Culture and the Deep Roots of Innovation in the United States 1870-2000

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Abstract

Cultural traits, such as trust and individualism, have been shown to be important determinants of innovation. Cross-country data indicate that these traits help explain variation in innovation rates between countries. Many of these cultural traits have deep roots in a country's past and are resistant to change. Given the large ethnic diversity of its population, the U.S. provides a unique environment in which we can study how these cultural values affect innovation when they are all operating under the same institutional structure. Using panel data on U.S. county patents and county ancestral origin over the last 130 years, we demonstrate that between 1870 and 2000, U.S. counties with ancestors having a history of technology use and a culture of high trust, high thrift, and high individualism also had higher innovation rates. Counties that move from the 25th percentile of these cultural scores to being in the 75th percentile see log patent per capita filings increase between 27%-50%. The fixed effects model is robust to multiple controls, including state-year fixed effects, race, diversity, and local economic conditions. We also use two instruments, shift-in-share and transportation network access, in an instrumental variable (IV) model to address potential time-varying endogeneity. The results are robust to these identification strategies. In terms of mechanisms, we suggest that these histories and cultural traits might affect innovation through a wide variety of channels. To test this, we control for years of education, the most likely mechanism by which culture could affect innovation. The results indicate that even when controlling for this most likely mechanism, these cultural traits remain large and significant. Thus, these cultural and historical traits still appear to be related to innovation rates even when controlling for their most likely and visible mechanisms. Future research is needed to explore and isolate the subtler ways in which these traits could affect innovation.

Keywords: Ancestry, Culture, Innovation, Economic development, Institutions, Technology.

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1 Introduction

Recent economic studies have demonstrated that culture and history are important determinants of economic growth (Jones 2022). Fernández (2011), Tabellini (2010), Comin, Easterly, and Gong (2010), Fulford, Petkov, and Schiantarelli (2020), and Putterman and Weil (2010) provide compelling evidence for this relationship. Trust, individualism, and cultures of thrift have all been shown to be important for economic growth (Tabellini 2010; Fulford, Petkov, and Schiantarelli 2020). A series of papers have shown that a country's deep roots of technology usage, settled agriculture, and state history explain a large amount of cross-country variation in economic growth (Comin, Easterly, and Gong 2010; Putterman and Weil 2010). The importance of these cultures and histories is robust and continues even when people migrate from one country to another. Much of the literature on the cultural attitudes of immigrants indicates that immigrants maintain their home country's cultural values down to the third and fourth generations (Algan and Cahuc 2010).

A narrower focus in this literature has been given to the ways in which these cultural traits help spur economic growth. Innovation is the most important phenomenon in regard to long-term economic growth, as it has positive spillovers that can increase productivity worldwide. We know that certain cultural traits predict cross-country innovation rates and that individuals who are more trusting and more individualistic are more likely to be entrepreneurs (Kostis, Kafka, and Petrakis 2018; Gorodnichenko and Roland 2011). However, do these traits continue to support innovation when they are removed from the country and the institutional structure that originated them? Culture and institutions have complex interactions with one another and can often reinforce each other's effects (Bennett and Nikolaev 2020). It is worth asking whether cultural traits can still have an impact on innovation separate from institutional changes.

The United States provides a unique environment within which to address this question. The U.S. has a diverse and continuously changing population spread out between geographically distinct counties, all operating under a unified federal legal structure. This makes it an excellent environment for examining just how important cultural and historical traits are for innovation rates and how robust these traits are when they are moved into different environments.

Using unique census data on county ancestry developed by Fulford, Petkov, and Schiantarelli (2020), we are able to generate and adopt a series of estimates of counties' ancestral history and culture. By combining this information with U.S. patent data at the county level from Berkes (2016), we can evaluate how counties' ancestral culture and history relate to innovation outcomes. When immigrants and migrants settle in the U.S., does the culture and ancestral history from their home country predict innovation rates in the counties in which they settle?

This dataset ranges from 1870–2000 and covers two large waves of immigration (1890–1920s and 1970–2000) from distinctly different regions of the world, thus generating significant variation in our cultural and historical variables (Daniels 2002). Using several variables that have been shown to be important for innovation and growth—including thrift, obedience, trust, and technological adoption—we use a fixed effects model to show that these variables all have a strong association with the number of patents filed in a particular U.S. county.

These results are robust to a series of controls, including census division and state-year fixed effects. This is of particular interest because, with the inclusion of state-level fixed effects, we can observe how cultural traits affect innovation when these cultures are operating under similar institutional structures (not just federal rules but also state rules). This potentially captures more purely the cultural relationship our variables have with innovation as opposed to culture working through institutions.

In addition to the base model, we run several other models that control for race and economic conditions. To ensure that any perceived relation of our ancestral traits to innovation is being driven by the actual cultural traits and not mistreatment of different ethnic groups, we control for the fraction of African Americans and Native Americans in a county, thus examining variation of cultural traits primarily in other population groups. Next, we control for different economic conditions including log income per capita and industry occupation breakdown for each county. These allow us to determine whether differences in these ancestral traits are important for variation in innovation even when other economic conditions are the same. We then run a model that controls for ancestries' home country economic outcomes and the human capital immigrants bring with them. Since the ancestral diversity is the result of immigration, it is possible that what appears to be cultural significance could actually be wealth and skills that immigrant groups bring over. All our results remain significant with these controls.

To control for potential county level time-varying endogeneity, we create an instrumental variable (IV) model using two instruments traditionally used in the immigration literature. The first is a shift-share instrument, and the second uses access to transportation network instruments. The results are robust to both of these instruments.

Due to data limitations, we cannot explore in depth the mechanism by which these cultural traits affect innovation rates, but we can offer interesting suggestions and directions for future research. We attempt to suggest here that these cultural traits likely affect innovation rates through multiple mechanisms as opposed to working primarily through obvious channels such as education and economic industry. If culture primarily affects innovation rates through its effect on education, then policies could be designed to mitigate any negative cultural effects on innovation. If the effects operate through more ambiguous channels that are not obvious, then designing policies to counteract any negative effects will be more difficult. We thus run a version of our previous models but now control for local education rates. This is the most obvious mechanism by which culture is likely to affect innovation rates. Our results indicate that most of these cultural traits remain robust after controlling for this likely mechanism. This suggests that cultural traits could affect innovation through multiple mechanisms that are not obvious to scholars. Throughout these models we find that culture is not only important for innovation but it is also more important in explaining innovation rates than it is in explaining more general economic growth such as income per capita and that culture is almost as important as education and income per capita at explaining innovation.

Section 2 reviews the literature relevant to the topic and explains how this paper contributes to it. Section 3 covers the datasets that are used. Section 4 outlines the model of the paper and presents the initial results. Section 5 goes over extra controls and instrumental variable results. Section 6 concludes.

2. Literature Review

Recent studies have shown that culture is important for economic growth (Fernández 2011). Tabellini (2010) reported that cross-country variation in growth across Europe can be explained in part by variation in certain cultural traits, such as trust, thrift, and individualism (measured inversely through obedience).

Although not as extensively studied as economic growth, the relationship between cultural traits and innovation has also received scholarly attention. Kostis, Kafka, and Petrakis (2018) examined 34 OECD countries between 1980 and 2010 and reported that cultural changes across these countries help explain cross-variation in innovation rates. Traits of trust and work ethic were positively associated with innovation, whereas obedience was negatively associated with innovation. Cultures of individualism and their potential relationship with innovation have received substantial attention. Gorodnichenko and Roland (2011) use several measures of individualism, such as the Hofstede (2001) index, and show that there is a significant relationship with cross-country patent filing. Taylor and Wilson (2012) examine 62 countries and show that individualism is positively associated with scientific publications and patents. Their work shows that some types of collectivist cultures can have a positive relationship with innovation. Bennett and Nikolaev (2020) demonstrated the interdependence between cultural traits and institutions with respect to innovation. They show that individualism has a positive effect on innovation, but this effect is much greater when it is accompanied by pro-market institutions. Individualistic cultures usually support pro-market institutions. Thus, they show that individualistic cultures have an effect on innovation both culturally and through their effect on institutions.

Another cultural trait that has been used to study innovation is thrift. Cultures that are thrifty have been shown to increase rates of entrepreneurship (Poirine, Dropsy, and Gay 2017) and savings rates (Guiso, Sapienza, and Zingales 2006).

A branch of this literature has focused on the idea that these cultural traits have deep roots in past historical development and are thus robust and slowly changing (Spolaore and Wacziarg 2013; Comin, Easterly, and Gong 2010; Putterman and Weil 2010). These works hypothesized that if the primary way by which geography and the environment affect economic growth is through their indirect effects on culture and institutions, then cross-country comparisons need to take into account the ancestral origins of the populations inhabiting any given country.

Putterman and Weil (2010) measure the effect of the earliest adoption of settled agriculture and early state development on a country's GDP per capita and inequality after adjusting for post-1500 A.D. migration patterns. These results indicate that adjusting for a modern country's

1500 A.D. ancestry predicts a large amount of current-day GDP per capita and income inequality. One-third of cross-country inequality in income can be explained by the heterogeneity of the population's ancestral agricultural and political experience. This result is robust to controls for minority European and African populations.

Comin, Easterly, and Gong (2010) take Putterman and Weil's (2010) migration data and use technological adoption rates to predict a country's GDP per capita. The dates of technological adoption go back to 1,000 B.C., 0 A.D., and 1500 A.D. Adoption rates for the first two time periods measure only whether the technology was in use, not how intense the use was. The 1500 A.D. adoption rates measure intensity. These long-term growth literature results indicate that ancestral technology adoption in 1500 A.D. is the best predictor of 2000 A.D. GDP per capita. The 1,000 B.C. and 0 A.D. rates predict a country's 1500 A.D. adoption rate, but their effects on A.D. 2000 GDP per capita dissipate after a series of control variables are implemented.

Fulford, Petkov, and Schiantarelli (2020) used IPUMS census data to make the first comprehensive mapping of the national ancestry of the U.S. population from 1850–2010. Using these data, deep root measures were generated for U.S. counties. They take cross-national measures, including state history, ancestral trust, political culture, and respect for authority, and multiply them by the percentage of each nationality within the county's population. This average is used to measure a county's deep root history. They then perform a series of fixed effects estimates, which demonstrate that several of these factors have robust effects on a county's economic growth.

The idea behind the long-term growth literature is that these historical developments affected peoples' cultures and values, were passed down from parent to child, and did not readily adjust to new environments. There is a large body of literature on this topic, best summarized by Algan and Cahuc (2015). These studies examine World Values Survey results on a host of beliefs that are thought to be important for economic development, such as trust and valuation of education of second- and, occasionally, third- and fourth-generation migrants.

A recent paper by Richwine (2023) shows that the savings rates of second-generation migrants in the U.S. are very similar to the savings rates of migrants in their home country. These results indicate that despite growing up in the host country, second- and third-generation immigrants' values are more closely aligned with the values of their native country. Convergence does not seem to be significant until the fourth generation.

Most studies examine inherited trust levels, but some have considered views on women in the workplace (Fernández and Fogli 2009), the value of education, and the number of preferred children (Salari 2018). All of these findings closely align with those of immigrants' native countries, and studies that examine real-world outcomes of these beliefs, such as educational importance and female work participation, indicate that these beliefs translate into real-world outcomes.

2.1 Purpose

This paper attempts to add to this literature by considering how differing cultural traits affect innovation under a uniform institutional structure. Innovation is the most important source of economic growth because of the positive spillovers associated with it. New ideas are non-rivalrous public goods that are capable of increasing everyone's standard of living. Thus, anything that affects the rate of innovation should be of concern for economists and policy makers. Here, we examine how differences in cultural values across the U.S. affect innovation rates. The U.S. is the ideal country for testing innovation and culture, as it is one of the most innovative and diverse countries in the world. This adds to the literature by allowing us to observe how robust cultural effects are when they are removed from the institutional structures that support them.

Due to the large and varied amounts of immigration throughout U.S. history, a wide variety of population groups have spread across the country, all of which differ culturally and historically from one another (Daniels 2002). Despite coming from different countries with varying formal institutions, these groups now all operate under the same federal institutional structure in America. This allows us to consider whether the cultural traits of a country that are traditionally associated with innovation remain persistent when these people settle in a new country with different institutional structures. This is important because formal institutions change more easily and quickly than ambiguous cultural behaviors do(Williamson 2000).

3 Data

3.1 Ancestry Data

The ancestry data comes from Fulford, Petkov, and Schiantarelli (2020). They used census data to measure ancestry distribution across the U.S. Using information on the national origin of a citizen or their parents, they are able to generate an accurate measure of all the various nationalities across the U.S. This is in contrast to the more commonly used self-reported ancestry census data since 1980. They use the boundaries of the 1980 Public Use Micro Areas (PUMAs) as their geographical borders and aggregate all their ancestry data up to this level. This area is regularly identified as county groups. This is used in place of the classic county measure because county-level census data on ancestry is not available in the post-1950 census. These county groups are thus the smallest and most consistent geographic units over this time frame for examining the changes we are interested in. Thus, they have an accurate measure of all the various nationalities across U.S. county groups from 1850–2010[2]. Throughout the remainder of the paper, we refer to these county groups as counties. We make use of this data from 1870–2000.

3.2 Cultural Measures

This ancestry data can be used to estimate certain cultural characteristics within U.S. counties to determine how they affect innovation rates. Many cross-national studies have shown national

[2] The complete time series from Fulford, Petkov, and Schiantarelli (2020) extends back to 1840, but we focus on 1870-2000 to ensure adequate coverage of both major immigration waves while maintaining data quality for the patent records.

differences, particularly in terms of cultural characteristics. A nation's average score on these traits can be assigned to a U.S. county and weighted by that nationality's representation within the county. This allows us to have a ancestral weighted measure of these cultural for U.S. counties. This paper focuses on four main cultural traits important for innovation: individualism (measured inversely through obedience), thrift, trust, and technology adoption. Most of these cultural traits come from international surveys such as the World Values Survey (WVS). These surveys ask respondents questions that reveal their views on cultural matters and then make cultural scores that compare how different countries respond to the questions. Unless stated elsewhere, the cultural variables we look at in the paper come from the World Values Survey.

Individualism is important for innovation, as it reflects people's ability to think 'outside the box' and introduce new ways of solving problems (Taylor and Wilson 2012). A way of measuring individualism is by measuring its inverse, asking people what importance they place on obedience. The more important obedience is to a culture, the less freedom people have to explore new avenues of creativity and innovation. Questions on obedience act as an inverse measure of individualism. The more obedient a culture is, the less individualistic it is. Obedience has previously been used as a measure of cultural individualism (Chen, Frey, and Presidente 2021).

Thrift reflects a culture's view on savings. Cultures that place high importance on saving and deferring consumption have higher investment rates, which are important for spurring innovation (Guiso, Sapienza, and Zingales 2006). Thrift is measured by the WVS by asking people if they think it is important to teach their children to save money.

Trust is another factor that is important for innovation. Societies with high trust levels are able to lower transaction costs and allow the type of large-scale cooperation that makes innovation possible. This is typically measured in surveys by asking people some variation of, "Do you think most people can be trusted?" The more likely people are to believe others can be trusted, the more trusting the culture is.

These three measures were previously generated for U.S. counties by Fulford, Petkov, and Schiantarelli (2020). They used data from the World Values Survey to gather data on each nationality's average score on these questions, assigned them to nationalities in U.S. counties, and weighted them by nationality share of the counties' population. Detailed information about their construction can be found in Fulford, Petkov, and Schiantarelli (2020)[3].

In addition to these measures, we generate a variable that measures a county's ancestral history of technology usage. We use the measure developed by Comin, Easterly, and Gong (2010), which looks at how widespread the use of all known technologies was across various countries in the years 1000 B.C., 0 A.D., and 1500 A.D. We take the 1500 A.D. measure for each nation and assign this score to that nation's population in U.S. counties. We then weight them by the nationality's share of the county's population. This variable is used because it showcases a

[3] Fulfor, Petkov, Schiantarelli appendix.

nation's openness to technology and new ways of doing things. This could signify a culture of openness that is fertile ground for future innovations.

3.3 Patent Data

Our patent data come from a newly designed dataset by Berkes (2016), Berkes, Manysheva, and Mestieri (2022), and Berkes Nencka (2021). This dataset, Comprehensive Universe of U.S. Patents (CUSP), gathers information on all patents filed within the United States between 1836 and 2016.[4] This data are unique in both the length of the time period it covers and the amount of information on individual inventors. Unlike most datasets, Berkes' set records the town in which the inventor resides. This information is then used to identify the geographical location of the inventor and where they are located within traditionally defined U.S. counties.

We aggregate these patent data at the county level to generate a measure of the total number of patents issued to inventors residing in particular counties. We do this aggregation so that we can match up our patent data to the ancestry and cultural data. The time period we consider is decade by decade because census data on ancestry are only gathered by decade. The data for each decade are calculated from the year ending at 0 through the corresponding 9, i.e., 1990–1999. Thus, we measure county patent filing for each decade from 1870–2000.

Table 1 below provides descriptive statistics on all the variables used in our models.

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Observations
Patents per capita (log)	-2.484	3.262	-13.756	11.991	13,836
Education	8.893	2.694	-3.753	15.624	18,748
Income per capita (log)	8.771	1.126	2.958	11.970	18,482
Thrift	0.294	0.034	0.194	0.439	18,686
Obedience	0.397	0.088	0.170	0.741	18,686
Trust	0.330	0.055	0.097	0.538	18,686
Technology adoption	0.835	0.092	0.215	0.976	18,686
Population (log)	11.068	1.357	0.460	15.511	18,824
Population density	0.279	1.163	0.000	46.060	19,516
Occupation 0 fraction	0.082	0.074	0.000	0.500	18,818
Occupation 1 fraction	0.102	0.131	0.000	1.000	18,818
Occupation 2 fraction	0.063	0.042	0.000	1.000	18,818
Occupation 3 fraction	0.085	0.076	0.000	0.500	18,818
Occupation 4 fraction	0.044	0.030	0.000	0.500	18,818
Occupation 5 fraction	0.103	0.061	0.000	1.000	18,818
Occupation 6 fraction	0.121	0.087	0.000	1.000	18,818
Occupation 7.1 fraction	0.023	0.025	0.000	0.412	18,818
Occupation 7.2 fraction	0.067	0.058	0.000	0.290	18,818

[4] The data is currently available at the discretion of the author, Berkes. You can contact them at berkes.8@osu.edu.

Variable	Mean	Std. Dev.	Min	Max	Observations
Occupation 8 fraction	0.063	0.079	0.000	0.765	18,818
Occupation 9 fraction	0.247	0.248	0.000	1.000	18,818
Fractionalization	0.721	0.139	0.034	0.949	18,686
Immigrant education	-0.926	0.740	-7.240	0.152	18,686
Ancestral country GDP (log)	8.524	0.723	6.427	10.029	18,686
Observations	19,572				

Note: This table summarizes the descriptive statistics of our primary variables of interest. These include county measurements of obedience, thrift, trust, technological adoption, and the log of a county's patent filings, log income per capita, fraction of population in various occupations, immigrant education, log of ancestral home country GDP, log population, population density, fraction of African American and Native American population, and ancestral diversity. Much of this data were constructed by Fulford, Petkov, and Schiantarelli (2020) using census micro-samples.

4 Model

In this section, we outline the model we use to determine whether there is a relationship between the ancestral culture of U.S. counties and county innovation rates. To make the most of the panel structure of our dataset, we run a series of fixed effects regression. This allows us to control for a large series of fixed effects, such as county, and state x year fixed effects. It also allows us to control for potential unobserved heterogeneity and any time-invariant unobserved factors. This model is used to determine how significantly these cultural traits affect innovation.

The model is as follows:

$$Yct = \emptyset c + \emptyset ct + \alpha ct + \beta Xct + \delta Zct + \mathcal{E}$$

In this model, Yct is the log patent per capita of county *c* at time *t*. We adjust the patent measure for population because one would naturally expect counties with more people to file more patents. More people mean more ideas. We take the log of patents per capita so that we can understand the coefficients of our dependent variables in percentage terms. $\emptyset ct$ controls for census division × year and state × year fixed effects. We use both census division-year and state-year fixed effects because the county measure used is a broader measure known as "County Groups." This census measure has a lower number of observations in every state. Using census division-year fixed effects is argued for by Fulford, Petkov, and Schiantarelli (2020) because it provides increased observations of consistent geographical sizes. We prefer to use state-year fixed effects because this controls for important effects, such as state-specific laws that might affect innovation rates. $\emptyset c$ represents county fixed effects, which control for time-invariant county characteristics.

Due to the panel nature of our data, these division-year and state-year fixed effects allow us to control for both unobserved time-varying and time-invariant factors at both the division and state level. This panel data also allows control of all unobserved time-invariant factors at the county level.

We examine what relationship a wide variety of cultural characteristics, βXct , have with Yct . The cultural measures we use are the Fulford, Petkov, and Schiantarelli (2020) measures of obedience (individualism), thrift, and trust, as described above. In addition, we also use the county measure of the population's ancestral history of technology use we created using Comin, Easterly, and Gong (2010) data.

In addition to the fixed effects outlined above, we also control for a series of other factors with δZct values that could contribute to innovation levels in the county. Controls for log population and population density are included since larger counties, by virtue of their size and resources, are simply more likely to be able to file patents and produce innovation. We also use two lags of log patent filing per capita to control for the counties' previous level of innovation. Later, we add other controls in the model for race, diversity, and economic outcomes. The results of this model are reported in Table 2.

Table 2: Base Model Results

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Thrift	20.126***				20.076***			
	(2.270)				(2.469)			
Obedience		-10.725***				-11.639***		
		(0.933)				(1.030)		
Trust			14.385***				17.429***	
			(1.440)				(1.641)	
Tech				6.829***				7.562***
				(0.685)				(0.777)
Log population	0.579***	0.607***	0.651***	0.664***	0.684***	0.683***	0.715***	0.737***
	(0.058)	(0.058)	(0.058)	(0.058)	(0.068)	(0.067)	(0.067)	(0.067)
Density	-0.258***	-0.186***	-0.203***	-0.216***	-0.269***	-0.198***	-0.204***	-0.227***
	(0.057)	(0.057)	(0.058)	(0.057)	(0.058)	(0.059)	(0.059)	(0.059)
Lag1 Log PatentPC	0.083***	0.078***	0.080***	0.080***	0.065***	0.058***	0.059***	0.061***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Lag2. Log PatentPC	0.055***	0.051***	0.052***	0.052***	0.045***	0.041***	0.041***	0.042***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	11,499	11,499	11,499	11,499	11,499	11,499	11,499	11,499
R-squared Overall	0.322	0.324	0.264	0.253	0.295	0.286	0.225	0.202
R-squared Within	0.232	0.236	0.234	0.234	0.252	0.256	0.255	0.254
Fixed Effects	Year × Division	Year × Division	Year × Division	Year × Division	Year × State	Year × State	Year × State	Year × State
County Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES

*Note: This table summarizes our base model fixed effects regression results. These results show the effects of a county's ancestral weighted culture and historical traits such as obedience, thrift, trust, and history of technological adoption on the log of that county's patent filing. Models 1–4 control for Census Division x Year fixed effects. Models 5–8 control for state x year fixed effects. All models 1–8 control for county fixed effects, log population, population density, and two decade lags of log patent filing per capita. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

The model shows that these cultural traits appear to have a strong and statistically significant association with a county's innovation rate. A one percentage increase in a county's obedience score lowers the county's log innovation rate by 12.07 (significant at the 0.01 level). A one percentage point increase in the county's culture of thrift and frugality increases the innovation rate by 21.773 (significant at the 0.01 level). A one percentage increase in a county's trust score raises the county's log innovation rate by 15.89 (significant at the 0.01 level). Lastly, a one percentage point increase in the county's technology adoption score increases the innovation rate by 7.229 (significant at the 0.01 level).

To better interpret these results and gauge the impact of these variables, we explain the percentage increase in innovation when going from low scoring counties to high scoring ones. Going from a county within the bottom 25% of thrift scores to one in the top 25% of thrift scores raises patent per capita filings by 47%. The same move with obedience lowers patent filing per capita by over 50%. Trust and technological adoption have more modest effects. Moving from the 25th percentile to the 75th percentile increases innovation rates by 40% and 27% respectively.

If one runs this identical model with the exception of replacing patent filing per capita with local income per capita numbers[5], one will see that the coefficient size of all these variables on innovation is larger than their coefficients on local economic growth. When going from 25th percentile to the 75th percentile of thrift, obedience, trust and technology, income per capita only increases by 8%, 11%, 10%, and 7.5%. These results suggest that cultural traits could be up to 5 times more important for innovation than more general economic growth.

Table 3 shows the relationship between these cultural traits and the log of income per capita so that one can compare these results to the relationship with innovation.

Table 3: Cultural Traits and Income Per Capita

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Thrift	1.453***				1.742***			
	(0.130)				(0.128)			
Obedience		-1.117***				-1.233***		
		(0.055)				(0.054)		
Trust			1.583***				1.788***	
			(0.082)				(0.083)	
Tech				0.746***				0.803***
				(0.039)				(0.040)
Log population	0.000	0.007***	0.010***	0.010***	0.004	0.010***	0.012***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Density	-0.028***	-0.017***	-0.018***	-0.019***	-0.028***	-0.017***	-0.018***	-0.020***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
L.Log incomePC	0.460***	0.448***	0.451***	0.453***	0.431***	0.415***	0.419***	0.424***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
L2.Log incomePC	0.057***	0.060***	0.061***	0.063***	0.083***	0.083***	0.086***	0.087***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	16,154	16,154	16,154	16,154	16,154	16,154	16,154	16,154
R-squared Overall	0.889	0.876	0.860	0.860	0.902	0.899	0.890	0.886
R-squared Within	0.975	0.976	0.976	0.976	0.981	0.981	0.981	0.981
Fixed Effects	Year × Division	Year × Division	Year × Division	Year × Division	Year × State	Year × State	Year × State	Year × State
County Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES

[5] This income data comes from the Fulford, Petkov, and Schiantarelli (2020).

*Note: This table re-runs the base regression in Table 2 with the exception that the dependent variable and the two lagged independent variables are log income per capita instead of log patent per capita. Shows that these ancestral weighted cultural variables are less important in explaining log income per-capita then log patent per capita. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

These findings suggest that these cultural traits may be more important for innovation in particular than for more generalized economic growth.

Figure 1 below visualizes the relationship between county innovation and these cultural traits.

Figure 1

figure 1.1

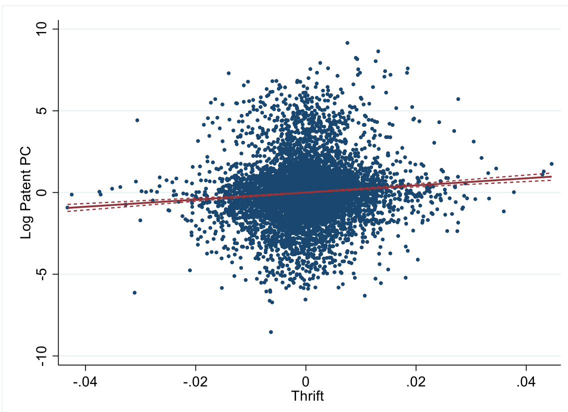

figure 1.2

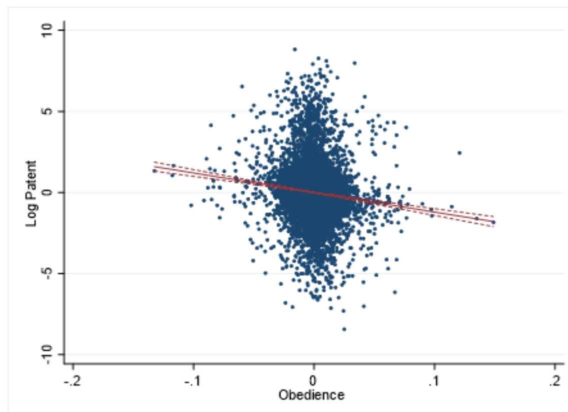

figure 1.3

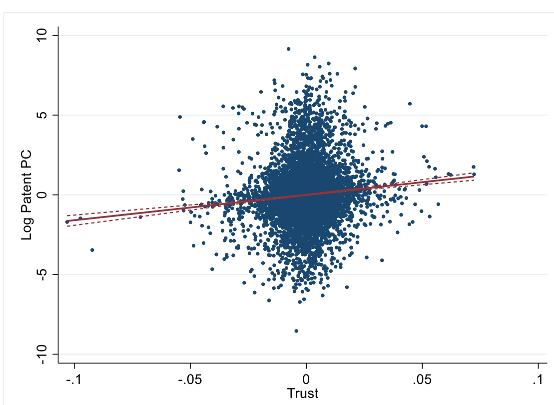

figure 1.4

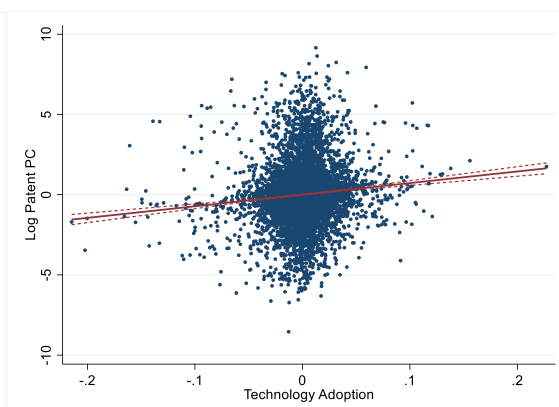

Figure 1: These graphs are added-variable plots that visualize the relationships between our cultural variables and county innovation rates. These are generated from the models 1-4.
Figure 1.1 shows the relationship between counties' ancestral thrift scores and the log of their patent filings.
Figure 1.2 shows the relationship between counties' ancestral obedience score and the log of their patent filing.
Figure 1.3 shows the relationship between counties' ancestral trust score and the log of their patent filings.
Figure 1.4 shows the relationship between counties' ancestral technological adoption score and the log of their patent filing.

These results are from the model that controls for county fixed effects as well as census division and year fixed effects. In addition to these effects, we also run a model that controls for state and year fixed effects.

It is important to control for state fixed effects so that we can control for potential policy differences that could affect patent rates. States with freer business laws, fewer licensing requirements, and more public funding for education and libraries could be more likely to attract both ambitious immigrants seeking to make a better living for themselves and enterprising native migrants looking to earn their fortune. By controlling for state-year fixed effects, we can control for all of these unobserved policy differences at the state level.

These results were previously reported in table(models 5-8). Controlling for state-year fixed effects does not significantly change our previous results. All the variables remain significant at the 0.01 level and have only slightly smaller coefficients.

Notably, when controlling for state-year fixed effects, we control not only for unobserved correlating factors but also for potential mechanisms by which culture could affect innovation rates. Individualist and less obedient cultures that are open to new technologies may manifest these values by passing laws that better defend intellectual property rights and make it easier to start businesses. This could be one of the mechanisms by which these cultural traits increase innovation rates. The fact that our results remain robust despite controlling for these mechanisms suggests that legal changes may not be the only mechanism by which culture can affect innovation.

4.2 Race, Diversity, and Ethnicity

In this section, we re-run the previous model but include control variables for race. In the United States, not all ethnic groups have had a level playing field. Certain minority groups, particularly African Americans, have been legally disadvantaged throughout U.S. history to varying degrees on the basis of race. If these groups originated in countries that had lower cultural measures of individualism (higher obedience), thrift, trust, and technological adaptation, our model could falsely attribute a negative correlation between their cultural traits and innovation rates or overstate the relationship. The association we have seen from our cultural measures and innovation rates could simply be the result of minority groups with certain cultural backgrounds not being given the same opportunities as the rest of the nation. Our cultural measure could be picking up only the effects of systemic racism.

To control for this, we control for the fraction of African American and Native Americans in a county. These controls were also used by Fulford, Petkov, and Schiantarelli (2020) and allow us to see how variations in these cultural traits within the non-African American and non-Native American populations relate to innovation rates. If there is a real association between our cultural variables and innovation, it should be apparent even when controlling for these populations. We run the model using both census division-year fixed effects and then state-year fixed effects. The results are presented in Table 4:

Table 4:

Cultural Traits and Innovation with Race Controls

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Thrift	8.906***				7.008***			
	(2.726)				(3.004)			
Obedience		-7.437***				-8.771***		
		(2.017)				(2.236)		
Trust			3.073				8.952***	
			(2.742)				(3.222)	
Tech				2.188*				1.903
				(1.189)				(1.354)
Log population	0.567***	0.593***	0.598***	0.610***	0.660***	0.668***	0.683***	0.684***
	(0.059)	(0.058)	(0.059)	(0.059)	(0.068)	(0.067)	(0.067)	(0.068)
Density	-0.209***	-0.187***	-0.200***	-0.201***	-0.217***	-0.196***	-0.201***	-0.210***
	(0.057)	(0.058)	(0.057)	(0.057)	(0.059)	(0.059)	(0.059)	(0.059)
African American	-4.520***	-2.035*	-4.704***	-4.340***	-5.198***	-1.824	-3.450***	-5.006***
	(0.612)	(1.100)	(0.971)	(0.866)	(0.693)	(1.234)	(1.117)	(0.977)
Native American	-1.659	-2.536	-2.186	-0.446	-5.936*	-6.886**	-6.683**	-4.988
	(2.678)	(2.674)	(2.674)	(2.840)	(3.163)	(3.154)	(3.154)	(3.332)
Lag1 Log PatentPC	0.078***	0.077***	0.079***	0.078***	0.059***	0.058***	0.058***	0.059***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Lag2. Log PatentPC	0.052***	0.051***	0.052***	0.052***	0.041***	0.040***	0.041***	0.041***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	11,499	11,499	11,499	11,499	11,499	11,499	11,499	11,499
R-squared Overall	0.318	0.318	0.287	0.281	0.278	0.289	0.251	0.251
R-squared Within	0.236	0.237	0.236	0.236	0.256	0.257	0.256	0.256
Fixed Effects	Year × Division	Year × Division	Year × Division	Year × Division	Year × State	Year × State	Year × State	Year × State
County Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES

*Note: This table summarizes our race and ethnicity model results. These results show the effects of a county's ancestral weighted culture and historical traits such as obedience, thrift, trust, and history of technological adoption on the log of that county's patent filing while controlling for race. All these models control for the fraction of African Americans and Native Americans in the county. Models 1–4 control for Census Division x Year fixed effects. Models 5–8 control for state x year fixed effects. All models 1–8 have the same controls used in the base model. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Once we control for race, the significance and size of our variables decrease, but they still remain significant. In the census division-year fixed effect model, the coefficient of thrift shrinks from approximately 21.2 to 9.85 but remains significant at the 0.01 level. The measure of obedience changes from -12.007 to -9.33, remaining significant at the 0.01 level. The measure of trust becomes insignificant once we control for the fraction of African Americans in the division-year fixed effects model. The coefficient of technological adoption decreases to 2.5 but remains significant at the 0.05 level.

These results remain largely robust when we switch to controlling for state-year fixed effects. Thrift and obedience remain significant at the 0.01 level. The significance of technological adoption shrinks to being insignificant. In contrast, the trust variable becomes significant at the 0.01 level once again after controlling for state-year fixed effects. These results are consistent with the idea that our cultural variables are associated with innovation rates and that this association is not solely driven by unique racial dynamics that have existed throughout U.S. history.

Next, we rerun the base model with a control for ethnic fractionalization, also developed by Fulford, Petkov, and Schiantarelli (2020). This measure looks at the diversity of ancestry in a county. The closer to zero the more homogeneous the county ancestry is. The closer to one, the more heterogeneous the county's ancestral makeup is. Ancestral diversity could potentially affect innovation rates in different directions. Galor (2011) shows that ethnic diversity has a non-linear relationship with economic growth. Large diversity could potentially lead to lower cooperation which could possibly lower innovation. On the other hand, counties with diverse ancestries could also generate more new ideas due to the diversity in thought and lack of groupthink. Here we examine how these cultural variables relate to innovation rates when controlling for ancestral fractionalization. Table 5 reports results when controlling for diversity. Table 6 reports results when controlling for diversity, Native American ancestry, and African American ancestry.

Table 5:

Cultural Traits and Innovation with Diversity Controls

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Thrift	16.815***				17.458***			
	(2.411)				(2.596)			
Obedience		-9.675***				-10.888***		
		(0.987)				(1.082)		
Trust			12.959***				16.253***	
			(1.466)				(1.671)	
Tech				6.421***				7.228***
				(0.688)				(0.779)
Log population	0.555***	0.582***	0.608***	0.612***	0.655***	0.661***	0.677***	0.685***
	(0.059)	(0.058)	(0.058)	(0.058)	(0.068)	(0.068)	(0.068)	(0.068)
Density	-0.257***	-0.192***	-0.206***	-0.214***	-0.270***	-0.203***	-0.209***	-0.228***
	(0.057)	(0.057)	(0.057)	(0.057)	(0.058)	(0.059)	(0.059)	(0.059)
Diversity	2.974***	2.372***	3.490***	4.050***	2.586***	1.782**	2.800***	3.614***
	(0.733)	(0.728)	(0.703)	(0.692)	(0.796)	(0.793)	(0.769)	(0.758)
Lag1 Log PatentPC	0.082***	0.077***	0.078***	0.077***	0.064***	0.058***	0.059***	0.061***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Lag2.Log PatentPC	0.054***	0.050***	0.051***	0.050***	0.045***	0.040***	0.041***	0.041***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	11,499	11,499	11,499	11,499	11,499	11,499	11,499	11,499
R-squared Overall	0.339	0.349	0.323	0.332	0.321	0.308	0.273	0.275
R-squared Within	0.233	0.237	0.236	0.236	0.252	0.257	0.256	0.255
Fixed Effects	Year × Division	Year × Division	Year × Division	Year × Division	Year × State	Year × State	Year × State	Year × State
County Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES

*Note: This table summarizes our diversity model results. These results show the effects of a county's ancestral weighted culture and historical traits such as obedience, thrift, trust, and history of technological adoption on the log of that county's patent filing while controlling for ancestral diversity. All these models control for the ancestral diversity in the county. Models 1–4 control for Census Division x Year fixed effects. Models 5–8 control for state x year fixed effects. All models 1–8 have the same controls used in the base model. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Table 6:

Cultural Traits and Innovation with Race & Diversity Controls

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Thrift	6.485**				5.336*			
	(2.812)				(3.073)			
Obedience		-5.806***				-7.744***		
		(2.072)				(2.280)		
Trust			3.510				9.386***	
			(2.742)				(3.223)	
Tech				3.153***				2.840**
				(1.206)				(1.382)
Log population	0.546***	0.566***	0.568***	0.584***	0.638***	0.647***	0.654***	0.657***
	(0.059)	(0.059)	(0.059)	(0.060)	(0.068)	(0.068)	(0.068)	(0.068)
Density	-0.210***	-0.193***	-0.202***	-0.204***	-0.219***	-0.201***	-0.205***	-0.214***
	(0.057)	(0.058)	(0.057)	(0.057)	(0.059)	(0.059)	(0.059)	(0.059)
Diversity	2.556***	2.504***	3.009***	3.305***	2.057***	1.817**	2.446***	2.678***
	(0.734)	(0.731)	(0.712)	(0.722)	(0.797)	(0.794)	(0.780)	(0.795)
African American	-4.345***	-2.357**	-4.011***	-3.155***	-5.031***	-1.985	-2.860***	-3.953***
	(0.614)	(1.103)	(0.984)	(0.903)	(0.696)	(1.236)	(1.132)	(1.025)
Native American	-1.845	-2.500	-2.227	0.282	-5.935*	-6.722**	-6.531**	-4.069
	(2.677)	(2.673)	(2.672)	(2.842)	(3.162)	(3.154)	(3.153)	(3.342)
Lag1 Log PatentPC	0.077***	0.077***	0.077***	0.076***	0.058***	0.057***	0.058***	0.058***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Lag2. Log PatentPC	0.051***	0.050***	0.051***	0.050***	0.041***	0.040***	0.040***	0.040***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	11,499	11,499	11,499	11,499	11,499	11,499	11,499	11,499
R-squared Overall	0.347	0.348	0.336	0.334	0.304	0.311	0.290	0.290
R-squared Within	0.237	0.237	0.237	0.237	0.256	0.257	0.257	0.257
Fixed Effects	Year × Division	Year × Division	Year × Division	Year × Division	Year × State	Year × State	Year × State	Year × State
County FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table summarizes our combined race and diversity model results. These results show the effects of a county's ancestral weighted culture and historical traits such as obedience, thrift, trust, and history of technological adoption on the log of that county's patent filing per capita while controlling for both race and ancestral diversity. All these models control for the fraction of African Americans and Native Americans in the county as well as ancestral fractionalization. Models 1-4 control for Census Division x Year fixed effects. Models 5-8 control for state x year fixed effects. All models 1-8 have the same controls used in the base model.

*Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

Our results show that fractionalization in the U.S. has had a positive relation to innovation rates. Our cultural variables are still significant at the 0.01 level even when controlling for fractionalization and are more significant than the measure of fractionalization itself. This finding is complements with the recent work by Posch, Schulz, and Heinrich (2025), who find that surname diversity positively affects innovation using U.S. county-level data.

We also run a version of the base model to determine how different specific ancestries affect patent rates. Are counties that see a growth in particular ancestry likely to see their innovation rates increase or decrease? The model is:

$$Yct = \emptyset c + \emptyset ct + \alpha ct + \beta Tct + \delta Zct + \mathcal{E}$$

Here, Yct is log patent per capita of county *c* at time *t*. $\emptyset ct$ controls for division/state x year effects. βTct represents the various ancestries used in the model. Our choice of ancestry follows Fulford, Petkov, and Schiantarelli's (2020) table of the largest national ancestry share across the U.S. We use this table to investigate the groups that have the largest ancestry share in the U.S. In doing so, we obtain a greater amount of variation in ancestry across counties. The ancestries we chose to consider include English, German, African American, Mexican, Italian, and others listed in Figure 2 above. δZct are basic controls for population size, density, and log income per capita.

The results are presented in Figure 2:

Figure 2

figure 2.1 figure 2.2

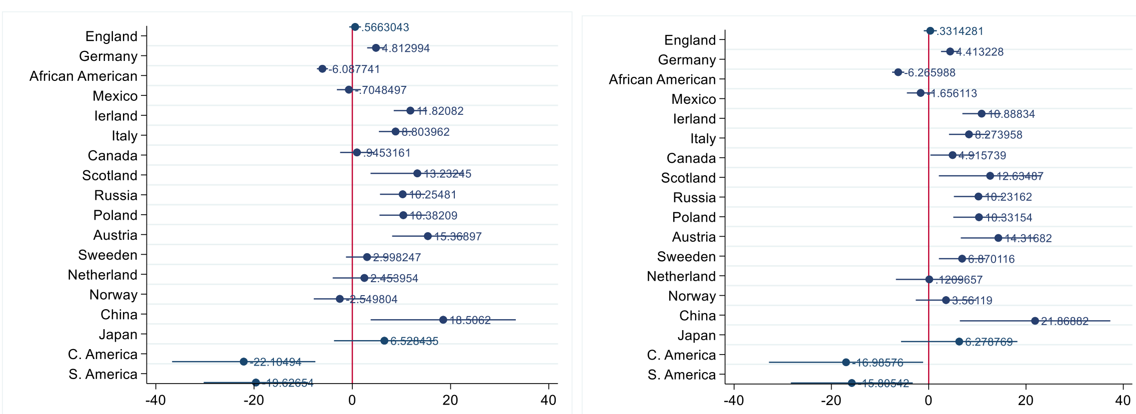

Figure 2: These coefficient plots display the coefficients of the largest ancestries across the U.S. and show their relationships with log patent rates. These coefficients are derived from our fixed effects model that controls for log population, population density, and two lags of log patent filing. Each graph shows the coefficients from a model that controls for a series of different fixed effects. Figure 2.1 controls for Division × Year Fixed Effects. Figure 2.2 controls for State × Year Fixed Effects.

There are large variations in the coefficient sizes these different groups have on innovation rates. The German share of a county has a very large and positive effect on a county's innovation rate, whereas the English effect, while positive, is much smaller. The share of the Mexican population has a negative but often statistically insignificant effect. Despite regularly scoring high on our cultural measurements, counties with large shares of Scandinavian ancestry have either insignificant or negative associations with patent filings.

A limitation on the interpretation of these ancestries should be noted. If these ancestries affect innovation rates through their effect on the cultural traits we examine, then where different ethnicities settle could play a role in the ancestry coefficient. For example, Irish have a higher generalized trust score than Italians do. Thus, when Italians immigrate into ethnically Irish counties in New York, their average trust score decreases. However, Italians have higher trust scores than Polish do. If they settled in Polish counties in New York, then they would be associated with an increase in the average trust score. The relationship of a particular ancestry is thus determined not only by its cultural traits but also by the cultural traits of the areas in which it moves.

To illustrate this point, we generate a scatter plot that shows the relationship between an ancestry's home country's cultural score and a coefficient that shows the degree to which the presence of this ancestry changes a county's cultural score. People of different ancestries will either raise or lower the county culture score, depending on the county population in which they decide to settle. The cultural scores we examine are obedience (individualism) and attitudes toward thrift. Similar relationships hold true for trust and technological adoption rates. The home country data come from the World Values Survey data that were gathered by Fulford, Petkov, and Schiantarelli (2020). The coefficients showing how different ancestries affect county-level cultural scores come from a model identical to the above model showing the effects of ancestry on innovation rates, with the exception of the dependent variable, which is now the counties' obedience and thrift cultural score. The results are shown in Figure 3.

Figure 3

figure 3.1:

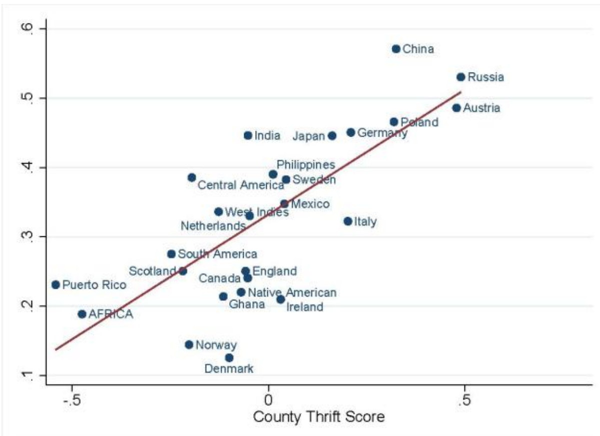

figure 3.2

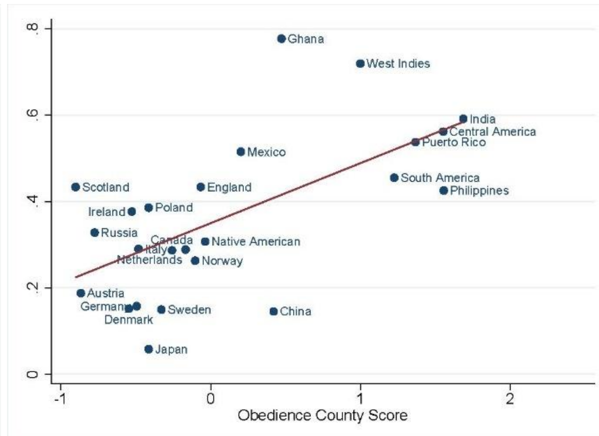

Figure 3: These figures are scatter plots that show the relationship between an ancestry's home nation's cultural score and the effect that ancestry has on the cultural score of U.S. counties. The Y axis shows the home country's cultural score. The X-axis reflects the coefficients of the effect of ethnicity on U.S. county cultural scores. These coefficients are derived from a nearly identical fixed effects model used to generate Figure 2. The difference in the dependent variables is thrift and obedience. The independent variables are a wide range of ancestries and control for factors such as log population, population density, log county GDP, and census division year fixed effects.

Figure 3.1 shows the relationship between an ancestral view of thrift in the home country and the degree to which that ancestry raises the U.S. county thrift score.

Figure 3.2 shows the relationship between an ancestral view of obedience in the home country and the degree to which that ancestry raises the U.S. county obedience score.

As the scatter plot shows, there is a strong positive relationship between the effect that ancestries have on U.S. counties' cultural score and the ancestral score of the ancestry's home country. However, the relationship is not perfect. Some ancestries that have identical scores in their home countries have different effects on U.S. county scores. English and Scottish have identical cultural scores but significantly differ in their county effects. Scots moving into a U.S. county are associated with a greater decrease in the obedience score than those of English ancestry. This suggests that Scots were more likely to settle in regions where their cultural scores are higher than the county's population average. Any perceived effect on cultural traits from a particular ancestry is the result of both the ancestral cultural traits and the cultural traits of the county population in which they are settling.

Notably, as the fractions of the population decrease, the confidence intervals of our estimates increase, as shown in Figure 2. The largest groups in the United States, English, German, African American, and Mexican, have lower standard errors, whereas smaller minorities, such as Chinese and Norwegian, have much larger intervals.

4.3 Economic Controls

Next, we run a series of models that control for economic conditions of the county. It is possible that different ancestry groups settled in areas with different economic conditions that were actually driving innovation rates. Counties that are wealthier could easily be more likely to have high innovation rates since they have the resources necessary to save and invest. To control for the county's prosperity, we use the log measure of county income per capita developed by Fulford, Petkov, and Schiantarelli (2020). This allows us to see if differences in our ancestral traits have a significant relationship to innovation even when the wealth of a county is the same.

There are more ways economic conditions can affect innovation rates than simple prosperity. The type of industry and occupation that dominates a county's economy will be important for determining innovation rates. If a county is dominated by businesses that are on the cutting edge of technological change, one would expect to see more innovation than a county of similar wealth but in a less technologically advanced economy. It is possible that different ancestries were attracted to different counties with different job opportunities and the perceived relationship between ancestry and innovation is actually driven by differing occupation.

To control for this, we make use of occupational employment data. This data originates from the U.S. census and was aggregated to the county group level by Fulford, Petkov, and Schiantarelli (2020). The census records each individual's job title, and these titles can be broken down into 10 broad categories which include trade, transportation, government service, mining, public utilities, government, construction, and personal services[6]. Taking these raw numbers, we calculate the fraction of a county employed in each occupation so one can control for the occupational makeup of the county.

We re-run the base model from section 4 with the exception that we are now controlling for log income per capita and the fraction of the county employed in each of our 10 occupation categories. The results are presented in Table 7.

[6] These number categories correspond to the first digit of the IPUMS codes for these occupations.

Table 7: Cultural Traits and Innovation with Economic Controls

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Thrift	10.880***				8.488***			
	(2.337)				(2.577)			
Obedience		-6.385***				-6.038***		
		(1.024)				(1.145)		
Trust			8.136***				9.297***	
			(1.563)				(1.793)	
Tech				4.381***				4.380***
				(0.737)				(0.833)
Log Income PC	0.767***	0.724***	0.732***	0.723***	1.166***	1.084***	1.074***	1.080***
	(0.132)	(0.132)	(0.132)	(0.132)	(0.160)	(0.161)	(0.161)	(0.161)
Log population	0.470***	0.484***	0.520***	0.531***	0.530***	0.523***	0.548***	0.560***
	(0.067)	(0.066)	(0.066)	(0.066)	(0.078)	(0.077)	(0.077)	(0.077)
Density	-0.145**	-0.113**	-0.119**	-0.122**	-0.138**	-0.113*	-0.111*	-0.118**
	(0.057)	(0.057)	(0.057)	(0.057)	(0.058)	(0.058)	(0.059)	(0.058)
occ0FRAC	8.522***	8.873***	8.837***	8.914***	8.309***	8.563***	8.515***	8.693***
	(1.282)	(1.281)	(1.281)	(1.281)	(1.356)	(1.355)	(1.355)	(1.355)
occ1FRAC	-2.512***	-2.868***	-3.078***	-3.221***	-2.742***	-2.930***	-3.185***	-3.272***
	(0.774)	(0.772)	(0.775)	(0.776)	(0.842)	(0.838)	(0.839)	(0.840)
occ2FRAC	1.789	1.386	1.393	1.423	2.494	2.146	2.208	2.334
	(1.623)	(1.624)	(1.626)	(1.624)	(1.744)	(1.744)	(1.744)	(1.742)
occ3FRAC	4.972***	4.114***	4.146***	3.958***	5.005***	4.323***	4.160***	4.101***
	(1.314)	(1.320)	(1.323)	(1.324)	(1.398)	(1.401)	(1.404)	(1.405)
occ4FRAC	1.156	0.169	0.339	0.102	0.239	-0.499	-0.437	-0.635
	(1.883)	(1.890)	(1.892)	(1.893)	(1.996)	(2.001)	(2.001)	(2.004)
occ5FRAC	1.697*	1.145	1.324	1.279	1.330	0.849	0.930	1.016
	(0.893)	(0.901)	(0.901)	(0.899)	(0.946)	(0.952)	(0.950)	(0.948)
occ6FRAC	1.042	0.869	0.909	0.873	0.515	0.453	0.466	0.415
	(0.795)	(0.795)	(0.796)	(0.795)	(0.858)	(0.857)	(0.857)	(0.858)
occ71FRAC	-1.083	-0.712	-0.850	-0.696	0.344	0.860	0.863	0.833
	(1.672)	(1.673)	(1.674)	(1.674)	(1.807)	(1.810)	(1.810)	(1.810)
occ72FRAC	-2.777**	-3.280**	-3.145**	-3.311**	-2.470	-2.860*	-2.895*	-2.937*
	(1.386)	(1.389)	(1.389)	(1.390)	(1.518)	(1.518)	(1.518)	(1.519)
occ8FRAC	-0.499	-0.280	-0.217	-0.214	0.185	0.415	0.516	0.445
	(0.776)	(0.776)	(0.778)	(0.777)	(0.878)	(0.878)	(0.879)	(0.878)
occ9FRAC	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Lag1 Log PatentPC	0.055***	0.052***	0.053***	0.052***	0.036***	0.034***	0.034***	0.033***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Lag2. Log PatentPC	0.034***	0.032***	0.033***	0.032***	0.025**	0.023**	0.023**	0.023**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	11,496	11,496	11,496	11,496	11,496	11,496	11,496	11,496
R-squared Overall	0.299	0.368	0.373	0.363	0.414	0.429	0.419	0.401
R-squared Within	0.255	0.256	0.255	0.256	0.274	0.275	0.275	0.275
Fixed Effects	Year × Division	Year × Division	Year × Division	Year × Division	Year × State	Year × State	Year × State	Year × State
County FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table summarizes our economic model results. These results show the effects of a county's ancestral weighted culture and historical traits such as obedience, thrift, trust, and history of technological adoption on the log of that county's patent filing per capita while controlling for economic conditions. All these models control for the log income per capita of the county and the fraction of employment in particular *occupations as defined by IPUMS occupational categories. Models 1–4 control for Census Division x Year fixed effects. Models 5–8 control for state x year fixed effects. All models 1–8 have the same controls used in the base model.*

*Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

These results show that all our ancestral coefficients remain large and significant at the 0.01 level when controlling for our various economic variables. The significance of these effects is larger than most of the occupation variables and is similar to log income per capita. Obedience appears to be highly significant and even more statistically significant than log income per capita in the census division model. This means that these cultural ancestral traits appear to be similarly important at explaining innovation as material economic conditions.

4.4 Immigrant Human Capital Controls

In this section, we introduce controls for other ancestral home country and immigrant characteristics. The ancestral diversity we observe in the U.S. is the result of the large amount of immigration. There is a large body of literature showing that immigrants have disproportionately contributed to innovation (Hunt and Gauthier-Loiselle 2010). This has been associated with the human capital they bring with them from their home country (Arkolakis, Lee, and Peters 2020). It is possible that these ancestries are affecting innovation not through their cultural traits, but from the skills they bring with them.

To control for this, we introduce two new controls. The first is ancestral GDP per capita, which looks at the GDP per capita of individuals' home country during the year the individual arrived in the U.S. Using this, one can generate an ancestrally predicted GDP per capita rate for every U.S. county. Ancestries coming from richer countries are more likely to bring skills and other resources that could make them more innovative that have little to do with their culture.

The problem with this measure is that it only looks at the wealth of the country of origin and not the individual immigrant themselves. We know if they are coming from a rich country, but not if they are high skilled or low skilled. To control for the individual immigrants' skill level, we use the census measure of arriving immigrant literacy and years of education. Fulford, Petkov, and Schiantarelli (2020) constructed county-level measures of immigrant education relative to natives at the time of arrival. Specifically, they identify recent immigrants as foreign-born individuals aged 20-30 in each census and measure the difference between their education levels (literacy before 1940, years of education after 1940) and those of native-born Americans in the same age cohort. For each county, they create an ancestry-weighted average of these education differences across all ancestry groups, where the weights are each ancestry's share of the county's population.

This gives a county-level measure of whether the county's ancestral composition consists of groups that historically brought higher or lower human capital relative to the existing U.S. population at the time of their arrival. By controlling for this, we are examining counties with a similar share of high skilled and low skilled immigrants relative to the native population. The only difference will be the cultural values between the immigrants' home countries.

We run a model that first looks at the effect that immigrant education and the log of home country GDP have on innovation. Then we control both of those while also using each of our cultural variables. For convenience, the table below reports the results using state x year fixed effects. Results are presented in Table 8.

Table 8: Cultural Traits and Innovation with Immigrant Controls

Variable	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**
Immigrant Education	0.639***		-0.016	-0.293	-0.661***	-0.334
	(0.150)		(0.217)	(0.218)	(0.224)	(0.219)
Ancestral GDP		2.365***	1.813***	-0.206	-1.065	-1.175
		(0.374)	(0.553)	(0.614)	(0.661)	(0.715)
Thrift			17.472***			
			(2.532)			
Obedience				-13.076***		
				(1.370)		
Trust					26.055***	
					(2.729)	
Tech						10.661***
						(1.336)
Log population	0.767***	0.739***	0.679***	0.670***	0.690***	0.732***
	(0.067)	(0.067)	(0.068)	(0.068)	(0.067)	(0.067)
Density	-0.256***	-0.241***	-0.239***	-0.204***	-0.214***	-0.240***
	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)
Lag1 Log PatentPC	0.069***	0.066***	0.062***	0.058***	0.057***	0.060***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Lag2 Log PatentPC	0.049***	0.046***	0.043***	0.040***	0.040***	0.041***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	11,499	11,499	11,499	11,499	11,499	11,499
R-squared Overall	0.232	0.227	0.282	0.296	0.236	0.203
R-squared Within	0.248	0.250	0.253	0.256	0.256	0.254
Fixed Effects	Year × State	Year × State	Year × State	Year × State	Year × State	Year × State

Note: This table summarizes our immigrant characteristics model results. These results show the effects of a county's ancestral culture and historical traits such as obedience, thrift, trust, and history of technological adoption on the log of that county's patent filing while controlling for immigrant human capital and home country economic conditions. Models 1-2 examine the individual effects of immigrant education and ancestral GDP. Models 3-6 add each cultural variable while controlling for both immigrant characteristics. All models control for state and year fixed effects and include the same baseline controls as previous models.

*Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

All our cultural values remain significant at the 0.01 level even when controlling for ancestral home country log GDP per capita and education level of arriving immigrants. These cultural traits are also more important than the GDP of the ancestries' home country and the education rate of these immigrants in comparison to the native population. Separately, immigrant education and home country GDP have statistically significant effects on county log patent per capita. When combined with our cultural variables they lose their significance. This apparent low significance of immigrant education when combined with other ancestral traits is similar to results from Fulford, Petkov, and Schiantarelli (2020) when they looked at migrant education and its effect on local GDP per capita. They believed this could potentially be explained by a quick convergence of education rates between natives and immigrants due to public schools responding to new immigrants as shown by Bandiera et al. (2019).

5. Robustness Checks and Identification

5.1 Instrumental Variables

Owing to the panel nature of our datasets, we are able to control for any county-level time-invariant heterogeneity that is unobserved in the model. Time-varying factors at the state and division level are also controlled for with our state-year fixed effects and division-year fixed effects. However, time-varying factors at the county level such as local economic and political shocks could affect our results. Economic shocks that bring jobs with more room for innovation could attract migrants from countries that have a deeper history with technologies and openness to innovation. Most of this potential confounds are controlled for with our economic model, but there is always the possibility of a subtle unknown economic factor having an effect.

To control for this, we use the shift-share instrument regularly used in the immigration literature (Card 1991) (Jaeger, Ruist, and Stuhler 2018). The specific instrument we use was generated by Fulford, Petkov, and Schiantarelli (2020) for U.S. counties and is described in detail there. They predict ancestry composition using past settlement patterns combined with national growth rates excluding the county's state. This creates variation in ancestry composition that is based on historical patterns rather than contemporaneous economic conditions.

Using this approach, we are able to generate a predicted cultural score across U.S. counties that's not driven by contemporaneous economic conditions. Fulford, Petkov, and Schiantarelli (2020) did this for trust, obedience, and thrift. We follow their method and generate a predicted ancestral history of technological adoption.

We then use this in an IV model similar to the model used in the economic section(Table 7). This model has all the controls used in the model that controlled for economic conditions. The economic controls strengthen the validity of these instruments since they control for potential underlying economic factors that could be affecting our instrument. The only difference is that we are now instrumenting our cultural variables with the shift-share estimated cultural traits. Results are in Table 9.

Table 9: Instrumental Variables Results -Shift-Share

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Thrift	14.425***				12.907***			
	(3.663)				(4.122)			
Obedience		-6.071***				-5.441***		
		(1.218)				(1.369)		
Trust			7.852***				8.521***	
			(1.994)				(2.359)	
Tech				3.807***				4.120***
				(0.985)				(1.140)
Log Income PC	0.756***	0.727***	0.734***	0.732***	1.148***	1.095***	1.085***	1.088***
	(0.132)	(0.132)	(0.132)	(0.133)	(0.160)	(0.162)	(0.163)	(0.162)
Log population	0.452***	0.486***	0.520***	0.530***	0.514***	0.527***	0.549***	0.560***
	(0.068)	(0.066)	(0.066)	(0.066)	(0.079)	(0.078)	(0.077)	(0.077)
Density	-0.144**	-0.115**	-0.120**	-0.125**	-0.139**	-0.115*	-0.113*	-0.119**
	(0.057)	(0.057)	(0.057)	(0.057)	(0.058)	(0.059)	(0.059)	(0.058)
occ0FRAC	8.468***	8.865***	8.833***	8.885***	8.235***	8.552***	8.510***	8.678***
	(1.283)	(1.281)	(1.282)	(1.282)	(1.358)	(1.355)	(1.355)	(1.356)
occ1FRAC	-2.431***	-2.863***	-3.078***	-3.221***	-2.620***	-2.934***	-3.168***	-3.255***
	(0.777)	(0.772)	(0.776)	(0.779)	(0.846)	(0.838)	(0.840)	(0.841)
occ2FRAC	1.704	1.418	1.414	1.503	2.305	2.216	2.262	2.365
	(1.624)	(1.625)	(1.629)	(1.627)	(1.750)	(1.747)	(1.747)	(1.745)
occ3FRAC	4.984***	4.163***	4.181***	4.097***	5.062***	4.380***	4.221***	4.149***
	(1.314)	(1.323)	(1.329)	(1.332)	(1.399)	(1.403)	(1.409)	(1.412)
occ4FRAC	1.082	0.221	0.367	0.258	0.117	-0.403	-0.361	-0.569
	(1.884)	(1.894)	(1.898)	(1.902)	(1.998)	(2.005)	(2.006)	(2.014)
occ5FRAC	1.566*	1.190	1.349	1.383	1.168	0.927	0.990	1.053
	(0.899)	(0.906)	(0.908)	(0.907)	(0.953)	(0.957)	(0.957)	(0.954)
occ6FRAC	1.023	0.881	0.916	0.903	0.496	0.463	0.474	0.423
	(0.795)	(0.796)	(0.796)	(0.796)	(0.858)	(0.858)	(0.858)	(0.858)
occ71FRAC	-0.950	-0.750	-0.873	-0.801	0.523	0.775	0.791	0.784
	(1.676)	(1.675)	(1.677)	(1.678)	(1.812)	(1.813)	(1.816)	(1.816)
occ72FRAC	-2.821**	-3.251**	-3.130**	-3.227**	-2.419	-2.831*	-2.868*	-2.915*
	(1.387)	(1.390)	(1.391)	(1.393)	(1.519)	(1.518)	(1.519)	(1.520)
occ8FRAC	-0.503	-0.289	-0.226	-0.249	0.184	0.392	0.489	0.430
	(0.776)	(0.776)	(0.779)	(0.778)	(0.878)	(0.879)	(0.881)	(0.880)
occ9FRAC	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Lag1 Log PatentPC	0.054***	0.053***	0.053***	0.053***	0.035***	0.034***	0.034***	0.034***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Lag2. Log PatentPC	0.034***	0.032***	0.033***	0.032***	0.024**	0.023**	0.023**	0.023**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	11,495	11,495	11,495	11,495	11,495	11,495	11,495	11,495
R-squared Overall	0.407	0.394	0.374	0.377	0.197	0.233	0.233	0.209
R-squared Within	0.255	0.256	0.255	0.256	0.274	0.275	0.275	0.275
Fixed Effects	Year × Division	Year × Division	Year × Division	Year × Division	Year × State	Year × State	Year × State	Year × State
County FE	YES	YES	YES	YES	YES	YES	YES	YES

*Note: This table summarizes the results of our IV model. These results show the effects of a county's ancestral culture and historical traits such as obedience, thrift, trust, and history of technological adoption on the log of that county's patent filing when instrumented via a shift-share estimate of a county's ancestry. Models 1–4 control for Census Division and Year fixed effects. Models 5–8 control for state and year fixed effects. All models 1–8 have the same controls used in the economic model. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

All our variables maintain their large coefficients and are still statistically significant at the 0.01 level. This holds for both census division-year fixed effects and state-year fixed effects controls.

The second instrument we use, building on Sequeira et al. (2019), exploits the fact that different immigrant groups arrived at different times and thus faced different transportation infrastructure. This instrument examine a county's access to transportation networks during certain waves of migration and estimate migration flows on the basis of these networks. Fulford, Petkov, and Schiantarelli (2020) predict settlement patterns based on the interaction between when groups migrated and the railroad/highway networks available at the time of their arrival. Since migration timing was largely determined by push factors in origin countries rather than pull factors in specific US counties, this creates exogenous variation in ancestry composition. Using this to create alternative predicted ancestral demographic make up of U.S. counties, they then use these new estimates to make alternative measurements of a county's trust, thrift, and obedience score. Results are reported in Table 10.

Table 10: Instrumental Variables Results - Transportation Networks

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Thrift	27.232***			31.732***		
	(7.986)			(7.844)		
Obedience		-12.219***			-16.203***	
		(3.611)			(3.557)	
Trust			10.454**			20.175***
			(5.149)			(6.627)
Log Income PC	0.708***	0.660***	0.713***	1.104***	0.948***	0.982***
	(0.142)	(0.144)	(0.144)	(0.172)	(0.180)	(0.187)
Log population	0.520***	0.585***	0.643***	0.546***	0.565***	0.636***
	(0.083)	(0.077)	(0.075)	(0.090)	(0.088)	(0.085)
Density	-0.091	-0.034	-0.071	-0.084	-0.011	-0.028
	(0.060)	(0.064)	(0.063)	(0.061)	(0.063)	(0.064)
occ0FRAC	6.892***	7.595***	7.608***	6.603***	7.406***	7.270***
	(1.371)	(1.354)	(1.354)	(1.444)	(1.433)	(1.430)
occ1FRAC	-2.538***	-3.388***	-3.667***	-2.738***	-3.472***	-4.118***
	(0.847)	(0.815)	(0.834)	(0.924)	(0.891)	(0.897)
occ2FRAC	1.410	0.723	1.263	0.954	0.343	0.806
	(1.766)	(1.798)	(1.799)	(1.903)	(1.919)	(1.929)
occ3FRAC	4.764***	3.093**	3.680**	5.160***	3.170**	3.104**
	(1.387)	(1.467)	(1.478)	(1.485)	(1.519)	(1.571)
occ4FRAC	0.751	-1.150	-0.469	-0.048	-1.880	-1.378
	(2.008)	(2.079)	(2.087)	(2.127)	(2.183)	(2.204)
occ5FRAC	1.176	0.336	1.183	0.324	-0.671	-0.115
	(0.993)	(1.092)	(1.065)	(1.048)	(1.111)	(1.131)
occ6FRAC	0.778	0.421	0.588	0.161	0.012	0.084
	(0.832)	(0.839)	(0.839)	(0.897)	(0.897)	(0.896)
occ71FRAC	-0.238	0.175	-0.470	1.794	2.779	2.363
	(1.772)	(1.794)	(1.786)	(1.913)	(1.949)	(1.981)
occ72FRAC	-4.109***	-5.062***	-4.262***	-3.720**	-4.989***	-4.744***
	(1.507)	(1.563)	(1.539)	(1.640)	(1.657)	(1.661)
occ8FRAC	-0.938	-0.625	-0.566	-0.195	0.316	0.475
	(0.830)	(0.829)	(0.836)	(0.936)	(0.940)	(0.954)
occ9FRAC	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Lag1 Log Patent PC	0.054***	0.050***	0.054***	0.034***	0.030***	0.031***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Lag2. Log Patent PC	0.023**	0.019*	0.021*	0.011	0.008	0.009
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
Observations	10,485	10,485	10,485	10,485	10,485	10,485
R-squared Overall	0.408	0.389	0.374	0.228	0.338	0.331
R-squared Within	0.254	0.258	0.258	0.272	0.274	0.276
Fixed Effects	Year × Division	Year × Division	Year × Division	Year × State	Year × State	Year × State
County FE	YES	YES	YES	YES	YES	YES

Note: This table summarizes the results of our IV model using transportation network instruments. These results show the effects of a county's ancestral culture and historical traits such as obedience, thrift, trust, and history of technological adoption on the log of that county's patent filing when instrumented based on a county's ancestry predicted by access to trade networks. Models 1–3 control for Census Division and Year *fixed effects. Models 4–6 control for state and year fixed effects. All models have the same controls used in the economic model. Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$*

All these findings support the idea that the relationships shown between our cultural variables and innovation rates are not the result of unobserved time-variant endogeneity. The coefficients remain significant at conventional levels across both instrumental variable specifications. We once again controlled for economic conditions to strengthen the validity of our IV.

5.2 Education Controls

What are the mechanisms by which these cultural traits might affect innovation rates? These traits may affect innovation through a few obvious mechanisms or multiple obscure mechanisms. The most obvious mechanism is through education. Cultures of trust, individualism (low obedience), thrift, and openness to technology may emphasize investing in education and giving people the human capital necessary to spur innovation. Culture can also affect innovation in broader and more intangible ways, such as community and family approval for novel ways of thinking and inventing. Fulford, Petkov, and Schiantarelli (2020) demonstrated that ancestral traits such as ancestry GDP and trust lead to an increase in education rates in U.S. counties.

What we do here is run a new version of the fixed effects model used throughout this paper:

$$Yct = \emptyset c + \emptyset ct + \alpha ct + \beta Xct + \delta Act + \mathcal{E}$$

where Yct is log patent per capita of county c at time t. $\emptyset ct$ controls for census division/state and year effects. βXct represents the various cultural measures used in the model. The difference is that we now include controls for county years of education developed by Fulford, Petkov, and Schiantarelli (2020) in δAct. The education varriables comes from the IPUMS census records and it is a combined measure of literacy rates for the first part of the century and years of education for the latter part. This is done along with the previous controls for GDP, population, and occupation.

By controlling for education, we control for the most obvious and easily controllable mechanism by which culture could affect innovation rates. Cultural traits have been associated with higher levels of education. Fulford, Petkov, and Schiantarelli (2020) showed that cultural traits explain variation in educational attainment across U.S. counties. More broadly, we could expect that cultural attitudes that make one more open to new ideas and a willingness to save and invest in them would also translate into valuing education. If our cultural variables remain significant when controlling for local differences in education, this suggests that our cultural variables could operate through mechanisms other than education.

Table 11: Cultural Traits and Innovation with Education Controls

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Thrift	11.177***				7.822***			
	(2.334)				(2.573)			
Obedience		-5.746***				-4.953***		
		(1.031)				(1.158)		
Trust			6.714***				7.261***	
			(1.589)				(1.824)	
Tech				3.754***				3.553***
				(0.748)				(0.844)
Log Income PC	0.736***	0.706***	0.719***	0.709***	1.112***	1.053***	1.051***	1.051***
	(0.132)	(0.132)	(0.132)	(0.132)	(0.160)	(0.161)	(0.161)	(0.161)
Education	0.324***	0.279***	0.273***	0.267***	0.427***	0.389***	0.383***	0.388***
	(0.056)	(0.056)	(0.057)	(0.057)	(0.065)	(0.066)	(0.066)	(0.066)
Log population	0.408***	0.436***	0.470***	0.481***	0.436***	0.442***	0.464***	0.473***
	(0.068)	(0.067)	(0.067)	(0.067)	(0.079)	(0.078)	(0.078)	(0.078)
Density	-0.130**	-0.104*	-0.112*	-0.113**	-0.116**	-0.097*	-0.097*	-0.102*
	(0.057)	(0.057)	(0.057)	(0.057)	(0.058)	(0.058)	(0.058)	(0.058)
occ0FRAC	6.638***	7.239***	7.228***	7.332***	6.182***	6.590***	6.580***	6.703***
	(1.321)	(1.321)	(1.323)	(1.323)	(1.392)	(1.393)	(1.394)	(1.395)
occ1FRAC	-3.526***	-3.735***	-3.883***	-3.998***	-3.803***	-3.890***	-4.076***	-4.165***
	(0.793)	(0.791)	(0.792)	(0.792)	(0.855)	(0.852)	(0.852)	(0.852)
occ2FRAC	0.403	0.266	0.345	0.375	1.176	1.044	1.140	1.208
	(1.638)	(1.638)	(1.639)	(1.638)	(1.752)	(1.751)	(1.751)	(1.750)
occ3FRAC	3.933***	3.305**	3.412**	3.244**	3.770***	3.306**	3.219**	3.136**
	(1.324)	(1.328)	(1.330)	(1.331)	(1.408)	(1.409)	(1.411)	(1.412)
occ4FRAC	1.240	0.365	0.592	0.355	0.565	-0.043	0.039	-0.146
	(1.880)	(1.888)	(1.891)	(1.892)	(1.992)	(2.000)	(1.999)	(2.002)
occ5FRAC	1.052	0.694	0.924	0.873	0.824	0.507	0.610	0.652
	(0.898)	(0.905)	(0.904)	(0.902)	(0.947)	(0.952)	(0.950)	(0.948)
occ6FRAC	0.868	0.744	0.797	0.763	0.471	0.428	0.443	0.398
	(0.794)	(0.795)	(0.795)	(0.795)	(0.856)	(0.856)	(0.856)	(0.856)
occ71FRAC	-0.105	0.042	-0.147	-0.013	1.548	1.829	1.779	1.795
	(1.678)	(1.678)	(1.679)	(1.679)	(1.813)	(1.814)	(1.814)	(1.814)
occ72FRAC	-2.917**	-3.334**	-3.174**	-3.329**	-2.655*	-2.970*	-2.983*	-3.029*
	(1.384)	(1.387)	(1.388)	(1.388)	(1.516)	(1.515)	(1.516)	(1.516)
occ8FRAC	-0.122	0.024	0.054	0.058	0.459	0.624	0.690	0.645
	(0.778)	(0.778)	(0.779)	(0.778)	(0.877)	(0.877)	(0.878)	(0.878)
occ9FRAC	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Lag1 Log PatentsPC	0.051***	0.049***	0.050***	0.050***	0.031***	0.030***	0.030***	0.030***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Lag2 Log. PatentsPC	0.031***	0.030***	0.030***	0.030***	0.021*	0.020*	0.021*	0.020*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	11,496	11,496	11,496	11,496	11,496	11,496	11,496	11,496
R-squared Overall	0.269	0.336	0.338	0.333	0.436	0.444	0.437	0.424
R-squared Within	0.257	0.258	0.257	0.258	0.277	0.278	0.278	0.278
Fixed Effects	Year × Division	Year × Division	Year × Division	Year × Division	Year × State	Year × State	Year × State	Year × State
County FE	YES	YES	YES	YES	YES	YES	YES	YES

*Note: This table summarizes our education model results. This model is identical to the economic model but also adds a control for the average number of years of education of people in the county. Models 1–4 control for Census Division and Year fixed effects. Models 5–8 control for state and year fixed effects. All models include county fixed effects and occupation controls. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01*

The cultural values are large and significant at the 0.01 level in their relation to innovation even after controlling for education as a potential mechanism by which they could affect patent rates. In these models, education is also shown to have a strong association with innovation rates, significant at the 0.01 level across all specifications. The significance of education is similar to log income per capita and most of our cultural variables.

Overall, these results are consistent with the theory that these cultural traits affect innovation. The relationship between these cultural traits and innovation is so significant that controlling for obvious mechanisms such as education only minimally affects their coefficients and statistical significance. In other words, even if culture is restricted from influencing local income, local occupation, and education it still operates through society and influences innovation rates. In every specification, cultural traits are similar in importance to explaining innovation as economic growth and education.

6 Conclusion

Cultural traits have been shown to be persistent and important determinants of a variety of economic factors. Innovation is the most important driver of economic growth, so cultural traits that boost or lower innovation should be given particular attention by researchers and policymakers. The United States provides an opportunity to explore the effects that different cultural traits have on innovation when all the cultures are operating under a broadly similar institutional framework. In this paper, we analyzed patent data from U.S. counties and ancestral data from the census to observe how changing the ancestral cultural characteristics of counties affected innovation rates.

The results demonstrated that counties whose ancestries were less obedient, more trusting, more thrifty, and had a history of technological usage had higher innovation rates between 1870 and 2000. These results were robust to a variety of controls, including controls for county income per capita, race, years of education, census division and year fixed effects, and state and year fixed effects. We expanded our robustness checks by using an instrumental variable model to control for potential time-varying endogeneity. We employed both a shift-share instrument and transportation network instrument.

The results were robust to these identification strategies. Our findings contribute to the literature by demonstrating that the relationship between cultural traits and innovation is distinct from and stronger than the relationship between these same traits and general economic development. This suggests that culture may be particularly important for innovative activities rather than just general economic output.

Future work on this topic should attempt to isolate the mechanisms by which these traits affect innovation. In this paper, we demonstrated evidence that is consistent with the theory that these traits operate through more than simple education channels. Future papers that include biographical information of the inventors should attempt to control for individual characteristics and determine whether being born in a county with higher scores on these cultural traits is associated with more innovation at the individual level.

Additionally, future research could explore the specific types of patents being filed to determine whether certain cultural traits are associated with particular types of innovation. This could further help identify whether the effects we observe are driven by immigrants bringing specific technical knowledge from their home countries or by more general cultural attitudes toward innovation and risk-taking.

The policy implications of our findings are significant. Unlike institutions, which can be changed relatively quickly, cultural traits appear to have deep roots and change slowly over generations. This suggests that the innovative capacity of regions may be influenced by long-term demographic and cultural factors that are difficult to modify through short-term policy interventions. However, understanding these cultural drivers of innovation can help policymakers design more effective strategies for promoting innovation by recognizing and working with existing cultural strengths rather than against them.

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