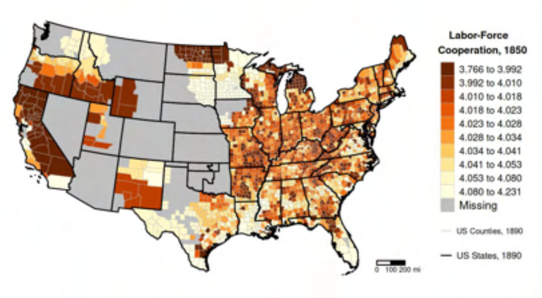
Residence with non-kin. Using IPUMS's `NFAMS` variable, which counts the number of families—defined as "any group of persons related by blood, adoption, or marriage"—in each household in the 1850-1920 full-count censuses (Ruggles et al., 2020), we define multifamily households as those with `NFAMS` ≥ 2. For each county-year, we compute the share of households that are multifamily. These households include non-kin (boarders, lodgers, unrelated co-residents), implying more day-to-day interaction beyond the family. Panels G and H of Appendix Figure A.8 plot the spatial distribution of the share of multifamily households in 1850 and 1920.

Civic engagement. Based on IPUMS industry codes `IND1950` in the 1850-1920 full-count censuses (Ruggles et al., 2020), we define a set of industries associated with civic life and recreation: 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), and miscellaneous entertainment and recreation services (859). For each county-year, we compute the share of employed residents working in these industries. Panels I and J of Appendix Figure A.8 plot the spatial distribution of civic engagement in 1850 and 1920.

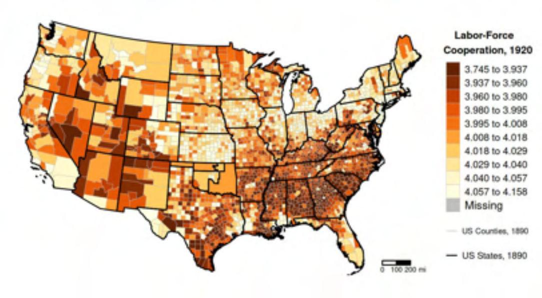
Discussion of limitations. As with the cultural and cooperative behavior outcomes, these interaction measures are noisy indicators of the underlying constructs. O*NET-based measures rely on contemporary assessments of occupations; inventor collaboration is among a highly selected group of formal inventors and has sparse coverage, especially in the early period; multifamily households may reflect economic or housing constraints; and employment in civic sectors is jointly determined by supply and demand.

To mitigate concerns that such measurement error might bias our estimates, our baseline specifications include county fixed effects and state-by-year fixed effects, which absorb time-invariant local characteristics and state-specific trends in development, regulation, and sectoral composition. Moreover, the interaction measures display robust, theoretically consistent correlations with both our cultural indices and our cooperation measures that are not explained away by local GDP per capita (Figure 1, Appendix Figures B.7 and B.9). We therefore interpret these variables as noisy but useful proxies for the prevalence of impersonal, mutually beneficial social interactions.

(A) Labor-force Cooperation, 1850

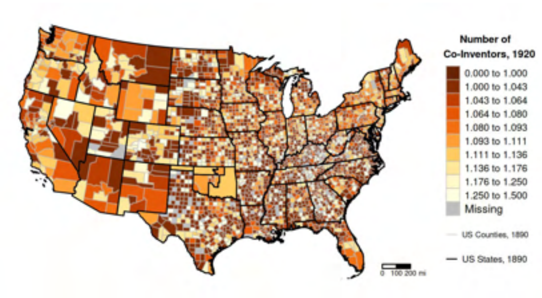


(B) Labor-force Cooperation, 1920



(C) Number of Co-Inventors, 1850

(D) Number of Co-Inventors, 1920



(E) Co-Inventors' Diversity, 1850

(F) Co-Inventors' Diversity, 1920

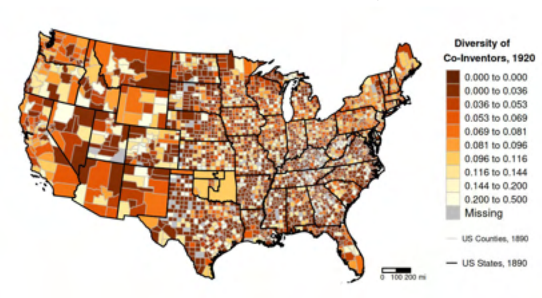
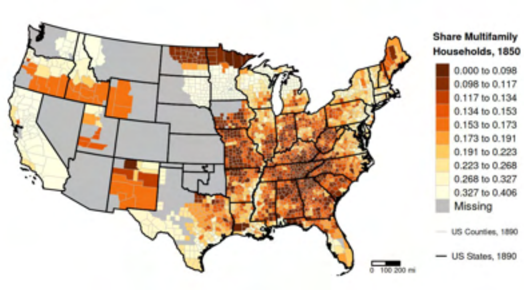


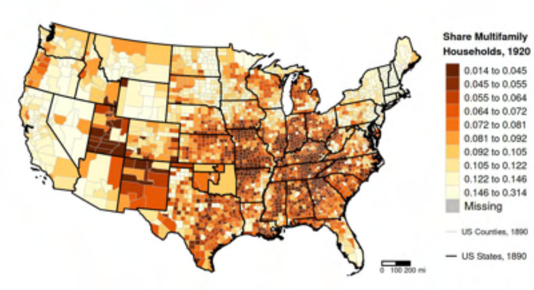
Figure A.8: Measures of Impersonal and Kin-based Cooperation, 1850 and 1920

Note: This figure plots the spatial distributions of five measures of broad social interactions, in the earlier period (left column) and the later period (left column). A lighter color implies a higher prevalence of broad social interactions.

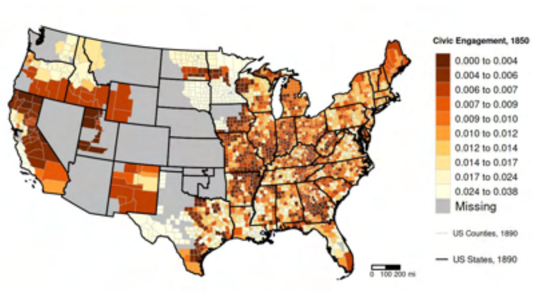
(G) Share Multifamily Households, 1850



(H) Share Multifamily Households, 1920



(I) Civic Engagement, 1850



(J) Civic Engagement, 1920

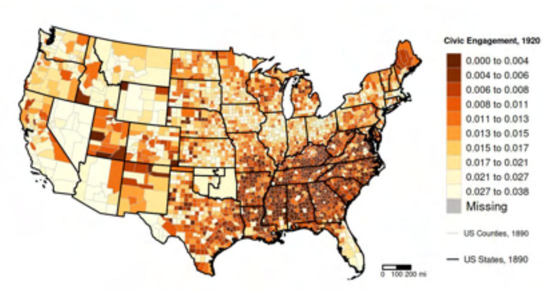


Figure A.8: Measures of Impersonal and Kin-based Cooperation, 1850 and 1920 (cont.)

Note: This figure plots the spatial distributions of five measures of broad social interactions, in the earlier period (left column) and the later period (left column). A lighter color implies a higher prevalence of broad social interactions.

A.5 Prevalence of Commerce

Market language in newspapers. We use *newspapers.com*, which provides OCR-based keyword counts by newspaper and time, but not full text downloads. Starting from seed words related to commerce and exchange (e.g., "buy," "sell," "money," "price," "trade"), we use a *ChatGPT 4* to expand the dictionary to 100 terms tailored to nineteenth-century U.S. newspaper language.[37] For each keyword and county-year, we compute the share of pages containing that keyword. Our baseline measure is the simple average of the shares for the top ten terms: "buy," "sell," "money," "price," "trade," "market," "exchange," "goods," "services," and "commerce." Panels A and B of Appendix Figure A.9 plot the spatial distribution of market language in 1850 and 1920.

We construct alternative measures based on the top 20, 50, and 100 keywords and find that all are strongly correlated ($\rho > 0.94$). Results are robust to using any of these alternative indicators.

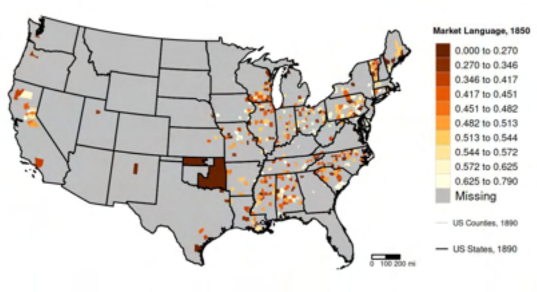
Wholesale and retail trade employment. Using `IND1950` codes in the 1850-1920 full-count censuses (Ruggles et al., 2020), we identify wholesale and retail trade industries and compute the share of employed residents working in these industries in each county-census year. Panels C and D of Appendix Figure A.9 plot the spatial distribution of the wholesale and retail employment share in 1850 and 1920.

Discussion of limitations. Our commerce measures have several limitations. First, the newspaper-based indicator depends on the coverage and OCR quality of *newspapers.com*; both vary across time and space, and some communities are underrepresented. The dictionary approach may pick up contexts in which commerce-related words appear metaphorically or in non-market settings. Second, the wholesale and retail employment share reflects both demand for market services (e.g., income, urbanization) and supply-side factors (e.g., transportation infrastructure, regulatory environments). Moreover, it can capture intra-county commerce and trade, whereas our market-access treatment focuses on inter-county market integration.

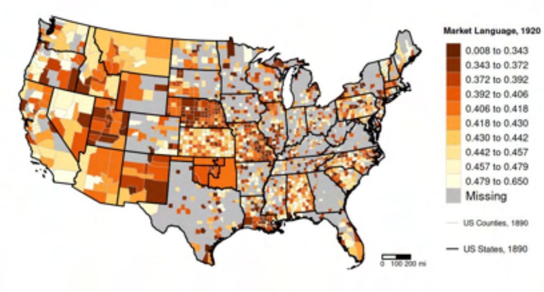
Rather than treating these variables as precise measures of integration, we use them as empirical indicators of the extent to which commercial activity permeated local life. County and state-by-year fixed effects in our regressions absorb time-invariant local differences and broad state-specific trends, so only residual variation in measurement error that is systematically related to within-county changes in market access could bias our estimates. Empirically, the two commerce measures move with our cultural and cooperation outcomes in theoretically consistent ways and these relationships remain when we control for local GDP per capita (Appendix Figure B.7). We therefore view the newspaper and employment series as informative indicators of exposure to commerce and market exchange, recognizing that they are necessarily measured with noise.

[37] 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.*

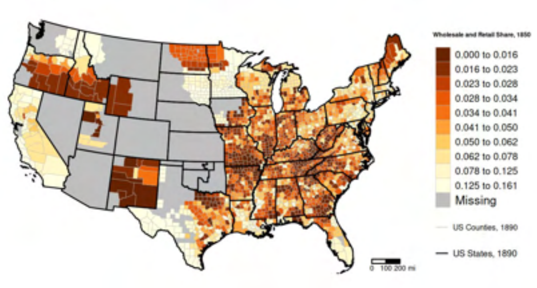
(A) Market Language, 1850



(B) Market Language, 1920



(C) Wholesale and Retail Share, 1850



(D) Wholesale and Retail Share, 1920

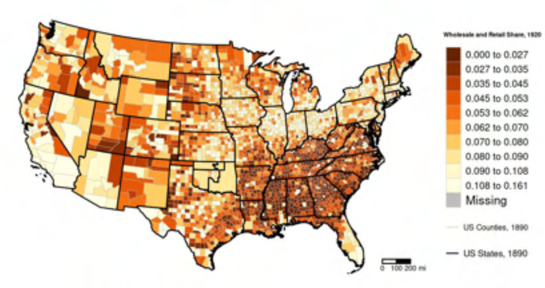


Figure A.9: Measures of the Prevalence of Commerce, 1850 and 1920

Note: This figure plots the spatial distributions of two measures of the prevalence of commerce, in the earlier period (left column) and the later period (left column). A lighter color implies a higher prevalence of commerce.

A.6 Other Demographic and Economic Measures

To probe mechanisms and robustness, we use several additional county-level variables constructed from the full-count and county-level census data 1850-1920 (Ruggles et al., 2020; Manson et al., 2020) and additional sources as detailed below.

Occupational income scores. We measure income using the IPUMS variable `OCCSCORE` from the full-count censuses, which provides occupation-level income scores based on 1950 occupational earnings. For each county-census year, we compute the mean occupational income score.

Log real GDP per capita. Estimates of real GDP per capita at the 1980 county-group level come from Fulford et al. (2020). We harmonize these data to 1890 county boundaries following Hornbeck (2010).

Share employed in agriculture. We use the IPUMS variable `IND1950` code 105 to identify residents employed in agriculture in the full-count censuses and compute the share of employed residents working in agriculture in each county-census year.

Share employed in manufacturing. We use the IPUMS variable `IND1950` codes 306 to 449 to identify residents employed in manufacturing in the full-count censuses and compute the share of employed residents working in manufacturing in each county-census year.

Manufacturing establishments. We use county-level data on the number of manufacturing establishments from Manson et al., 2020.

Share of urban population. We compute the share of the population living in urban areas, defined as incorporated places of at least 2,500 inhabitants, using the county-level census data from Manson et al., 2020.

Share of immigrants. We use IPUMS variable `BPL` to identify foreign-born residents in the full-count censuses and compute the share of residents who are foreign-born in each county-census year.

Birthplace diversity index. Using IPUMS variable `BPL`, we compute the Herfindahl-based diversity of birthplaces—country of birth for immigrants and state of birth for natives—for each county-year from the birthplace shares recorded in the full-count censuses.

Information workers per 1,000 workers. We measure access to information with number of workers in information-related occupations (e.g., editors, reporters, newsboys, mail carriers, and telegraph operators) per 1,000 workers in each county, calculated using full-count census data. Specifically, we include the following `OCC1950` codes: 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).

Lawyers and judges per 1,000 workers. Finally, we use the IPUMS variable `OCC1950` code 55 in the full-count censuses to calculate the number of lawyers and judges per 1,000 workers in each county-census year to proxy for local legal institutional development.

B Further Figures, Analysis and Results

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

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

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

B.2 Impersonal Cooperative Culture

Table B.1: Impersonal Cooperative Culture, Cooperative Behavior, and Broad Social Interactions

	Dependent variable:				
	(1)	(2)	(3)	(4)	(5)
	Panel A: Voters Turnout (mean = 0.63 , sd = 0.24)				
Cooperative Culture	0.0924***	0.0100**	0.0169***	0.0135***	0.0098*
	(0.0118)	(0.0050)	(0.0057)	(0.0052)	(0.0053)
Fit statistics					
Observations	44,405	44,405	44,405	44,405	43,977
	Panel B: Local to Total Tax Ratio (mean = 0.67 , sd = 0.198)				
Cooperative Culture	0.0975***	0.0235***	0.0216***	0.0243***	0.0233***
	(0.0128)	(0.0054)	(0.0081)	(0.0081)	(0.0086)
Fit statistics					
Observations	4,804	4,804	4,804	4,804	4,690
	Panel C: Share in Family Care (mean = 0.778 , sd = 0.111)				
Cooperative Culture	-0.0141***	-0.0136***	-0.0107***	-0.0126***	-0.0132***
	(0.0042)	(0.0038)	(0.0035)	(0.0034)	(0.0034)
Fit statistics					
Observations	17,255	17,255	17,255	17,255	16,730
State × Year Fixed-Effects		Yes	Yes	Yes	Yes
County Fixed-Effects			Yes	Yes	Yes
Location cubic polynomial × Year				Yes	Yes
Log GDP per capita					Yes

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

Table B.1: Impersonal Cooperative Culture, Cooperative Behavior, and Broad Social Interactions (cont.)

	Dependent variable:				
	(1)	(2)	(3)	(4)	(5)
	Panel D: Labor-Force Cooperation (mean = 3.996 , sd = 0.059)				
Cooperative Culture	0.0283***	0.0211***	0.0134***	0.0135***	0.0124***
	(0.0026)	(0.0021)	(0.0019)	(0.0020)	(0.0019)
Fit statistics					
Observations	17,249	17,249	17,249	17,249	16,721
	Panel E: Number of Co-Inventors (mean = 1.092 , sd = 0.116)				
Cooperative Culture	0.0066***	0.0057**	0.0025	0.0014	0.0020
	(0.0022)	(0.0022)	(0.0034)	(0.0033)	(0.0035)
Fit statistics					
Observations	16,966	16,966	16,966	16,966	16,740
	Panel F: Co-Inventors' Diversity (mean = 0.076 , sd = 0.106)				
Cooperative Culture	0.0041**	0.0033	0.0009	0.0005	0.0010
	(0.0020)	(0.0021)	(0.0031)	(0.0031)	(0.0033)
Fit statistics					
Observations	16,966	16,966	16,966	16,966	16,740
State × Year Fixed-Effects		Yes	Yes	Yes	Yes
County Fixed-Effects			Yes	Yes	Yes
Location cubic polynomial × Year				Yes	Yes
Log GDP per capita					Yes

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

Table B.1: Impersonal Cooperative Culture, Cooperative Behavior, and Broad Social Interactions (cont.)

	Dependent variable:				
	(1)	(2)	(3)	(4)	(5)
	Panel G: Share Multifamily Households (mean = 0.151 , sd = 0.084)				
Cooperative Culture	0.0171***	0.0257***	0.0168***	0.0184***	0.0173***
	(0.0035)	(0.0027)	(0.0026)	(0.0024)	(0.0025)
Fit statistics					
Observations	17,263	17,263	17,263	17,263	16,735
	Panel H: Civic Engagement (mean = 0.012 , sd = 0.009)				
Cooperative Culture	0.0039***	0.0044***	0.0034***	0.0036***	0.0034***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Fit statistics					
Observations	17,249	17,249	17,249	17,249	16,721
State × Year Fixed-Effects		Yes	Yes	Yes	Yes
County Fixed-Effects			Yes	Yes	Yes
Location cubic polynomial × Year				Yes	Yes
Log GDP per capita					Yes

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

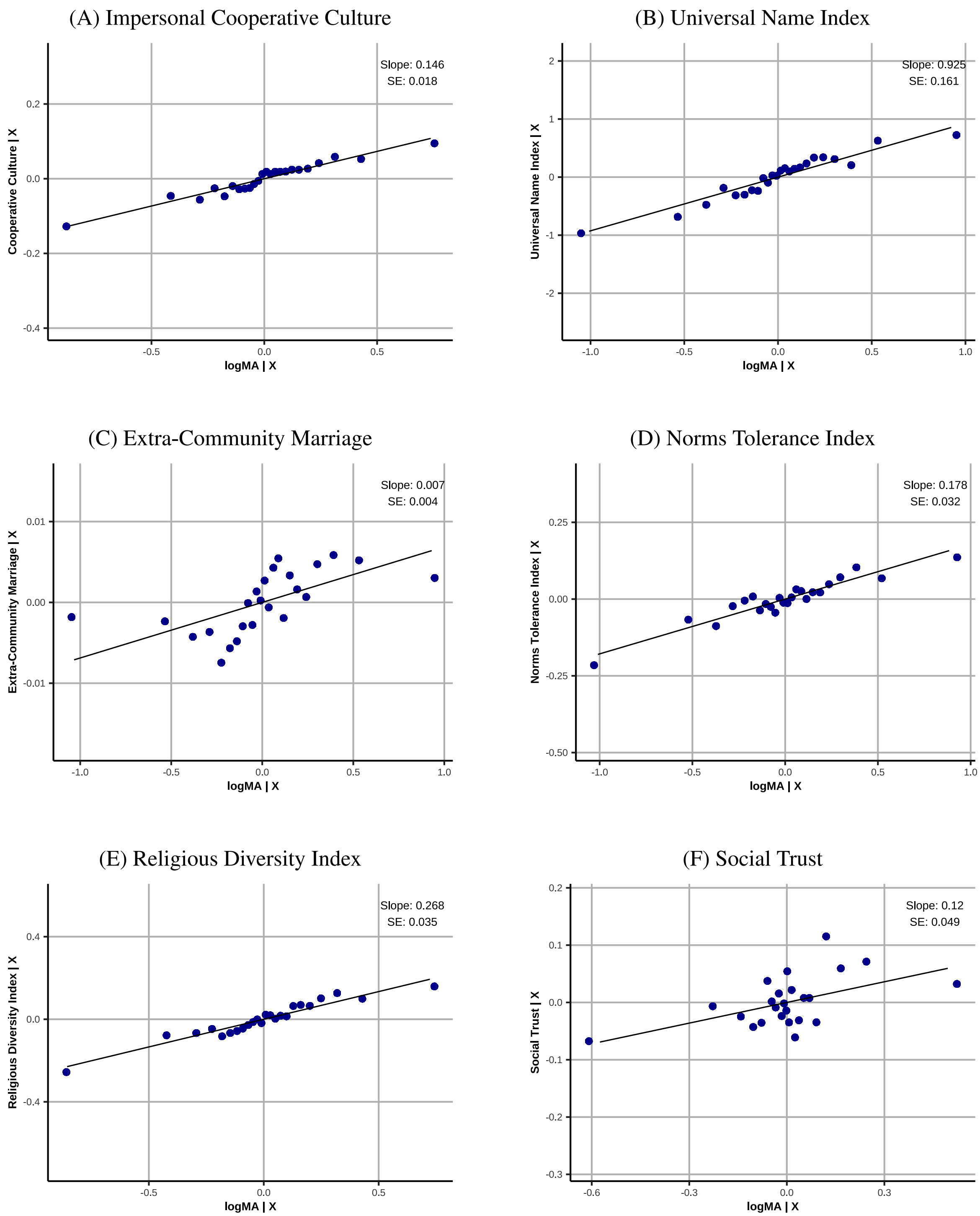


Figure B.3: Market Access and Impersonal Cooperative Traits: County-level Bin Scatter Plots

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

Table B.2: Impersonal Cooperative Culture: Instrumental Variable

	Dependent variable:			
	1^{st} stage	2^{nd} stage	1^{st} stage	2^{nd} stage
	Log market access	Impersonal Cooperative Culture	Log market access	Impersonal Cooperative Culture
	(1)	(2)	(3)	(4)
Log market access		0.1400***		0.0831***
		(0.0169)		(0.0228)
Recentered log market access	1.006***			
	(0.0036)			
Log water market access in 1850 × year = 1860			-0.3026***	
			(0.0323)	
Log water market access in 1850 × year = 1870			-0.5145***	
			(0.0347)	
Log water market access in 1850 × year = 1880			-0.7535***	
			(0.0311)	
Log water market access in 1850 × year = 1890			-0.8227***	
			(0.0282)	
Log water market access in 1850 × year = 1900			-0.8489***	
			(0.0272)	
Log water market access in 1850 × year = 1910			-0.8624***	
			(0.0265)	
Log water market access in 1850 × year = 1920			-0.8740***	
			(0.0262)	
Wald (1st stage)	77,575.7		163.8	
Observations	19,891	19,891	17,378	17,378
R^2	0.999	0.755	0.975	0.766

Note: This table reports the results of two instrumental variable strategies. Columns 1-2 report the results of a recentered IV (Borusyak and Hull, 2023) in which the log expected market access is based on the network of proposed canals from Fogel (1964). Columns 3-4 report the results of a waterways IV (Donaldson and Hornbeck, 2016; Hornbeck and Rotemberg, 2024) in which log water market access in 1850, interacted with year fixed effects is used to predict changes in log market access. All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 Impersonal and Kin-based Cooperation

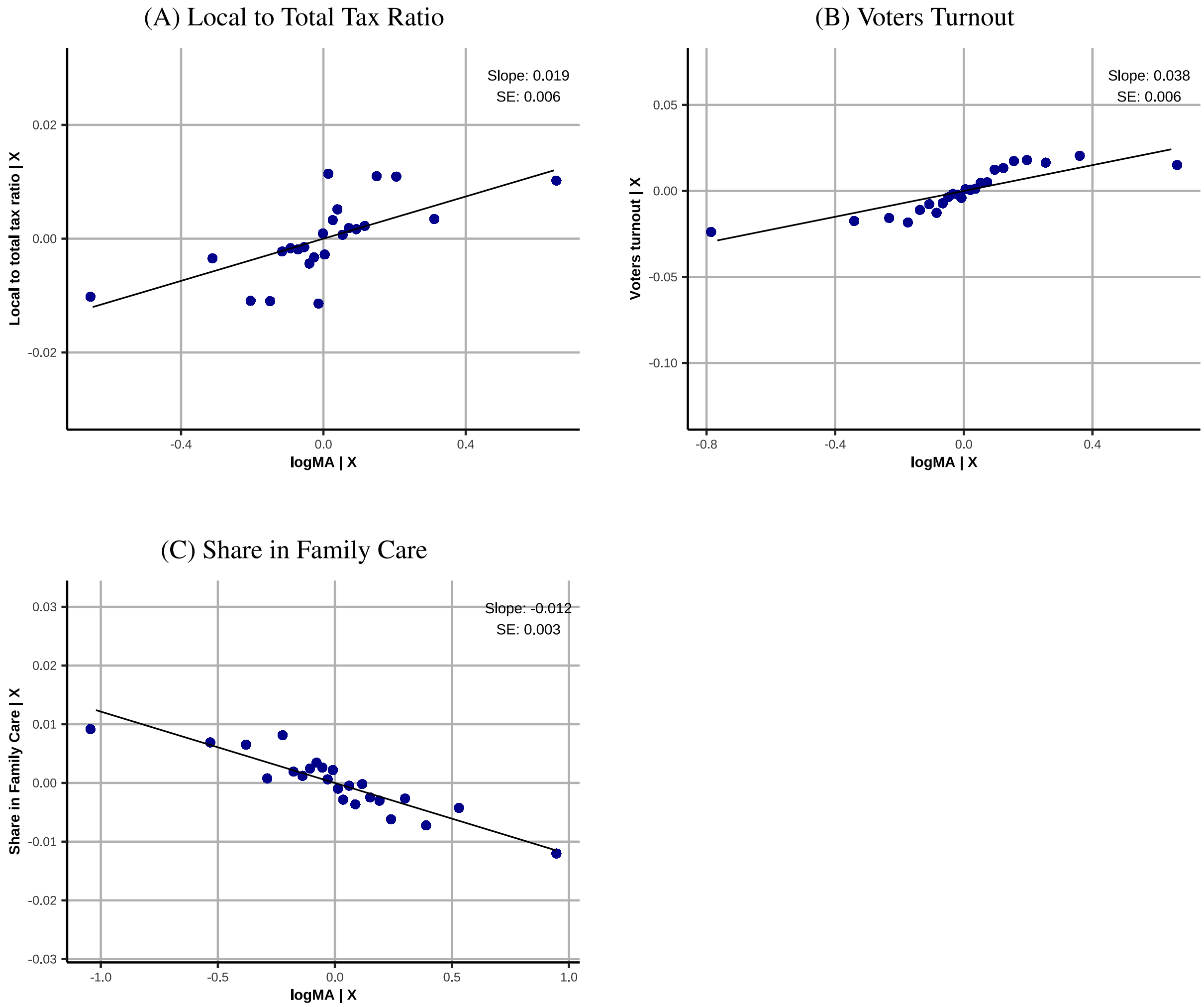


Figure B.4: Market Access and Patterns of Cooperation: County-level Bin Scatter Plots

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

B.4 Selective Sorting

Table B.3: The Relationship is Not Driven by Selective Sorting of Domestic Migrants

	UNI	ECM	Labor-force Cooperation	Multifamily Households	Kinship Propinquity	Number of Children	Urban Origin	Native Born	Occ. Income Score	Agriculture	Manufacturing	Trade
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log market access	0.0615	-0.0128	-0.0018	0.0153**	0.0115	-0.0320	-0.0109*	-0.0054	0.2605	-0.0068	-0.0029	0.0052
	(0.1954)	(0.0102)	(0.0028)	(0.0074)	(0.0096)	(0.0365)	(0.0059)	(0.0057)	(0.1604)	(0.0084)	(0.0037)	(0.0032)
DV mean	44.05	0.4230	4.033	0.1670	0.4080	2.893	0.2150	0.8430	20.08	0.5210	0.1110	0.0700
DV sd	13.13	0.4940	0.1750	0.3730	0.4910	1.696	0.4110	0.3640	10.00	0.5000	0.3140	0.2540
Observations	101,369	107,662	107,662	107,662	107,662	107,662	107,662	107,662	107,662	107,662	107,662	107,662
R^2	0.055	0.079	0.052	0.051	0.084	0.087	0.329	0.183	0.135	0.223	0.090	0.067

Note: This table reports estimates of β from a family-level version of equation (2), estimated on a dataset of incoming domestic migrants into counties. The dependent variables are two measures of migrants pre-migration universalism: mean UNI of children born before migration and ECM; two measures of pre-migration broad beneficial social interactions: labor-force cooperation and residing with a non-kin; four social attributes measured before migration: kinship propinquity, the number of children, urban vs rural origin, and nativity; pre-migration occupational income score; and dummy variables for working in three different sectors before migration: agriculture, manufacturing, and trade. All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.5 Cultural Adaptation

Table B.4: Migrants Become More Universalistic After Moving to a Higher Market Access County

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

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

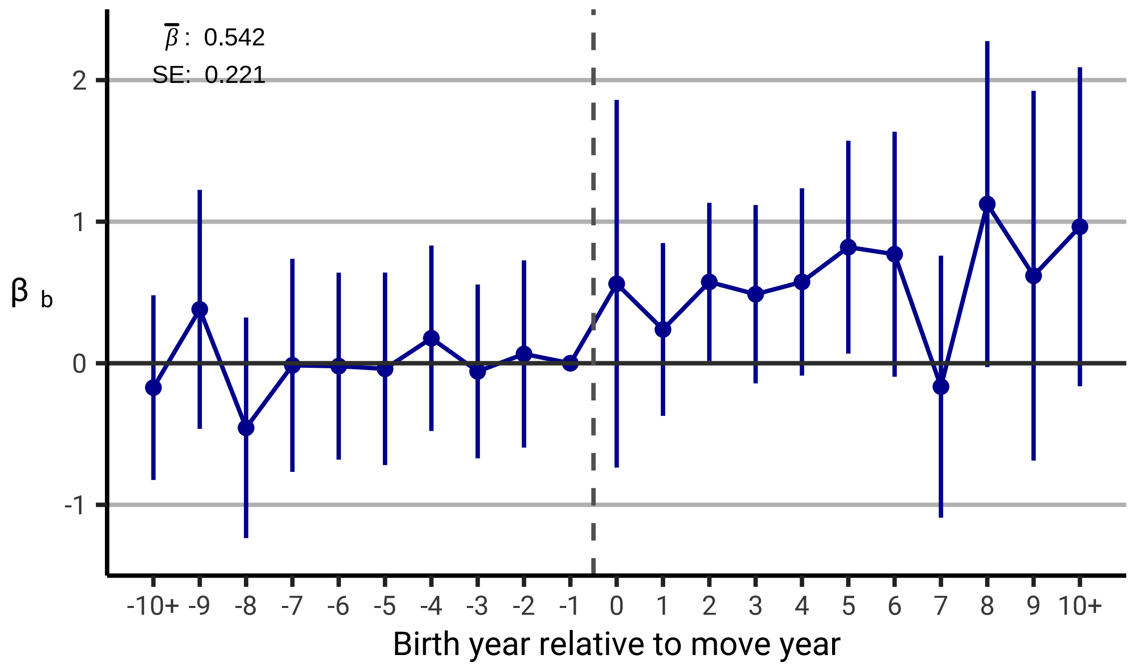


Figure B.5: The Impact of Moving to a Higher Market Access County on Universalism

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

B.6 Channels

B.6.1 Exposure to Commerce and Impersonal Beneficial Interactions

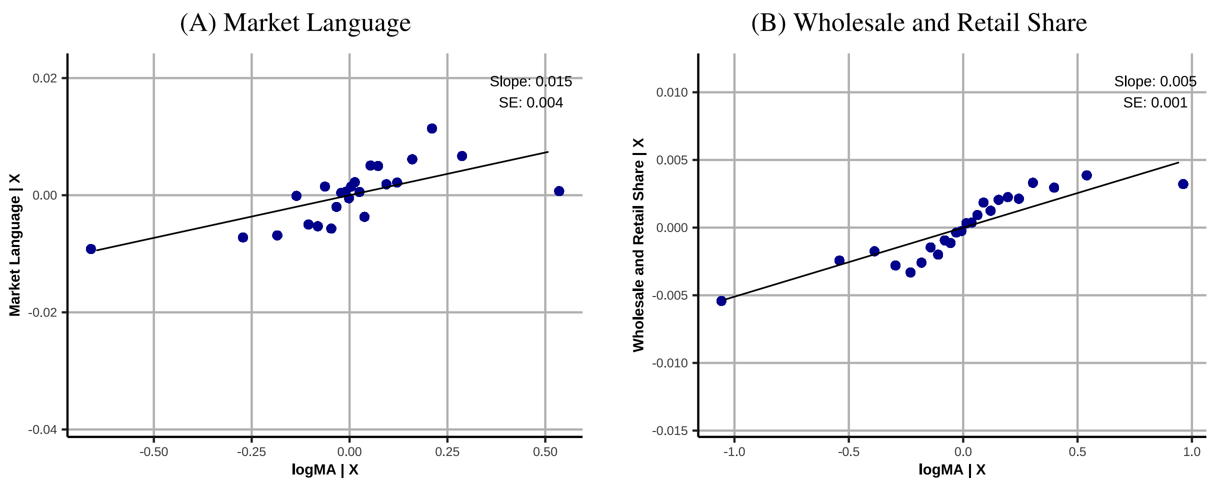


Figure B.6: Market Access and the Prevalence of Commerce: County-level Bin Scatter Plots

Note: This figure presents bin scatter plots of the relationship between log market access and the prevalence of commerce, using equation (2). The plots present the conditional relationship after partialling out the baseline controls, corresponding to columns 1-2 in Table 3. All bins have the same number of observations.

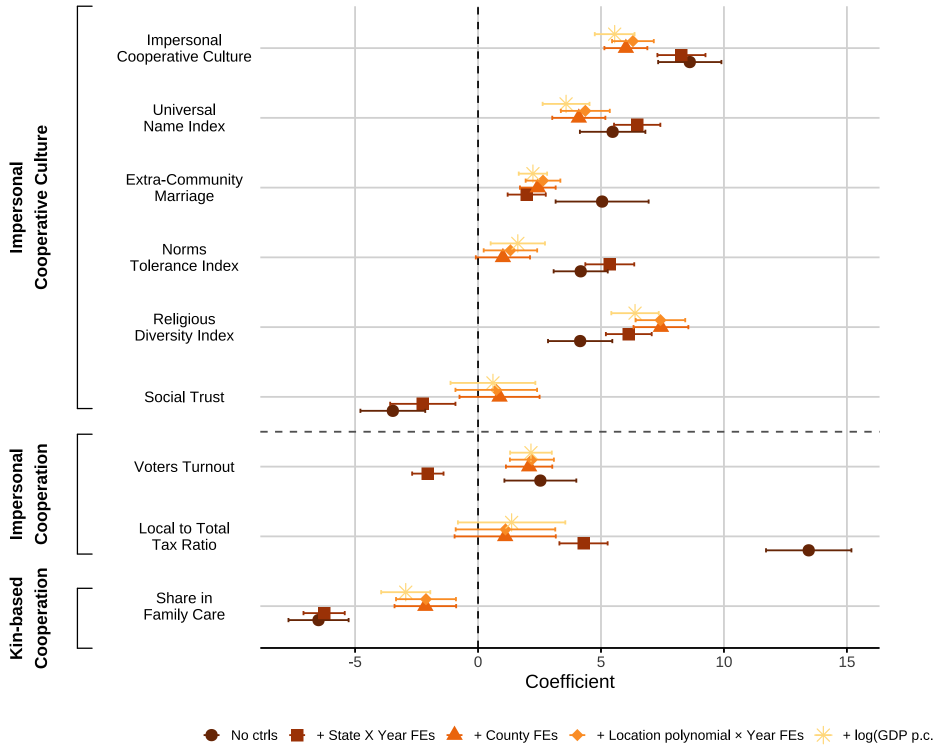


Figure B.7: Commerce, Impersonal Cooperative Culture, and Cooperative Behavior

Note: This figure plots the estimates of β and 95% confidence intervals from the estimation equation of the form: $outcome_{ct} = \beta\ Share\ Trade_{ct} + \delta_{s(c)t} + \delta_c + f(x_c, y_c)\delta_t + \gamma X_{ct} + \epsilon_{ct}$; for all five measures impersonal cooperative cultural traits and three historical measures of cooperation, standardize into z-scores, and five different specifications, sequentially adding controls to the estimation equation: without any controls, with state-by-year fixed effect $\delta_{s(c)t}$, with additional county fixed effect δ_c, with additional cubic spatial polynomial interacted with year fixed effects $f(x_c, y_c)\delta_t$, and with additional time-varying control for log GDP per capita (Fulford et al., 2020). Standard errors are clustered at arbitrary grid cells of 100 miles square (Bester et al., 2011).

Table B.5: Market Access Increases the Prevalence of Commerce

	Dependent variable:							
	Baseline	Recentering	Controlling for local railroads and population					Both
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Mean top 10 market terms share (mean = 0.466 , sd = 0.116)							
Log market access	0.0146***	0.0152***	0.0106**	0.0158***	0.0156***	0.0154***	0.0145**	0.0147**
	(0.0045)	(0.0045)	(0.0050)	(0.0053)	(0.0055)	(0.0058)	(0.0058)	(0.0059)
Observations	8,625	8,588	8,625	8,625	8,625	8,625	8,625	8,588
R^2	0.633	0.633	0.633	0.635	0.635	0.637	0.639	0.639
	Panel B: Wholesale and Retail Share (mean = 0.055 , sd = 0.036)							
Log market access	0.0051***	0.0050***	0.0038***	0.0025***	0.0021**	0.0016*	0.0018**	0.0017*
	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Observations	18,266	18,238	18,266	18,266	18,266	18,266	18,266	18,238
R^2	0.780	0.779	0.781	0.789	0.790	0.790	0.793	0.793
Expected log market access		Yes						Yes
Any railroad			Yes	Yes	Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes	Yes	Yes
Railroads within further buffers						Yes	Yes	Yes
Population within further buffers							Yes	Yes

Note: This table reports estimates of equation (2). The dependent variables are two historical measure for the prevalence of commerce: the share of market language in local newspapers (Panel A), the share of residence working in the wholesale and retail trade industries (Panel B). Column 1 is our baseline estimation. Column 2 implements the approach recommended by Borusyak and Hull (2023) using Fogel (1964)'s proposed canal to control for the expected log market access. Columns 3-7 add additional controls for local railroad infrastructure and population. Column 8 controls for both the expected log market access and local railroads and population. Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

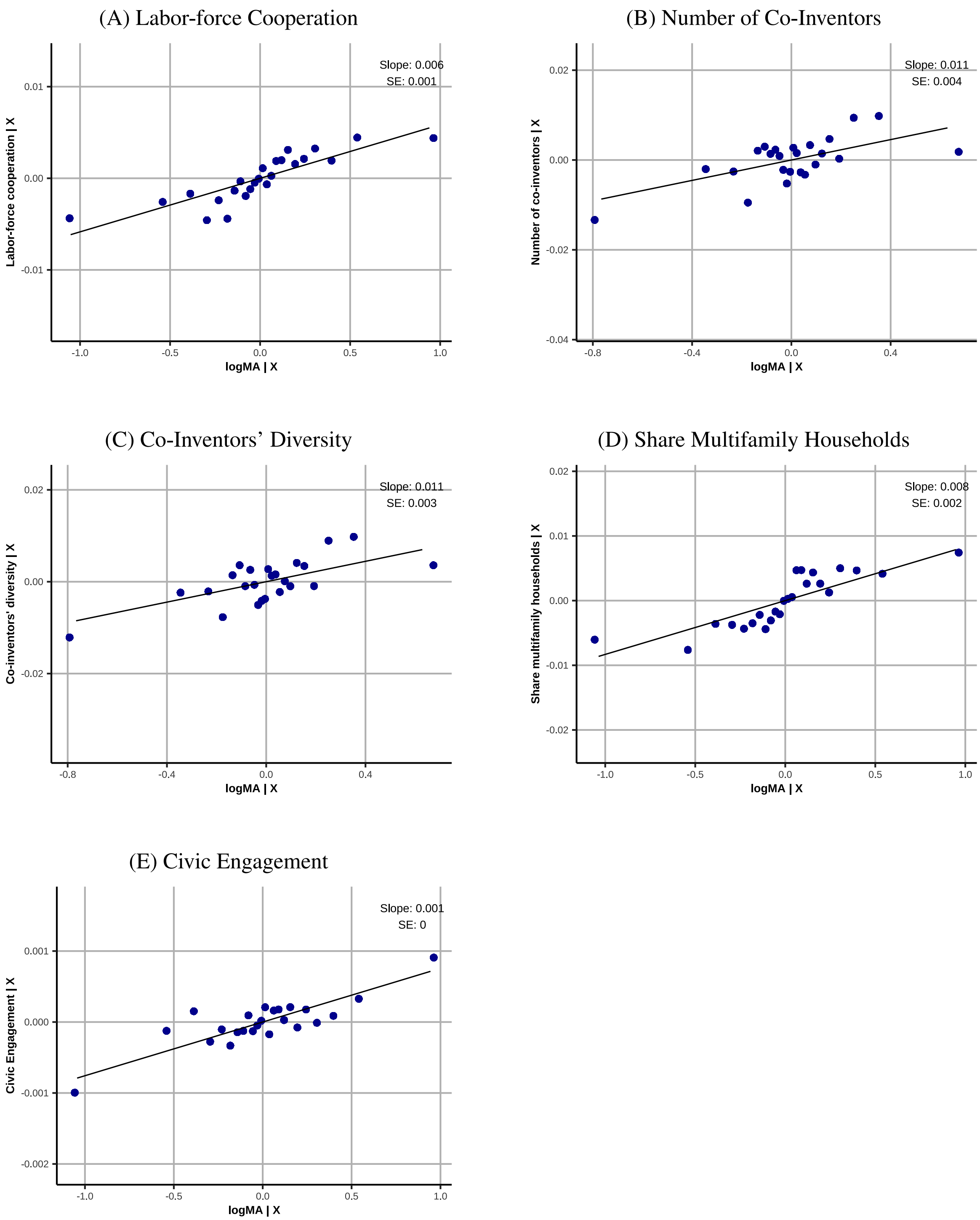


Figure B.8: Market Access and Impersonal Beneficial Interactions: County-level Bin Scatter Plots

Note: This figure presents bin scatter plots of the relationship between log market access and impersonal beneficial social interactions, using the baseline specification of equation (2). The plots present the conditional relationship after partialling out the baseline controls, corresponding to columns 3-7 in Table 3. All bins have the same number of observations.

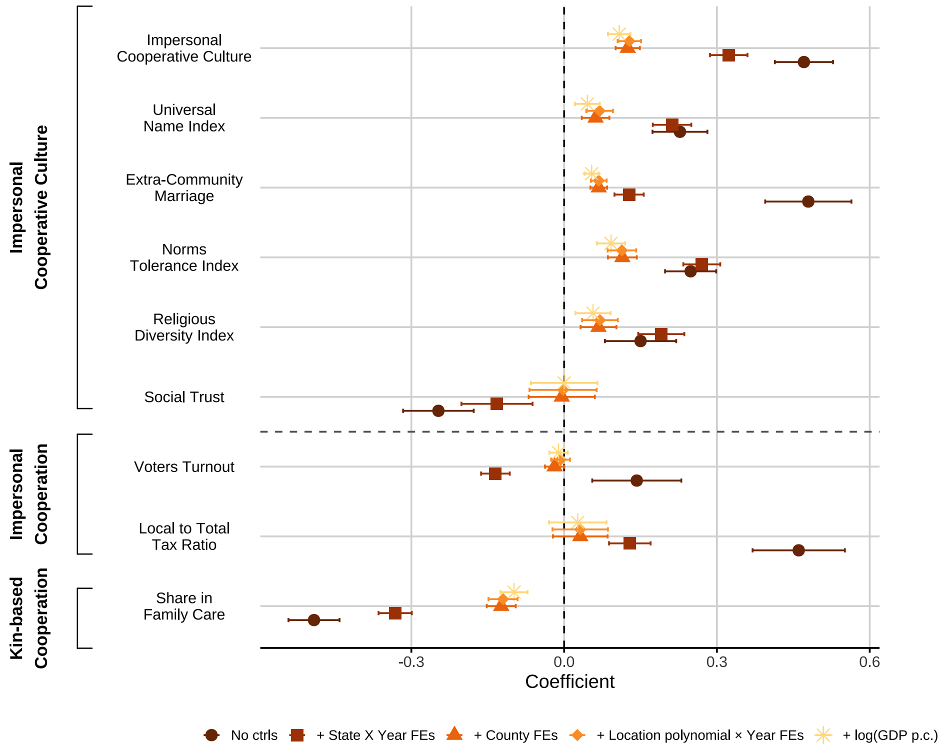


Figure B.9: Impersonal Interactions, Impersonal Cooperative Culture, and Cooperative Behavior

Note: This figure plots the estimates of β and 95% confidence intervals from the estimation equation of the form: $outcome_{ct} = \beta\ Impersonal\ Interactions_{ct} + \delta_{s(c)t} + \delta_c + f(x_c, y_c)\delta_t + \gamma X_{ct} + \epsilon_{ct}$; for all five measures impersonal cooperative cultural traits and three historical measures of cooperation, standardize into z-scores, and five different specifications, sequentially adding controls to the estimation equation: without any controls, with state-by-year fixed effect $\delta_{s(c)t}$, with additional county fixed effect δ_c, with additional cubic spatial polynomial interacted with year fixed effects $f(x_c, y_c)\delta_t$, and with additional time-varying control for log GDP per capita (Fulford et al., 2020). Standard errors are clustered at arbitrary grid cells of 100 miles square (Bester et al., 2011).

Table B.6: Market Access Broadens Impersonal Social Interactions

	Dependent variable:							
	Baseline	Recentering	Controlling for local railroads and population					Both
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Labor-Force Cooperation (mean = 3.996 , sd = 0.059)							
Log market access	0.0058***	0.0056***	0.0048***	0.0037***	0.0034***	0.0025*	0.0026**	0.0023*
	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Observations	18,267	18,239	18,267	18,267	18,267	18,267	18,267	18,239
R^2	0.680	0.680	0.680	0.683	0.683	0.678	0.685	0.686
	Panel B: Number of Co-Inventors (mean = 1.092 , sd = 0.116)							
Log market access	0.0114***	0.0122***	0.0082**	0.0098**	0.0098**	0.0090**	0.0094**	0.0102**
	(0.0037)	(0.0037)	(0.0040)	(0.0042)	(0.0045)	(0.0045)	(0.0045)	(0.0045)
Observations	17,360	17,323	17,360	17,360	17,360	17,360	17,360	17,323
R^2	0.241	0.241	0.241	0.242	0.239	0.242	0.243	0.243
	Panel C: Co-Inventors' Diversity (mean = 0.076 , sd = 0.106)							
Log market access	0.0111***	0.0119***	0.0078**	0.0088**	0.0088**	0.0084*	0.0087**	0.0095**
	(0.0034)	(0.0034)	(0.0038)	(0.0039)	(0.0042)	(0.0043)	(0.0043)	(0.0043)
Observations	17,360	17,323	17,360	17,360	17,360	17,360	17,360	17,323
R^2	0.241	0.242	0.242	0.242	0.240	0.243	0.243	0.243
	Panel D: Share Multifamily Households (mean = 0.151 , sd = 0.084)							
Log market access	0.0083***	0.0079***	0.0062**	0.0051**	0.0048*	0.0051**	0.0055**	0.0050*
	(0.0022)	(0.0024)	(0.0024)	(0.0025)	(0.0025)	(0.0025)	(0.0026)	(0.0030)
Observations	18,277	18,249	18,277	18,277	18,277	18,277	18,277	18,249
R^2	0.782	0.782	0.783	0.784	0.784	0.786	0.787	0.743
	Panel E: Civic Engagement (mean = 0.012 , sd = 0.009)							
Log market access	0.0008***	0.0007***	0.0007***	0.0004*	0.0003	0.0002	0.0003	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	18,266	18,238	18,266	18,266	18,266	18,266	18,266	18,238
R^2	0.688	0.687	0.688	0.697	0.698	0.698	0.707	0.707
Expected log market access		Yes						Yes
Any railroad			Yes	Yes	Yes	Yes	Yes	Yes
Railroad length				Yes	Yes	Yes	Yes	Yes
Railroads within nearby buffer					Yes	Yes	Yes	Yes
Railroads within further buffers						Yes	Yes	Yes
Population within further buffers							Yes	Yes

Note: This table reports estimates of equation (2). The dependent variables are different historical impersonal cooperative cultural traits: labor-force cooperation (Panel A), the number of co-inventors (Panel B), the diversity of co-inventors (Panel C), residence with a non-kin (Panel D), and civic engagement (Panel E). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Column 1 is our baseline estimation. Column 2 implements the approach recommended by Borusyak and Hull (2023) using Fogel (1964)'s proposed canal to control for the expected log market access. Columns 3-7 add additional controls for local railroad infrastructure and population. Column 8 controls for both the expected log market access and local railroads and population. Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

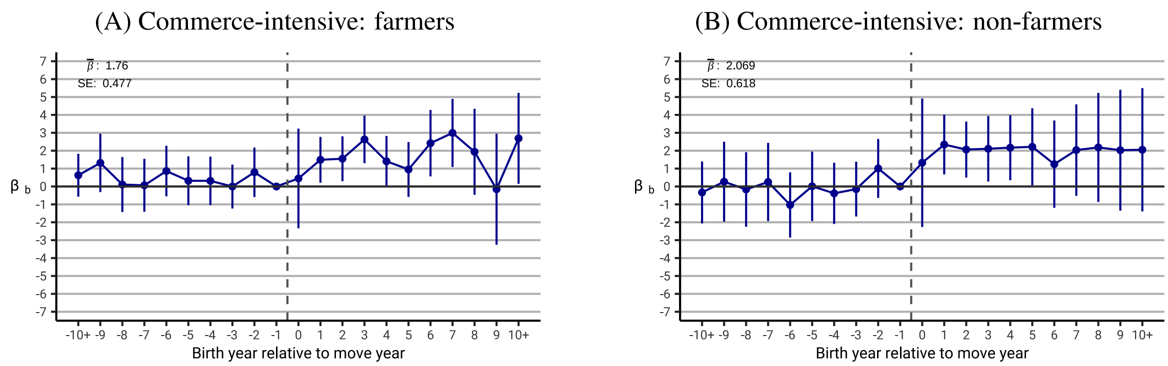


Figure B.10: DID: The Impact on Farmers and Migrants Working in Other Commerce-intensive Industries

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

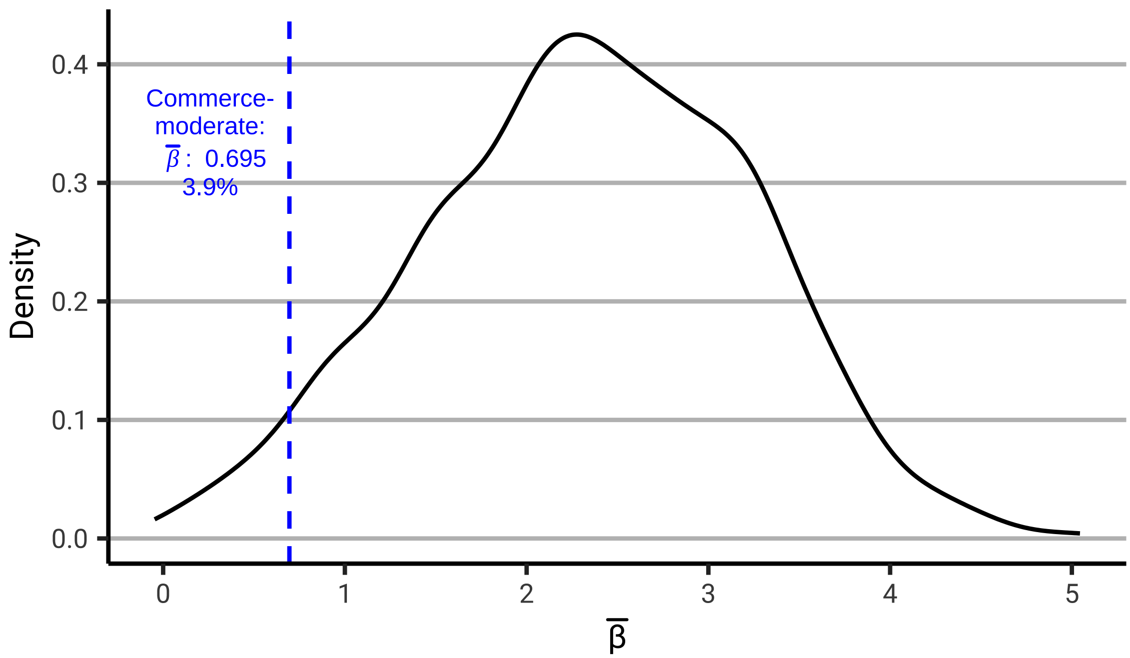


Figure B.11: Heterogeneous Impact is Not Driven by Sample Size

Note: This figure plots the distribution of estimates of $\bar{\beta}$, the average treatment effects from the difference-in-differences equation (3), estimated on 1,000 random sample draws without replacements of 5,985 families from the commerce-intensive group. The blue dashed vertical line plots the estimation of $\bar{\beta}$ for the commerce-moderate group (Figure 4, Panel B).

Table B.7: 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	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.

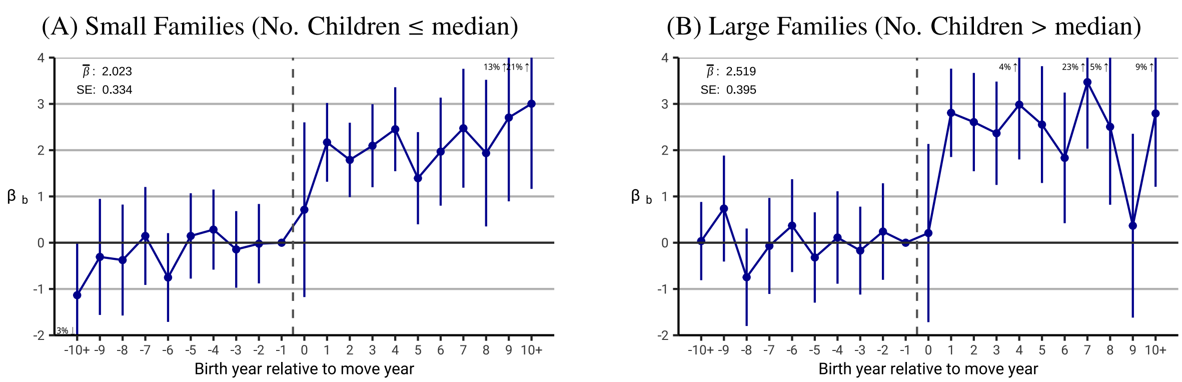


Figure B.12: Heterogeneous Impact is Not Driven by Family Size

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

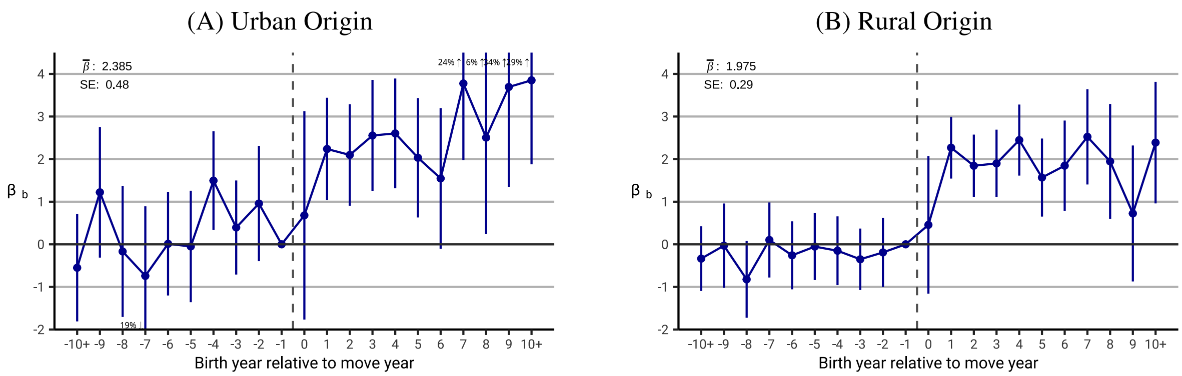


Figure B.13: Heterogeneous Impact is Not Driven by Urban vs. Rural Origins

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

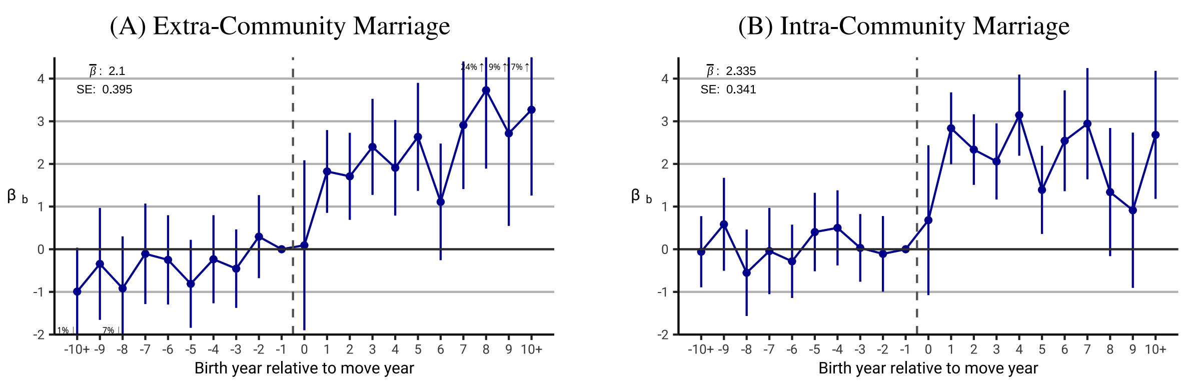


Figure B.14: Heterogeneous Impact is Not Driven by Intra- vs. Extra-Community Marriage

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

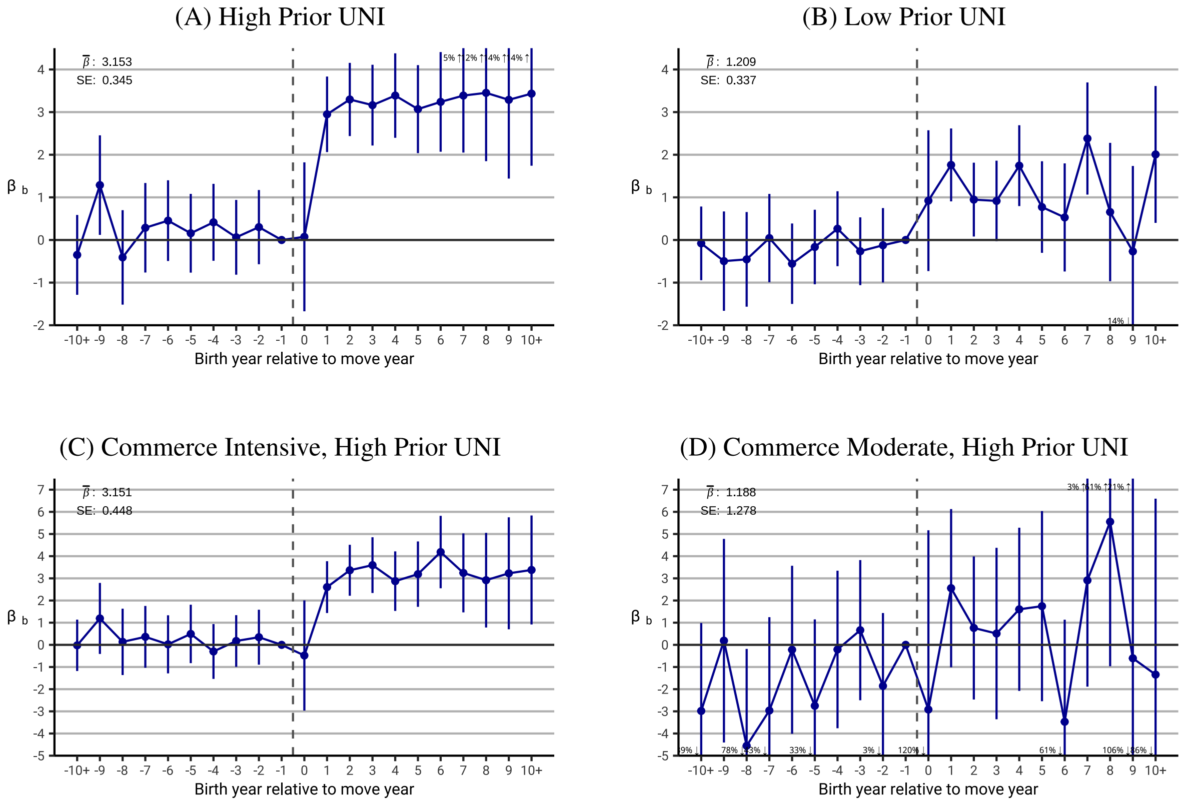


Figure B.15: Heterogeneous Impact is Not Driven by High vs. Low Prior Universalism Identification

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

(A) Tradable Industries and the Trade Sector (B) Non-Tradable Industries

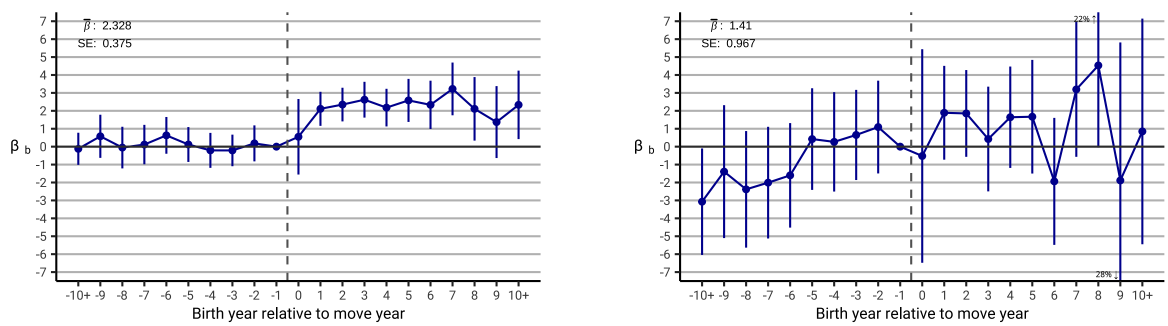


Figure B.16: Market Access Only Affects Individuals Working in Tradable Industries and the Trade Sector

Note: This figure plots the estimates of β_b and 95% confidence intervals from the dynamic difference-in-differences equation (3). The dependent variable is children's UNI. In Panel A, the sample is restricted to households in which the father was working in a tradable industry or the trade sector before and after the migration. In Panel B, the sample is restricted to households in which the father was working in a non-tradable 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.

B.6.2 Competing Pathways

B.6.2.1 Income and The Transition Out of Agriculture

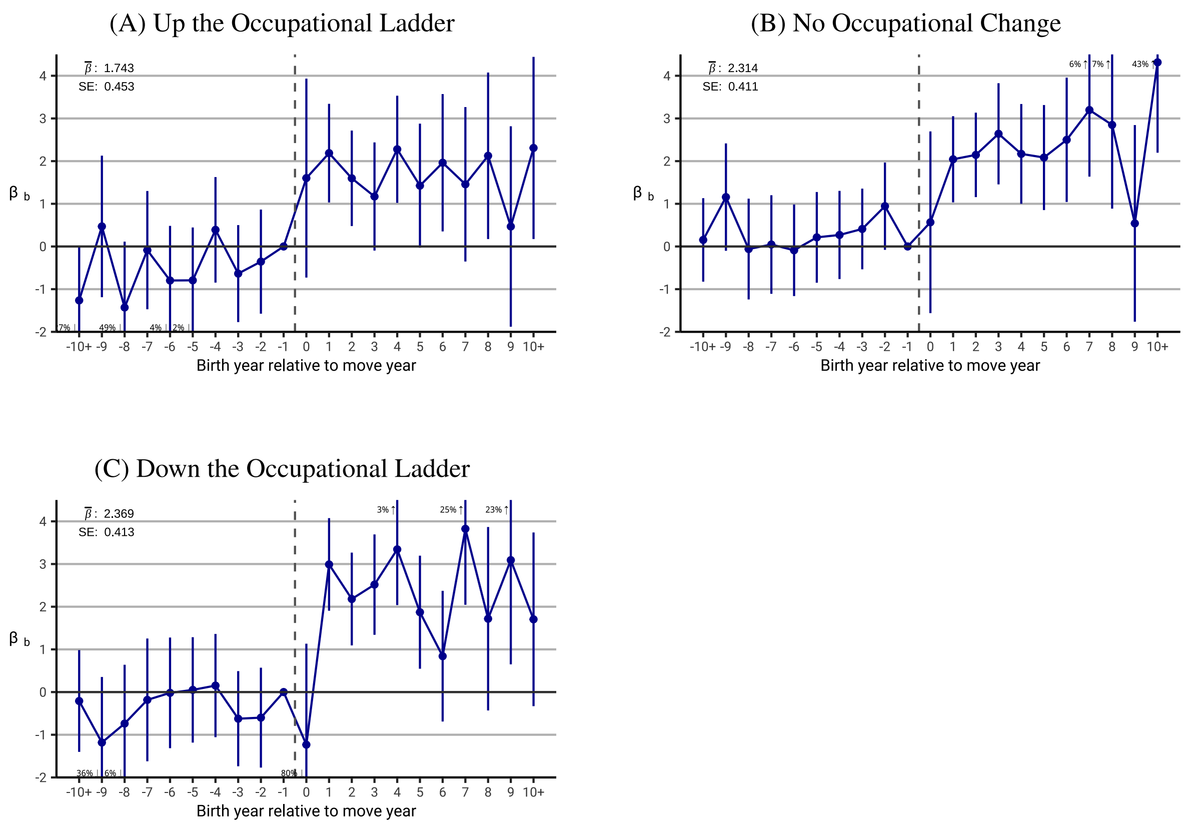
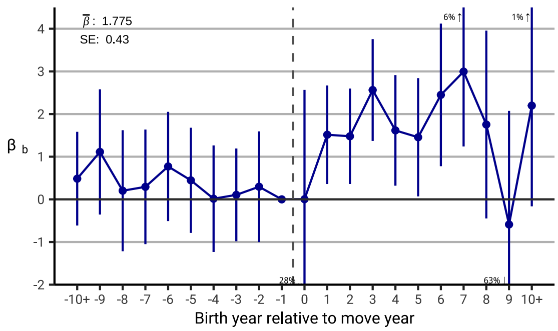


Figure B.17: The Impact is Not Driven by Income

Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences equation (3). $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year in each sample. The sample varies across panels: Panel A includes only the children of domestic migrants who climbed up the occupational ladder between the pre- and post-migration periods, Panel B includes those who did not switch occupation, and Panel C those who climbed down the ladder.

(A) Stayed In Agriculture



(B) Switched Out of Agriculture

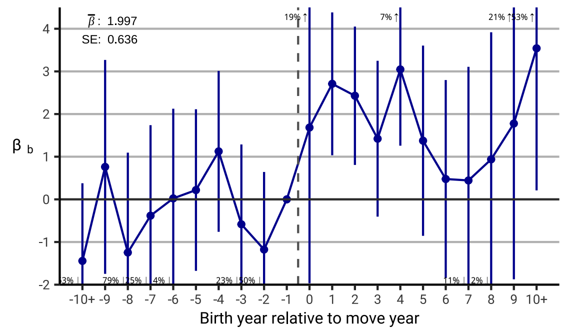


Figure B.18: The Impact is Not Driven by Transition Out of Agriculture

Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences equation (3). $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year in each sample. The sample varies across panels: Panel A includes only the children of domestic migrants who worked in agriculture both before and after their migration, and Panel B includes only the children of domestic migrants who worked in agriculture before their migration but switched out of agriculture after it.

B.6.2.2 Social Contact

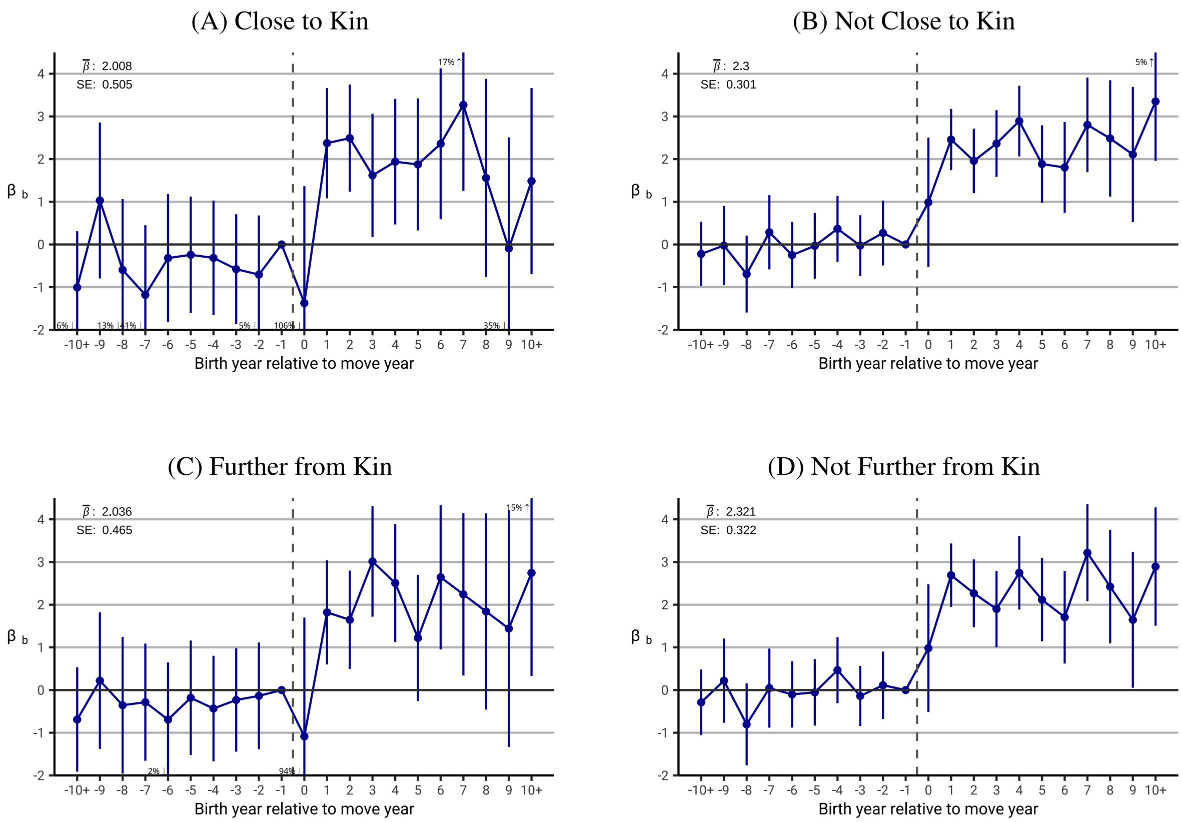


Figure B.19: The Impact is Not Driven by a Change in Social Contact

Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences equation (3). $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year in each sample. The sample varies across panels: Panel A includes only the children of domestic migrants who live close to kin after the migration, while Panel B includes only those who don't. Panel C includes only the children of domestic migrants whose distance to kin increased after their migration, and Panel D includes only the children of domestic migrants whose distance to kin did not change. Living close to kin and distance to kin are defined using a binary measure for having a likely kin residing in the same enumeration district, using data from Nelson (2020).

B.6.2.3 Multiple Competing Hypotheses and Mediators

Here, we explore the possible role of multiple competing hypotheses and mediators. Specifically, we provide a few tests to evaluate the potential role of the following candidate channels: income, transition out of agriculture, industrialization, urbanization, population diversity, access to information, and the development of legal institutions. The construction of all these measures is described in Appendix A.6.

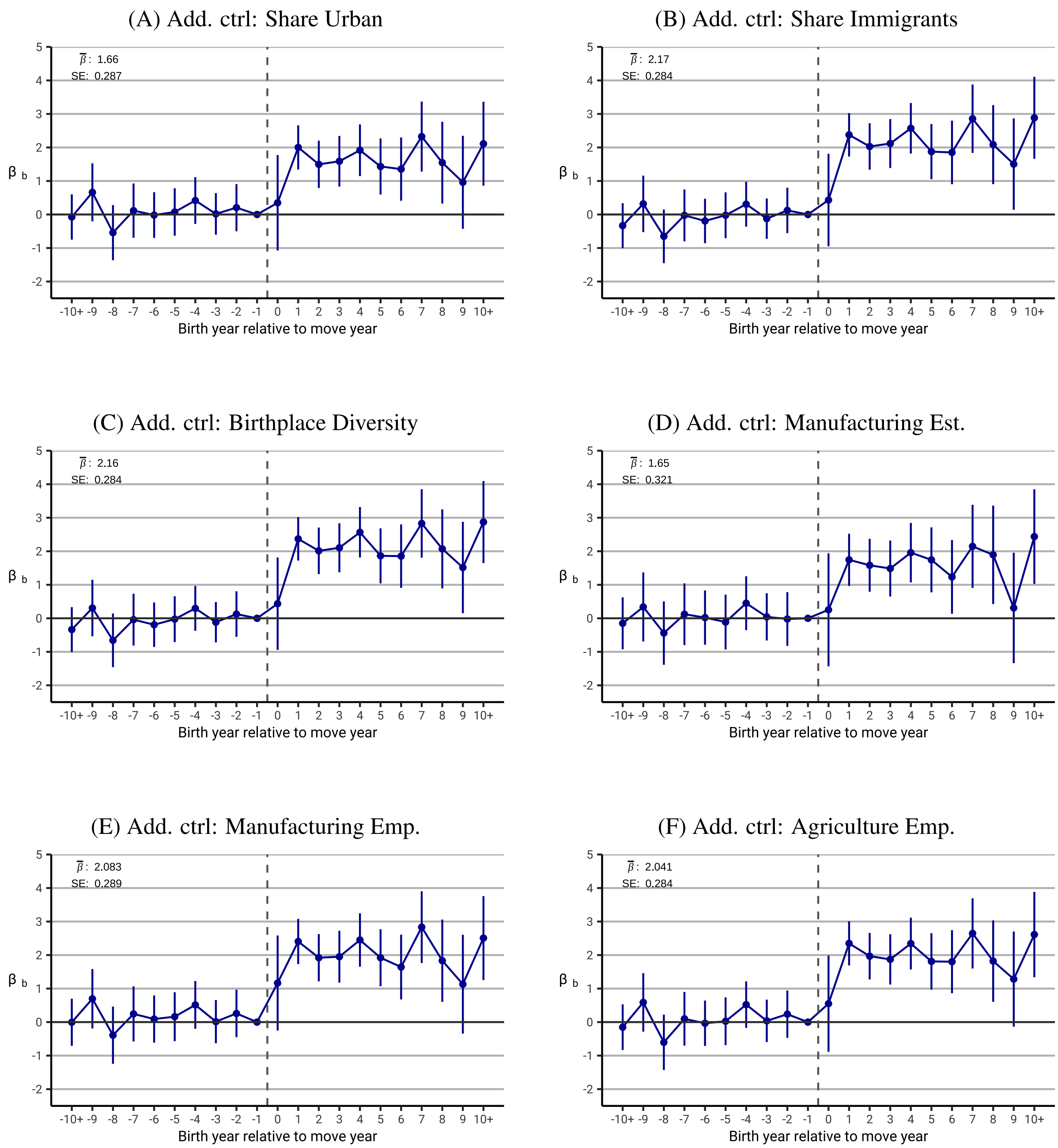


Figure B.20: The Impact is Not Driven by Alternative Channels and Potential Mediators

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

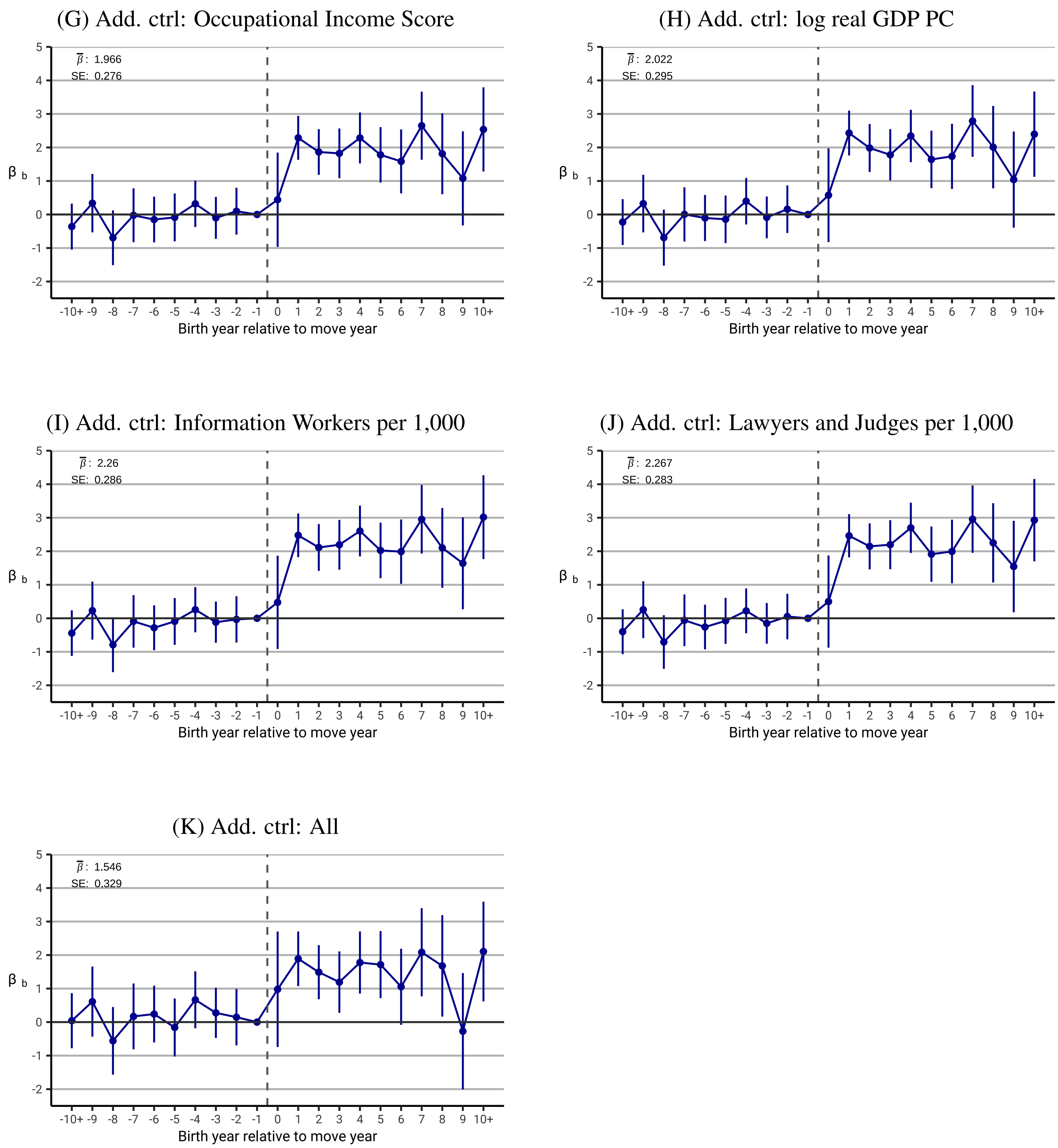


Figure B.20: The Impact is Not Driven by Alternative Channels and Potential Mediators (cont.)

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

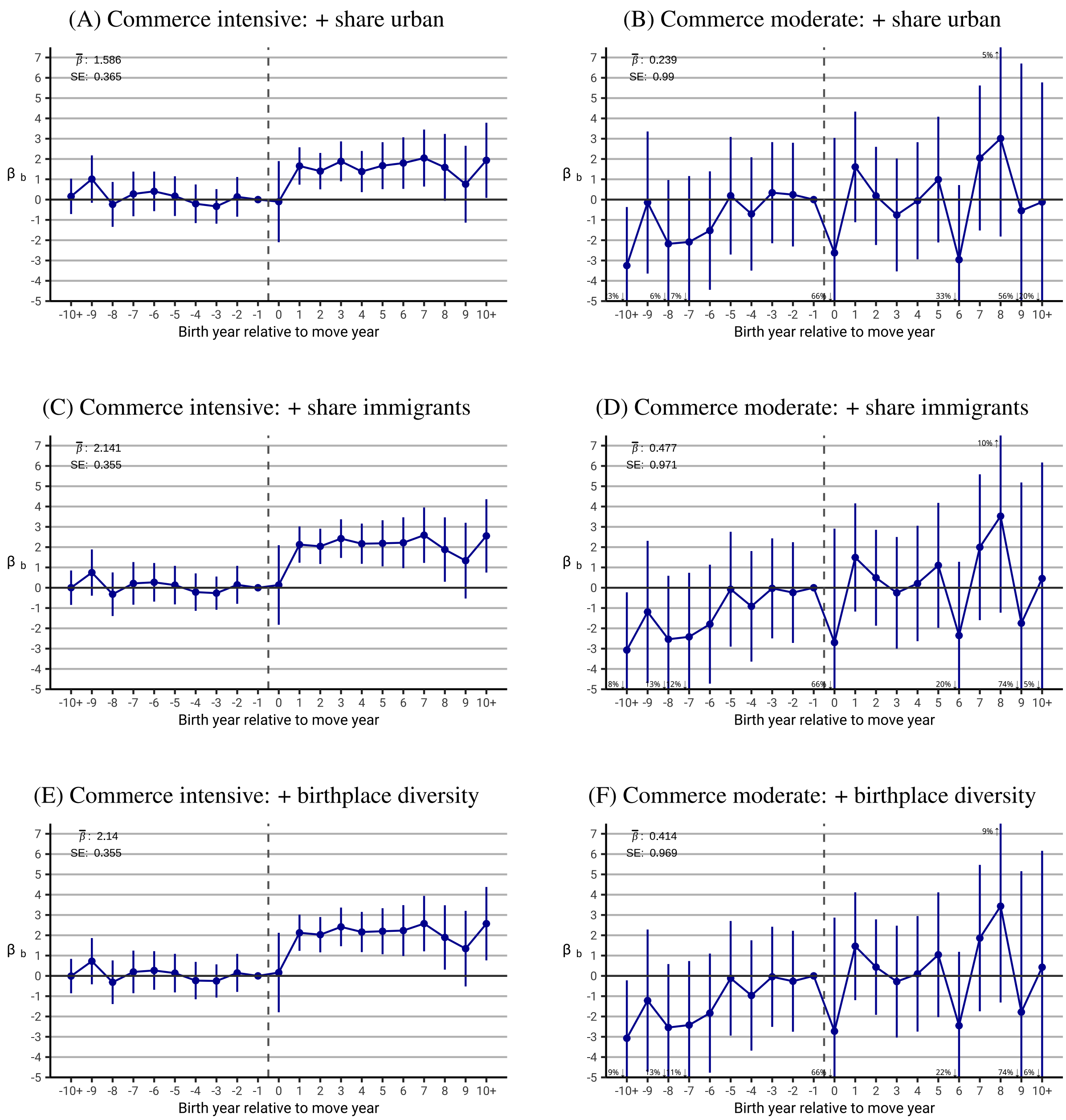
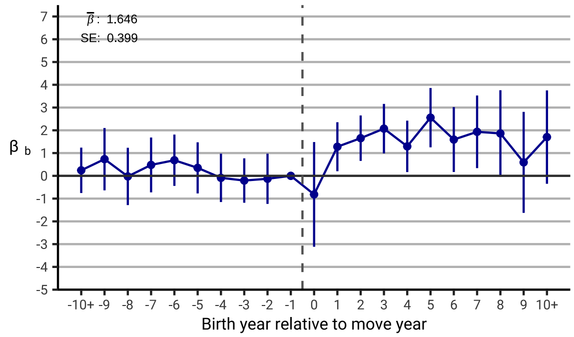


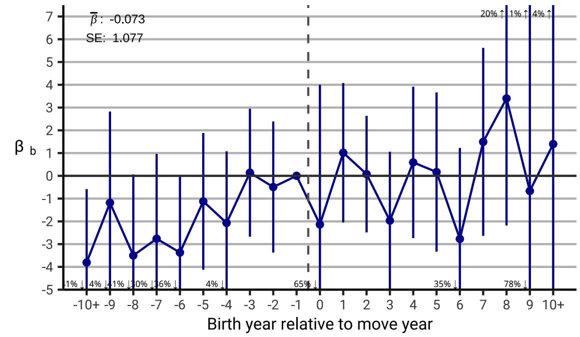
Figure B.21: The Differential Impact is Not Driven by Alternative Channels and Potential Mediators

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

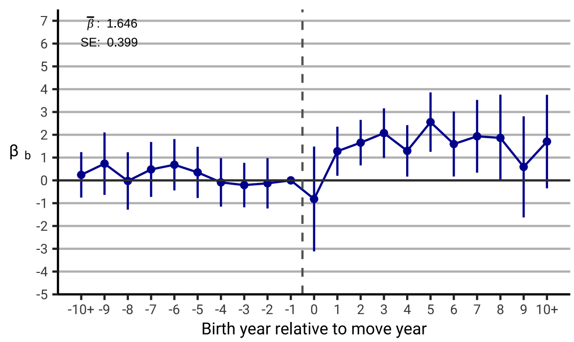
(G) Commerce intensive: + manufacturing est.



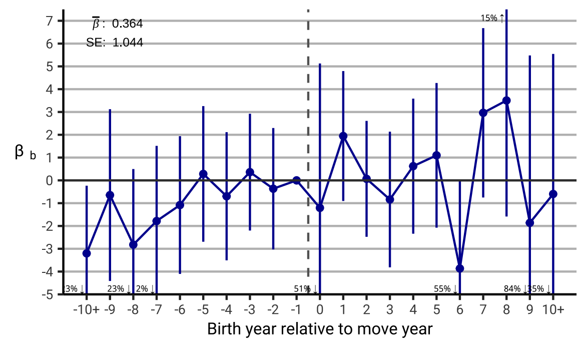
(H) Commerce moderate: + manufacturing est.



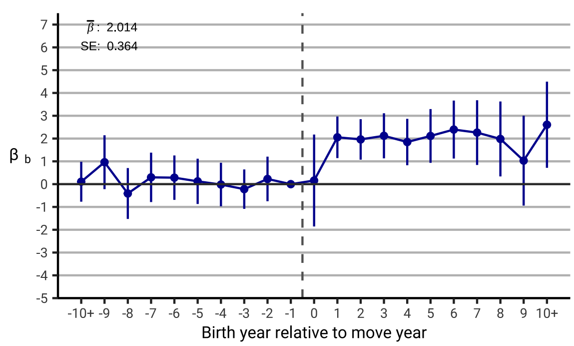
(I) Commerce intensive: + manufacturing emp.



(J) Commerce moderate: + manufacturing emp.



(K) Commerce intensive: + agriculture emp.



(L) Commerce moderate: + agriculture emp.

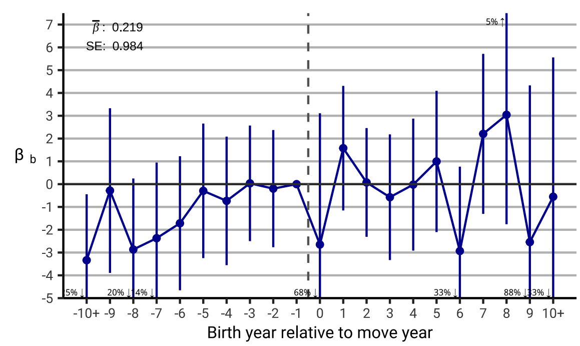


Figure B.21: The Differential Impact is Not Driven by Alternative Channels and Potential Mediators (cont.)

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

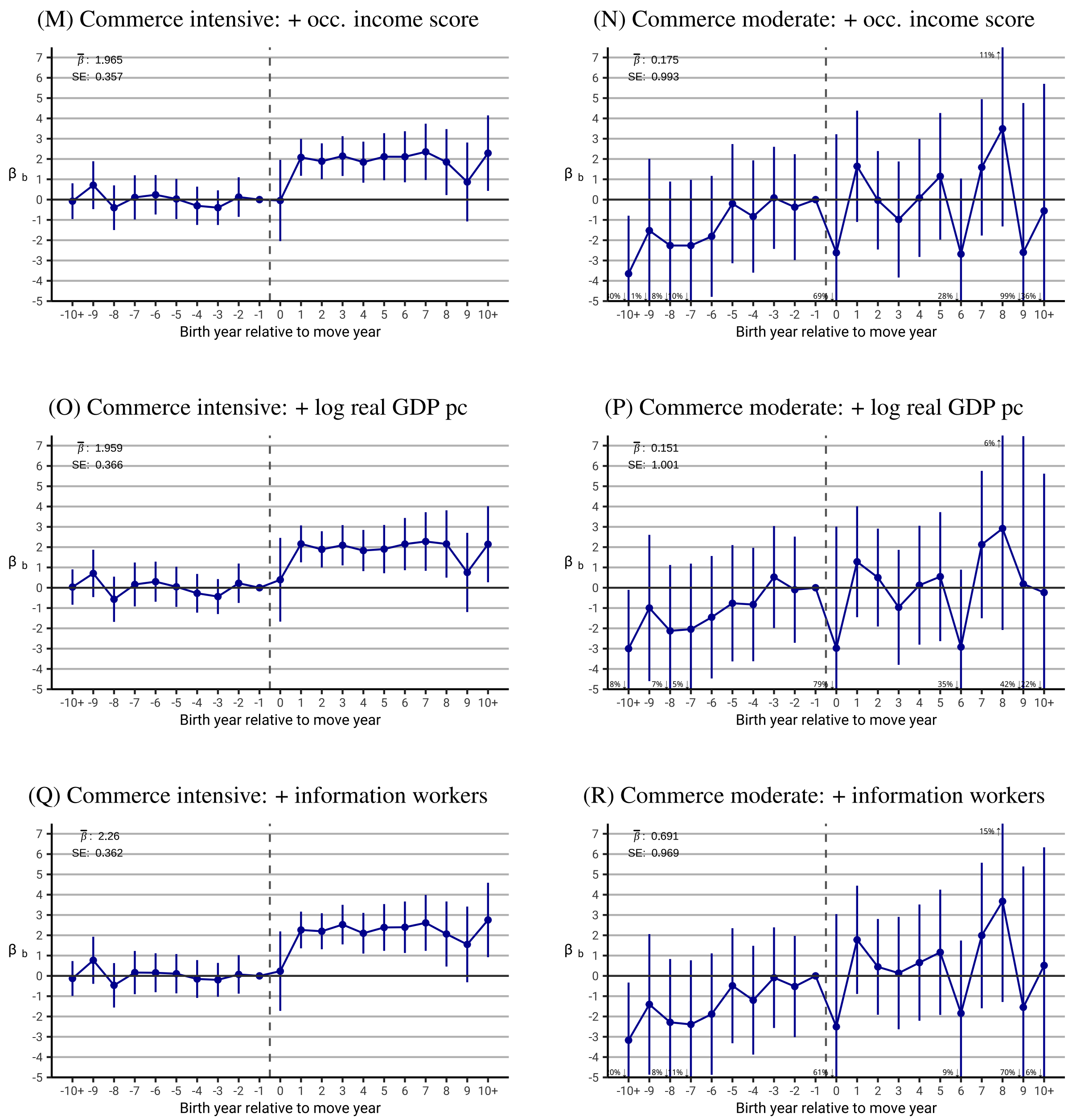


Figure B.21: The Differential Impact is Not Driven by Alternative Channels and Potential Mediators (cont.)

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

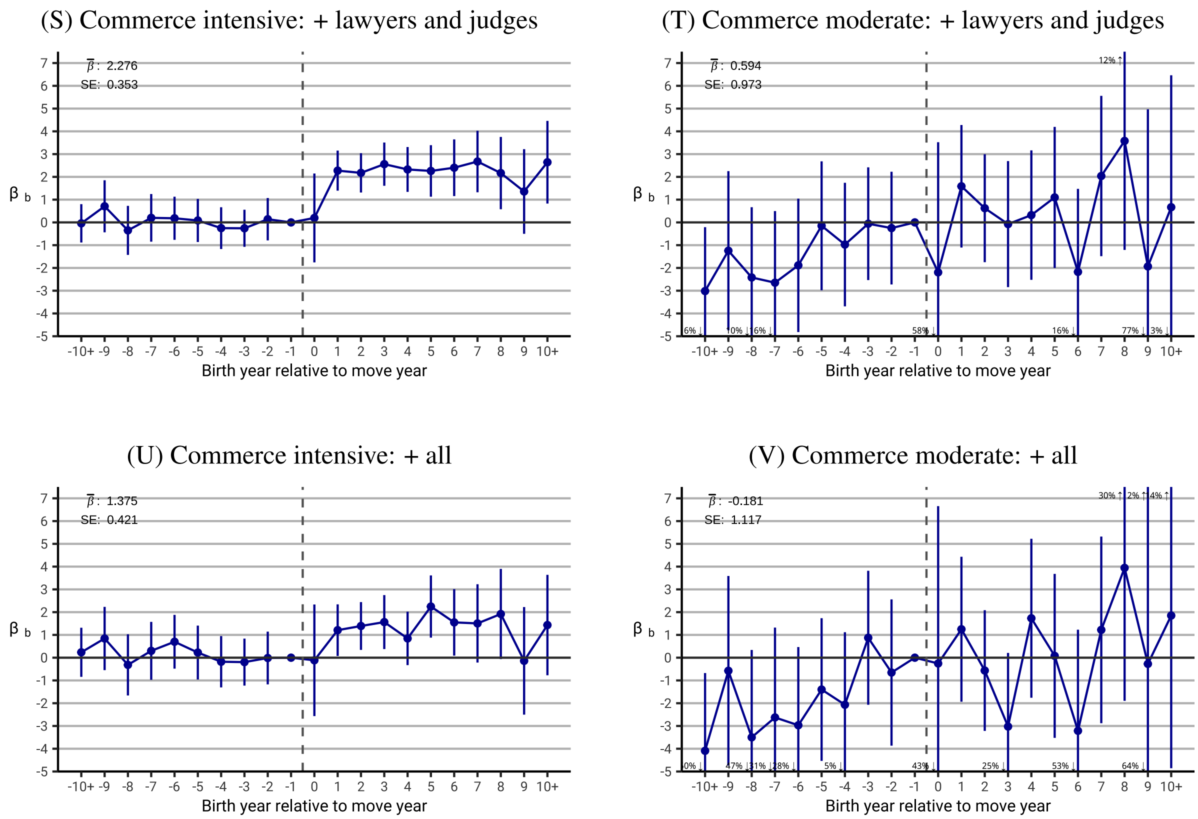


Figure B.21: The Differential Impact is Not Driven by Alternative Channels and Potential Mediators (cont.)

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

Table B.8: Market Access and Impersonal Cooperative Culture: Controlling for Competing and Mediating Factors

	Dependent variable:											
	Baseline	Controlling for Alternative Channels										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Universal Name Index											
logMA	0.9250***	0.9720***	0.8690***	0.7985***	0.9974***	0.8934***	0.8396***	0.8630***	1.181***	0.9173***	0.8367***	0.9870***
	(0.1610)	(0.1606)	(0.1576)	(0.1545)	(0.1806)	(0.1610)	(0.1543)	(0.1585)	(0.1681)	(0.1606)	(0.1594)	(0.1927)
Observations	18,182	18,179	18,182	18,182	12,683	18,168	18,168	18,168	17,267	18,168	18,168	12,268
R^2	0.805	0.799	0.808	0.812	0.848	0.807	0.810	0.808	0.806	0.805	0.808	0.849
	Panel B: Extra-Community Marriage											
logMA	0.0069*	0.0076**	0.0078**	0.0064*	0.0093*	0.0060*	0.0045	0.0051	0.0060	0.0059	0.0060	0.0022
	(0.0037)	(0.0037)	(0.0037)	(0.0036)	(0.0047)	(0.0036)	(0.0033)	(0.0036)	(0.0037)	(0.0036)	(0.0036)	(0.0040)
Observations	18,179	18,176	18,179	18,179	12,674	18,163	18,163	18,165	17,262	18,165	18,165	12,256
R^2	0.908	0.909	0.909	0.908	0.923	0.911	0.914	0.911	0.929	0.910	0.909	0.946
	Panel C: Norms Tolerance Index											
logMA	0.1785***	0.1801***	0.1782***	0.1783***	0.1638***	0.1763***	0.1737***	0.1741***	0.1527***	0.1797***	0.1738***	0.1449***
	(0.0321)	(0.0320)	(0.0323)	(0.0324)	(0.0394)	(0.0322)	(0.0325)	(0.0326)	(0.0330)	(0.0321)	(0.0323)	(0.0421)
Observations	18,098	18,095	18,098	18,098	12,634	18,084	18,084	18,084	17,233	18,084	18,084	12,233
R^2	0.698	0.700	0.698	0.698	0.721	0.699	0.699	0.699	0.701	0.698	0.699	0.718
	Panel D: Religious Diversity Index											
logMA	0.2681***	0.2698***	0.2422***	0.2338***	0.1977***	0.2429***	0.2299***	0.2241***	0.2681***	0.2429***	0.2382***	0.1781***
	(0.0347)	(0.0342)	(0.0357)	(0.0357)	(0.0359)	(0.0363)	(0.0363)	(0.0365)	(0.0380)	(0.0363)	(0.0367)	(0.0414)
Observations	17,303	17,301	14,626	14,626	12,248	14,612	14,612	14,612	16,755	14,612	14,612	9,358
R^2	0.681	0.683	0.708	0.709	0.716	0.706	0.708	0.709	0.677	0.706	0.707	0.743
	Panel E: Social Trust											
logMA	0.1201**	0.1199**	0.1025*	0.1050*	0.1024*	0.0985*	0.1075**	0.0988*	0.1101**	0.0962*	0.0894*	0.0636
	(0.0485)	(0.0484)	(0.0539)	(0.0539)	(0.0564)	(0.0527)	(0.0536)	(0.0537)	(0.0521)	(0.0528)	(0.0534)	(0.0684)
Observations	6,821	6,820	5,861	5,861	5,256	5,853	5,853	5,853	6,736	5,853	5,853	4,249
R^2	0.680	0.681	0.683	0.684	0.704	0.684	0.684	0.684	0.682	0.684	0.684	0.711
Share Urban		Yes										Yes
Share Immigrants			Yes									Yes
Birthplace Diversity				Yes								Yes
log(1+Manufacturing Est.)					Yes							Yes
Manufacturing Emp.						Yes						Yes
Agriculture Emp.							Yes					Yes
Occupational Income Score								Yes				Yes
Log Real GDP PC									Yes			Yes
Information Workers per 1,000										Yes		Yes
Lawyers and Judges per 1,000											Yes	Yes

Note: This table reports estimates of equation (2) with additional controls for competing channels and potential mediators. The dependent variables are: the UNI (Panel A), the ECM (Panel B), the NTI (Panel C), the RDI (Panel D), and Social Trust (Panel E). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. 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: Market Access and Patterns of Cooperative Behavior: Controlling for Competing and Mediating Factors

	Dependent variable:											
	Baseline	Controlling for Alternative Channels										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Voter turnout											
logMA	0.0375***	0.0362***	0.0405***	0.0410***	0.0420***	0.0397***	0.0423***	0.0379***	0.0461***	0.0386***	0.0349***	0.0452***
	(0.0061)	(0.0061)	(0.0064)	(0.0064)	(0.0065)	(0.0065)	(0.0064)	(0.0063)	(0.0068)	(0.0064)	(0.0059)	(0.0064)
Observations	45,308	45,304	40,242	40,242	36,915	40,213	40,213	40,213	44,713	40,213	40,213	31,535
R^2	0.804	0.805	0.807	0.807	0.807	0.806	0.807	0.806	0.811	0.806	0.810	0.820
	Panel B: Provision of public goods											
logMA	0.0185***	0.0196***	0.0171***	0.0158**	0.0162***	0.0186***	0.0174***	0.0183***	0.0209***	0.0178***	0.0173***	0.0177**
	(0.0060)	(0.0060)	(0.0061)	(0.0062)	(0.0060)	(0.0061)	(0.0061)	(0.0060)	(0.0068)	(0.0059)	(0.0061)	(0.0072)
Observations	4,942	4,940	4,942	4,942	4,940	4,929	4,929	4,929	4,799	4,929	4,929	4,782
R^2	0.908	0.908	0.908	0.908	0.908	0.908	0.908	0.908	0.909	0.908	0.908	0.911
	Panel C: Share in Family Care											
logMA	-0.0121***	-0.0126***	-0.0113***	-0.0106***	-0.0164***	-0.0116***	-0.0101***	-0.0114***	-0.0133***	-0.0119***	-0.0116***	-0.0111***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0034)	(0.0032)	(0.0030)	(0.0032)	(0.0028)	(0.0032)	(0.0032)	(0.0032)
Observations	18,173	18,170	18,173	18,173	12,674	18,159	18,159	18,159	17,267	18,159	18,159	12,263
R^2	0.721	0.723	0.724	0.725	0.780	0.724	0.735	0.723	0.751	0.722	0.722	0.797
Share Urban		Yes										Yes
Share Immigrants			Yes									Yes
Birthplace Diversity				Yes								Yes
log(1+Manufacturing Est.)					Yes							Yes
Manufacturing Emp.						Yes						Yes
Agriculture Emp.							Yes					Yes
Occupational Income Score								Yes				Yes
Log Real GDP PC									Yes			Yes
Information Workers per 1,000										Yes		Yes
Lawyers and Judges per 1,000											Yes	Yes

Note: This table reports estimates of equation 2 with additional controls for competing channels and potential mediators, when the dependent variables are different historical measures of impersonal or kin-based cooperative behavior: voters turnout (Panel A), local to state tax ratio (Panel B), and family care (Panel C). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). The table continues of the next page. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

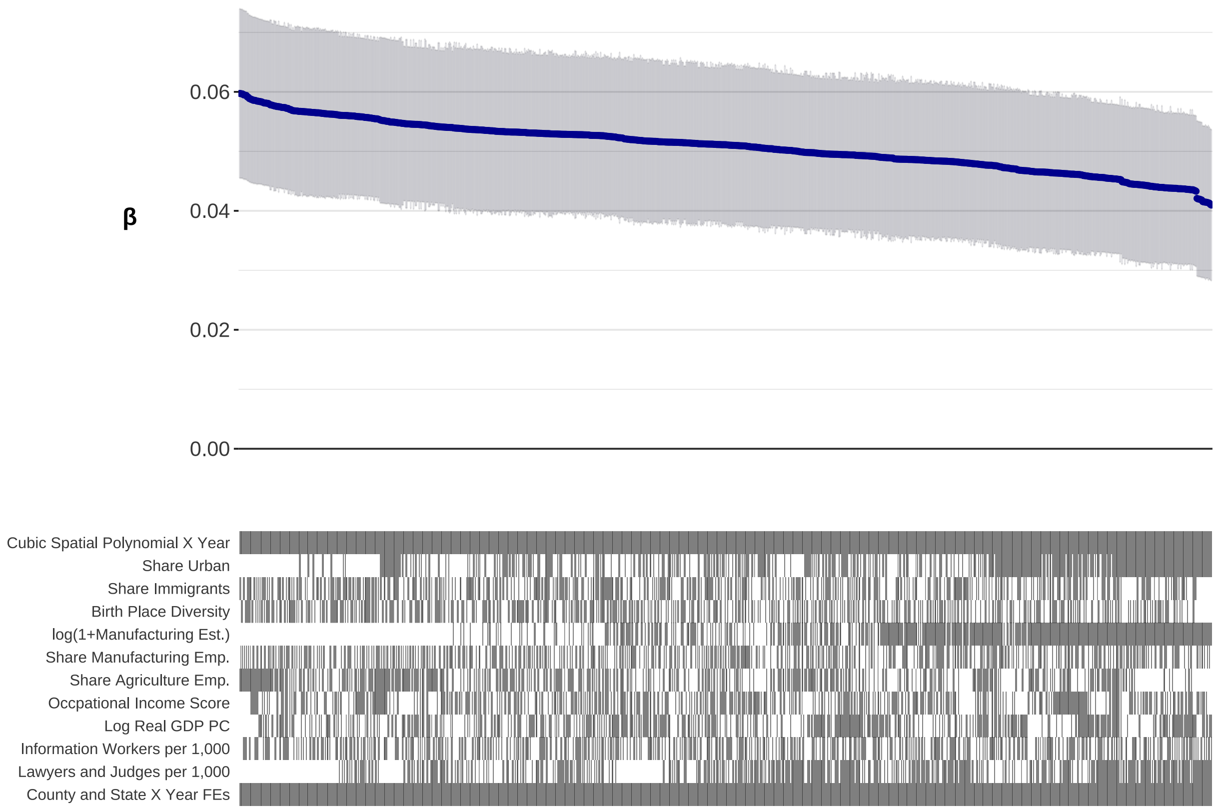


Figure B.22: The Impact on Turnout is Robust to Controlling for Competing and Mediating Factors

Note: This figure plots estimates of β and 95% confidence intervals from Equation (2) when the dependent variable is voter turnout in presidential elections. In addition to the baseline controls, the regressions control for all possible combination of the considered competing and mediating factors: the share of urban population, the share of immigrants, birthplace diversity, log of one plus the number of manufacturing establishments, the share working in manufacturing, the share working in agriculture, the mean occupational income score, log real GDP PC, the number of information workers per 1,000, and the number of lawyers and judges per 1,000. Standard errors are clustered at arbitrary grid cells of 100 miles square (Bester et al., 2011).

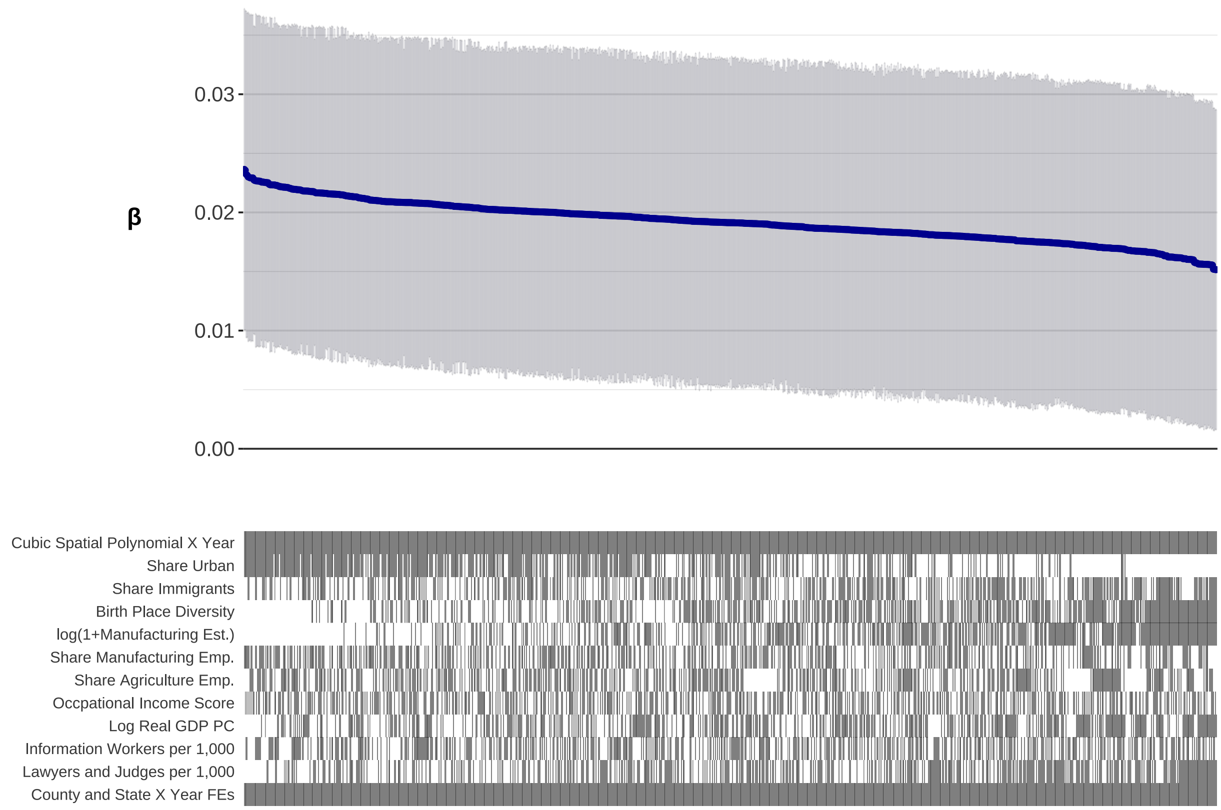


Figure B.23: The Impact on Public Goods Provision is Robust to Controlling for Competing and Mediating Factors

Note: This figure plots estimates of β and 95% confidence intervals from Equation (2) when the dependent variable is the share of local taxes. In addition to the baseline controls, the regressions control for all possible combination of the considered competing and mediating factors: the share of urban population, the share of immigrants, birthplace diversity, log of one plus the number of manufacturing establishments, the share working in manufacturing, the share working in agriculture, the mean occupational income score, log real GDP PC, the number of information workers per 1,000, and the number of lawyers and judges per 1,000. Standard errors are clustered at arbitrary grid cells of 100 miles square (Bester et al., 2011).

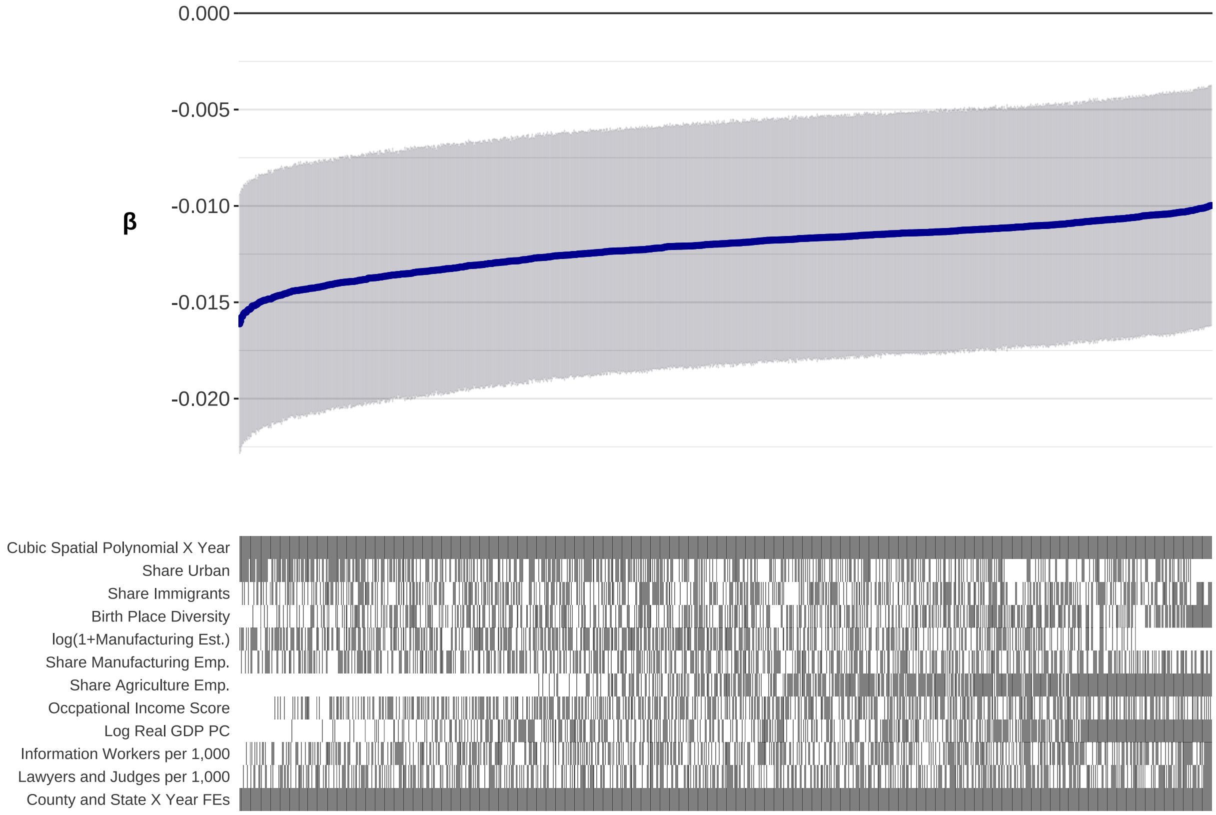


Figure B.24: The Impact on Family Care is Robust to Controlling for Competing and Mediating Factors

Note: This figure plots estimates of β and 95% confidence intervals from Equation (2) when the dependent variable is the share of vulnerable individuals in family care. In addition to the baseline controls, the regressions control for all possible combination of the considered competing and mediating factors: the share of urban population, the share of immigrants, birthplace diversity, log of one plus the number of manufacturing establishments, the share working in manufacturing, the share working in agriculture, the mean occupational income score, log real GDP PC, the number of information workers per 1,000, and the number of lawyers and judges per 1,000. Standard errors are clustered at arbitrary grid cells of 100 miles square (Bester et al., 2011).

Table B.10: Market Access and the Prevalence of Commerce: Controlling for Competing and Mediating Factors

	Dependent variable:											
	Baseline	Controlling for Alternative Channels										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Mean top 10 market terms share											
logMA	0.0146***	0.0145***	0.0155***	0.0152***	0.0137***	0.0154***	0.0164***	0.0159***	0.0151***	0.0154***	0.0143***	0.0155***
	(0.0045)	(0.0045)	(0.0048)	(0.0048)	(0.0049)	(0.0048)	(0.0048)	(0.0049)	(0.0047)	(0.0048)	(0.0048)	(0.0059)
Observations	8,625	8,625	7,320	7,320	6,693	7,313	7,313	7,313	8,513	7,313	7,313	5,324
R^2	0.633	0.633	0.624	0.624	0.665	0.624	0.624	0.624	0.635	0.624	0.624	0.664
	Panel B: Wholesale and Retail Share											
logMA	0.0051***	0.0056***	0.0048***	0.0044***	0.0047***	0.0045***	0.0035***	0.0031***	0.0069***	0.0046***	0.0039***	0.0030***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0008)	(0.0007)	(0.0006)	(0.0008)	(0.0008)	(0.0008)	(0.0006)
Observations	18,266	18,263	18,266	18,266	12,739	18,266	18,266	18,266	17,303	18,266	18,266	12,306
R^2	0.780	0.801	0.784	0.788	0.828	0.795	0.841	0.863	0.815	0.791	0.801	0.912
Share Urban		Yes										Yes
Share Immigrants			Yes									Yes
Birthplace Diversity				Yes								Yes
log(1+Manufacturing Est.)					Yes							Yes
Manufacturing Emp.						Yes						Yes
Agriculture Emp.							Yes					Yes
Occupational Income Score								Yes				Yes
Log Real GDP PC									Yes			Yes
Information Workers per 1,000										Yes		Yes
Lawyers and Judges per 1,000											Yes	Yes

Note: This table reports estimates of equation 2 with additional controls for competing channels and potential mediators, when the dependent variables are two measures for the prevalence of commerce: the share of market language in local newspapers (Panel A) and the share of residents working in the wholesale and retail trade industries (Panel B). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). The table continues of the next page. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table B.11: Market Access and Impersonal Beneficial Interactions: Controlling for Competing and Mediating Factors

	Dependent variable:											
	Baseline	Controlling for Alternative Channels										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Labor-force cooperation											
logMA	0.0058***	0.0062***	0.0059***	0.0058***	0.0071***	0.0053***	0.0040***	0.0025**	0.0084***	0.0053***	0.0042***	0.0029*
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0016)	(0.0012)	(0.0012)	(0.0011)	(0.0013)	(0.0012)	(0.0012)	(0.0016)
Observations	18,267	18,264	18,267	18,267	12,739	18,265	18,265	18,267	17,304	18,267	18,267	12,306
R^2	0.680	0.686	0.662	0.680	0.692	0.691	0.717	0.765	0.701	0.687	0.693	0.804
	Panel B: Number of co-inventors											
logMA	0.0114***	0.0114***	0.0097**	0.0097**	0.0114***	0.0099**	0.0104***	0.0101***	0.0101***	0.0103***	0.0103***	0.0057
	(0.0037)	(0.0037)	(0.0038)	(0.0038)	(0.0043)	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0039)	(0.0051)
Observations	17,360	17,357	14,781	14,781	13,421	14,768	14,768	14,768	17,018	14,768	14,768	10,664
R^2	0.241	0.241	0.266	0.266	0.286	0.267	0.267	0.267	0.244	0.266	0.267	0.327
	Panel C: Diversity of co-inventors											
logMA	0.0111***	0.0112***	0.0100***	0.0101***	0.0121***	0.0102***	0.0105***	0.0104***	0.0092***	0.0105***	0.0103***	0.0070
	(0.0034)	(0.0034)	(0.0035)	(0.0035)	(0.0040)	(0.0035)	(0.0036)	(0.0036)	(0.0035)	(0.0035)	(0.0036)	(0.0047)
Observations	17,360	17,357	14,781	14,781	13,421	14,768	14,768	14,768	17,018	14,768	14,768	10,664
R^2	0.241	0.242	0.269	0.269	0.287	0.269	0.269	0.269	0.245	0.269	0.269	0.328
	Panel D: Residence with a non-kin											
logMA	0.0083***	0.0087***	0.0079***	0.0071***	0.0113***	0.0074***	0.0054	0.0070***	0.0085***	0.0083***	0.0080***	0.0057**
	(0.0022)	(0.0022)	(0.0022)	(0.0021)	(0.0029)	(0.0022)	(0.0034)	(0.0022)	(0.0020)	(0.0022)	(0.0022)	(0.0024)
Observations	18,277	18,274	18,277	18,277	12,749	18,261	18,261	18,263	17,317	18,263	18,263	12,305
R^2	0.782	0.785	0.783	0.786	0.818	0.788	0.391	0.789	0.801	0.783	0.783	0.850
	Panel E: Engagement in civic activities											
logMA	0.0008***	0.0009***	0.0007***	0.0006***	0.0006***	0.0006***	0.0004*	0.0003*	0.0006***	0.0006***	0.0005**	-9.17×10^{-5}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	18,266	18,263	18,266	18,266	12,739	18,266	18,266	18,266	17,303	18,266	18,266	12,306
R^2	0.688	0.714	0.691	0.693	0.738	0.702	0.741	0.749	0.715	0.700	0.705	0.823
Share Urban		Yes										Yes
Share Immigrants			Yes									Yes
Birthplace Diversity				Yes								Yes
log(1+Manufacturing Est.)					Yes							Yes
Manufacturing Emp.						Yes						Yes
Agriculture Emp.							Yes					Yes
Occupational Income Score								Yes				Yes
Log Real GDP PC									Yes			Yes
Information Workers per 1,000										Yes		Yes
Lawyers and Judges per 1,000											Yes	Yes

Note: This table reports estimates of equation 2 with additional controls for competing channels and potential mediators, when the dependent variables are different historical measures broad social interactions outside kinship lines: labor-force cooperation (Panel A), the number of co-inventors (Panel B), co-inventors' diversity (Panel C), the share of multifamily households (Panel D), and civic engagement (Panel E). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Robustness Checks

C.1 Impersonal Cooperative Culture and Behavior

C.1.1 Impersonal Cooperative Culture

Table C.1: Impersonal Cooperative Culture: 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: Impersonal Cooperative Culture			
Log market access	0.1461***	0.1457***	0.1427***	0.1471***
	(0.0175)	(0.0173)	(0.0174)	(0.0173)
Observations	19,912	19,899	19,912	19,896
R^2	0.739	0.745	0.735	0.751
	Panel B: Universal Name Index			
Log market access	0.9250***	0.8057***	1.004***	0.8976***
	(0.1609)	(0.1678)	(0.1649)	(0.1739)
Observations	18,182	18,182	18,182	18,182
R^2	0.805	0.812	0.810	0.815
	Panel C: Extra-Community Marriage			
Log market access	0.0069*	0.0145***	0.0011	0.0081*
	(0.0037)	(0.0044)	(0.0035)	(0.0042)
Observations	18,179	18,170	18,178	18,162
R^2	0.908	0.912	0.909	0.917
	Panel D: Norms Tolerance Index			
Log market access	0.1785***	0.1652***	0.1945***	0.1823***
	(0.0321)	(0.0306)	(0.0323)	(0.0305)
Observations	18,098	17,997	18,076	17,969
R^2	0.698	0.697	0.698	0.696

Note: This table reports estimates of the baseline specification of equation (2) when the dependent variables are the composite impersonal cooperative culture index (Panel A), the UNI (Panel B), the share of ECM (Panel C), and the NTI (Panel D). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. 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. 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 C.2: Impersonal Cooperative Culture: Different Market Access Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Baseline and Robustness							
	Baseline	Robustness						
	$P = 35$	$P = 38.7$		$P = 35$				
	$\theta = 8.22$	$\theta = 3.05$	$\theta = 8.22$	$\theta = 1$	$\theta = 2$	$\theta = 3$	$\theta = 4$	$\theta = 5$
Cooperative Culture	0.146***	0.393***	0.154***	1.14***	0.569***	0.379***	0.285***	0.229***
	(0.018)	(0.049)	(0.018)	(0.140)	(0.070)	(0.046)	(0.041)	(0.028)
UNI	0.925***	2.43***	0.963***	7.08***	3.54***	2.37***	1.78***	1.44***
	(0.161)	(0.450)	(0.171)	(1.30)	(0.647)	(0.430)	(0.322)	(0.258)
ECM	0.007*	0.018*	0.007*	0.052*	0.026*	0.017*	0.013*	0.011*
	(0.004)	(0.010)	(0.004)	(0.030)	(0.015)	(0.010)	(0.007)	(0.006)
NTI	0.178***	0.485***	0.189***	1.40***	0.699***	0.465***	0.350***	0.281***
	(0.032)	(0.090)	(0.034)	(0.261)	(0.130)	(0.086)	(0.065)	(0.052)
RDI	0.268***	0.732***	0.282***	2.13***	1.06***	0.705***	0.529***	0.425***
	(0.035)	(0.097)	(0.037)	(0.280)	(0.140)	(0.093)	(0.070)	(0.056)
Trust	0.120**	0.341**	0.127**	0.998**	0.495**	0.329**	0.246**	0.197**
	(0.049)	(0.139)	(0.052)	(0.399)	(0.199)	(0.132)	(0.099)	(0.079)

Note: This table reports estimates of β from the baseline specification of equation (2) when the dependent variables are different historical impersonal cooperative culture: the composite impersonal cooperative culture index, the UNI, the ECM, the NTI, the RDI, and social trust (rows), and market access is calculated using different average costs P and different trade elasticities θ (columns). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). The table continues to the next page. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: Impersonal Cooperative Culture: Different Market Access Measures (cont.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel B: Robustness							
	$P = 35$							
	$\theta = 6$	$\theta = 7$	$\theta = 8$	$\theta = 9$	$\theta = 10$	$\theta = 11$	$\theta = 12$	$\theta = 13$
Cooperative Culture	0.193***	0.168***	0.149***	0.135***	0.124***	0.115***	0.108***	0.102***
	(0.025)	(0.020)	(0.018)	(0.016)	(0.015)	(0.013)	(0.012)	(0.011)
UNI	1.21***	1.06***	0.946***	0.858***	0.789***	0.737***	0.699***	0.672***
	(0.217)	(0.187)	(0.165)	(0.148)	(0.134)	(0.123)	(0.114)	(0.107)
ECM	0.009*	0.008*	0.007*	0.006*	0.006*	0.005*	0.005*	0.005**
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
NTI	0.237***	0.206***	0.183***	0.165***	0.150***	0.138***	0.129***	0.121***
	(0.043)	(0.037)	(0.033)	(0.029)	(0.027)	(0.025)	(0.023)	(0.021)
RDI	0.357***	0.309***	0.275***	0.248***	0.228***	0.213***	0.200***	0.190***
	(0.047)	(0.040)	(0.035)	(0.032)	(0.029)	(0.026)	(0.025)	(0.023)
Trust	0.164**	0.141**	0.123**	0.110**	0.100**	0.092**	0.087**	0.082***
	(0.066)	(0.057)	(0.050)	(0.044)	(0.040)	(0.037)	(0.034)	(0.031)

Note: This table reports estimates of β from the baseline specification of equation (2) when the dependent variables are different historical impersonal cooperative culture: the composite impersonal cooperative culture index, the UNI, the ECM, the NTI, the RDI, and social trust (rows), and market access is calculated using different average costs P and different trade elasticities θ (columns). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

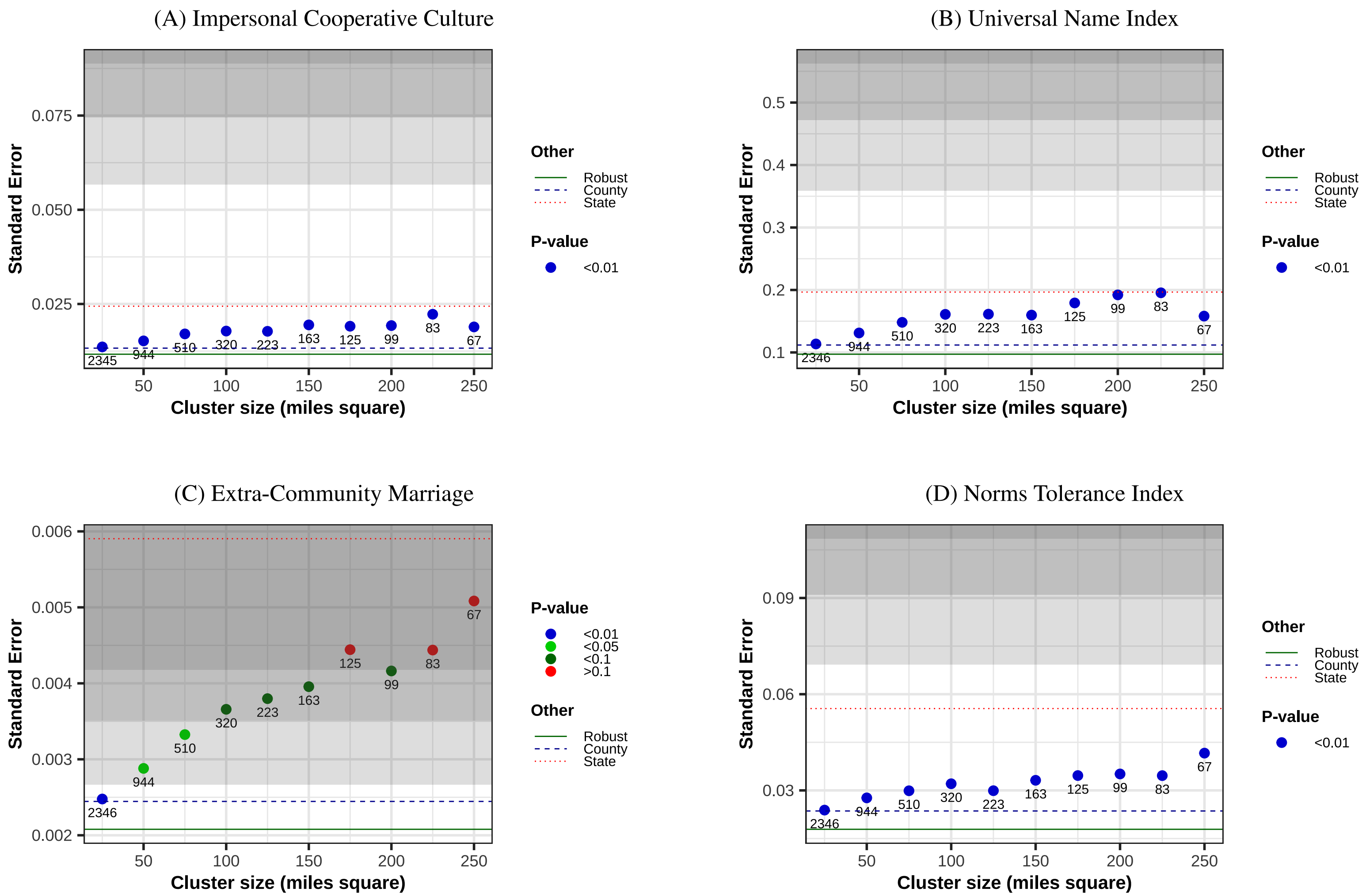


Figure C.1: Impersonal Cooperative Culture: Different Standard Errors

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. The figure continues to the next page.

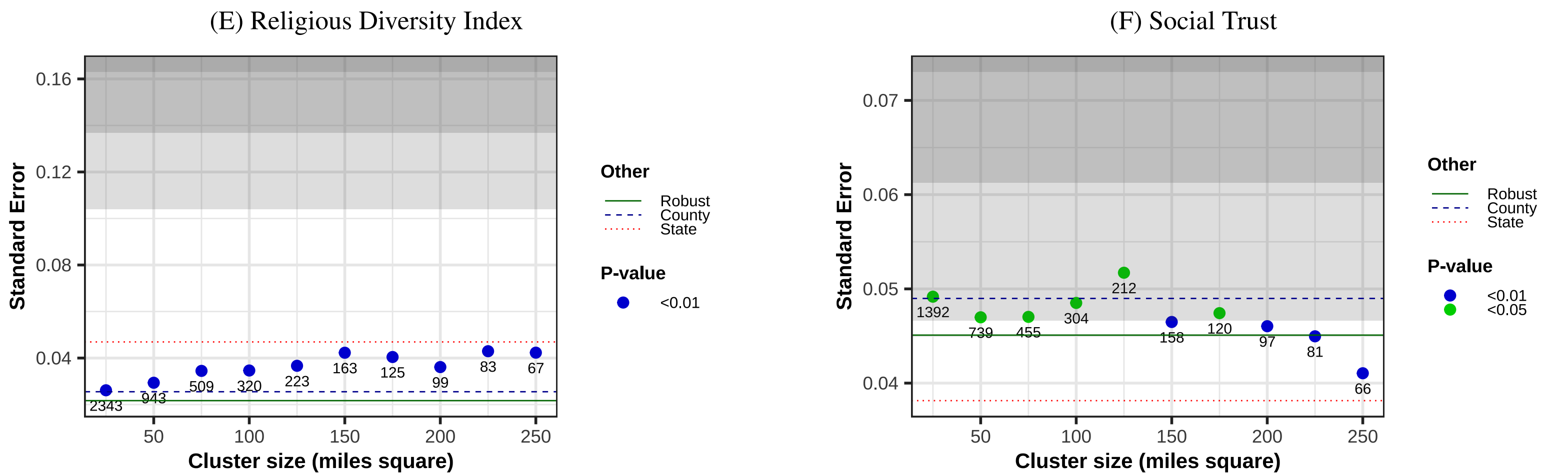


Figure C.1: Impersonal Cooperative Culture: Different Standard Errors (cont.)

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

Table C.3: Impersonal Cooperative Culture: Exclusion of Regions

	Dependent variable:				
Sample:	Baseline	Exclude Northeast	Exclude Midwest	Exclude South	Exclude West
	(1)	(2)	(3)	(4)	(5)
	Panel A: Impersonal Cooperative Culture				
Log market access	0.1461***	0.1467***	0.1173***	0.1594***	0.1464***
	(0.0175)	(0.0171)	(0.0202)	(0.0212)	(0.0197)
Observations	19,912	18,192	12,834	10,650	18,060
R^2	0.739	0.753	0.742	0.769	0.752
	Panel B: Universal Name Index				
Log market access	0.9250***	0.9084***	0.9096***	0.8586***	1.016***
	(0.1609)	(0.1613)	(0.1930)	(0.1944)	(0.1871)
Observations	18,182	16,677	11,573	9,882	16,414
R^2	0.805	0.789	0.813	0.830	0.799
	Panel C: Extra-Community Marriage				
Log market access	0.0069*	0.0074**	0.0038	0.0085**	0.0034
	(0.0037)	(0.0037)	(0.0051)	(0.0042)	(0.0039)
Observations	18,179	16,674	11,565	9,884	16,414
R^2	0.908	0.904	0.927	0.865	0.906
	Panel D: Norms Tolerance Index				
Log market access	0.1785***	0.1791***	0.0711**	0.2389***	0.1856***
	(0.0321)	(0.0324)	(0.0355)	(0.0403)	(0.0404)
Observations	18,098	16,593	11,541	9,820	16,340
R^2	0.698	0.686	0.656	0.755	0.698
	Panel E: Religious Diversity Index				
Log market access	0.2681***	0.2656***	0.2258***	0.2922***	0.3026***
	(0.0346)	(0.0350)	(0.0404)	(0.0384)	(0.0398)
Observations	17,303	15,798	11,203	9,191	15,717
R^2	0.681	0.676	0.703	0.739	0.616
	Panel F: Social Trust				
Log market access	0.1201**	0.1117**	0.0851	0.1055*	0.1959***
	(0.0486)	(0.0490)	(0.0664)	(0.0556)	(0.0586)
Observations	6,821	5,893	3,762	4,814	5,994
R^2	0.680	0.678	0.711	0.664	0.676

Note: This table reports estimates of the baseline specification of equation (2) when the dependent variables are the composite impersonal cooperative culture index (Panel A), the UNI (Panel B), the share of ECM (Panel C), the NTI (Panel D), the RDI (Panel E), and social trust (Panel F). Column 1 reports the baseline estimate. Columns 2-5 exclude different regions of the country: the Northeast, the Midwest, the South, and the West. All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.1.2 Impersonal and Kin-based Cooperative Behavior

Table C.4: Patterns of Cooperation: Different Market Access Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Baseline and Robustness							
	Baseline	Robustness						
	$P = 35$	$P = 38.7$		$P = 35$				
	$\theta = 8.22$	$\theta = 3.05$	$\theta = 8.22$	$\theta = 1$	$\theta = 2$	$\theta = 3$	$\theta = 4$	$\theta = 5$
Voters Turnout	0.037***	0.107***	0.040***	0.309***	0.154***	0.103***	0.077***	0.061***
	(0.006)	(0.018)	(0.007)	(0.051)	(0.025)	(0.017)	(0.013)	(0.010)
Local Taxes	0.018***	0.051***	0.019***	0.149***	0.074***	0.049***	0.037***	0.030***
	(0.006)	(0.017)	(0.006)	(0.049)	(0.025)	(0.016)	(0.012)	(0.010)
Family Care	-0.012***	-0.035***	-0.013***	-0.101***	-0.050***	-0.033***	-0.025***	-0.020***
	(0.003)	(0.009)	(0.003)	(0.026)	(0.013)	(0.009)	(0.006)	(0.005)
	Panel B: Robustness							
	$P = 35$							
	$\theta = 6$	$\theta = 7$	$\theta = 8$	$\theta = 9$	$\theta = 10$	$\theta = 11$	$\theta = 12$	$\theta = 13$
Voters Turnout	0.051***	0.044***	0.038***	0.034***	0.031***	0.029***	0.027***	0.025***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
Local Taxes	0.025***	0.021***	0.019***	0.017***	0.016***	0.015***	0.014***	0.013***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
Family Care	-0.017***	-0.014***	-0.013***	-0.011***	-0.010***	-0.009***	-0.008***	-0.008***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)

Note: This table reports estimates of β from the baseline specification of equation (2) when the dependent variables are different measures of historical impersonal or kin-based cooperation and market access is calculated using different average costs P and different trade elasticities θ. All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

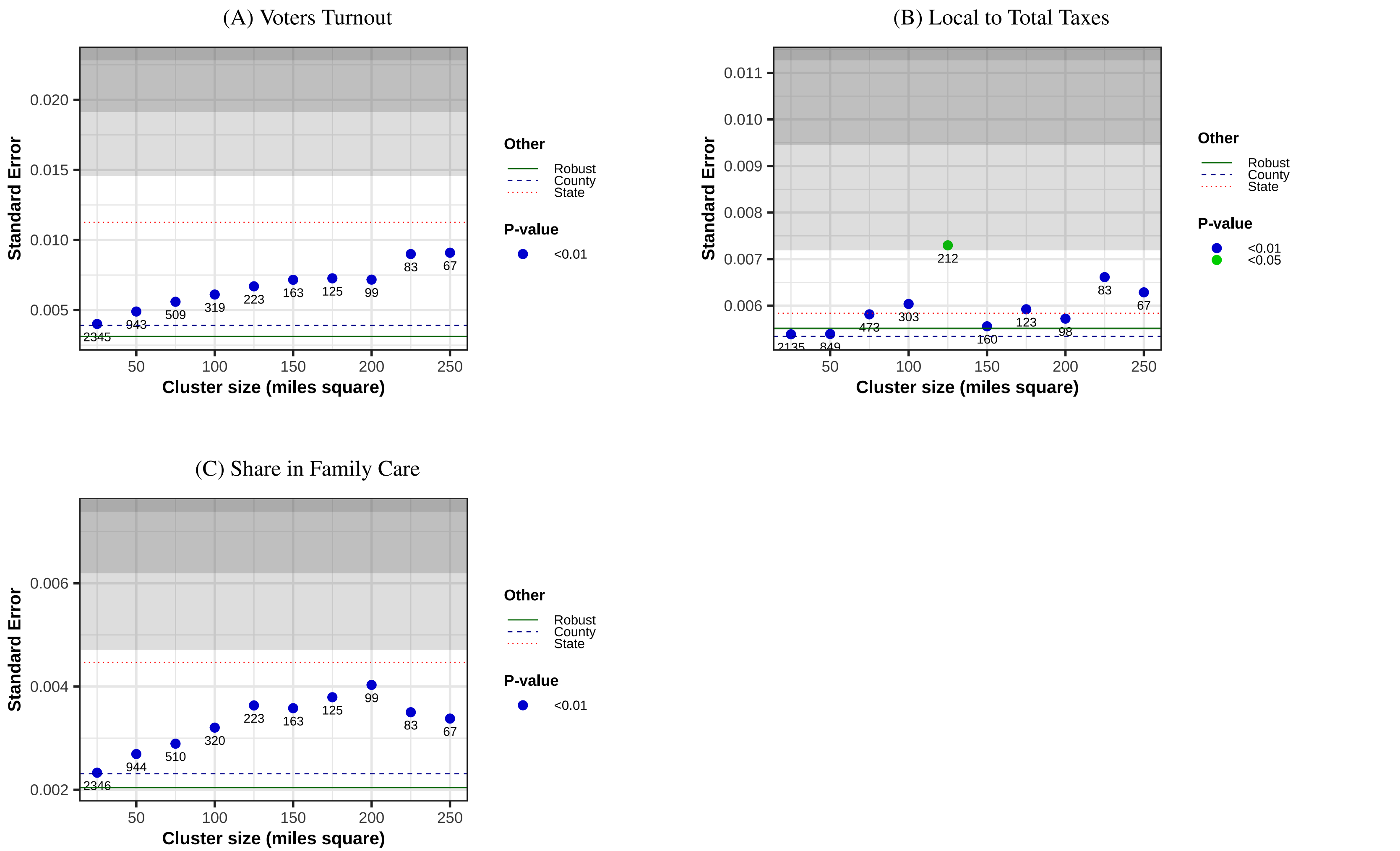


Figure C.2: Patterns of Cooperation: Different Standard Errors

Note: This figure plots the standard errors of β from the baseline specification of equation (2) using different approaches for inference. The blue dots represent the standard errors (on the y-axis) using arbitrary grid-cells 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 C.5: Family Care: Winsorize at Different Percentiles

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

Note: This table reports estimates of the baseline specification of equation (2) when the dependent variable is the share of vulnerable individuals in family care. In each column the outcome is winsorizied at different percentile at the bottom, between 0% (i.e., not winsorized, column 1) and 5% (column 6). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. 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 C.6: Patterns of Cooperation: Exclusion of Regions

	Dependent variable:				
Sample:	Baseline	Exclude Northeast	Exclude Midwest	Exclude South	Exclude West
	(1)	(2)	(3)	(4)	(5)
	Panel A: Voter turnout				
Log market access	0.0382***	0.0402***	0.0434***	0.0187***	0.0388***
	(0.0061)	(0.0062)	(0.0076)	(0.0068)	(0.0065)
Observations	45,308	41,241	28,218	24,534	41,931
R^2	0.800	0.797	0.795	0.740	0.809
	Panel E: Provision of public goods				
Log market access	0.0185***	0.0189***	0.0164**	0.0120*	0.0302***
	(0.0060)	(0.0061)	(0.0065)	(0.0072)	(0.0088)
Observations	4,942	4,512	3,237	2,673	4,404
R^2	0.908	0.899	0.893	0.855	0.910
	Panel H: Share in Family Care				
Log market access	-0.0121***	-0.0122***	-0.0153***	-0.0132***	-0.0081**
	(0.0032)	(0.0032)	(0.0033)	(0.0046)	(0.0035)
Observations	18,173	16,668	11,572	9,873	16,406
R^2	0.721	0.715	0.761	0.715	0.700

Note: This table reports estimates of equation (2) when the dependent variables are voter turnout in presidential elections (Panel A), the share of local tax revenues (Panel B), and the share of vulnerable individuals in family care (Panel C). Column 1 reports the baseline estimate. Columns 2-5 exclude different regions of the country: the Northeast, the Midwest, the South, and the West. The table continues to the next page. All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.2 Adaptation vs. Sorting

C.2.1 Cultural Adaptation

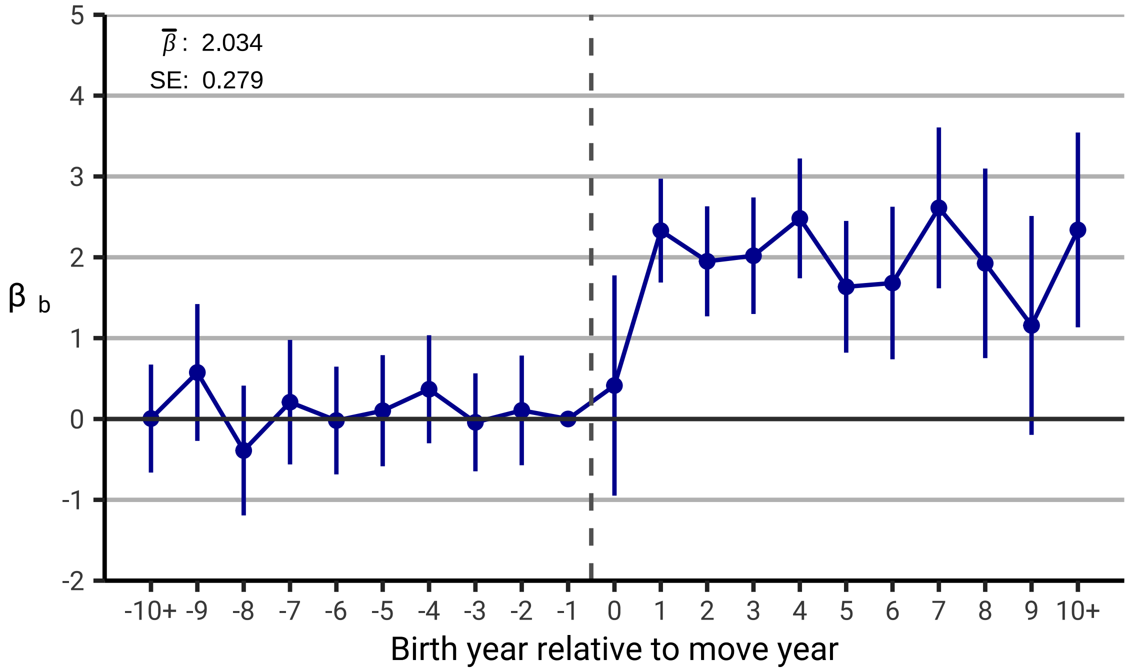


Figure C.3: DID Robustness: Controlling for Children's Characteristics

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

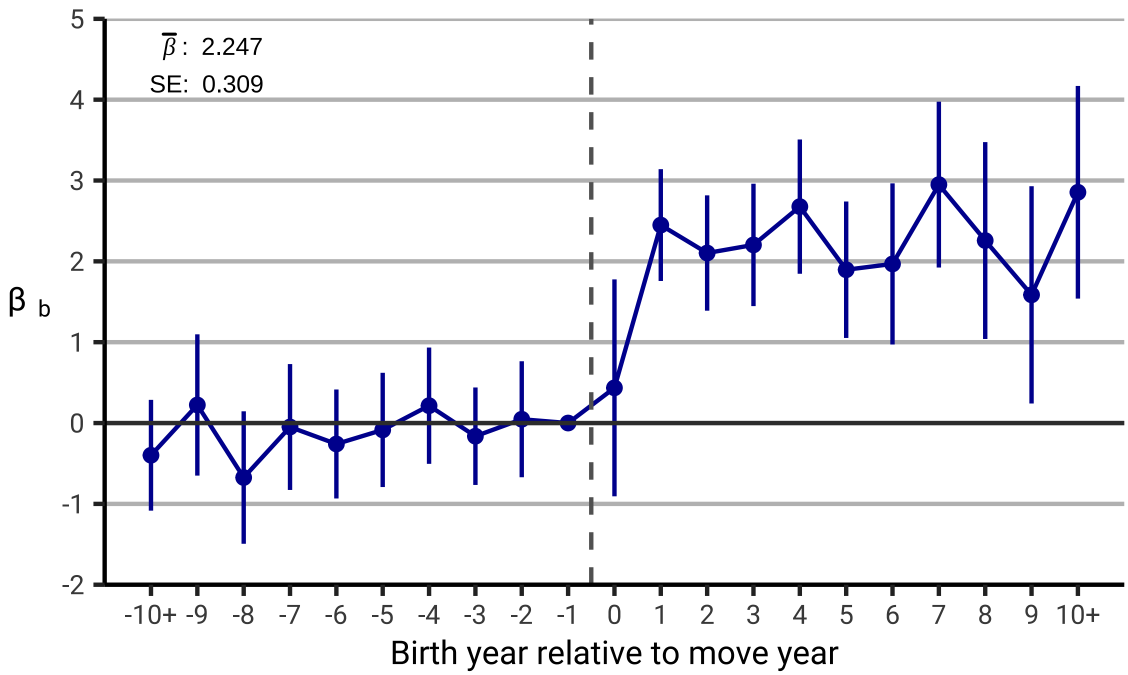


Figure C.4: DID Robustness: Two-way Clustering at Origin and Destination Counties

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

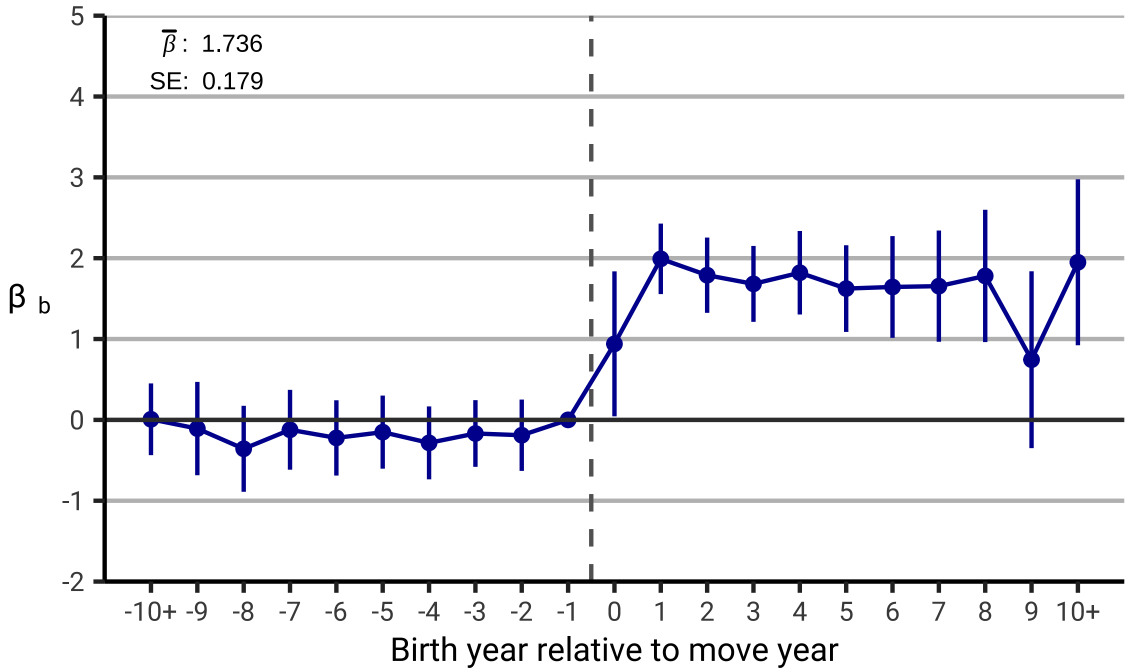


Figure C.5: DID Robustness: Continuous Treatment

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

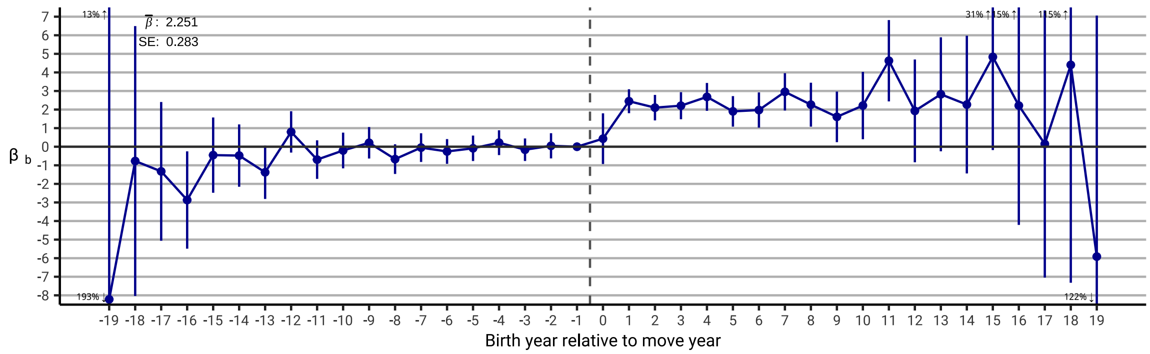


Figure C.6: DID Robustness: Longer Horizon

Note: This figure plots the estimates of β_b and 95% confidence intervals from the difference-in-differences equation (3) with longer horizons, instead of aggregating the effects 10 or more years before and after the migration. $\bar{\beta}$ is the average treatment effect across post-migration periods weighted by the number of children born in each relative year.

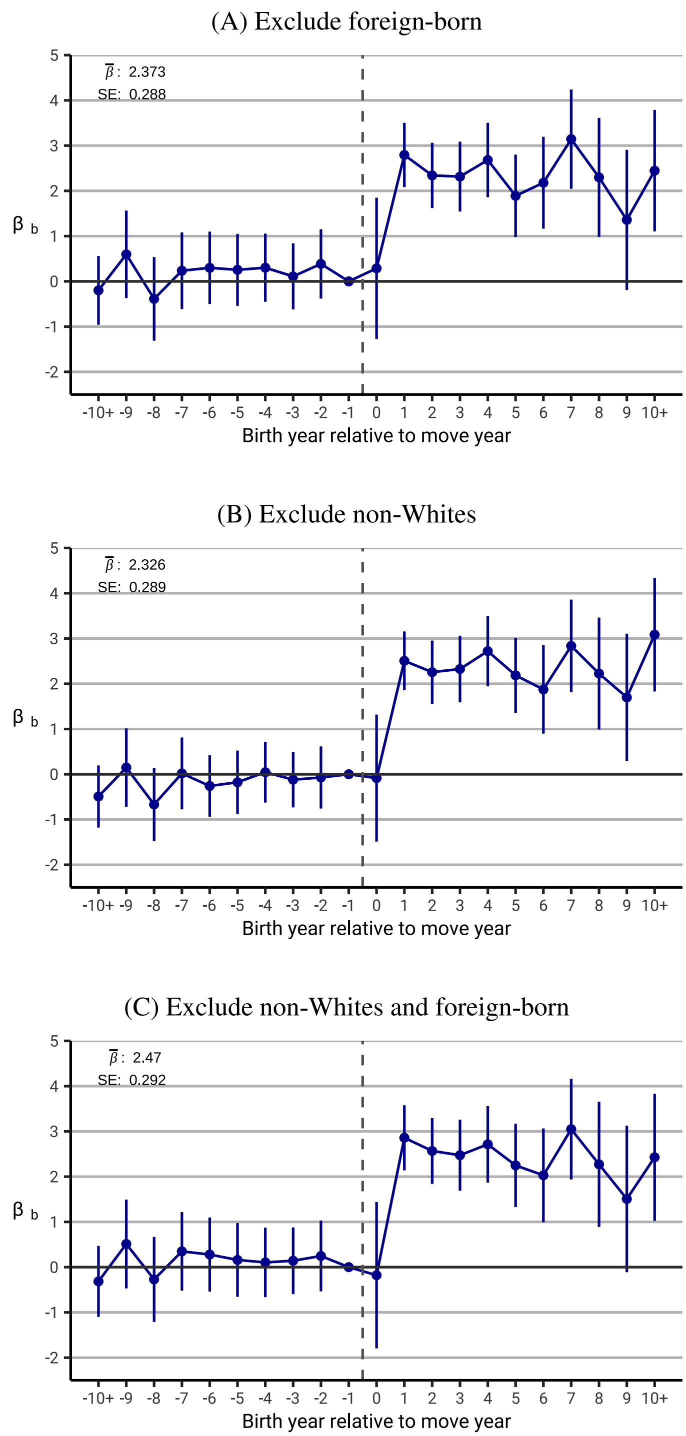


Figure C.7: DID Robustness: Exclusion of Immigrants and Non-Whites

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

C.2.2 Returns to Adaptation

Table C.7: The Returns to Cultural Adaptation

	Dependent variable:					
	Total Property Value (mean = 3461.5 , sd = 4114.0)			Personal Property Value (mean = 838.0 , sd = 1284.2)		
	(1)	(2)	(3)	(4)	(5)	(6)
More Universalistic	-138.0	-133.8	-129.2	-8.660	-8.978	-6.952
	(167.3)	(164.6)	(163.7)	(41.82)	(41.59)	(41.37)
Higher Market Access × More Universalistic	471.1	564.1	547.3	-35.91	-27.83	-30.51
	(356.7)	(345.9)	(342.4)	(92.31)	(90.35)	(90.50)
Observations	23,962	23,962	23,962	33,158	33,158	33,158
R^2	0.886	0.895	0.895	0.865	0.872	0.872
Origin × Destination × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Ctrls. (demographics)		Yes	Yes		Yes	Yes
Individual Ctrls. (traits)			Yes			Yes

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

Table C.8: The Returns to Cultural Adaptation

	Dependent variable:					
	Children Survival Rate (mean = 0.879 , sd = 0.163)			Real Property Value (mean = 2321.0 , sd = 2711.7)		
	(1)	(2)	(3)	(4)	(5)	(6)
More Universalistic	-0.0031	-0.0018	-0.0018	-106.0	-93.20	-93.92
	(0.0059)	(0.0063)	(0.0063)	(125.3)	(122.2)	(122.0)
Higher Market Access × More Universalistic	0.0192**	0.0194**	0.0195**	559.0**	606.2**	599.7**
	(0.0075)	(0.0082)	(0.0082)	(271.9)	(246.4)	(243.8)
Observations	25,432	25,432	25,432	24,835	24,835	24,835
R^2	0.777	0.789	0.789	0.883	0.892	0.892
Origin × Destination × Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Ctrls. (demographics)		Yes	Yes		Yes	Yes
Individual Ctrls. (traits)			Yes			Yes

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

Table C.9: Cultural Adaptation and Real Property: Winsorize at Different Percentiles

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

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

Table C.10: Cultural Adaptation and Real Property: Different Transformations

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

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

C.3 Channels

C.3.1 The Prevalence of Commerce

Table C.11: The Prevalence of Commerce: Different Market Access Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Baseline and Robustness							
	Baseline	Robustness						
	$P = 35$	$P = 38.7$		$P = 35$				
	$\theta = 8.22$	$\theta = 3.05$	$\theta = 8.22$	$\theta = 1$	$\theta = 2$	$\theta = 3$	$\theta = 4$	$\theta = 5$
Market Language	0.015***	0.042***	0.015***	0.122***	0.060***	0.040***	0.030***	0.024***
	(0.004)	(0.013)	(0.005)	(0.037)	(0.018)	(0.012)	(0.009)	(0.007)
Share in Trade	0.015***	0.042***	0.015***	0.122***	0.060***	0.040***	0.030***	0.024***
	(0.004)	(0.013)	(0.005)	(0.037)	(0.018)	(0.012)	(0.009)	(0.007)
	Panel B: Robustness							
	$P = 35$							
	$\theta = 6$	$\theta = 7$	$\theta = 8$	$\theta = 9$	$\theta = 10$	$\theta = 11$	$\theta = 12$	$\theta = 13$
Market Language	0.008***	0.007***	0.006***	0.005***	0.005***	0.005***	0.004***	0.004***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.0010)	(0.0009)	(0.0008)
Share in Trade	0.007***	0.006***	0.005***	0.005***	0.004***	0.004***	0.004***	0.003***
	(0.001)	(0.0009)	(0.0008)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0005)

Note: This table reports estimates of β from the baseline specification of equation (2) when the dependent variables are two measures for the prevalence of commerce and market access is calculated using different average costs P and different trade elasticities θ. All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

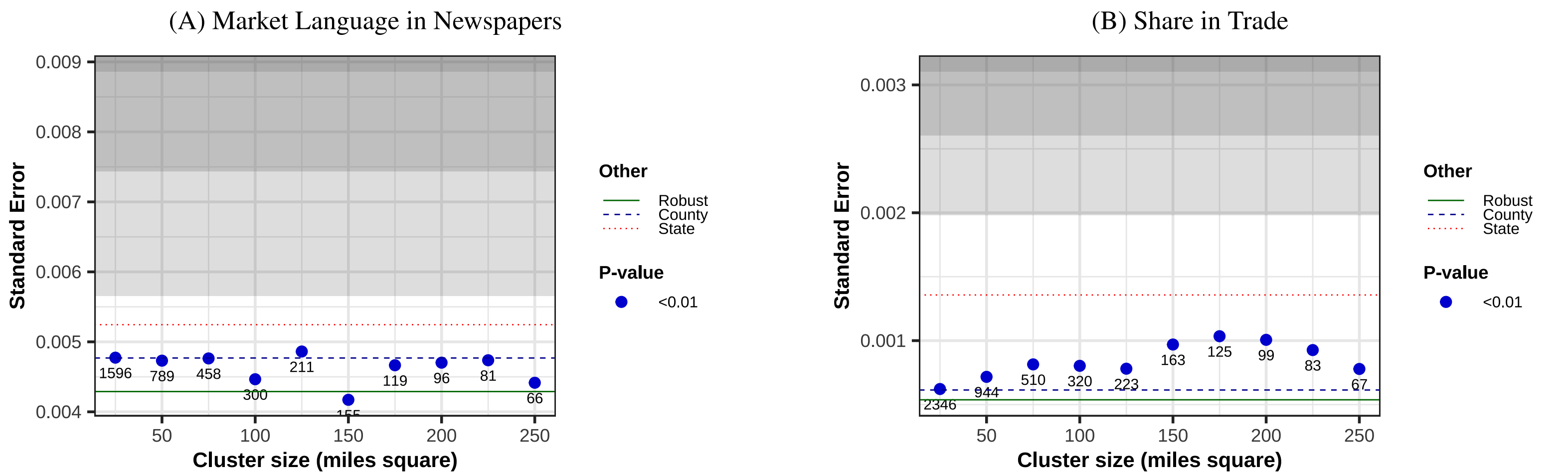


Figure C.8: The Prevalence of Commerce: Different Standard Errors

Note: This figure plots the standard errors of β from the baseline specification of equation (2) using different approaches for inference. The blue dots represent the standard errors (on the y-axis) using arbitrary grid-cells 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 C.12: Market Access and Market Language: More Market Terms

	Dependent variable:							
	Baseline	Recentering	Controlling for local railroads and population					Both
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Mean top 20 market terms share (mean = 0.365 , sd = 0.097)							
Log market access	0.0121***	0.0126***	0.0087**	0.0126***	0.0124***	0.0122**	0.0113**	0.0113**
	(0.0038)	(0.0038)	(0.0042)	(0.0045)	(0.0046)	(0.0049)	(0.0049)	(0.0050)
Observations	8,625	8,588	8,625	8,625	8,625	8,625	8,625	8,588
R^2	0.646	0.646	0.646	0.648	0.649	0.650	0.652	0.652
	Panel B: Mean top 50 market terms share (mean = 0.226 , sd = 0.062)							
Log market access	0.0080***	0.0082***	0.0059**	0.0081***	0.0078***	0.0076**	0.0072**	0.0073**
	(0.0024)	(0.0024)	(0.0027)	(0.0028)	(0.0029)	(0.0030)	(0.0030)	(0.0031)
Observations	8,625	8,588	8,625	8,625	8,625	8,625	8,625	8,588
R^2	0.646	0.646	0.646	0.648	0.649	0.651	0.652	0.652
	Panel C: Mean top 100 market terms share (mean = 0.169 , sd = 0.047)							
Log market access	0.0058***	0.0060***	0.0042**	0.0057***	0.0054**	0.0053**	0.0051**	0.0052**
	(0.0019)	(0.0019)	(0.0020)	(0.0022)	(0.0022)	(0.0023)	(0.0023)	(0.0023)
Observations	8,625	8,588	8,625	8,625	8,625	8,625	8,625	8,588
R^2	0.646	0.646	0.646	0.648	0.648	0.650	0.652	0.652

Note: This table reports estimates of equation (2). The dependent variables are the mean shares of top market words: top 20 (Panel A), top 50 (Panel B), and top 100 (Panel C). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Column 1 is our baseline estimation. Column 2 implements the approach recommended by Borusyak and Hull (2023) using Fogel (1964)'s proposed canal to control for the expected log market access. Columns 3-7 add additional controls for local railroad infrastructure and population. Column 8 controls for both the expected log market access and local railroads and population. Any railroad is a dummy variable that equals one if the county o had any railroads in it in year t, and zero otherwise. Railroad length is a cubic polynomial in the length of railroads in county o and year t. Railroad within nearby buffer is a railroad dummy and length polynomial calculated for a 10-mile buffer around county o in year t. Railroad within further buffers are railroad dummies and length polynomials calculated for 20, 30, and 40-mile buffers around county o in year t. Population within further buffers are third order polynomials in total population calculated within the county o and for 10, 20, 30, and 40-mile buffers around it in year t. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.13: Wholesale and Retail Share: Winsorize at Different Percentiles

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

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 percentiles at the top, between 4% (column 1) and 1% (column 6). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. 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 C.14: Wholesale and Retail Share: Alternative Ways to Address Skewed Distributions With Zeros

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

Note: This table reports estimates of equation (2) when the dependent variable is the share of individuals working in the wholesale and retail trade industries. Each column deals with the skewness of the outcome that contains zeros differently: column 1 uses a Poisson regression, column 2 uses an inverse hyperbolic sine transformation of the dependent variable, and columns 3-4 use log transformations. All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. 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 C.15: Wholesale and Retail Share: Exclusion of Immigrants and Non-Whites

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

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. All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. 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 C.16: The Prevalence of Commerce: Exclusion of Regions

	Dependent variable:				
Sample:	Baseline	Exclude Northeast	Exclude Midwest	Exclude South	Exclude West
	(1)	(2)	(3)	(4)	(5)
	Panel A: Market Language in Newspapers				
Log market access	0.0146***	0.0141***	0.0142**	0.0062	0.0144**
	(0.0045)	(0.0045)	(0.0066)	(0.0060)	(0.0058)
Observations	8,625	7,720	4,906	5,651	7,598
R^2	0.633	0.626	0.636	0.532	0.633
	Panel B: Wholesale and Retail Share				
Log market access	0.0051***	0.0050***	0.0064***	0.0040***	0.0058***
	(0.0008)	(0.0008)	(0.0010)	(0.0009)	(0.0009)
Observations	18,266	16,769	11,596	9,943	16,490
R^2	0.780	0.760	0.796	0.755	0.792

Note: This table reports estimates of equation (2) when the dependent variables are wo measures for the prevalence of commerce: the share of market language in local newspapers (Panel A), the share of residents working in the wholesale and retail trade industries (Panel B). Column 1 reports the baseline estimate. Columns 2-5 exclude different regions of the country: the Northeast, the Midwest, the South, and the West. The table continues to the next page. All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.3.2 Impersonal Beneficial Social Interactions

Table C.17: Impersonal Social Interactions: Different Market Access Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Baseline and Robustness							
	Baseline	Robustness						
	$P=35$	$P=38.7$		$P=35$				
	$\theta=8.22$	$\theta=3.05$	$\theta=8.22$	$\theta=1$	$\theta=2$	$\theta=3$	$\theta=4$	$\theta=5$
L. F. Cooperation	0.006***	0.016***	0.006***	0.047***	0.024***	0.016***	0.012***	0.009***
	(0.001)	(0.004)	(0.002)	(0.010)	(0.005)	(0.004)	(0.003)	(0.002)
No. Co-Inventors	0.011***	0.033***	0.012***	0.095***	0.048***	0.032***	0.024***	0.019***
	(0.004)	(0.011)	(0.004)	(0.031)	(0.016)	(0.010)	(0.008)	(0.006)
Co-Inventors' Div.	0.011***	0.033***	0.012***	0.095***	0.047***	0.032***	0.024***	0.019***
	(0.003)	(0.010)	(0.004)	(0.029)	(0.015)	(0.010)	(0.007)	(0.006)
Multifamily Households	0.008***	0.025***	0.009***	0.071***	0.036***	0.024***	0.018***	0.014***
	(0.002)	(0.006)	(0.002)	(0.018)	(0.009)	(0.006)	(0.005)	(0.004)
Civic Engagement	0.0008***	0.002***	0.0008***	0.006***	0.003***	0.002***	0.001***	0.001***
	(0.0002)	(0.0006)	(0.0002)	(0.002)	(0.0008)	(0.0005)	(0.0004)	(0.0003)

Note: This table reports estimates of β from the baseline specification of equation (2) when the dependent variables are five historical measures of impersonal social interactions (rows), and market access is calculated using different average costs P and different trade elasticities θ (columns). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). The table continues on the next page. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table C.17: Impersonal Social Interactions: Different Market Access Measures (cont.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel B: Robustness							
	$P = 35$							
	$\theta = 6$	$\theta = 7$	$\theta = 8$	$\theta = 9$	$\theta = 10$	$\theta = 11$	$\theta = 12$	$\theta = 13$
L. F. Cooperation	0.008***	0.007***	0.006***	0.005***	0.005***	0.005***	0.004***	0.004***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.0010)	(0.0009)	(0.0008)
No. Co-Inventors	0.016***	0.013***	0.012***	0.010***	0.009***	0.009***	0.008***	0.007***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Co-Inventors' Div.	0.015***	0.013***	0.011***	0.010***	0.009***	0.008***	0.008***	0.007***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Multifamily Households	0.012***	0.010***	0.009***	0.007***	0.007***	0.006***	0.005***	0.005***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
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)

Note: This table reports estimates of β from the baseline specification of equation (2) when the dependent variables are five historical measures of impersonal social interactions (rows), and market access is calculated using different average costs P and different trade elasticities θ (columns). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

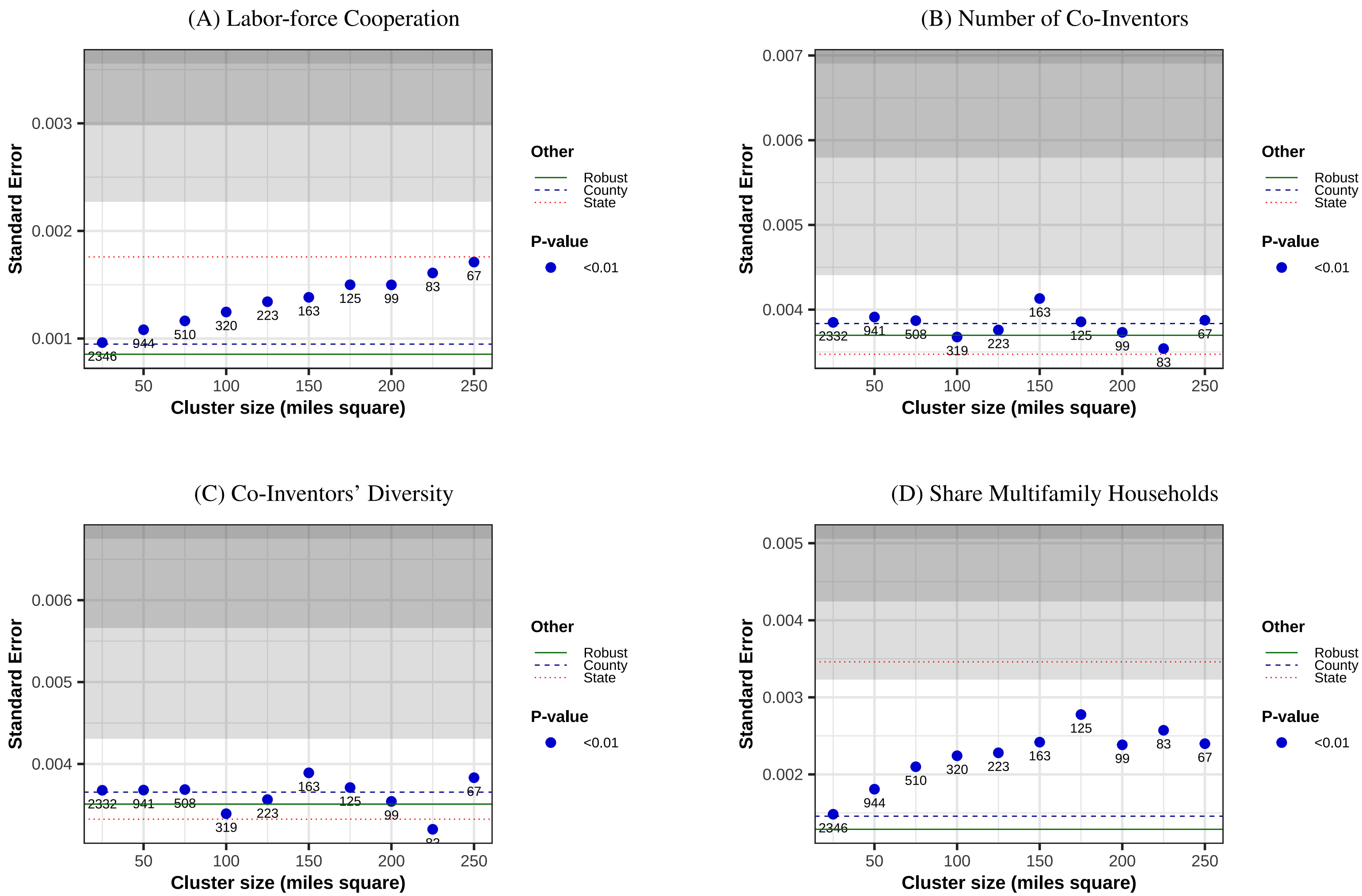


Figure C.9: Impersonal Social Interactions: Different Standard Errors

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

(E) Civic Engagement

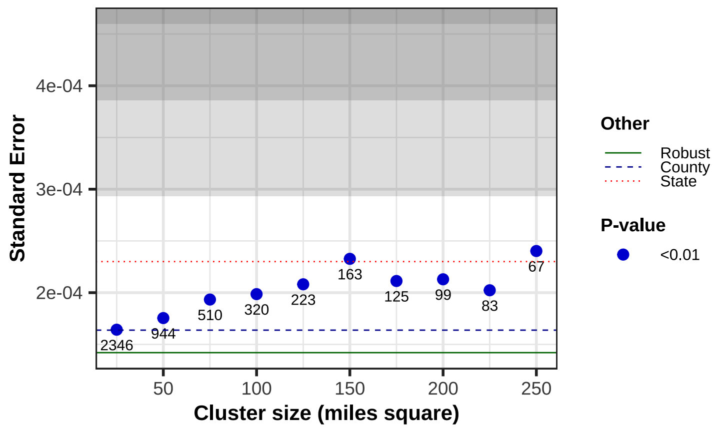


Figure C.9: Impersonal Social Interactions: Different Standard Errors (cont.)

Note: This figure plots the standard errors of β from the baseline specification of equation (2) using different approaches for inference. The blue dots represent the standard errors (on the y-axis) using arbitrary grid-cells 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 C.18: Impersonal Social Interactions: Winsorize at Different Percentiles

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

Note: This table reports estimates of the baseline specification of equation (2) when the dependent variables are three winsorized historical measure of impersonal social interactions: 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, the outcome is winsorizied at a different percentile at the top, between 4% (column 1) and 1% (column 6). All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. 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 C.19: Impersonal Social Interactions: Alternative Ways to Address Skewed Distributions With Zeros

	Dependent variable:			
	Poisson Regression	asinh(y)	log(1+y)	log(0.0001+y)
	(1)	(2)	(3)	(4)
	Panel A: Number of Co-Inventors (mean = 1.1 , sd = 0.158)			
Log market access	0.0069	0.0062*	0.0043*	0.0089**
	(0.0048)	(0.0032)	(0.0023)	(0.0040)
Observations	17,360	17,360	17,360	17,360
R^2		0.24407	0.24404	0.24452
Pseudo R^2	0.002			
	Panel B: Co-Inventors' Diversity (mean = 0.082 , sd = 0.14)			
Log market access	0.0885*	0.0095**	0.0094**	0.7430***
	(0.0483)	(0.0045)	(0.0037)	(0.0861)
Observations	16,149	17,360	17,360	17,360
R^2		0.24656	0.24613	0.43870
Pseudo R^2	0.077			
	Panel C: Share Multifamily Households (mean = 0.155 , sd = 0.099)			
Log market access	0.0283**	0.0070**	0.0061***	0.0712***
	(0.0134)	(0.0028)	(0.0023)	(0.0204)
Observations	18,277	18,277	18,277	18,277
R^2		0.76391	0.77261	0.69213
Pseudo R^2	0.058			
	Panel D: Civic Engagement (mean = 0.013 , sd = 0.011)			
Log market access	0.0759***	0.0011***	0.0010***	0.2071***
	(0.0190)	(0.0003)	(0.0003)	(0.0364)
Observations	18,258	18,266	18,266	18,266
R^2		0.59370	0.60456	0.56624
Pseudo R^2	0.039			

Note: This table reports estimates of the baseline specification of equation (2) when the dependent variables are three historical measure of impersonal social interactions: the average number of patents co-inventors (Panel A), the diversity of of patents co-inventors (Panel B), the share of multifamily households (Panel C), and civic engagement (Panel D). Each column deals with the skewness of the outcome that contains zeros differently: column 1 uses a Poisson regression, column 2 uses inverse hyperbolic sine transformation of the dependent variable, and columns 3-4 use log transformations. All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. 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 C.20: Impersonal Social Interactions: Exclusion of Regions

	Dependent variable:				
Sample:	Baseline	Exclude Northeast	Exclude Midwest	Exclude South	Exclude West
	(1)	(2)	(3)	(4)	(5)
	Panel A: Labor-force cooperation				
Log market access	0.0058***	0.0059***	0.0090***	0.0055***	0.0035**
	(0.0012)	(0.0013)	(0.0016)	(0.0015)	(0.0014)
Observations	18,267	16,770	11,596	9,943	16,492
R^2	0.680	0.673	0.694	0.601	0.688
	Panel B: Number of co-inventors				
Log market access	0.0114***	0.0110***	0.0090*	0.0112**	0.0141***
	(0.0037)	(0.0038)	(0.0046)	(0.0048)	(0.0042)
Observations	17,360	15,666	10,670	10,067	15,677
R^2	0.241	0.242	0.246	0.238	0.238
	Panel C: Diversity of co-inventors				
Log market access	0.0111***	0.0108***	0.0080*	0.0133***	0.0126***
	(0.0034)	(0.0035)	(0.0041)	(0.0046)	(0.0038)
Observations	17,360	15,666	10,670	10,067	15,677
R^2	0.241	0.243	0.247	0.240	0.238
	Panel D: Residence with a non-kin				
Log market access	0.0083***	0.0083***	0.0096***	0.0079**	0.0086***
	(0.0022)	(0.0023)	(0.0025)	(0.0031)	(0.0024)
Observations	18,277	16,772	11,606	9,951	16,502
R^2	0.782	0.773	0.808	0.791	0.772
	Panel F: Engagement in civic activities				
Log market access	0.0008***	0.0008***	0.0006**	0.0010***	0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Observations	18,266	16,769	11,596	9,943	16,490
R^2	0.688	0.682	0.712	0.677	0.664

Note: This table reports estimates of the baseline specification of equation (2), when the dependent variables are labor-force cooperation (Panel A), the number of co-inventors (Panel B), co-inventors' diversity (Panel C), the share of multifamily households (Panel D), and the share employed in civic activities (Panel E). Column 1 reports the baseline estimate. Columns 2-5 exclude different regions of the country: the Northeast, the Midwest, the South, and the West. The table continues on the next page. All columns control for county fixed effects, state-by-year fixed effects, and a cubic spatial polynomial interacted with year fixed effects. Standard errors clustered at arbitrary grid cells of 100 miles square in parentheses (Bester et al., 2011). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$